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Dear Esteemed Readers, Authors, and Colleagues,

I hope this letter finds you in good health and high spirits. It is my distinct pleasure to address you as the Editor-in-Chief of Integrative Omics and Applied Biotechnology (IIOAB) Journal, a multidisciplinary scientific journal that has always placed a profound emphasis on nurturing the involvement of young scientists and championing the significance of an interdisciplinary approach.

At Integrative Omics and Applied Biotechnology (IIOAB) Journal, we firmly believe in the transformative power of science and innovation, and we recognize that it is the vigor and enthusiasm of young minds that often drive the most groundbreaking discoveries. We actively encourage students, early-career researchers, and scientists to submit their work and engage in meaningful discourse within the pages of our journal. We take pride in providing a platform for these emerging researchers to share their novel ideas and findings with the broader scientific community.

In today's rapidly evolving scientific landscape, it is increasingly evident that the challenges we face require a collaborative and interdisciplinary approach. The most complex problems demand a diverse set of perspectives and expertise. Integrative Omics and Applied Biotechnology (IIOAB) Journal has consistently promoted and celebrated this multidisciplinary ethos. We believe that by crossing traditional disciplinary boundaries, we can unlock new avenues for discovery, innovation, and progress. This philosophy has been at the heart of our journal's mission, and we remain dedicated to publishing research that exemplifies the power of interdisciplinary collaboration.

Our journal continues to serve as a hub for knowledge exchange, providing a platform for researchers from various fields to come together and share their insights, experiences, and research outcomes. The collaborative spirit within our community is truly inspiring, and I am immensely proud of the role that IIOAB journal plays in fostering such partnerships.

As we move forward, I encourage each and every one of you to continue supporting our mission. Whether you are a seasoned researcher, a young scientist embarking on your career, or a reader with a thirst for knowledge, your involvement in our journal is invaluable. By working together and embracing interdisciplinary perspectives, we can address the most pressing challenges facing humanity, from climate change and public health to technological advancements and social issues.

I would like to extend my gratitude to our authors, reviewers, editorial board members, and readers for their unwavering support. Your dedication is what makes IIOAB Journal the thriving scientific community it is today. Together, we will continue to explore the frontiers of knowledge and pioneer new approaches to solving the world's most complex problems.

Thank you for being a part of our journey, and for your commitment to advancing science through the pages of IIOAB Journal.

Yours sincerely,

Vasco Azevedo

Vasco Azevedo, Editor-in-Chief
Integrative Omics and Applied Biotechnology
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ARTICLE

IOT AND CLOUD BASED BRAIN TUMOR DETECTION AND CLASSIFICATION MODEL USING OPTIMAL DENSELY CONNECTED CONVOLUTIONAL NETWORKS

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ABSTRACT

In recent times, the advanced developments in the field of Internet of Things (IoT) and cloud computing find helpful in the healthcare sector to assist doctors as well as patients. This paper presents a new IoT and cloud-based Brain Tumor detection model using Optimal Dense Convolutional Network (DenseNet), called the ODEN model. The proposed ODEN model involves various sub-processes namely image acquisition, preprocessing, K-means based segmentation, feature extraction, and multiclass support vector machine (M-SVM) based classification and K-means clustering based segmentation. Here, feature extraction takes place by the use of the hyperparameter tuned DenseNet (PTDEN) model; where the tuning of hyper parameters takes place using Orthogonal Array Tuning Method (OATM). Once the input MRI images are captured by the IoT devices, it will be transmitted to the cloud where the actual diagnosis process takes place, i.e. ODEN model will be executed to determine the existence of disease. The proposed ODEN model is tested against a benchmark BRATS challenge dataset. A brief set of experimental analysis ensured the effective performance of the proposed model under several aspects.

KEY WORDS
IoT, Cloud, Healthcare, Hyper Parameter Tuning, Deep Learning, BRATS

INTRODUCTION

Rapid development in data as well as MEMS method tends to introduce the internet of things (IoT) which enables people, things, information, and a temporary atmosphere which communicates with each other [1]. Various domains exploit IoT while collecting data from modern platforms such as transports, homes, clinics, cities, etc. Due to the faster growth of IoT-based medical tools and sensors, many developers focus on this application [2]. The increase in costly medications and the existence of different defects, it requires the evolution of healthcare from the point of hospital centric structure to patient-centric structure. To manage the diseases, there is a requirement of establishing a model that exploits the ubiquitous sensing potentials of IoT devices to predict the possibilities of disease. IoT and cloud computing (CC) are interconnected with each other and this combination would be more applicable to observe the defected patients residing in remote areas by providing logical support from physicians as well as caretaking volunteers [3].

Here, IoT can be managed by using virtual unconstrained qualities as well as sources available in CC to handle the corresponding technical constraints such as storage, processing, power, and so on. Simultaneously, CC provides the merits of IoT by upgrading its value to react with real-time applications to offer various services from distributed as well as dynamic manner. Therefore, IoT and CC could be applied to model fresh domains and facilities in medicinal fields [4]. Then, the Internet of Medical Things (IoMT) is combined with IoT and healthcare, which has been deployed recently in the healthcare sector [5]. From massive scale of IoT, the duties of big-data explanatory as well as CC are familiar. [6] proposed a backend structure which allows cognitive services in the medicinal field that states that CC must not be identical, and provides clinical data transfer as well as cloud service layers.

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The unusual development of cells is created by can be formed by unmanageable cell division within the human brain. Such types of developing cells could influence the normal functioning of the brain and other healthy tissue of the brain is affected by abnormal cells. It is named a brain tumor. This tumor causes human death and sometimes affects the functions of body parts like the liver, and several other problems might occur. Generally, the tumor is classified into 2 categories: Benign and Malignant tumor. The initial tumor named as benign could not be distributed immediately where the nearby cells are not affected, whereas a malignant tumor is a type of cancerous one which leads directly to the death of a patient and affects normal tissues of brain. Consequently, the Magnetic Resonance Imaging (MRI) scanning technique is proposed to find the tumor present in the human brain at the initial stage to eliminate human death. This MRI model is a specialized one to identify the tumor which is an optimal cancer monitoring process when compared with Computerized Tomography (CT). From this model, it can identify the size, structure, functioning as well as the location of brain tumor to diagnose the disease. Generally, MRI technique ensures the tissue contrast by applying a process of normalization which produces a completely flexible system for imaging feature structures to classify the benign as well as malignant tumors.

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Now a days, brain tumor works have become a well-known section in the educational sector. Typically, a cancerous tumor classification is the division of tumor area [7]. Brain is placed in the middle of the nervous system. Hence, a tumor that emerges in the brain causes life-threatening ailments, and, a solution

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to this problem is the primary diagnosis. Features applied for classifying the brain tumors are most essential to determine the class of tumor. Recently, Convolutional Neural Network (CNN) model is an optimal one in extracting features [8]. A study on segmenting brain tumor states that [9] presented a 2-way CNN that considers the features of pixel and corresponding pixels. [10] divided brain tumors to estimate the density, density variations, adjacent as well as wavelet procedures of isolated brain tumors and undergoes classification with the application of random forest (RF) classifier model. [11] acquired the properties of tumor area by applying density histogram, gray level co-occurrence matrix (GLCM) as well as bag-of-words (BoW) models, and improved brain tumor accuracy. [12] showed an accurate analyzing function of capsule networks (CapsNets) approach to classify the brain tumor. Nowadays, deep learning (DL) has been evolved in contrast with traditional image processing models. It is composed of several works that denote the quality of DL techniques to the classical approach [13]. When related to the previous image processing, most benefits of DL method are that, it removes the requirement for feature extraction. CNN framework depicts the qualified work to classify image and pattern recognition when compared with existing techniques. It has attained the best results in image analysis, segmentation, and recognition, and applied image as well as video analysis.

This paper presents a new IoT and cloud based BT detection model using Optimal Dense Convolutional Network (DenseNet), called the ODEN model. The proposed ODEN model involves various subprocesses namely image acquisition, preprocessing, feature extraction, and multiclass support vector machine (M-SVM) based classification and K-means clustering based segmentation. Here, feature extraction takes place by the use of hyper parameter tuned DenseNet (PTDEN) model; where tuning of hyper parameters takes place using Orthogonal Array Tuning Method (OATM). The proposed ODEN model finds useful for the remote patients to receive the diagnosis results instantly. It will reduce the labor and allows access to data globally due to the storage of data in cloud environment.

MATERIALS AND METHODS

The proposed ODEN model operates on different stages, as shown in [Fig. 1]. Initially, the IoT devices are used to capture the MRI brain image of the patient. Then, preprocessing of the gathered image takes place in two ways, namely median filtering (MF) based noise removal and contrast enhancement. Afterwards, preprocessed image undergoes feature extraction process using PTDEN model. Then, the extracted features are provided into an M-SVM classifier, which classifies the input image into a respective class (either benign or malignant). Along with that, the classified image will be segmented by the use of K-means clustering technique, which group the areas into diseased/non-diseased portions and correctly mark the tumor region. The use of the K-means technique helps to precisely mark the affected tumor area which finds it useful for the doctors to start proper treatment.

Preprocessing

Then, the preprocessing of the gathered image takes place in two ways, namely MF based noise removal and contrast enhancement.

Feature extraction using PTDEN model

Here, feature extraction takes place by the use of PTDEN model; where tuning of hyper parameters takes place using OATM.

DenseNet Model

Assume an individual image $\mathbf{x}_0$ which has been provided with the help of convolutional network. This system is composed with $\mathbb{L}$ layers, where every layer executes a non-linear transformation $H_\ell(\cdot)$, where ℓ denotes the layer [14]. $H_\ell(\cdot)$ could be a composite function of task namely, Batch Normalization (BN), Rectified Linear Units (ReLU), Pooling, or Convolution (Conv). Then, the output is presented as ℓ^{th} layer as $\mathbf{X}\ell$. ResNets. Conventional feed-forward networks link the result of ℓth layer as input to $(\ell+1)^{th}$ layer, that tends to develop transition layer: $\mathbf{x}_\ell = H_\ell(\mathbf{x}_{\ell-1})$.

ResNets includes a skip-connection which ignores non-linear transformations using an identity function:

$$\mathbf{x}_\ell = H_\ell(\mathbf{x}_{\ell-1}) + \mathbf{x}_{\ell-1}. \quad (1)$$

The merit of ResNets is that a gradient could be passed by an identity function from the secondary layer to primary one. But, identity function as well as result of H_ℓ has been integrated, that impedes the data flow of a system.

PT using OATM model

Here, it has been projected with Orthogonal Array Tuning Method emerged from the fundamental strategy of OATM. Though, DL techniques are capable of attaining optimized result in several works of literature, simulating the hyper-parameters such as count of layers, numbers of nodes in every layer as well as

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learning rate which are time-consuming and based on customer expertise. In OATM, these hyper-parameters are considered as factors and diverse values of all hyper-parameter are named as levels. The principle is given as follows.

Step 1: Construct an FL (factor-level) table. Compute the factor that has to be tuned and count of levels for all factors. This level has to be estimated by using experience as well as study. Furthermore, every factor has equal number of values.
Step 2: Build an OATM. Hence, the created table must follow the fundamental composition rules. It demonstrates a few generally used tables. The OATM model is termed as L_M (h^k)) that is comprised of k factors, h levels, and M rows.
Step 3: Execute the application with hyper-parameters obtained by OATM.
Step 4: Range prediction. It is the major step of OATM. According to the simulation outcome at existing level, range analysis model has been applied for examining the outcome as well as report the significant steps. A dimension of a factor can be described by its own influence of outcome derived from the experiments. It has to be pointed out that, range analysis can optimize very factor and integrates optimized levels that refers that optimized hyper-parameter concatenation has no limitation to the previous OATM model.
Step 5: Execute the function with optimized hyper-parameters settings.

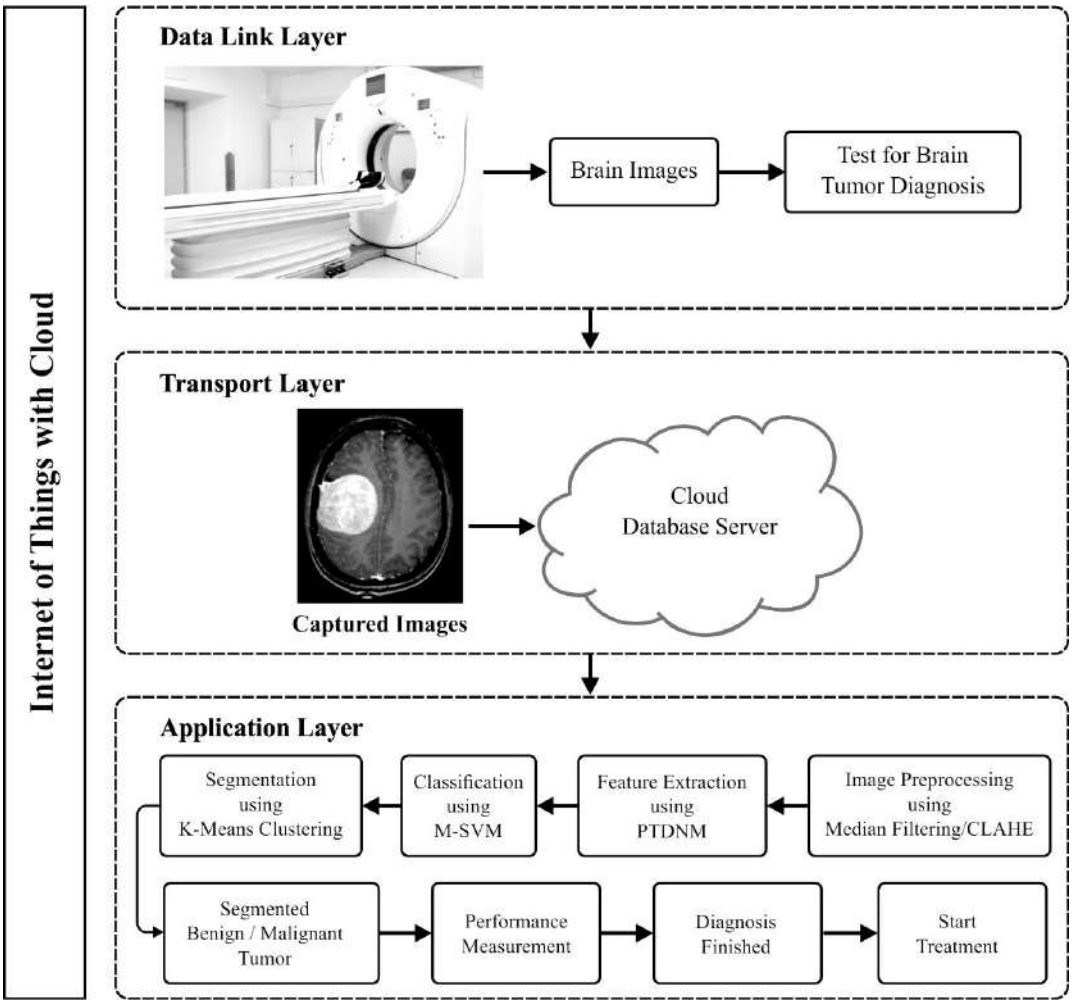

Fig. 1: Overall Process of Proposed ODEN Model

M-SVM based classification

The classification applied here process with the selected features which have been provided to the M-SVM (Multiclass-SVM) classification model to divide the MRI image into usual and unusual. Generally, SVM is a binary classification which makes use of 2 class classifying complexities. In case of M-SVM, SVM could not be applied directly as it has various difficulties. In order to eliminate these complexities, SVM is combined with a multi-class classifier. From the supervised learning model, a group of hyperplanes is employed to classify 6 classes of data from an MRI image. The support vectors are induced as input data elements which define the boundaries, as well as decision boundaries, are found from training data. SVM provides rapid development and systematic neural networks (NN). It is based on decision planes. A decision plane

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could divide a collection of items with different membership classes. The SVM application has 2 basic steps: training as well as testing of image.

A 2-class classification model is developed on the basis of feature vector $\Phi(\bar{a},b)$ where these vectors could be obtained from the pair which has input features of brain. From this classification, a classifier finds a class at the time of testing and estimated as given,

$$b = argmax_b \bar{w}^T \Phi(\bar{a},b) \quad (2)$$

While a training process is conducted, a margin could be developed a gap among a value for accurate class and neighboring class. Hence, a quadratic program (QP) formulation is provided in the following.

$$\forall_i \forall_b \neq b_i \bar{w}^T \Phi(\bar{a}_i,b_i) - \bar{w}^T \Phi(\bar{a}_i,b_i) \geq 1 - \xi_i \quad (3)$$

This type of general technique is improved to offer a multiclass formulation for diverse classification. Therefore, MRI image is divided by using M-SVM classification into the normal or anomalous image on the basis of chosen features of the tumor. In case of abnormal MRI image, then it represents that the brain is affected by a tumor.

K-means clustering based segmentation

In order to process image segmentation, the K-means clustering model has been initialized. Clustering is defined as the process of collecting images as clusters. The defected regions filtered from MRI image by using clustering technique. This method is used on a massive portion of the HSV technique of background eliminated image. Here, the pure color exists in hue element which does not consist of data such as brightness or darkness. According to the histogram of hue elements, centroid measure is inputted to produce accurate blocks to solve the randomness issue. Furthermore, in the affected region, extract the irrelevant part and eliminate them. In a background avoided image for a hue component, a histogram has been developed. Later, from the developed histogram hue rates as well as number of all bins are obtained. Based on the histogram and defected image specific threshold rate has been identified to distinguish normal and abnormal portions. From 2 different arrays, the hue measures of usual as well as affected parts are isolated.

Dataset

The proposed ODEN model has been tested using a freely accessible BRATS dataset [15]. The dataset holds a set of three sub datasets namely Training, Challenge and Leader board. The former one holds a total of 20 High Grade Tumor (HGT) images and 10 Low Grade Tumor (LGT) images along with its ground truth images. The second one has a total of 10 HGT images with the respective ground truth images. The third one has a total of 21 HGT images and 4 LGT images with its ground truth images.

RESULTS AND DISCUSSION

Fig. 2 shows the attained confusion matrix by the proposed ODEN model against the applied dataset. The figure clearly stated that the ODEN model has properly classified a set of 79 images under benign type and a total of 80 images under malignant type.

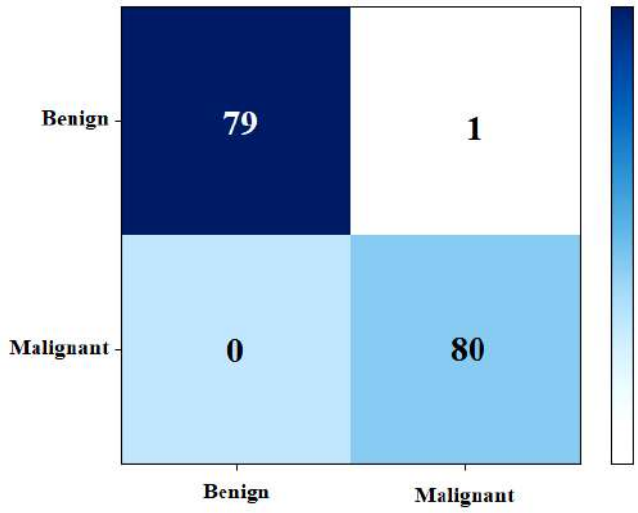

Fig. 2: Confusion Matrix of Proposed ODEN Model

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Fig. 3 visualizes the results attained by the ODEN model on the tested set of images. [Fig. 3a] shows the set of input images and the corresponding pre-processed images are provided in [Fig. 3b]. Next, [Fig. 3c] shows the classified set of images and [Fig. 3d] clearly pointed out the tumor portion present in the image.

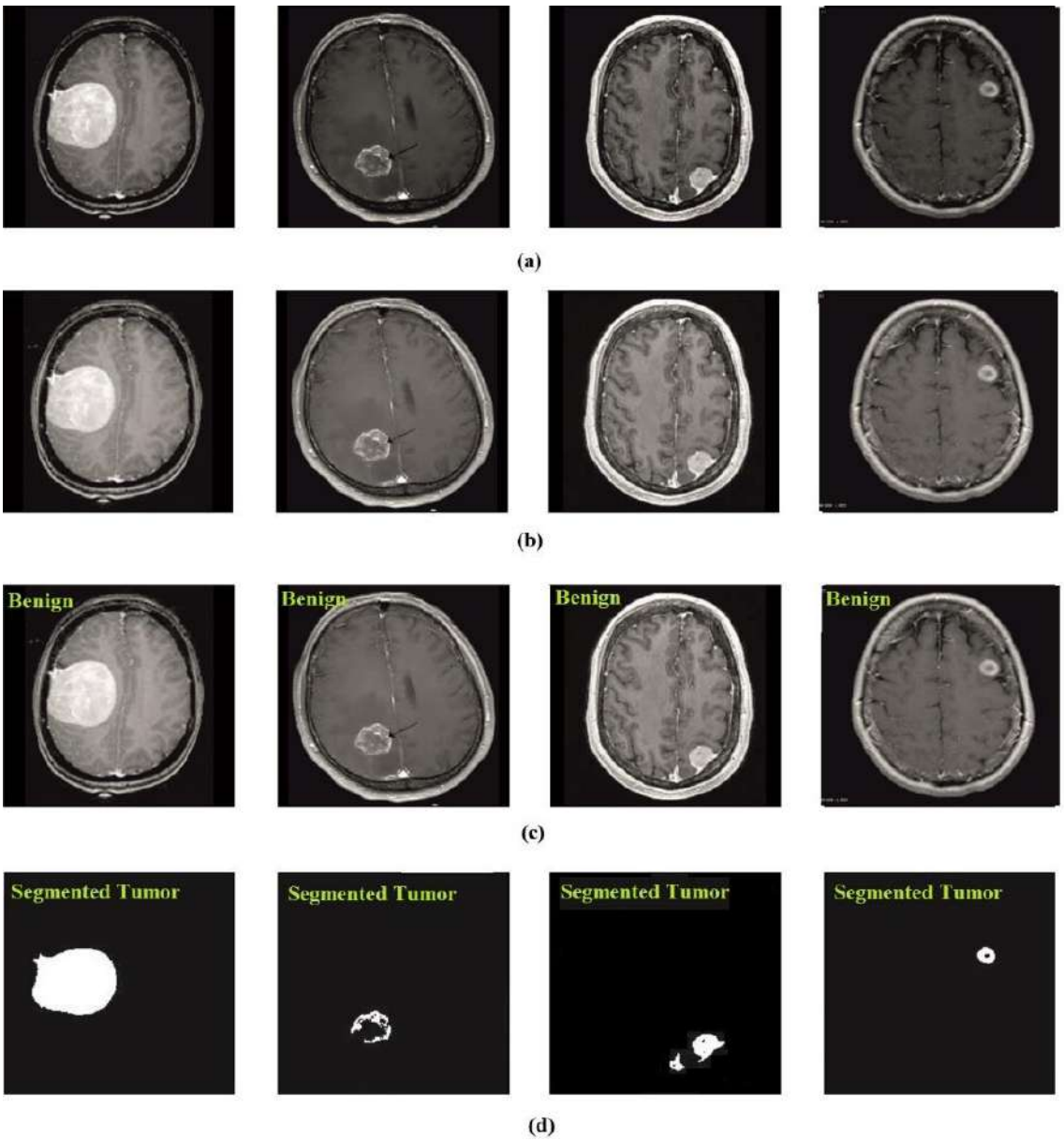

Fig. 3: a. Original Images b. Preprocessed Images c. Classified Images d. Segmented Images

Fig. 4 illustrates the accuracy determination of various modules on identical set of instant images used. It is obvious that the RBF SVM method is worse when compared with other ones that reached less accuracy rate of 89.88%. Next, the NS-EMFSE+CNN+KNN technique performs better and attained an accuracy measure of 90.62%. On the other hand, the CNN as well as MM-DCNN an approach has shown a similar outcome with the accuracy rate of 93.30%. Then, a near optimized outcome is provided by AS-CNN and DT methodologies with maximum accuracy rates of 94.60% and 94.95% correspondingly. Simultaneously, a Modified AdaBoost, NS-EMFSE+CNN+SVM as well as Poly SVM frameworks have depicted a manageable and closer accuracy of 95.90%, 95.62% and 96.18% respectively. Followed by, the ANFIS method implements a better performance with an accuracy of 96.40%. Concurrently, a little higher accuracy measure of 98.74% is obtained from Linear SVM approach. Likewise, the D-CNN technology attained a good accuracy rate of 98.07%. Consequently, the presented ODEN technique demonstrated a best final outcome by reaching qualified accuracy measure of 99.37%.

By looking into the above-mentioned tables and figures, it is evident that the proposed ODEN model has offered superior performance by attaining a maximum sensitivity of 100%, specificity of 98.77% and accuracy of 99.37% respectively. These values clearly portrayed the effectiveness of the ODEN model on the detection and classification of MRI brain images.

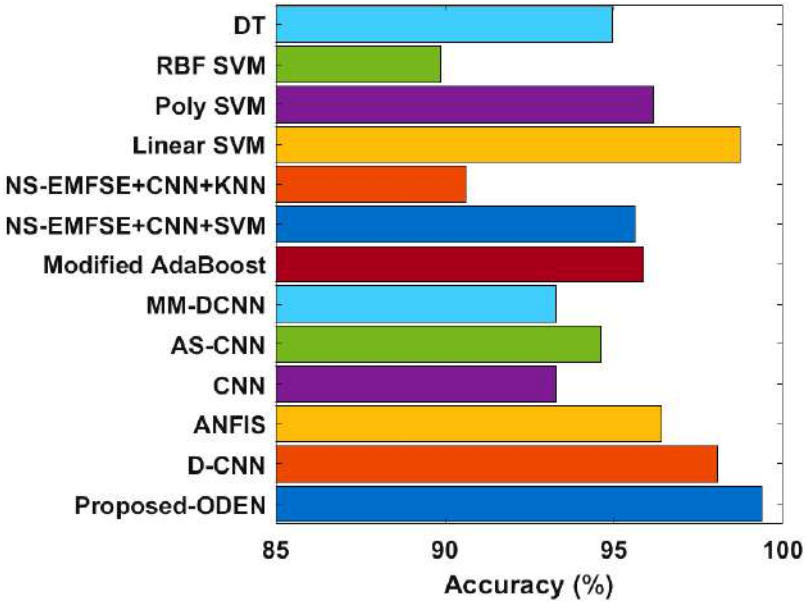

Fig. 4: Accuracy analysis of diverse models

CONCLUSION

This paper has presented a new IoT and cloud based BT detection model using ODEN model, which involves various sub processes namely image acquisition, preprocessing, feature extraction and M-SVM based classification and K-means clustering based segmentation. Here, feature extraction takes place by the use of PTDEN model; where tuning of hyper parameters takes place using OATM. The proposed ODEN model finds useful for the remote patients to receive the diagnosis results instantly. It will reduce the labor and allows access to data globally due to the storage of data in the cloud environment. It is evident that the proposed ODEN model has offered superior performance by attaining a maximum sensitivity of 100%, specificity of 98.77%, and accuracy of 99.37% respectively. These values portrayed the effectiveness of the ODEN model on the detection and classification of MRI brain images.

CONFLICT OF INTEREST
There is no conflict of interest.

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ARTICLE

ANALYSIS OF POSITIVE IMPACT OF LOCKDOWN ON SKILLS ACQUISITION USING ONLINE COLLABORATION TOOLS

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ABSTRACT

In recent days, COVID-19 has affected economical, psychological, and societal parameters. During Lockdown, People were forced to stay at home for a long period as never before. During this scenario, the only medium to communicate with each other was virtual platforms such as collaborating apps /tool etc. Apart from leisure activities, people have utilized this time to enhance their existing skills either willingly or forcefully. The focus of the present paper is to analyze the positive impact of Lockdown on the common people in terms of their skills enhancement. A survey was conducted in the NCR region where Lockdown was strictly imposed. Percentage analysis and Chi-Square test were employed to analyze the data. In the paper, willingness to learn new tools, types of skills learnt, selection of a tool and most used feature of a tool have been described on the basis of statistical results. The findings have statistically proven that people have learnt new technology via using new tools. Furthermore, statistical tests were employed to gain insight about association of selection of tools with gender and job status. No significant association was found among gender and selection of tools. In contrast, a significant association was found between selection of collaboration tools and respondents' job status. Observations on how common people have utilized their time to learn new skills-be it a technical or non-technical have been discussed thoroughly to achieve the objectives of study.

KEY WORDS
Communication/ Collaboration Tools, COVID -19, Lockdown, Digitization, Tele-communication, Skill Enhancement

INTRODUCTION

COVID-19 took over the world as a pandemic with devastating effect which no government and citizens had ever thought off [1]. Among four lockdowns in India, the first two were more strictly imposed and common people were not allowed to even move out of the houses [2]. People were forced to stay at home and handle all their household and official activities from their places [3]. They had opted different modes of communicating and collaborating with each other in which technology and collaborating tools have played a vital role [4]. Lockdown was the time when people have thought about highly creative ways to spend their free time. Every person whether willingly, unwillingly or under professional pressure had to learn, whatever was required to survive in their jobs [5]. Skill development without much investment was introduced by many online e- learning platforms. There is a huge impact of COVID 19 on education, 1.2 billion of students globally are no more in the classrooms but are either learning through e-learning mode or in virtual classes with their teachers who are sitting in remote [6,7]. This way of teaching may stay post pandemic also making a shift in the education industry. The surge in software and related platforms shows the quick drift of teaching methodology. Globally it has witnessed a large "Online Movement" in the education industry [9]. UNESCO Institute in Education's reveals that we need to come together not only to address the immediate educational consequences of this unprecedented crisis, but to build up the longer-term resilience of education systems [12]. As rightly said that busy minds will be more pertinent in bearing and sailing through this tough time. More we engage the population in learning mode, whether it is related to technology, self-grooming, physical fitness, home related activities, the less they are inclined towards boredom and anxiety. Free access to such courses and specialization courses has helped a common person to avail knowledge easily [10]. Many organizations have come forward for the students to help them and the society in keeping up the pace with the time, in spite of the odds of pandemic COVID 19 [14,15]. The major loss during COVID 19 is loss of lives because of this pandemic and much worse is what is being faced by old couples [8]. These old people are living in solitude but Impact of technology can surely be seen in the lives of old people as well because they have now learnt new technology as a necessity – may be for digital payment, online banking or asking Siri or an apple phone, Google Home about the home remedy or getting a solution of a problem. They have learnt using video conferencing calls to reach their family members [11]. A report says that nearly two out of every three of the 3.81 billion active social media users are Facebook users, next in line are YouTube, Instagram, WhatsApp, and Twitter [16]. In all these methods of reaching remote people – collaborative tools have definitely played an important role with unique features. As per the comparative study on various collaborating tools - among Zoom, Google Meet, Microsoft Teams, WebEx Meetings and Blue Jeans are the top five popular apps/tools for virtual meetings which are priced differently, user interactivity etc. The collaboration app: Microsoft Teams, has given a tough competition to skype for its more flexible and advanced features [15]. Besides the pressure to learn the technology for professional fitness (work from home); common people have also switched from normal WhatsApp calling to video conference calls, messengers, unused options of social media platforms etc. [12]. The need for finely tuned social and emotional skills have also rapidly grown as this pandemic has also brought cognition problems like uncertainty, psychological pressure, social distancing, lockdown and behavioral issues like precautionary behavior, economic behavior and Nudging behavior [13]. Accompanying the adoption of advanced technologies into the workplace has generated demand for workers with finely tuned social, emotional skills and technical skills. Emotional issues like stress, coping, public trust, isolation, job insecurity, family health, work – life balance have taken a strong toll on everybody's thinking [17, 18]. Developing countries like India, which has huge potential to become the global hub of talented and skilled people, got a chance during this lockdown to enhance and empower

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their skill set through various online portals which are coming a step ahead to help them either free or at subsidized rate [10]. Thus lockdown period has come as s a learning period for a common man and help them in disguise in their skill enhancement.

Purpose of the study

The aim of the study is to examine the positive impact of changed environment due to COVID-19 lockdown on common people in terms of their skills enhancement by using different collaboration tools. The study is proposed to assess types of skills learnt, selection of collaboration tool, most frequent used feature of tools, on the basis of gender and status of employment.

MATERIALS AND METHODS

This study revolves around the respondents of NCR region. To collect the data, a 20-item structured questionnaire (refer web link) was constructed on the basis of secondary data available (Websites, News agencies, Blogs, discussion, webinars, research papers etc.). The questionnaire contains a combination of questions like dichotomous, open and closed ended, five -point Likert scale to make it a strong tool. This structured questionnaire (Google form) was e-mailed to 200 NCR residents. Out of which only 153 respondents have submitted their responses, out of which, 151 fully completed questionnaires in all sense were utilized for analysis of the data. Telephonic interviews were also conducted to gain depth knowledge and insights about the response's selection. Respondents were made assured about data privacy and usage for research purposes. Percentage analysis, Chi-Square test and correlation analysis were employed to examine the data Respondents were chosen from different demographic backgrounds, different profiles (working, non-working), different age groups (kids, teenage, adults and old), skill set (technical, semi technical, and non-technical), areas (rural and urban) and were assured for utilizing their personal information only for research purpose and maintaining secrecy of the data. The responses were analyzed thoroughly on different parameters. Furthermore, a reliability analysis was performed to test the reliability of the scale. For this purpose, Cronbach's alpha coefficients were calculated as 0.727 which is above the criteria of 0.60 and considered acceptable as an indication of scale reliability. The statistical tool SPSS Ver 21.0 has been used to convert the primary data into information. Data has been analyzed descriptively by using pie charts and crosstab frequency table. For Inferential analysis, statistical test such as chi-square test and spearman correlation mean between variables was calculated.

RESULTS

To analyze the drift towards learning of new skills by using technology, results of the present study have been examined on the three basis - Types of skills learnt by respondents, Selection of collaboration tools, Most frequent used feature of tools. The findings are analyzed descriptively, and inferences have been made using statistical test:

Willingness of learning of new tools

To understand the overall responses for question statement on willingness to learning of new technology during lockdown and their expertise on handling new tools and technology, results are presented through pie charts in the [Fig.1].

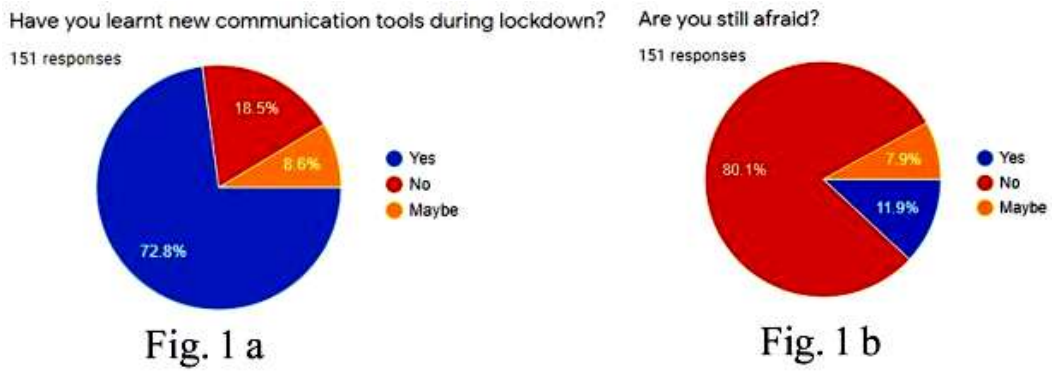

Fig. 1 a Fig. 1 b

Fig. 1: Respondent's Responses

As per the [Fig.1 a], the study reveals that 72.8 % have agreed upon that they had learnt usage of new communication tools during lockdown whereas 18.5 % have agreed upon that they didn't try new communication tools in the period of lockdown while 8.5% respondents are not sure about their learning of new skills in the lockdown. Thus, it can be observed that a large number of respondents have tried to explore new communication tools and gradually adapted and learnt to operate it comfortably.

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Respondents' either learnt new tools willingly or might be forced to operate new tools and gradually learnt it. Few more observation has been highlighted on the basis of these observations – respondents have agreed upon that they were a little afraid of technology earlier and hesitated in using new features of existing technology/tool or opting a completely new advanced tool. But as a necessity when they tried new methods, soon became comfortable using new collaboration tool, now they are less afraid of technology. [Fig.1 b] represents that (80.1%) respondents have accepted that they are no more afraid of technology now, whereas 11.9% respondents said that they are still not comfortable with technology and (7.9%) were not sure about this answer. Such a good percentage of positive response towards not getting afraid of technology also supports the claim of the present study that common people have utilized their lockdown time period in exploring and learning new technology and tools

Types of skills learnt

The prime aim of this research paper is to understand the types of skills learnt by common people who belong to different age groups, gender, educational background, working profiles etc. and to explore the impact of gender and status of employment on the respondent's selection of a particular collaboration tools. The complete percentage analysis of skills learnt on the basis of Gender and Employment Status has been analyzed and presented further. The results propose that some people have enhanced their previously existing skill sets such as- technical and programming skills which were the requirements of their profession but it is surprising to know that many people learnt few new skills which may be their passion earlier and due to lacking of time, they didn't pursue them. Therefore, present study shows that this lockdown period has provided an opportunity to people for fulfillment of their hobbies and passions and of course the professional requirements. To have in depth examination of types of skills learnt by respondents, a detailed analysis by using crosstab on the statistical tool SPSS (VER 21.0) has been presented in the [Table 1]. The observations are bifurcated on the basis of respondent's gender and respondent's status of employment. It has been observed that males have given highest responses to the option of new technology and using new tools (25%) and then to learning new programming skills (22.6%) whereas female have given highest weightage to enhanced education (20.0%) and after opting enhancing education, they opt for refining communication skills (16.3%) and New technology and using new tools (16.3%). Furthermore, observations have been analyzed the basis of status of employment, we observe that working people have chosen new technology and new tools (21.6%) to learn and get adapted with the new technology. The next highest rated skills by working people was learning and enhancing their education (21.3%). Such results also support the information that many digital learning platforms have offered extremely attractive discounts and offered free courses on almost all fields. This shows that people have very well utilized their time and discounted offers to enhance their knowledge in which collaboration tools have played an important role. The study also reveals that respondents has given more weightage to the – learning Digital Payment (38.5%) which reflects that due to Lockdown, digital mode of purchasing and selling forced common people to learn new ways of making digital payments. Respondents have also shown a trend to learn communication skills (26.6%) and personal grooming skills (33.3%) which might be a bane in their career growth earlier.

Table 1: Percentage analysis of skills learnt on the basis of gender and employment status

What have you learnt during Lockdown* Cross tabulation									
		Skills Related to Household Activities	Using New Technology and Tools	Digital Payments	Communication Skills	Personal Grooming Skills	Enhanced Education	Programming Language	Total
Gender	M	5.30%	25%	14.60%	4%	9.30%	19%	22.60%	75
	F	13.20%	16.30%	13.20%	16.30%	7.90%	20.00%	13.10%	76
Total		18.50%	41.30%	27.80%	20.30%	17.20%	39.50%	35.70%	151
Job Status	Working	5.20%	21.60%	16.80%	10.40%	11.70%	21.30%	12.90%	77
	Non-Working	8.10%	19.90%	21.70%	16.20%	21.60%	6.80%	3.10%	74
Total		13.30%	41.50%	38.50%	26.6%	33.30%	28.10%	16.00%	151

Many professional agencies conducted grooming classes and communication enrichment classes and promoted it as well. It captured the common people mindset to improve their communication by utilization free time which they had due to complete lockdown. People who seemed incredibly happy by just posting videos, images and normal chats on WhatsApp suddenly felt the need of seeing their loved ones on video calling of WhatsApp initially singularly and then video conferencing with multiple family members together. The office conference room which was functioning well with just a projector and presentation, during lockdown felt the need to have all its members onboard on the same platform of Microsoft teams sharing their videos, their ideas and carry forward any discussion. As there was no diversion of focus due to a fixed lifestyle during lockdown, people have had much time to utilize it. One of the another skills which is learnt by a good percentage of respondent's is programming languages (15.9 %), these are those people who either by curiosity learnt new programming skills or it was a necessity of their career. This can be observed with positive aspects that in such a terrific environment along with the concern about health and hygiene, bend towards learning new skills by common people is a positive impact of Lockdown. Among all the kind of skills included in the questionnaire, respondents have given maximum responses to new technology and tools (41.3%) and (41.5%) on the basis of gender and employment status respectively

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which shows that this lockdown time has been optimally utilized by people to become technology - friendly and more comfortable in intermingling technology with their daily base utilities, which is a good sign to support digitization - future of India. In the 21st century, where everything is going to be digitized and technology is going to supervise human being -- this is a good initiative which reflect growth of Indian citizens towards digitization Thus we can have another view to see lockdown in reference to positive impact on society - time for themselves, insight to learn something new for own self.

Most common tool used/learnt

As during the lockdown, the only way to communicate was technology and collaboration tools. Before this period, generally Tele communication modes were utilized mainly for reaching each other but during lockdown, requirement of reaching to large group of people at one time forced people to go beyond traditional methods. They explored and tried different platforms to reach and communicate a greater number of people together. Before COVID- 19, people knew only two three methods such as – various features of mobile phones, landlines, WhatsApp calling etc. During lockdown, people were forced to explore new options available for their communication methods, new tools etc. People learnt and understood its working and gradually became comfortable in handling this new way of living. By this way, they became familiar with either new options in an old tools or switched to a new tool with more advanced options. In the present study, respondents were asked to tell about the specific tools which they did use more during the Lockdown period. Authors have included tools in the questionnaire such as - Zoom, Microsoft Teams, Skype, WebEx, Hangouts, any educational websites, Google Meet, WhatsApp etc. Data were analyzed to further know about choices of respondents to use these tools for their official or individual learning purposes. This analyzed data has been represented in the [Table 2] on the basis of respondents' gender and Table 3] on the basis of respondent's status of employment. Data Analysis proposes that amongst the given options, male respondents have been utilizing the Microsoft teams (22.6%) as the most used communication tool during lockdown period which was earlier not even known by many common people as it was the communication platform for corporate (especially IT segments) only. It has been mainly used by either working people or by student's community because of its more formal features in it such as - creating teams, creating channels, adding members, conducting and recording meetings in a more advanced manner with features of audio and video facilities and screen sharing options. Secondly male respondents' have used Zoom (20%) and What App (20%). Whereas Female has rated ZOOM platform (36.8%) as the most frequent used collaboration tool and second place was given to MS Team (22.4%). This might be different as per the types of skills learnt by female respondents' and other requirements. Though Zoom is also an official communication tool, it is very widely used by professional bodies to conduct webinars, grooming classes etc. Because of its very generalized feature and easy link generation of any scheduled meeting, it is used by people by just clicking the link after downloading zoom on their devices. Many people revealed that they used Zoom tool for attending webinars on life skills, grooming classes arranged by professional agencies very frequently during the lockdown. Further, to check the significance of association between the selection of collaboration tool and respondent's gender, Chi- square test has been implied. The [Table 2] shows the Sig (2 tailed) value of the Chi Square test which is greater than o.o5, (0.147> 05), Thus, we can conclude that there is no significant relationship between selection of tool and the gender as (p value > 0.05) at 5 % level of significance; which indicates that there is no statistical evidence which can prove that male and female have chosen different communication tools as per their gender. Thus, the present study does not claim to support the significance of association between gender and selection of a particular collaboration tool.

Table 2: Most Used tools by respondents on the basis of gender

		Which Communication Tool You Used Most						Total	Pearson Chi-Square (Asymp. Sig. 2-sided)
		Microsoft Team	Zoom	Skype	Webex	WhatsApp	Google Meet		
Gender	M	22.6%	20 %	9.3%	13.3%	20 %	14.6%	75	
	F	22.4%	36.8%	7.9%	11.8%	11.8%	9.2%	76	.147
Total		20.5%	28.5%	8.6%	12.6%	15.9%	13.9%	151	

Table 3: Most used tools by respondents on the basis of status of employment

		Which Communication Tool You Used Most						Total	Pearson Chi-Square (Asymp. Sig. 2-sided)
		Microsoft Team	Zoom	Skype	Webex	WhatsApp	Google Meet		
Job Status	Working	29.9%	20.8%	11.7%	15.6%	16.9%	5.2%	77	
	Non Working	10.8%	36.4%	5.4%	9.5%	20.9%	16.9%	74	0.01
Total		20.5%	28.5%	8.6%	12.6%	15.9%	13.9%	151	

Data Analysis on the basis of respondents' status of employment [Table 3] reveals that working people again given highest weightage to MS Team (29.9%) and to Zoom (20.8 %). This might be due to as these two tool offers many advanced features to fulfill professional requirements – be it virtual meeting portals, or more advanced application for mass training, conferences etc. Apart from this, Non- working respondents' have given highest weightage to Zoom (36.4%). The more usage of Zoom may be due to increase in number of virtual classes for kids by schools. Initially almost all these virtual classes were

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conducted on zoom later on schools have been switched to Google Meet and other modes of virtual classes. Next percentage was given to WhatsApp (20. 9%).for non-working respondents' and (16.9%) for working respondents' During lockdown, respondents have agreed that they found what App a very user-friendly App for and they have used its different features such as - Video calling, conference video calling etc. All age groups respondents' have used it because of its easy handling and mobile based software. Though google has added feature of Google meet later but still (16.9%) non- working respondents' opted for Google Meet as well. Thus based on overall analysis, author have observed that MS team and Zoom were most utilized by the working people whereas non – working respondents' have given more positive responses towards zoom and Google Meet. Among rest of tools examined in the present study were almost equally utilized by the respondents.

In addition to this, to check the association between the selection of collaboration tool and respondent's status of employment, Chi – Square test was employed. The [Table 3] shows Pearson Chi-Square value ($\chi 2 = 0.01$) , (0.01< 0,05) which means there is a significant relationship between selection of tool and the status of employment as (p value < 0.05) at 5 % level of significance which indicates that there is a statistical evidence which can prove that selection of collaboration /communication tools is statistically associated with respondent's status of employment. The reason behind this observation may be working respondents' have used such communication tool which satisfies their professional requirements due to advanced official features. Thus, the present study has claimed the significance of association between status of employment and selection of tool.

Most commonly used feature of tools

Another objective of the study was to understand which feature of collaboration/ communication tools was mostly used by people during lockdown. Therefore, author have analyzed observations to examine the most commonly used feature of collaboration tool. Results are presented in the [Table4].

Table 4: Most used feature of collaboration/ communication tools

		Web Conference	Video Conference	Audio Conference	Screen Sharing	Virtual Interaction	Socially collaboration	Total
Gender	M	18.60%	19.00%	9.30%	17.30%	20%	15.60%	75
	F	20.40%	25.80%	14.90%	11.80%	15.80%	11.20%	76
Total		14.90%	25%	19.30%	13.10%	15.30%	12.40%	151
Job Status	Working	25.30%	26.60%	16.30%	15.30%	2.60%	14.60%	75
	Non-Working	2.60%	34.20%	27.60%	o%	6.60%	28.90%	76
Total		13.90%	30.50%	20.50%	6.60%	4.60%	23.80%	151

Author have observed that in total Video conferencing (30.5%) was most used feature by all respondent's in which bifurcation of percentage - female respondents (25.8%) and Male (19.0%) whereas, the working respondents (26.6%) and non-working respondents (34.2 %) shows a bend towards utilization of this feature other than official purposes also. The reason might be - people were forcefully locked in their houses for almost three months. People were not able to meet their family and friends for a longer time. To have a real time feeling of meetings with family members and friends may have encouraged them to use more video conferencing or calls rather than audio calling. Second mostly used feature of communication/collaboration tool by working people is web conferencing (25.3%) and then audio conferencing (16.3%). Also, in total as well, Audio conferencing (20.5%) was used by respondents. The reason for shifting from individual calls to web and audio conference calls might be - in the absence of operating from offices and interacting with many people together to reach out on a decision was missing during lockdown. Therefore, reaching out too many people at same time, this feature of audio conference was widely opted by many team leads. The next most opted application by non – working people was social collaboration (28.9%) and out of total (23.8%) respondents did use socially collaboration features. Thus, these findings reveal that this lockdown period has forced common person to explore new ways to contacting others or due to necessity of office or daily routine, they had to find new methods of execution of task. Persons with different demographic characteristics have had opted different platforms and therefore learnt different skills by using suitable mode of learning as per their requirement and convenience.

Schools which were reverberating with the echoes of the sounds of children asking questions from their teachers started looking for a zoom platform, Google meet where all of them can learn through online mode. It can also be observed that operating mobile applications suddenly became disciples of you tube to cook, to transform their looks, for communication skills. Old people who were confined to age boundaries, have started taking online tutorials not only in their country but across the world through WebEx. Teachers who always were confident to take a class of 100 students together but was afraid to face the camera happily and rather more confidently facing the camera but giving her best shot by being more and better prepared. Nonworking women who were not awfully familiar with the computers and technology had to learn in a hard way as a compulsion to assist their kids for the online classes. Thus, we can conclude from this extensive data analysis of the present study that the lockdown period has been utilized by many

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common people in enhancing their skill sets be it a technical or a non- technical skill. These observations support the objectives of the present paper and can be considered as a positive impact of lockdown on people during such a frightening and serious condition.

CONCLUSION

The results of the study confirmed that People have definitely tried to expand the horizons of their knowledge and have learnt new skills ranging different domains of life during lockdown. To learn new skills, they have learnt to operate new tools/technology and various applications. Though this dreadful time and fear cannot be welcomed but updating knowledge /skills by people can definitely considered as positive impact of lockdown. The study also claims that there is significant association between the type of skills learnt by respondents and gender, but selection of tools was not statistically proven to be associated with gender. A strong association between selection of tools and respondents job status reveals the dependencies on communication/collaboration tools during the lockdown. Before lockdown they may not be computer/technology savvy but after lockdown, they know much more than ever before. So, during this lockdown, though people may or may not know it but surely, they have surpassed the line from un-digitized to a digital world. At last the study concluded that though lockdown was of course very tough time but still, another face of coin says that it has affected our lives in a positive way by changing traditional methods of managing our daily base activities into digitization.

CONFLICT OF INTEREST
There is no conflict of interest.

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FINANCIAL DISCLOSURE
None.

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ARTICLE

MULTIVARIATE REGRESSIVE FULLY RECURRENT NEURAL CLASSIFIER FOR FIRE DETECTION

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ABSTRACT

Background: *Forest fire is a demanding function to identify fire from visual scenes or videos due to substantial dissimilarities in the feature of color, texture, intensity, shapes, and so on. The current fire detection mechanisms are specifically designed by considering all features, but increasing the complexity, which results in low fire detection accuracy or higher error rate.* ***Methods:*** *To attain higher fire detection accuracy and reduce the error rate, a Multivariate Regressive Fully Recurrent Neural Classifier (MR-FRNC) method is presented for forest fire detection using a time series model. Firstly, a Histogram Mean Frame Extraction algorithm based on histogram and mean function is proposed to extract the inherent frame. Then, the fire features are extracted by using the Multivariate Robust Statistical Feature Extraction algorithm. Finally, the classification between features is made using the Multivariate Robust Regressive model, and accordingly, the detection of fire is made accurately with less error rate by applying the Fully Recurrent Neural Classifier.* ***Results:*** *The results illustrate that the MR-FRNC method increases fire detection accuracy by 19% and reduces the false positive rate by 68% as compared to state-of-the-art works.* ***Conclusions:*** *Our algorithm improves fire detection accuracy with minimum complexity. Also, the algorithm has good fire detection performance by testing under various video scenes.*

KEY WORDS
Histogram, Mean Frame Extraction, Multivariate, Regressive, Fully Recurrent Neural Classifier

INTRODUCTION

Forest fire is one of the most important natural agents that change the terrestrial ecosystems in the earth. Fusing raster classification with pixel-based time series was presented in [1] for analyzing the changes observed in the forest using Landsat data at the large-area scale. However, the time consumed in generating the decision tree for random forest generation was found to be higher. A novel radar-based burned area mapping algorithm was designed in [2] based on change detection guided by thermal anomalies. However, the misclassification of the burned area was not reduced and hence the accuracy was found to be compromised.

The remainder of the paper is organized as follows: Related work is presented in detail Section 2. Section III describes the detection of fire regions and describes the proposed MR-FRNC method with a neat diagram and algorithms. Finally, experimental results are discussed in Section 4, while conclusions are drawn in Section 5.

A novel land cover model was developed in [3] using Monte Carlo estimation of nonlinear time-varying parameters for early fire detection. However, accuracy detection was not said to be performed with minimum time complexity. Yet another method using linear regression analysis was designed in [4] using the Burned Area Spectral Mixture Analysis (BASMA) algorithm. A Random Forest classifier was introduced in [5] to calculate class probabilities for all pixels in the time series for detecting the fire. A Continuous Subpixel Monitoring (CSM) technique was introduced in [6] by constructing the random forest regression models. Logistic regression and temporal smoothing were introduced in [7] for fire flame detection in surveillance video. In [8], a computer vision approach for fire-flame detection was used by an early-warning fire monitoring system. A case study of fire reports involving the extraction steps required was detailed in [9]. A cost-effective fire detection method using a convolutional neural network (CNN) for surveillance videos was presented in [10]. Yet another dynamic channel selection algorithm was designed in [11] for CCTV surveillance cameras. In [12], a smoke detection algorithm was designed based on the motion characteristics of smoke and the convolutional neural networks (CNN). Transfer learning using deep neural networks was applied in [13] for detecting side fire data. In [14], a spatial prediction model was designed and hyper parameters were optimized to improve the prediction accuracy. In [15], learning in recurrent neural networks was performed using tangent planes. However, the false positive rate was not considered. To address this issue, in [16], both local and global analyses were carried out for image-based early warning system. Fire detection in the aspect of the dynamical system was presented in [17] using mutual information and multidimensional scaling. A detailed comparison of the fire mapping system called a hazard mapping system was designed in [18] to increase the detection rate. However, with the lack of localization, accuracy with complexity was not addressed. To focus upon on this issue, in [19], a computationally efficient CNN architecture was presented. Rule-based image processing algorithm was designed in [20] for forest fire detection. A real-time dynamic texture recognition method was introduced in [21] for texture recognition of flame with a minimum computational cost. A vision-based method to detect smoke using Deep Convolution Generative Adversarial Neural Networks (DC-GANs) was implemented in [22]. Multiplication-free neural network (AddNet) architecture was designed for forest fire detection in [23]. Aim of the work: To increase the fire detection accuracy with minimum time complexity, Multivariate Regressive Fully Recurrent Neural Classifier (MR-FRNC) is introduced. To reduce the computational complexity involved in fire detection, Histogram Mean Frame Extraction model is used. To reduce the processing time, Multivariate Robust Statistical Feature Extraction (MRS-FE) model is applied. To minimize

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the least absolute error of the forest fire detection, the Multivariate Robust Regressive model employed in the deep learning via polynomial regression. To reduce the complexity and the error, Fully Recurrent Neural Learning Classifier (FRNLC) model is applied.

METHODS

In this section, a Multivariate Regressive Fully Recurrent Neural Classifier (MR-FRNC) for forest fire detection using a time series model with higher accuracy and lesser time complexity is presented. [Fig. 1] shows the flow diagram of the MR-FRNC method.

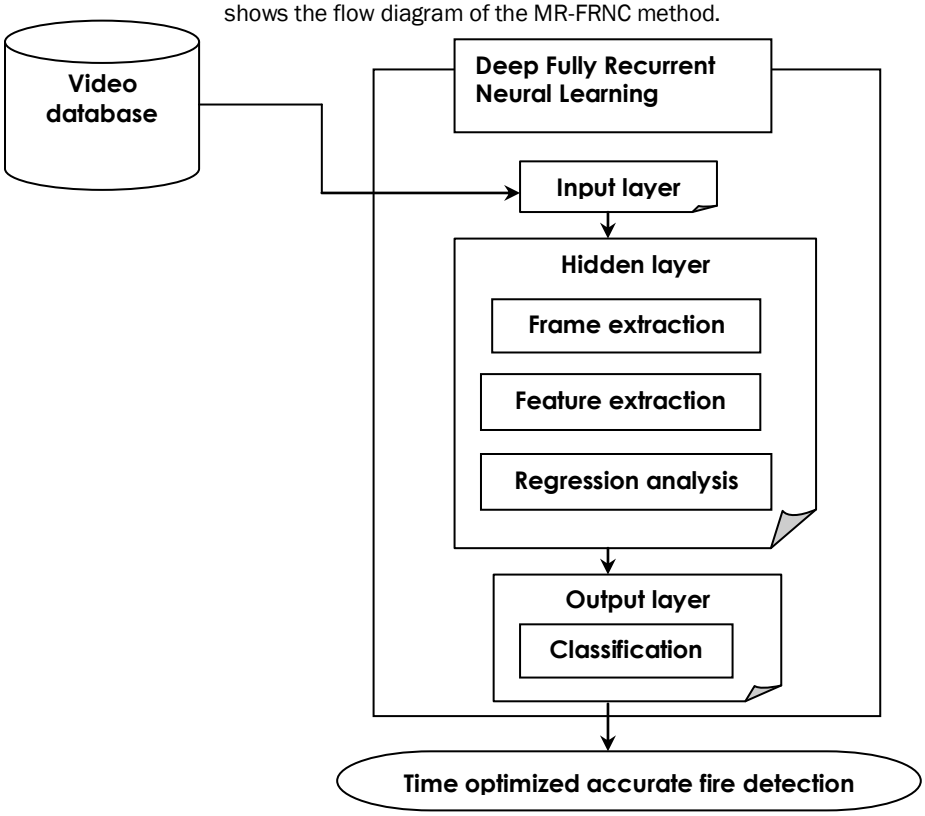

Fig. 1: Flow diagram of MR-FRNC method

As shown in the figure, the Multivariate Regressive Fully Recurrent Neural Classifier (MR-FRNC) method uses three different layers, such as the input layer, three hidden layers, and the output layer for forest fire detection. In the input layer, the video database, FIRESENSE database of videos for flame and smoke detection [21] is used as input. In the input layer, the video sequences are provided as input. Next, forms the three hidden layers, the first hidden layer for frame extraction, the second hidden layer for feature extraction, and the third hidden layer for estimating the relationships between variables (i.e. features). Finally, in the output layer, classification is performed for forest fire detection.

Frame extraction - histogram mean frame extraction model

With the input FIRESENSE database provided as input to acquire the videos for flame and smoke detection, the first step forms the frame extraction. In this work frame extraction from the input, a video database is performed by applying the histogram mean function. The pseudo-code representation of Histogram Mean Frame Extraction is given below.

Input: Video database '$V = V_1, V_2, \ldots, V_n$', Frame '$F = F_1, F_2, \ldots, F_m$'
Output: Inherent frame extraction 'InF'
1: Begin 2: For each video database '$V = V_1, V_2, \ldots, V_n$' with Frame '$F$' 3: Obtain matrix representation using (2) 4: Obtain candidate keyframes using (3) 5: Obtain optimized keyframes using (6) 6: End for 7: Return (inherent frames '$InF = InF_1, InF_2, \ldots, InF_m$') 8: End

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Algorithm 1 Histogram Mean Frame Extraction

As given in the above algorithm, let us assume that the video database consists of 'n' number of sample video files '$V = V_1, V_2, \ldots, V_n$' and each video consists 'm' number of frames is represented as given below.

$$V = V_i = F_1, F_2, \ldots, F_m \quad (1)$$

With the overall frames '$F_1, F_2, \ldots, F_m$' for each video 'V_i', the frames are first obtained by storing the frames of the subsequent videos in matrix representation. This is expressed as given below.

$$V = \begin{bmatrix} V_1F_1 & V_1F_2 & \ldots & V_1F_m \\ V_2F_1 & V_2F_2 & \ldots & V_2F_m \\ \ldots & \ldots & \ldots & \ldots \\ V_nF_1 & V_nF_2 & \ldots & V_nF_m \end{bmatrix} \quad (2)$$

Followed by the matrix representation, the candidate key frames are obtained via the histogram of all frames. This is expressed as given below.

$$CKF = \frac{HIS[V_iF_i]}{n} \quad (3)$$

From the above equation (3), the candidate keyframes 'CKF' are extracted by applying the histogram value of the pixel in a specific location of the video. To obtain the histogram value, first the overall frames 'm' is observed. Then, the sample frame ranges are said to be obtained by measuring the difference between the highest value '$HV[V_iF_i]$' (i.e. highest frame pixel) and the lowest value '$LV[V_iF_i]$' (i.e. lowest frame pixel). This is mathematically expressed as given below.

$$HIS[V_iF_i] = HV[V_iF_i] - LV[V_iF_i] \quad (4)$$

With the obtained candidate keyframes, finally, the optimized keyframes are obtained via a mean function. This is mathematically expressed as given below.

$$\sigma_{pq} = \sum_{i=1}^{N}(p_i - \mu_i)(q_i - \mu_i) \quad (5)$$

In the histogram mean model, the mean histogram of all the frames is evaluated. Next, all the frames whose histogram is nearer to the mean histogram are chosen as the keyframe. This is mathematically expressed as given below.

$$InF = SIM(p,q) = CKF\left[\frac{\sigma_{pq}}{\sigma_p\sigma_q}\right] * HIS[V_iF_i] \quad (6)$$

The extracted frames now form the input to the second hidden layer. This frame possesses the advantage of both low computational complexity and also possessing mean representative meaning.

Multivariate robust statistical feature extraction model

In this work, to reduce the processing time involved in detecting fires, Multivariate Robust Statistical Feature Extraction (MRS-FE) model is used using two different descriptors, forming vital factors. Those visual factors are either in the form of low-level descriptors like color, shape, texture, or high-level descriptors like spatiotemporal energy color, motion, and temperature or intensity. With the two said descriptors, optimized fire features are said to be extracted. The pseudo-code representation of Multivariate Robust Statistical Feature Extraction is given below.

Input: Inherent frame extraction 'InF'
Output: Optimized fire features 'OpF'
1: Begin 2: For each inherent frame extracted 'InF' 3: Measure color analysis using equation (7) and (8) 4: Measure fire shape analysis using equation (9) and (10) 5: Obtain texture analysis using equation (11) 6: Obtain Spatio Temporal Energy Color using equation (12) 7: Obtain motion and temperature analysis using equation (15), (16), and (17) 8: Obtain intensity analysis using equation (18) 9: Return (Optimized fire features 'OpF') 10: End for 11: End

Algorithm 2 Multivariate Robust Statistical Feature Extraction

As given in the above algorithm, fire color analysis involves the calculations that are used in our work to discriminate fire images. In our work, two pivotal instant of fire (inherent feature) image color distribution like mean and standard deviation are utilized. Besides, RGB (Red, Green, and Blue) color is used to define

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three instants for each three color channels. Then, the mean and standard deviation of the 'ith' color channel at the 'jth' inherent frame is obtained and expressed as given below.

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} InF_{ij} \quad (7)$$

$$\sigma_i = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(InF_{ij} - \mu_i\right)^2} \quad (8)$$

From the above two equations (7) and (8), fire color analysis of the inherent frame extracted 'InF' for several videos are obtained. Next, the fire shape normally varies approximately and swiftly in comparison to the comparatively smooth features of other objects in the inherent frame extracted. In this work, objects actual perimeter length 'PL' and perimeter length proportion 'PLP' of the convex body nearest to this object is used to ascertain the exterior of the fire. They are expressed as given below.

$$PL = InF_i * 4S \quad (9)$$

$$PLP = \frac{1}{N}\sum_{i=1}^{N} PL_i \quad (10)$$

Next, the third texture analysis is arrived at based on the weighted divergence analysis and is mathematically formulated as given below.

$$D(L) = \frac{\sum_{i=1}^{N} W(InF_i - \mu)^2}{N} \quad (11)$$

From the above equation (11), the divergence analysis 'D' for label 'L' refers to the specific connecting feature (i.e. inherent frame) with 'μ' and 'N' representing the mean value and the overall frames considered for testing. 'W' denotes the Weight function. With the above three local descriptors, values are logically and with the three global descriptors. To start with the first global descriptor, Spatio Temporal Gabor wavelet measured. This is obtained using triplet frequency elements in horizontal 'H', vertical 'V', and diagonal 'D' directions. The Spatio Temporal Energy Color of the video in inherent frame 'InF_i' is defined as given below.

$$STEn_i(\theta, T) = \frac{\sum_{(p,q)\in InF_i} wc(p,q)}{\sum_{(p,q)\in InF_i} WC(p,q)} \quad (12)$$

$$wc\,(p,q) = H(p,q) + L(p,qv) + D(p,q) \quad (13)$$

$$WC(p,q) = D(p,q) \quad (14)$$

From the above equation (12), the spatiotemporal energy color analysis '$STEn_i$' is obtained based on the wavelet coefficient of the horizontal, vertical and diagonal directions '$wc\,(p,q)$' and the overall wavelet coefficients that refer to the diagonal parts '$WC(p,q)$' respectively. Besides 'θ' and 'T' represents the direction and magnitude. Next, the motion and temperature analysis and intensity analysis work in coordination with each other. To obtain the motion temperature and intensity analysis, the average of the three components, Red, Green, and Blue space in the entire video is obtained as follows.

$$R_{mean} = \frac{1}{N}\sum_{i=1}^{N} R(p_i, q_i) \quad (15)$$

$$G_{mean} = \frac{1}{N}\sum_{i=1}^{N} G(p_i, q_i) \quad (16)$$

$$B_{mean} = \frac{1}{N}\sum_{i=1}^{N} B(p_i, q_i) \quad (17)$$

For certain high temperature, vicinity to white color, detection of high-intensity fire are not said to be possible. Hence, the color model is split into three channels and their mean values are obtained from (15), (16), and (17). Based on the results, intensity fire analysis is made. They are normal intensity fire and high-intensity fire. This is mathematically obtained as given below.

$$I(p,q) = \begin{cases} 1, if\ InF(p,q) > R_{mean} \cup G_{mean} \cup B_{mean} \\ 0, Otherwise \end{cases} \quad (18)$$

Finally, from the above local and global descriptors, the features extracted that characterize the fire features are obtained as given below.

$$FE = \mu_i \cup \sigma_i \cup PLR \cup D(L) \cup STEn_i(\theta, T) \cup R_{mean} \cup G_{mean} \cup B_{mean} \cup I(p, q) \quad (19)$$

Finally, all the salient features extracted are combined to produce the final features being extracted. As only the salient and optimized features are extracted and used for further analysis, the processing time involved in fire detection is said to be reduced.

Multivariate robust regressive model

In the third hidden layer, a polynomial regression analysis is carried out to detect the fire in the given video frame with multiple extracted features hence the name is called a Multivariate Robust Regressive model. The Multivariate Robust Regressive model used in deep learning via polynomial regression reduces the least absolute error of the forest fire detection. The Polynomial Regression procedure for fire detection is intended to design a statistical model depicting the influence of a single quantitative factor X (i.e. inherent frames extracted) on a dependent variable Y (i.e. features extracted). A polynomial model involving inherent frames extracted and powers of features extracted is fit to the data. This is expressed as given below.

$$c_0 + c_1 p + c_2 p^2 + c_3 p^3 + \dots c_n p^n = RInF \quad (20)$$

$$RInF = \begin{bmatrix} 1 & p_1 & p_1^2 & \dots \\ 1 & p_2 & p_2^2 & \dots \\ 1 & p_3 & p_3^2 & \dots \\ \dots & \dots & \dots & \dots \\ 1 & p_n & p_n^2 & \dots \end{bmatrix} \begin{bmatrix} c_0 \\ c_1 \\ c_2 \\ c_3 \\ \dots \\ c_n \end{bmatrix} \approx \begin{bmatrix} q_1 \\ q_2 \\ q_3 \\ \dots \\ q_n \end{bmatrix} \quad (21)$$

From the above equation (20) and (21), 'p' and 'q' corresponds to coefficients denoted by 'c_0', 'c_1'... 'c_n'. Here, the coefficients 'c_0' refers to the optimal features extracted.

Fully recurrent neural learning classifier for forest fire detection

Finally, the output is obtained at the output layer with minimum error using the Fully Recurrent Neural Learning Classifier. To reduce the complexity and also to minimize the error, in this work, the Fully Recurrent Neural Learning Classifier (FRNLC) model is used. This helps to improve fire detection accuracy and minimize the false positive rate. The pseudo-code representation of Fully Recurrent Neural Learning Classifier is given below.

Input: Optimized fire features 'OpF'
Output: Accurate fire detection
1: Initialize regressive features '$RInF$' 2: Begin 3: For each Optimized fire features 'OpF' 4: Formulate recurrent neural network using equation (22) 5: Formulate classification result using equation (23) 6: If '$Prob_0$' then 7: Possibility of fire 8: End if 9: If '$Prob_1$' then 10: No possibility of fire 11: End if 12: End for 13: End

Algorithm 3 Fully Recurrent Neural Learning Classifier

From the above algorithm, initially, optimized fire features are provided as input. Next, the regressive features are initialized for the classification of fire images and perform fire detection. Due to the nonlinearity nature of data (i.e. fire), in this work, Fully Recurrent Neural Learning Classifier is applied to the fire features extracted for fire detection. The main advantage of using this type of FRNLC classifier is the existence of a feedback mechanism in the nodes of the recurrent network. The FRNLC is formulated as given below

$$h(T) = \left| Fun_H \left(W_I(p(T)) \right) + W_H(h(T-1)) \right| \quad (22)$$

$$q(T) = \left[Fun_O(W_O h(T)) \right] \quad (23)$$

From the above equations (22) and (23), let us consider the neural network inputs and outputs as the vectors '$p(T)$' and '$q(T)$', with the three connection weight matrices being 'W_I', 'W_H' and 'W_O', and the hidden and output unit activation functions being 'Fun_H' and 'Fun_O', the behavior of the recurrent network is then described by the pair of non-linear matrix equations. The network uses the output function 'q(T)' to realize feature classification after the last non-linear matrix equations. The output function 'q(T)' is then utilized to measure the probability that the eigenvectors belong to each class. The probability vector '<⟦Prob⟧_0,⟦Prob⟧_1' is then said to be obtained in our algorithm, with '⟦Prob⟧_0' representing the

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probability that the suspected region belongs to the fire region and '⟦Prob⟧_1' represents the probability that the suspected region does not belong to the fire region. The final classification results are obtained through the equation (23) and on that, the detection of fire is said to be performed ultimately.

RESULTS

In this section, the result of the MR-FRNC method is compared with existing methods namely, fusing raster classification with pixel-based time series [1], and novel radar based burned area mapping algorithm [2] is implemented in MATLAB using the FIRESENSE database [21]. The result is carried out on factors such as fire detection accuracy, computational complexity, time complexity, and false positive rate with respect to a number of video frames.

Qualitative analysis

In this section, the qualitative analysis of fire detection is presented. With the input video obtained from FIRESENSE are input, first, inherent frames are extracted. With the extracted inherent frames, certain features for further classification are acquired in the output layer, here training images (i.e., input image) are compared with a testing image (Pre-stored), and their qualitative is analyzed.

Performance measure of fire detection accuracy

One of the most important metrics in analyzing fire detection is the accuracy rate. The fire detection accuracy in this work is referred to as the percentage ratio of the number of video frames properly detected with fire $Fire_{Det}$ to the number of video frames F_i provided as input.

$$FDA = \sum_{i-1}^{N} \frac{Fire_{Det}}{F_i} * 100 \quad (\%) \tag{24}$$

From the above equation (24), the accuracy rate 'FDA' is measured according to the fire detected rate to the sample's video frames and is measured in terms of percentage (%). A higher accuracy rate ensures the efficiency of the method.

Table 1: Results of the fire detection accuracy

Number of video frames	Fire detection accuracy (%)		
	Proposed MR-FRNC method	Fusing raster classification with pixel-based time series	Novel radar based burned area mapping algorithm
25	98	84	80
50	96	82	78
75	95	80	75
100	92	78	74
125	95	80	75
150	94	81	77
175	93	82	75
200	91	80	74
225	89	82	72
250	87	80	74

The results of the fire detection accuracy are shown in [Table 1]. The result of the fire detection accuracy is increased by 15% as compared to fusing raster classification with pixel-based time series [1] and 23% as compared to novel radar based burned area mapping algorithm [2].

Performance measure of fire detection computational complexity

The second parameter used for fire detection is the computational complexity rate. The computational complexity is measured as given below.

$$FDCC = \sum_{i=1}^{N} F_i * MEM\,[Fire_{Det}] \tag{25}$$

From the above equation (25), the fire detection computational complexity $FDCC$ is measured based on the number of video frames 'F_i' and the memory consumed in fire detection $MEM\,[Fire_{Det}]$. It is measured in terms of kilobytes (KB). Lower complexity measures the efficiency of the method.

Table 2: Results of the computational complexity

Number of video frames	Computational complexity (KB)		
	MR-FRNC	Fusing raster classification with pixel-based time series	Novel radar based burned area mapping algorithm
25	50	75	100
50	100	150	175
75	125	175	225
100	125	200	250
125	150	225	255
150	175	250	275
175	200	275	300
200	250	275	325
225	275	300	350
250	300	325	375

The results of the computational complexity are shown in [Table 2]. The result of the computational complexity is reduced by 25% as compared to fusing raster classification with pixel-based time series [1] and 36% as compared to novel radar based burned area mapping algorithm [2].

Performance measure of time complexity

The third parameter used in measuring fire detection is the time complexity involved. Lower the time complexity involved in fire detection, swift is the action to be taken place, and therefore the method is said to be efficient. It is measured as milliseconds (ms) and given below.

$$TC = \sum_{i=1}^{N} F_i * Time\ [Fire_{Det}] \quad (26)$$

From the above equation (26), the time complexity 'TC', is measured according to the video frames considered 'F_i' and the time involved in fire detection '$Time\ [Fire_{Det}]$'.

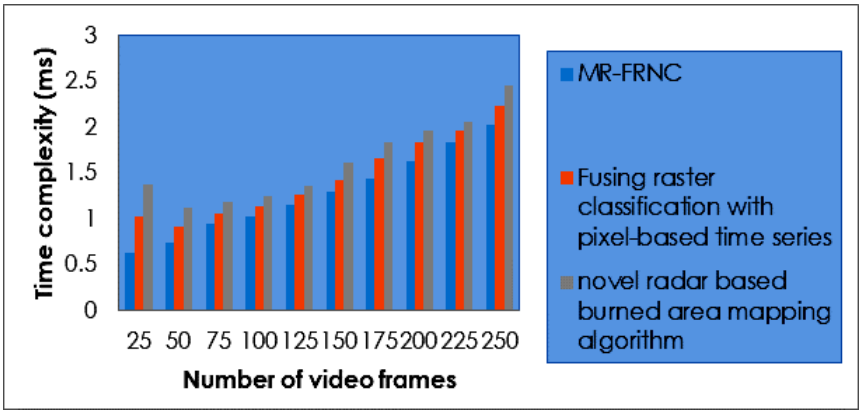

Fig. 2: Result of time complexity

The result of time complexity is presented in [Fig. 2]. The result of time complexity involved using MR-FRNC method was found to be reduced by 14% as compared to fusing raster classification with pixel-based time series [1] and 23% as compared to novel radar based burned area mapping algorithm [2].

Performance measure of false positive rate

Finally, the parameter used in measuring fire detection is the error involved. It is defined as the ratio of the number of frames that are incorrectly classified to the total number of video frames as input. The FPR is determined in terms of percentage (%) and mathematically estimated as,

$$FPR = \frac{M_{IC}}{n} * 100 \quad (27)$$

Here, 'M_IC' represents the number of frames that are inaccurately classified and 'm' refers a total number of video frames.

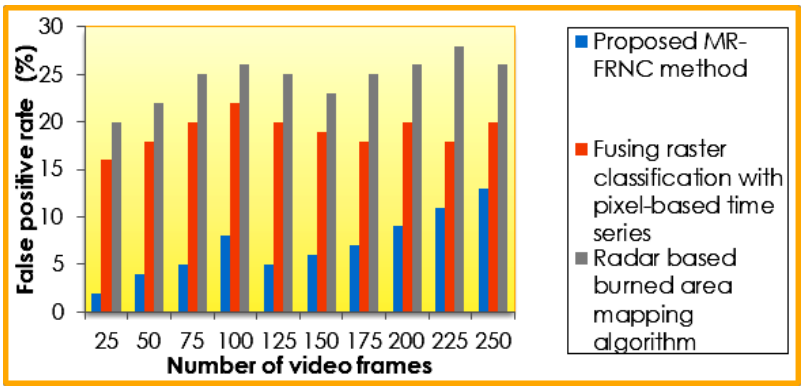

Fig. 3: Result of false positive rate

The result of false positive rate is presented in [Fig. 3].As a result, the false positive rate involved using MR-FRNC method was found to be reduced by 63% compared to fusing raster classification with pixel-based time series [1] and 72% compared to novel radar based burned area mapping algorithm [2].

DISCUSSION

In this section, the proposed MR-FRNC method is used to improve the forest fire detection performance in terms of fire detection accuracy, computational complexity, time complexity, and false positive rate. The fire detection accuracy with respect to 250 different video frames obtained from different videos at different time intervals in [Table 1]. With the '25' number of video frames provided as input, the existing fusing raster classification with pixel-based time series [1] and novel radar based burned area mapping algorithm [2] obtains '84' and 80' frames of detection accuracy. Whereas '90 frames is achieved in MR-FRNC method. From that fire detection accuracy is better than existing methods. By applying Fully Recurrent Neural Learning Classifier algorithm, a feedback mechanism is included that uses the information (i.e. features) from the preceding samples along with the present inputs. This is in turn increases the fire detection accuracy by using MR-FRNC method. In [Table 2] shows the computational complexity for 250 different video frames acquired from different videos at different time intervals. With the '25' number of video frames provided as input, the existing fusing raster classification with pixel-based time series [1] and novel radar based burned area mapping algorithm [2] obtains '75KB' and 100KB' frames of computational complexity. Whereas 50KB frames complexity is achieved in MR-FRNC method. The computational complexity was found to be better than fusing raster classification with pixel-based time series [1] and novel radar based burned area mapping algorithm [2]. By applying Histogram Mean Frame Extraction algorithm, inherent frames are first extracted from the given input videos. Here, three different steps are applied, first a matrix representation of video to the corresponding frames are formed, followed by which, candidate key frames are applied using the statistical model and finally, a histogram model is applied to obtain optimized key frames. Though three steps are applied in extracting the inherent frames, it is computationally efficient. Hence, the computational complexity was found to be less by using MR-FRNC method.

The novelty involved in the technique can be described as:

We propose a Fully Recurrent Neural Learning Classifier along with the Multivariate Robust Regressive model that not only improves the accuracy but also reduces the error. A novel method is proposed for fire detection based on the combination of local and global descriptors extracted from spatiotemporal fire modeling and inherent frame extraction analysis. In this way, the proposed method not only concentrates on the detection of local descriptors (e.g. analysis of color, texture, shape) but also exploits also the global descriptors (e.g. analysis of spatiotemporal energy, motion temperature, and intensity) to analyze both the spatial and temporal ability of fire detection systems to increase the robustness of the algorithm. An efficient fire detection modeling is introduced to identify the color of the fire, texture of the fire, and the texture characteristics as well as the intensity and temperature analysis. A novel model for enhancing the fire detection accuracy by applying the Fully Recurrent Neural Learning Classification algorithm is introduced by exploiting: i) feedback mechanism with weight matrices using non-linear matrix and ii) measuring the eigenvectors to obtain the probability rate of classification. Inspired by the time series model, the proposed method Multivariate Regressive Fully Recurrent Neural Classifier (MR-FRNC) is designed for forest detection with higher accuracy and minimum complexity.

CONCLUSION

In this paper, a method for fire detection is presented. By modeling both the presence of the fire using local and global descriptors of spatiotemporal features and the histogram mean evaluation of the pixels' intensities in a video database through statistical and histogram analysis, we showed that high fire detection accuracy is said to be achieved while reducing the false positive alarms. The use of the

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Multivariate Robust Regressive model with the Fully Recurrent Neural Learning Classifier increases the robustness of the algorithm by exploiting multiple extracted features and classifying them according to the output function to measure the probability that the eigenvectors belong to each class. The benefits of reduce the computational complexity than the existing fusing raster classification with pixel-based time series [1] and novel radar based burned area mapping algorithm [2]. To improve the fire detection accuracy and false positive alarms with minimum time complexity, MR-FRNC is introduced. Fully Recurrent Neural Learning Classifier is used to improve the fire detection performance. Experimental results with two hundred and fifty video frames containing both fire and non-fire videos showed that the proposed method outperforms existing state-of-the-art methods. In future, the work of our proposed work is also proceed using wavelet preprocessing to extract fire features and remove the complexity involved in fire detection. In addition, future work is focused to analyze more parameters to get better performance of the proposed technique.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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ARTICLE

EMPIRICAL DECOMPOSED KERNEL HOUGH FEATURE TRANSFORM BASED VECTOR AUTOREGRESSIVE BAGGING ENSEMBLE FOR FOREST FIRE DETECTION

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ABSTRACT

Background: *Forest fire detection attains a great attention due to the frequent threat from fire to both economic properties and public safety. Automatic fire detection from video data in real-time based on a combination of features is still faced the challenging one.* ***Methods:*** *The paper presents the time series forecasting technique called Empirical Decomposed Hough Feature Transform Based Vector Autoregressive Bagging Ensemble (EDHFT-VABE) for improving the accuracy of fire detection with minimum time. The video is taken from the dataset for fire detection with higher accuracy. EDHFT-VABE technique includes three major processes namely keyframe extraction, feature extraction, and classification. Initially, the input video is divided into a number of frames and finds the keyframes using the empirical mode decomposition approach. Then, the local features and global features are extracted from the given keyframe using generalized kernel Hough transform. Finally, the classification is performed using the time series model called Stochastic Vector Autoregressive Bagging Ensemble for identifying the fires in the given video frames by analyzing the extracted features using Ruzicka similarity. EDHFT-VABE technique is experimented using a video dataset and the final results show that the presented EDHFT-VABE achieves higher fire detection accuracy with minimum time and false-positive rate.* ***Results:*** *The experimental result evident that EDHFT-VABE technique increases fire detection accuracy by 10% and minimizes false-positive rate by 52%.* ***Conclusion:*** *Our EDHFT-VABE technique achieves accurate automatic forest fire-alarm systems with improved fire detection accuracy and lesser time as well as a false-positive rate.*

KEY WORDS
Forest fire detection, empirical mode decomposition feature extraction, generalized kernel Hough transform, Stochastic Vector Autoregressive Bagging Ensemble

INTRODUCTION

Forest Fire is destructive natural or man-made disaster and it is the most harmful natural hazard affecting everyday life. A hybrid Adaboost-MLP (multi-layer perceptron) model was introduced in [1] to efficiently predict a fire with higher accuracy. However, the time consumption of fire detection was not minimized. A deep CNN model was developed in [2] for accurate fire detection from the video. However, the designed model failed to use the fire detection methods with the detailed experiments of the quantitative analysis. The rest of paper is organized as follows: Section 2 describes the proposed EDHFT-VABE in a detailed manner. In Section 3, an experimental evaluation of proposed methods and existing methods are presented. In section 4, the quantitative results and discussions are presented with different metrics. Conclusions are drawn in Section 5.

A Robust AdaBoost (RAB) classifier was developed in [3] to enhance the classification accuracy of fire smoke detection. But the time series model was not applied for improving the accuracy of fire detection. A CNN was developed in [4] for forest fire image recognition by extracting the fire features. But the designed CNN failed to minimize the time consumption taken for forest fire detection. An efficient rule-based forest fire detection technique was introduced in [5]. Though the technique achieves a higher detection rate, the multiple fire feature extraction was not performed to minimize the time complexity. In order to minimize the computation time, a multi-feature fusion of flame method was proposed in [6]. The method uses the SVM classifier for fire detection but the false positives were not minimized. ICA K-medoids-based fire region detection method was introduced in [7] based on the spatiotemporal visual features. But the designed method failed to use different types of local and global features for fire region detection. An early fire detection framework was developed in [8] with fine-tuned convolutional neural networks for CCTV surveillance cameras to identify the fire in different indoor and outdoor environments. However, the framework failed to achieve higher accuracy and minimum false alarms. A spatial prediction method using CNN was developed in [9] for forest fire susceptibility. However, the method was not improving the forest fire prediction with minimum time consumption. Cost-effective fire detection was performed in [10][21] using CNN architecture for surveillance videos. But the designed architecture has higher false alarms in the fire detection. A CNN based system was introduced in [11] for identifying fire detection from videos. But early forest fire detection was not performed with higher accuracy and minimum time. A CNN inspired by Mobile Network was developed in [12] for fire detection with the color features. But it failed to analyze the multiple features for accurate fire detection. A Faster Region-based Convolutional Neural Network (R-CNN) was introduced in [13] to identify the suspected regions of fire and of non-fire based on their spatial features. However, the accuracy rate of fire frame detection was not improved. A Gaussian Mixture Model-based background subtraction was developed in [14] to extract the moving objects from a video stream. A sequential Monte Carlo estimation approach of time-varying frequency was developed in [15] using particle filter (PF). But, the error rate was not minimized using sequential Monte Carlo estimation approach. A spatial fuzzy C-means clustering (SpFCM) method was introduced in [16] for fire detection. The designed method failed to use the multiple Spatio-temporal fire features for improving the accuracy of

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fire detection. The multi-feature based fire detection was performed in [17] for minimizing the error rate. But the false positive rate was not minimized using the designed approach. A vision-based forest fire detection method was introduced in [18] based on color and motion analysis. The designed method failed to use the efficient machine learning technique to improve the performance of forest fire detection and decrease the false positive rate. A K-medoids Clustering was designed in [19] to detect fire frames according to color space using a particle swarm optimization approach. A new video-based fire detection algorithm was developed in [20] based on a rule-based method using RGB and HSV color space.

The aim of the work is to improve the accuracy of forest fire detection; an EDHFT-VABE technique is introduced. This contribution is achieved by extracting the keyframes and learning the multiple local and global features from the input frames. The Stochastic Vector Autoregressive Bagging Ensemble is applied for identifying the forest fires by analyzing the extracted fire features with testing features. The Ruzicka similarity coefficient is used for matching the feature vectors. Based on the similarity value, the fired frames are correctly identified. To minimize the false positive rate of forest fire detection, the EDHFT-VABE technique uses Bagging Ensemble technique by applying the voting scheme. The majority votes of the input samples are taken as final classification results from the weak learner. To minimize the forest fire detection time, the EDHFT-VABE uses the empirical mode decomposition approach to divide the video into the number of key frames.

METHODS

An EDHFT-VABE technique is introduced for detecting fire flame in surveillance video scenes in an early stage. Due to the climatic condition changes, the accurate detection of fire flames is a severe problem in the forest area. These problems are overcome by EDHFT-VABE technique to improve accurate fire detection by extracting the multiple fire features.

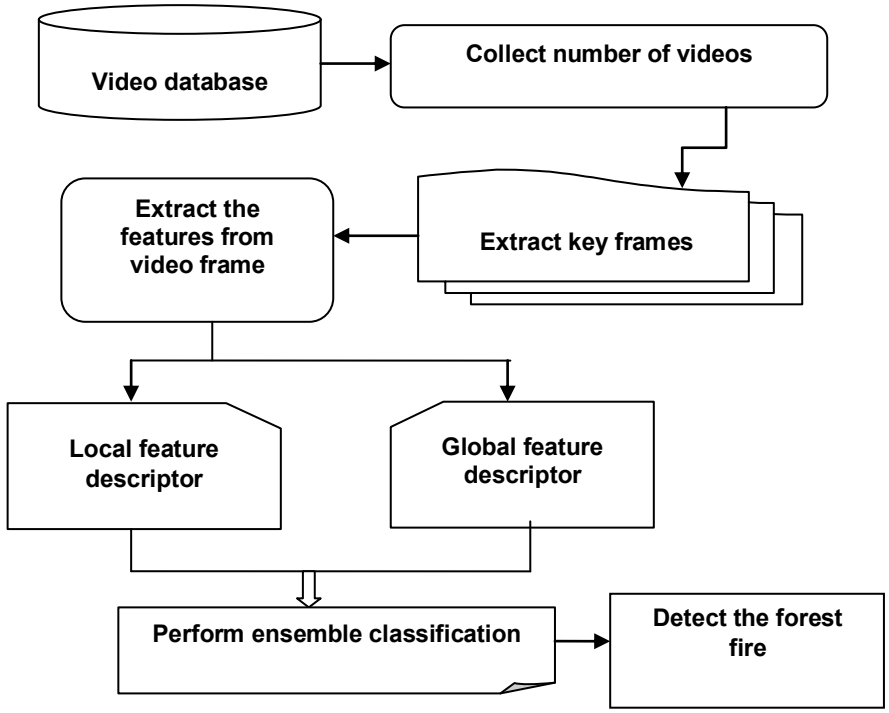

Fig. 1: Architecture of the proposed EDHFT-VABE technique

The architecture of the EDHFT-VABE technique is shown in [Fig. 1]. Initially, the videos are collected from the database. Forest fire detection is carried out with number of video frames $V_i = F_1, F_2, \ldots, F_m$. Then, key frames are extracted to perform fire detection. With the key frames, the local feature descriptor such as color, shape, texture and global feature descriptors like, spatiotemporal energy color, Spatial wavelet energy, temporal analysis, Motion analysis are extracted to improve the classification performance with minimum time. At last, the ensemble classification is performed using the time series model with the extracted features to find the fired region in the given video frame. These three processes of the EDHFT-VABE technique are described in the following section.

Empirical mode decomposition based keyframe extraction

The first process in EDHFT-VABE technique is to extract the video frames from the given input video. With development of multimedia information technology, efficient access to video is a difficult task. Therefore, Empirical Mode Decomposition (EMD)[22][23] approach is applied to divide the total video into number of frames and accurately find key frames for fire detection with minimum time. Let us consider number of

videos from dataset $V_1, V_2, V_3, \dots V_n \in D$. For each video, the multiple video frames $F_1, F_2, \dots, F_m$ are obtained based on similarity measure. The similarity between frames are measured as follows,

$$Sim\left(F_i, F_j\right) = \sqrt{\sum_{i,j=1}^{m}\left(F_i - F_j\right)^2} \quad (1)$$

From (1), $Sim\left(F_i, F_j\right)$ denotes a similarity between i^{th} frame (F_i) and j^{th} frame (F_j) . The similarity distance between two frames is calculated to find the adjacent frames. The minimum distance similarity is taken as next successive frame. Key frames are extracted by finding each local minimum frame pixels and maxima pixels. With minimum and maximum ranges, the mean frame pixels are identified. By using Empirical mode approach, a center value of minimum and maximum is set as a mean. From the calculated mean, the standard deviation is calculated to find key frames for fire detection.

$$S = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}(F_i - m_n)} \quad (2)$$

Where, S indicates standard deviation, m_n denotes a mean, F_i denotes a frame, 'm' denotes number of video frames. Then threshold is set to identify the keyframes. Based on the above-said process, all the keyframes are extracted and it used for further processing to minimize the time consumption. The algorithmic process of the step by step process of keyframe extraction is given below,

\\ Algorithm 1 Empirical Mode Decomposition based keyframe extraction
Input: Dataset D, Videos $V_1, V_2, V_3, \dots V_n$
Output: Keyframe extraction

Begin
1. For each video V_i
2. Extract multiple frames $F_1, F_2, \dots, F_m$
3. For each F_i
4. Measure distance similarity $Sim\left(F_i, F_j\right)$
5. Compute the deviation 'S'
6. If ($S < S_{th}$) then
7. Select the keyframes
8. End if
9. End for
10. End for
End

Algorithm 1 describes the Empirical Mode Decomposition (EMD) approach to extract the keyframes for minimizing the forest fire detection time. First, the number of consecutive frames is extracted from the video using a similarity distance measure. Among the frames, the keyframes are extracted based on the mean and deviation. A threshold is set for selecting the keyframes. If the deviation is lesser than the threshold, then the first image of that pair is taken as keyframe. The process is stopped when the frame list is empty.

Generalized kernel hough transform-based feature extraction

After extracting the keyframes, feature extraction is carried out to extract the two different descriptors such as local feature descriptors like color, shape, texture and high-level feature descriptors like spatiotemporal energy color, Spatial wavelet energy, temporal analysis, motion analysis. The Generalized kernel Hough transforms is applied to extract the features from given video frames. Generalized kernel Hough transforms is a feature extraction technique used in image analysis to find fire from the video frame with minimum time. The input frame is taken in the two-dimensional space (x_a, y_a) and it transformed into a single point in the parameter space (φ, θ) . Then the transformation from two-dimensional space into the parameter space is given below,

$$\varphi = x_a \cos(\theta) + y_a \sin(\theta) \quad (3)$$

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Where, φ is the distance from the origin to the closest point on the straight line, θ is an angle between the ' x_a' axis and the line connecting origin with that closest point. Followed by, the distance from the center to the object edge is measured to find the shape. The distance between the origin and the edge of the object is expressed using Gaussian kernel.

$$d = \sqrt{(u_2 - u_1)^2 - (v_2 - v_1)^2} \quad (4)$$

$$K = e^{(-\vartheta\, d^2)} \quad (5)$$

$$\vartheta = \frac{0.5}{\sigma^2} \quad (6)$$

Where, d indicates the distance, the point (u_1, v_1) is the origin i.e. location of the center of the object $(0,0)$, (u_2, v_2) denotes an edge of the object, K denotes a Gaussian kernel, is the deviation. From which, each point on the perfect shape of the boundary is extracted from the given video frame. For accurate fire detection, color is a useful feature that measures the color distribution of image. The color features are extracted from the input by converting the RGB image into HSV (hue, saturation, value) color spaces. For each block, a color probability feature is calculated by averaging the color probability of each pixel.

$$C = \frac{1}{N}\sum_{i,j} p_C(i,j) \quad (7)$$

In (7), C represents the color feature, $\sum_{i,j} p_C(i,j)$ denotes averaging the color probability of each pixel intensity, N denotes a total number of pixels. The texture features are calculated based on the correlation of pixel intensity using mean and standard deviation.

$$T = \sum_i \sum_j \frac{1}{D^2}\,((p-\mu)(q-\mu)) \quad (8)$$

Where, T denotes a correlation between the pixel p and its neighboring pixels q based on the mean $(\mu)$and the deviation D. After identifying the local feature descriptor, then the global feature is extracted. The Spatio Temporal Energy Color is defined as given below.

$$STEn_i(\theta, T) = \frac{\sum_{(p,q)\in InF_i} wc(p,q)}{\sum_{(p,q)\in InF_i} WC(p,q)} \quad (9)$$

$$wc\,(p,q) = H(p,q) + L(p,q) + D(p,q) \quad (10)$$

$$WC(p,q) = D(p,q) \quad (11)$$

Where, ' $STEn_i$denotes a spatiotemporal energy color analysis is performed based on the wavelet coefficient ($wc\,(p,q)$) of the horizontal $H(p,q)$, vertical $L(p,qv)$ and diagonal directions $D(p,q)$, ' θ' and 'T ' denotes a direction and magnitude, $WC(p,q)$ denotes an overall wavelet coefficient that refers to the diagonal parts $D(p,q)$. Spatial wavelet energy at each pixel is powerful fire feature is measured by following formula,

$$SE\,(p,q) = hl\,(p,q)^2 + lh\,(p,q)^2 + hh\,(p,q)^2 \quad (12)$$

Where, $SE\,(p,q)$ denotes spatial energy at each pixel (p,q) , hl denotes a high-low frequency subband of the wavelet coefficient, lh denotes a low-high frequency subband, hh denotes a high-high frequency subband. For each subband, the spatial wavelet energy is calculated as the average of the energy of the pixels in the band.

$$E_b = \frac{1}{N}\sum E(p,q) \quad (13)$$

Where, E_b denotes the energy of the band, $E(p,q)$ denotes an energy of band in a particular pixel intensity, N denotes the number of pixels in a band.

Temporal analysis

Temporal analysis is applied to identify the flickering effect. To measure the effect of flickering in a pixel, the number of transitions from fire candidate i.e. moving fire colored pixel, to the non-fire colored pixel. Therefore, the flickering effect for a particular pixel is mathematically expressed as a function of the number of transitions '$v(p,q)$' which is mathematically calculated as follows,

$$f(p,q) = 2^{v(p,q)} - 1 \quad (14)$$

Where, $f(p,q)$ denotes a flickering effect of a particular pixel. The overall flicker effect is estimated as the average of individual flickering contributions of the pixels in the block.

Motion analysis

The motion analysis is used for detecting the fire regions is the movement of fire pixels in successive frames. In order to detect the foreground objects, the frame difference map is estimated as follows,

$$F_{map} = |F_i - F_{i-1}| > th \quad (15)$$

From (15), F_{map} denotes a frame difference map, F_i denotes a current frame, F_{i-1}denotes a consecutive frame. The pixels which are not moving for a long time in the next consecutive frames are considered a reliable background. The pixels which moving from one frame to another is called foreground (i.e. movement of the object). From the motion analysis, the moving pixels of the objects are identified. Finally, local and global features are combined to perform forest fire detection. Algorithm 2 describes the generalized kernel Hough transform based feature extraction. Initially, the Hough transform is employed to extract different features and finally combined all the features for classification. The feature extraction process minimizes fire detection time.

Input: Number of keyframes $KF_1, KF_2, \ldots . KF_n$
Output: Extract the features

1: Begin
2: For each keyframe 'KF'
3: Measure shape analysis using Hough transformation
4: Measure color probability feature 'C'
5: Measure texture feature 'T'
6: Calculate Spatio-temporal Energy Color $STEn_i(\theta, T)$
7: Calculate Spatial wavelet energy $SE(p,q)$
8: Calculate Flickering features $f(p,q)$
9: Measure the motion analysis using F_{map}
10: Obtain combined features
10: End for
11: End

Algorithm 2 Generalized kernel Hough transform based feature extraction

Stochastic bayesian vector autoregressive bagging ensemble-based classifications

Finally, the classification is performed using Stochastic Vector Autoregressive Bagging Ensemble (SVABE) technique with the help of a time series model. The Stochastic vector auto regression is the time series model that uses extracted features as input to predict the value at the next time step. The bagging ensemble is the machine learning algorithm designed to improve the accuracy of classification with the help of stochastic vector auto regression. In the SVABE technique, stochastic is a general method for constructing the classifiers based on combining random numbers of weak components and provides accurate classification results and minimizes the error. The ensemble technique is to convert the weak classifier into a strong one by applying the voting scheme.

[Fig. 2] shows the block diagram of SVABE technique. SBVABE uses a set of extracted features (EF_i) as input over the sample period ($t = 1,2, \ldots v$). The features are collected in a vector 'A' in the form of a

matrix. The Stochastic Bayesian Vector Autoregressive model acts as a weak learner to analyze the extracted features and classifies the fire in the given video frame.

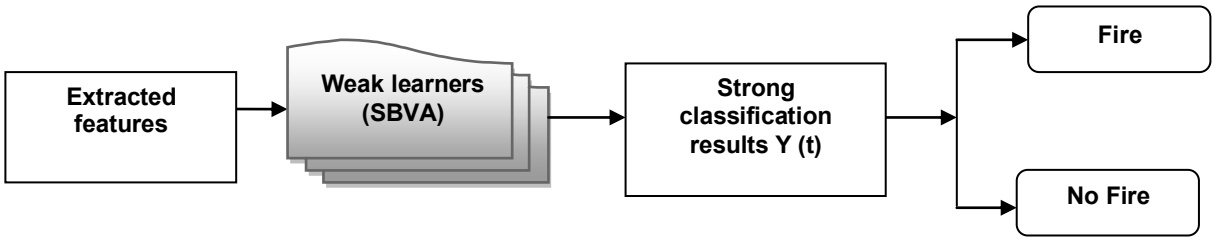

Fig. 2: Stochastic Vector Autoregressive Bagging Ensemble techniques

$$f(t) = b + \sum_{i=1}^{c} A\ f(t-i) + \gamma_t \quad (16)$$

Where, the observation $f(t-i)$ is called the i-the lag of $f(t), f(t)$ indicates the frame at a time't', b denotes a constant, γ_t is a vector of the error term, A denotes an extracted feature vector. Then the regression function analyzes the extracted features with the testing fire features using Ruzicka similarity. The Ruzicka similarity coefficient is used to measure the similarity between the feature vectors such as extracted feature vector 'A' and testing feature vector 'B'. The mathematical formula for calculating the similarity is given below,

$$\beta = \frac{A \cap B}{\sum A + \sum B - A \cap B} \quad (17)$$

Where, β represents a Ruzicka similarity coefficient, A, B are the two feature vector, $\sum A$ denotes sum of A score, $\sum B$ denotes the sum of B score, '$\cap$' denotes score, denotes a mutual dependence between the two feature vectors. The Ruzicka similarity coefficient (β) provides a value between 0 and 1. Based on the similarity, the regression function uses observations from previous time steps as input to predict the value at the next time. The training and testing fire features are exactly matched, and then the fired frame is correctly detected. Otherwise, there is no possibility of fire in the given frame. The weak learner has some training error hence the performance is minimized. In order to obtain the higher accuracy of fire detection, ensembles technique combines all weak learner to obtain the strong classification as follows,

$$Y(t) = \sum_{k=1}^{M} v_i(t) \quad (18)$$

Where, $Y(t)$ denotes an output of strong classifier, $v_i(t)$ indicates the weak learner. After combining the weak learner, the voting scheme is applied for accurately detecting the forest fire. The majority votes of the weak learner results are considered as a final strong output as given below,

$$Y(t) = arg \max_{M} \tau(v_i(t)) \quad (19)$$

From the above (19), τ denotes a majority votes whose decision is known in the M^{th} classifier, '$arg \max_{M}$' denotes argumentation of maximum function which helps to find majority votes of weak learner output. In this way, the fires in given input frames are correctly identified with a minimum false positive rate. The Stochastic Bayesian Vector Autoregressive Bagging Ensemble (SBVABE) algorithm is given below. The regression function analyzes the extracted features with the testing fire features. If these two features are similar, fire is detected in the given input frame.

\\ Algorithm 3 Stochastic Vector Autoregressive Bagging Ensemble Input: Extracted features Output: Improve the fire detection accuracy
1: Begin 2: For each key frame 'KF' with extracted features EF_i 3: Construct 'M' number of weak learners

4: Analyze the EF_i with testing features $f(t)$
5: if ($\beta > th$) then
6: Higher probability of fire
7: else
8: No probability of fire
9: end if
10: Combine all weak learner outputs $\sum_{k=1}^{M} v_i(t)$
11: For each $v(t)$
12: Apply votes 'τ'
13: Find majority vote $arg \max_{M} \tau(v_i(t))$
14: Obtain strong classification results $Y(t)$
15: End for
16: End for
17: End

RESULTS

Results of the EDHFT-VABE technique and existing methods Adaboost-MLP model [1] and DEEP CNN MODEL [2] are implemented using MATLAB with FIRE SENSE database (https://zenodo.org/record/836749). The dataset includes several forest fire videos for conducting the simulation. The collected video frames are used for fire detection.

Qualitative analysis

To conduct simulation, the method uses different numbers of video frames ranging from 25 to 250. Specifically, the state-of-the-art methods, Adaboost-MLP model [1] and deep CNN model [2] and EDHFT-VABE technique have been tested with the FIRESENSE database. The effectiveness of the proposed technique is compared along with the different performance metrics such as fire detection accuracy, false positive rate and fire detection time with the help of tables and graphs.

Performance metrics

Fire detection accuracy (FDA): Fire Detection Accuracy is referred to as a number of frames correctly detected as fire to the total number of frames taken as input. The fire detection accuracy is calculated as follows,

$$FDA = \frac{Number\ of\ F_i\ are\ correctly\ detected}{m} * 100 \quad (20)$$

Where FDA denotes a fire detection accuracy, F_i denotes the number of frames, m denotes a total number of frames. FDA is measured in terms of percentage (%).

False-positive rate (FPR): It is defined as the ratio of the number of video frames that are incorrectly detected to the total number of video frames. The mathematical formula for calculating the FPR is given below,

$$FPR = \frac{Number\ of\ F_i\ are\ incorrectly\ detected}{m} * 100 \quad (21)$$

Where, F_i denotes number of frames, denotes a total number of frames. FPR is measured in percentage (%).

Fire detection time (FDT): It is measured as an amount of time taken by the algorithm to detect the fire from the given video frame. It is expressed as follows,

$$FDT = m * t\ (detecting\ fire\ in\ one\ frame) \quad (22)$$

Where m denotes a total number of frames, t denotes a time taken to identify the frame from a single frame.

Table 1 describes the results of the fire detection accuracy from the input video frames. The numbers of input frames are taken as input in the ranges from 25 to 250. The estimated results show that the

accuracy of the EDHFT-VABE technique is improved by 7% as compared to [1] and 12% when compared to [2].

Table 1: Fire detection accuracy

Number of frames	Fire detection accuracy (%)		
	EDHFT-VABE	Existing Adaboost-MLP model	Existing deep CNN model
25	96	88	84
50	90	82	78
75	93	87	83
100	91	86	83
125	92	88	84
150	93	87	83
175	91	86	82
200	93	88	85
225	96	89	84
250	94	86	83

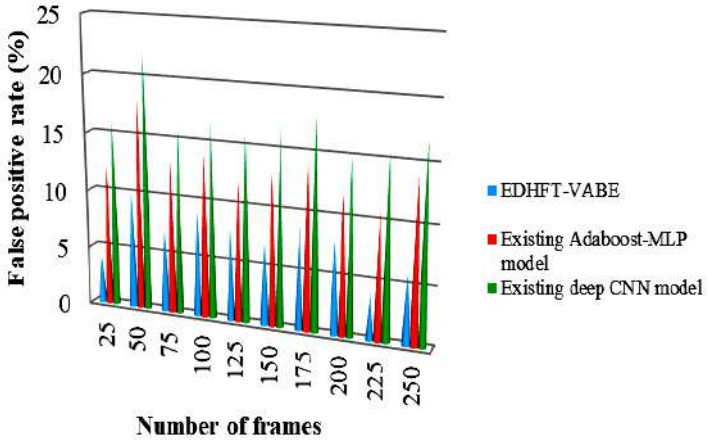

Fig. 3: Result of false-positive rate.

[Fig. 3] illustrates the false positive rate with number of video frames. The results of EDHFT-VABE technique reduces the false positive rate of frame classification by 46% and 58% when compared to [1] and [2].

Table 2: Fire detection time

Number of frames	Fire detection time (ms)		
	EDHFT-VABE	Existing Adaboost-MLP model	Existing deep CNN model
25	0.575	0.700	1.000
50	0.700	0.900	1.100
75	0.900	1.050	1.200
100	1.000	1.200	1.300
125	1.062	1.250	1.500
150	1.215	1.350	1.575
175	1.312	1.575	1.662
200	1.440	1.700	1.900
225	1.597	1.845	2.070
250	1.800	2.000	2.275

Table 2 shows the fire detection time of the three techniques. The video frames count ranges from 25, 50 ...250 and it is given as input. The average of ten results shows that the EDHFT-VABE technique minimizes the 15% of the time for fire detection compared to the Adaboost-MLP model [1] and also minimizes the detection time by 27% as compared to deep CNN MODEL [2].

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From the discussed quantitative and qualitative results, the EDHFT-VABE technique improves the fire detection accuracy with minimum time as well as a false positive rate.

DISCUSSION

In this section, the forest fire detection performance of EDHFT-VABE technique is discussed with metrics namely fire detection accuracy, false positive rate, fire detection time with 250 number of frames taken from FIRESENSE database. Forest fire detection accuracy in [Table 1] provides the results of three different methods. When considering 250 number of features, fire detection accuracy of EDHFT-VABE technique is 94 % whereas the existing method [1] and [2] provides 86% and 83 % of accuracy. This is because, the EDHFT-VABE technique uses the stochastic Vector Autoregressive model for analyzing the extracted features vector with the testing fire feature vector. The Ruzicka similarity is applied for matching the frames with the features. The higher similarity used for identifying the fire and lesser similarity indicates no fire in the given video frame. The ensemble bagging technique improves the classification performance of video frames. This result in EDHFT-VABE provides enhanced performance of fire detection. [Fig. 3] depicts the results of false positive rate. From [Fig. 3], the EDHFT-VABE technique reduces the false positive rate of video frame classification. When Considering 250 number of frames; the EDHFT-VABE technique provides 6% of false positive rate. Whereas, existing [1] and [2] provides 14 % and 17% of false positive rate. The EDHFT-VABE technique utilizes autoregressive model with ensemble technique to analyze feature vectors for providing training and testing features from that particular frame. In addition, the bagging ensemble technique uses the voting scheme for the decision making process. This minimizes the error rate and improves classification accuracy. In [Table 2], the results of fire detection time are provided for existing and proposed methods. At the 25 input frames, fire detection time incurred by the fire detection time is 0.575 ms whereas the fire detection time for the Adaboost-MLP model [1], deep CNN model [2] is 7ms and 1ms. Here, the result shows that the fire detection time of existing methods is comparatively high. Whereas, the fire detection time of the proposed EDHFT-VABE technique is relatively less.

Novelty of the work

On the contrary to existing work, we introduce the Empirical Decomposed Hough Feature Transform Based Vector Autoregressive Bagging Ensemble (EDHFT-VABE) technique with three different processes namely empirical mode decomposition approach, generalized kernel Hough transform, Stochastic Vector Autoregressive Bagging Ensemble for improving the accuracy of forest fire detection. At first, the input video is partitioned to finds the key frames using the empirical mode decomposition approach. Then, the local features and global features are extracted using generalized kernel Hough transforms on the contrary to existing work. After that, Stochastic Vector Autoregressive Bagging Ensemble is utilized for detecting the forest fires through scrutinizing the extracted fire features with testing features. The extracted features are analyzed with Ruzicka similarity. The Ruzicka similarity provides the value between 0 and 1. Based on the similarity value, the fired frames are correctly identified. The EDHFT-VABE technique uses Bagging Ensemble technique by applying the voting scheme to lessen the false positive rate of forest fire detection. The majority votes of the input samples are taken as final classification results from the weak learner. In this way, the fire frames are correctly identified with higher accuracy with minimum false positive rate and fire detection time.

CONCLUSION

Developing a robust fire detection system is a significant process in a video surveillance system. A number of successful methods have been applied to address these issues. The conventional classification algorithms are not sufficient to solve real-world fire detection problems with higher accuracy. An efficient time series model called EDHFT-VABE is introduced to handle a fire detection problem. By modeling both the behavior of the key frame extraction and various Spatio-temporal features as well as the temporal evolution of the pixels' intensity extraction is carried out using generalized kernel Hough transform to obtain higher detection rates while reducing the false positive caused by fire-colored moving objects. With the use of a stochastic vector autoregressive based begging ensemble algorithm, the features are analyzed and classification is performed. As a result, the robustness of the EDHFT-VABE technique is improved hence it improves the fire detection accuracy. Experimental results with videos containing frames showed that the proposed algorithm outperforms the existing fire detection algorithms. The qualitative and quantitative results show that the proposed EDHFT-VABE technique achieves better performance in terms of higher detection accuracy with the minimum false positive rate as well as fire detection time than the state-of-the-art methods. In future, we perform the fire detection using deep learning techniques for achieving more accurate results.

CONFLICT OF INTEREST
There is no conflict of interest.

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None

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ARTICLE

METHODS FOR HEMATOGENESIS STIMULATION IN CATTLE

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ABSTRACT

The paper presents experimental data on changes in hematological parameters during daily feeding of calves (aged 3.5-4 months, weighing 120 kg) with phytopreparation – coniferous energy supplement in doses of 25, 50, and 100 ml per animal, which was used for 30 days. It was found that the phytopreparation has hematopoietic (especially erythropoietic) properties – it led to pronounced stimulation of the increase of red blood cell count and hemoglobin level in the blood and normalized the hematocrit and the level of platelets (plateletcrit). It was noted that a dose of 50 ml per animal per day stimulated these processes more intensively. The research showed that a new method can be used for stimulation of erythropoiesis in cattle, which would allow to stimulate cattle erythropoiesis due to the effective erythropoietic characteristics of the components of the original coniferous energy supplement. As a result, the treatment expense for animals can be reduced due to the absence of the need for expensive medications and the simplicity of use.

KEY WORDS
erythropoiesis, blood, red blood cells, hemoglobin, hematopoiesis, cattle, coniferous energy supplement

INTRODUCTION

The intensive development of animal agriculture largely depends on the improvement of the technology of veterinary measures through the introduction of new methods and means of prevention and treatment of animal diseases. The progress of veterinary pharmacology is facilitated by the constant research and creation of new highly effective and safe drugs [1-4]. Known methods for correcting the hematopoietic status of animals are based mainly on stimulation of hematopoiesis, use of medication (for example, medicines containing iron, cobalt, and copper), or intramuscular and subcutaneous administration of stabilized allogeneic or heterogeneous blood, as well as non-specific globulin and polyglobulin. These methods of treatment of anemia and anemic syndromes and prevention of anemic conditions in animals have several disadvantages: the complexity of the drug administration, the high cost of medicines and complexity of treatment using them, as well as certain counterindications and limitations. They are complex in execution and not effective enough to stimulate the red lineage of hematopoiesis in animals [5]. In recent years, much attention has been given to medications and natural supplement feeds, which have high bioavailability and accessibility and are used to normalize physiological processes in animals. Their sustainability, economic efficiency, and the absence of any side effects (including addiction) are also important [6-8].

The study aimed to develop a method for stimulating red hematopoietic lineage (including erythropoiesis) in cattle.

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MATERIALS AND METHODS

Experiments with animals were conducted in accordance with the "Rules for the use of experimental animals" (annex to the order of the Ministry of Health of the USSR dated 08.08.1977 No. 755). A coniferous energy supplement (CES) was obtained using the technology of processing wood leaves based on the extraction of biologically active substances with a new selective extragent (manufactured by the Scientific and Technical Center (STC) "KHIMINVEST" LLC, Nizhny Novgorod) [8]. The CES is a homogeneous viscous liquid with a distinct coniferous smell, olive green or dark green in color. Water content is less than 50%, pH is 8.0-9.0, density is not lower than 1,126, and mass fraction of carotene per 100 g of the extract is not lower than 3 mg%. Studies of the chemical composition of the CES showed that it contains vitamins B1, B2, B3, B5, B6, B9, as well as carotenoids and many other biologically active compounds. The energy value of CES is 250 kcal/100 g. Acerous leaves contain cobalt, copper, manganese, zinc, and iron (which play an important role in the formation of blood cells), chlorophyll and xanthophyll (which play an important role in the metabolism), a large number of phytoncides, sugar, glucose, fructose, pectin, and tannins. The additive in the form of the finished product was supplied by the STC "KHIMINVEST" LLC.

The STC "KHIMINVEST" LLC, jointly with the Ogarev Agrarian Institute of Moscow State University, developed a unique technology for processing wood leaves based on the extraction of biologically active substances with a new selective extractant. The extractant is non-toxic, allows one to improve the performance properties of the products, and has antibacterial properties, ensuring the preservation of properties of products for a long period. The developed technology is one-stage, waste-free, sustainable,

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and has lower energy costs. The technology for the production of CES includes: 1) extractant, 2) mincing of wood leaves, 3) extraction of biologically active substances, 5) coniferous energy supplement.

The studies were conducted on calves owned by the Bolotnikovskoye LLC of the Lambirsky District of the Republic of Mordovia. The duration of the experiment was five months (the cattle were fed with the additive for one month and observed for changes in blood parameters for four months). According to the principle of analogues, four experimental groups of animals were formed (five animals per group). Of these, the first, second, and third groups were experimental and the fourth group was control.

For the experiment, animals of around the same age (3.5-4 months) were selected. They were clinically healthy and were kept in similar conditions and fed the same diet. At the beginning of the experiment, individual weighing of animals and morphological blood tests were carried out. Every day for 30 days, animals (age: 3.5-4 months, weight: 120 kg) of the first, second, and third experimental groups received the original CES in doses of 25, 50, and 100 ml per animal, respectively. Animals of the control group did not receive the CES. The effectiveness of the original CES was analyzed using clinical observation and hematological parameters. Hematological studies were conducted at the veterinary clinic of the Agrarian Institute using a MICROCC-20Vet (HTI, USA) automatic hematology analyzer for veterinary medicine. Digital data was processed using parametric statistical methods; the degree of reliability was determined using the Student t-test using the Microsoft Excel (2000) and STAT 3 software.

RESULTS AND DISCUSSION

There were no deviations from the physiologically normal state in the calves, the appetite remained high, and the clinical status was stable during the four months of observation after feeding the original CES. The original CES did not cause negative consequences for the clinical condition of animals, while it was noted that the calves' appetite was improved. The use of the CES in the diet led to a significant (10-23%) increase in meat productivity.

The red blood cell count in all experimental calves was within normal limits, or significantly higher than normal [Fig. 1]. It was also established that the use of the CES at a dose of 50 ml per animal significantly stimulated an increase in the level of hemoglobin in the blood [Fig. 2]. In addition to erythropoietic properties, the CES normalized hematocrit, platelet count, and plateletcrit. Fig. 1 and 2 show the changes in the red blood cell count and hemoglobin level in the blood of experimental animals after feeding them with CES. Further studies showed that similar changes were noted in cows that received the CES in doses up to 250 ml per animal.

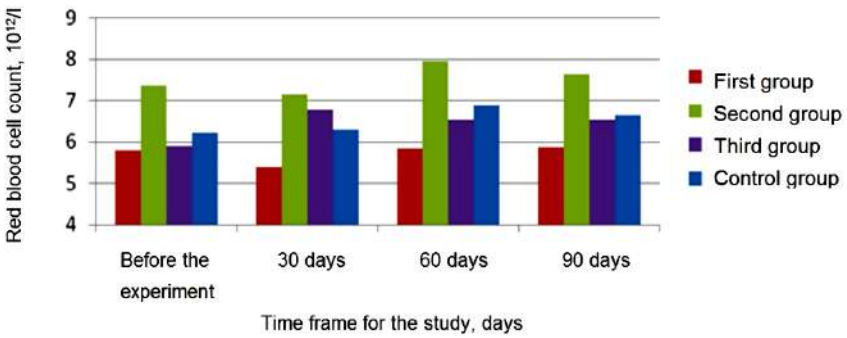

Fig. 1: The effect of the use of the CES in different doses on the red blood cell count in calves

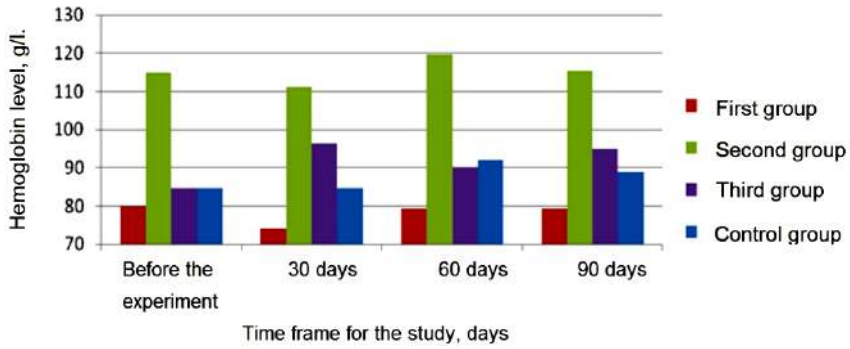

Fig. 2: The effect of the CES in different doses on the level of hemoglobin in the blood of calves

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Studies showed a significant increase in the red blood cell count and hemoglobin level in animals that used CES. The increase in the parameter in the second group (the most indicative) averaged 31.7%, compared to the control. This indicates that the phytopreparation showed hematopoietic properties. Cconsequently, the phytopreparation showed hematopoietic (erythropoietic) properties, led to an increase of red blood cell count and hemoglobin level. It was noted that the dosage of 50 ml of CES per animal per day stimulated these processes more intensively.

Compared with the commonly used solution, the proposed method allows one to increase the stimulation of erythropoiesis of cattle due to the effective hematopoietic properties of the components of the original CES. At the same time, the cost of treating animals is reduced due to the lack of expensive medication and simplicity of use.

The results of this study allowed us to determine the most effective dosage of the drug – 50-100 ml per animal per day. The results are consistent with previous studies on calves and cows with the use of phytopreparations [9-10]. This stimulating hematopoiesis method has real prospects for practical veterinary medicine.

CONCLUSION

A unique technology for processing wood leaves based on the extraction of biologically active substances with a new selective extractant has been developed. The phytopreparation has a commercial name – coniferous energy feed supplement, for which technical conditions have been developed and a certificate of conformity have been received. Modification of cattle with a natural drug leads to reduction of the cost of treating animals with nutritional anemia, diseases accompanied by anemic symptoms that arose in the setting of a weakening of the hematopoietic function of the red bone marrow, as well as age-related, physiological (pregnancy), and acquired anemia, and reduction of the cost of prevention of anemic conditions and correction of anemic syndromes. The tested method of stimulating hematopoietic function of the red bone marrow in cattle involves daily feeding calves with CES at a dose of 50-100 ml per animal for 30 days. With the introduction of CES, the profitability of production reaches 25%.

CONFLICT OF INTEREST
The authors declare no competing interests in relation to the work.

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FINANCIAL DISCLOSURE
None.

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ARTICLE

THE ADRENAL GLAND MORPHOLOGY IN LAYING HENS WITH NONSPECIFIC STRESS SYNDROME

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ABSTRACT

The use of a coniferous feed additive for laying hens with nonspecific stress syndrome allows improving the general condition of the poultry and normalizing the secretory activity in the adrenal glands. Sixty days after the beginning of the experiments, a decrease in the number of chromaffinocytes and lipid inclusions in the adrenal glands was noted. These changes indicate the development of protective adaptive reaction in laying hens and the effectiveness of treatment.

KEY WORDS
laying hens, stress, chromaffinocytes, lipid inclusions, adaptive reaction, biohacking

INTRODUCTION

Stress is a borderline state between the pathology and the norm, the diseased and the healthy state, which allows considering it as a general nonspecific adaptive syndrome, which, according to H. Selye, proceeds in stages [1-3]. In the case of stress in animals and poultry, the hypothalamo-pituitary-adrenal axis activates, which leads to significant releases of the adrenocorticotropic hormone (ACTH) and glucocorticosteroids (cortisol), and suppresses the output of the sex hormones and the growth hormone [4-6]. Morphofunctional characterization of the adrenal glands in laying hens is a direct method for diagnosing stress syndrome and is an important criterion for assessing the treatment made [7, 8].

It has been established that under stress, lipid inclusions, which are glucocorticosteroids (GCS), accumulate in the adrenal glands of laying hens. The use of a coniferous feed additive allows reducing the amount of lipid inclusions in the adrenal glands and decreasing the production of GCS.

The research was aimed at studying the morphological structure of the adrenal glands of laying hens to assess the protective adaptive response of the bird's body. In this regard, the following tasks were to be solved:

- to assess the main structures of the adrenal glands in laying hens by the development and distribution of chromaffin tissue, regulating the production of glucocorticoids, in the medullary and cortical substances;
- to identify lipid inclusions in the adrenal glands using the histological preparations at the beginning of the experiments and after 60 days of using the coniferous feed additive.

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MATERIALS AND METHODS

The experiments were performed at a poultry farm with the laying hens that had symptoms of stress syndrome. For this purpose, two groups of laying hens were selected, 20 birds in each group. The laying hens in the experimental group received the coniferous feed additive together with the feed at the dosage of 800 g per 1 ton of the feed, while the laying hens in the second group were used for reference. The hens were observed for 60 days.

The basis of the coniferous feed additive was the biologically active substances of woody greens, extracted by the composition of polyhydric alcohols widely used in the food industry and showing no negative side effects, when compared to many other similar products. Excellent taste improved the appetite of animals and poultry and improved the palatability of feed.

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The coniferous feed additive contained glycerin and coniferous paw natural carrier. Glycerin was rapidly and completely absorbed in the gastrointestinal tract of animals and served as a source of glucoplastic substance. Coniferous paw was the main carrier of natural bioregulators in the coniferous feed additive. Coniferous paw was comprised of cut young shoots of softwoods covered with needles. The maximum

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diameter of the shoots at the cut was 6-8 mm. They were harvested from the crowns of freshly cut trees and processed in a short time. Coniferous paw storage at the positive temperature for more than 7 days could lead to the loss of its valuable properties, the destruction of vitamins, carotene, chlorophyll, etc.

The dry matter of coniferous paw contained fat- and water-soluble vitamins. The maximum content of carotene and other vitamins in needles was from October to May. In addition, the needles contained the following microelements: iron, manganese, cobalt.

The coniferous feed additive was used for glucose synthesis and direct energy production. It normalized various types of metabolism: carbohydrate, fat and energy, restrained the development of fatty hepatosis, prevented the development of ketosis, promoted the rapid recovery of reproductive function after calving, normalized the production of sex hormones, which reduced the duration of the service period and the risk of complications with a new pregnancy, satiated the animal organism with vitamins, micro- and macroelements. In addition, glycerin in the additive had antibacterial properties that ensured the preservation of consumer qualities of the product for a long period [9].

The morphological status of the adrenal glands of the laying hens was assessed with the use of the histological preparations prepared according to the methods and recommendations several investigators [10- 13]. To identify lipid inclusions in the adrenal glands of the laying hens, staining of histological sections with Sudan III was used. For staining slices, pieces of the adrenal glands after formalin fixation were used, as well as fresh organs. The procedure of organ staining with Sudan III included the following stages: washing frozen slices (fresh organs and organs fixed in neutral formalin) in 50 % ethyl alcohol, staining for 15 – 30 minutes in an alcohol solution of Sudan III, rinsing in 50 % ethyl alcohol, washing in distilled water, nuclei staining with Ehrlich's hematoxylin, and rinsing and placing the slices in the glycerin-and-gelatin mixture. The histological preparations were studied using a Motic BA310 Digital microscope with a built-in digital camera. During the research all the legal and ethical standards of using laying hens in the experiments were observed.

RESULTS AND DISCUSSION

Clinical status assessment

At the beginning of the experiments, for assessing the general state of the laying hens, attention was paid to their behavioral reactions. The overall excitement of the poultry was noted. The hens made rapid aimless movements around the cage, some of them showed aggression against the nearby hens and the hens in the neighboring cells. Most hens showed signs of cannibalism. Pecking of the eye area, the scallop, and the cloaca occurred. Panic fear was noted in the hens when someone passed between the cages. The hens crowded at the wall opposite to the passage and remained motionless for 4 – 7 seconds. After that, the fright passed, and the signs of excitation and anxiety repeated.

The examinations of the feather and skin cover revealed extensive areas of alopecia, which was a consequence of premature molting. Some laying hens had no feather cover at all. Most hens showed a loss of feathers in the area of the neck, the back, and the abdomen. The examinations of the skin revealed various wounds in the area of scallop and jowls, which arose from mechanical injuries from metal parts of the cells. Some hens had hematomas in the subcutaneous tissue of the neck, the base of the wings, and the abdomen.

Several cases of wing bone fractures were also noted. These changes could occur in the chickens due to their aggressive behavior and the struggle for leadership. In assessing the behavioral reactions during feeding, it was found that not all laying hens had free access to the feeder due to dense placing. Most injuries and aggressive behavior incidents occurred near the feeders during feeding. In general, the overall anxiety and excitement of the laying hens also persisted in the dark, which prevented the hens from resting. The skeletal muscles in most laying hens were well developed. There was a normal ossification of the middle processus of the keel bone, the tracheal rings were strong and did not compress. The skin was pale; the scallops were pale pink to bright red.

Thirty days after the beginning of the experiments, the overall state of the laying hens changed. They had no panic fear anymore. They behaved less aggressively with each other. In the experimental group, the laying hens took food calmly. No anxiety was observed. Extensive areas of alopecia remained in all the laying hens. Sixty days after the beginning of the experiments, the laying hens adequately reacted to each other and the service personnel. No signs of excitement were noted. The feather cover had completely recovered. Egg productivity over the 60 days of the experiments was 93.6 %. In the reference hens, this value was 62.6 %.

In the reference hens, the signs of aggression and anxiety remained. Some cages contained the hens that had died of pecking. Egg productivity sharply reduced. It was decided to slaughter the entire livestock of this poultry house.

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Morpho-functional characteristics of the adrenal glands in laying hens

The adrenal glands of the laying hens were dark brown. They were located on both sides of the abdominal aorta on the ventral surface of the kidneys. The weight of the right adrenal gland was approximately 0.19 – 0.37 g, of the left one — 0.12 – 0.27 g. The left adrenal gland received blood through the artery that started from the aorta or the renal artery. The right adrenal gland received blood through the branch starting from the right renal artery. There is no central vein in the adrenal glands of poultry; venous blood flows out of the adrenal glands through several vascular branches [14, 15]. On the outside, the adrenal glands were covered with a thin translucent shell consisting of collagen and elastic fibers. The cells of the cortex and the medulla of the adrenal glands formed cords that intertwined with each other; therefore, there was no clear separation of the layers in poultry, unlike the adrenal glands of mammals. The effect of the coniferous feed additive on the adrenal glands of the laying hens with nonspecific stress syndrome was assessed by observing the presence of lipid inclusions and chromaffin cells in the studied tissue.

At the beginning of the studies, the following changes were found using histological preparations from the adrenal glands of the reference laying hens. On the outside, the adrenal glands were covered with a single-layer connective tissue capsule [Fig. 1a]. Epithelial strands departed from it and formed glomeruli containing cells of loose connective tissue. In poultry, unlike mammals, the adrenal glands are not pronouncedly divided into cortical and medullary substances. A definite tendency in the development of the connective tissue cords, the location of chromaffin cells, and the presence of powerful blood vessels in the center of the adrenal glands indicate the structuredness of the adrenal glands in poultry. It should be noted that 30 days after the beginning of the experiments, no differences from the initial data were noted in the adrenal gland ultrastructure of the laying hens. Under stress reactions, redistribution of chromaffin tissues occurs in poultry. Chromaffin cells are subdivided into adrenocytes and noradrenocytes, which produce adrenaline and noradrenaline, respectively. In healthy poultry, chromaffin cells are located mainly in the adrenal medulla. When the organism is exposed to harmful factors, chromaffin cells leave the adrenal cortex. The number of chromaffinocytes depends on the severity of the stress factor and its duration. In the studies, chromaffin cells had high density of distribution throughout the organ tissue [Fig. 1b]. At the end of the experiments, their number reduced. Sixty days after the beginning of the experiments, the number of chromaffinocytes in the experimental laying hens decreased, which indicated the development of the adaptive capabilities of their organisms [Fig. 1c]. The positive effect of the coniferous feed additive on the adrenal glands of the laying hens was assessed by the content of large lipids which were inclusions of GCS (cortisol, corticosterone, and hydrocortisone). The most important is cortisol. Numerous light vacuoles of dissolved lipid inclusions in the adrenal glands signify an increased production of GCS in the poultry organism and the severity of the stress syndrome [Fig. 1d, 1e]. Sixty days after the beginning of the experiments, the number of light vacuoles of dissolved lipid inclusions in the adrenal glands of the laying hens in the experimental group decreased, compared with the reference hens [Fig. 1f, 1g]. These changes may indicate the development of the protective adaptive reaction in the laying hens and a decreased production of GCS.

Using the histological preparations stained with Sudan III, lipid inclusions of various localizations were identified. On the 30th day after the beginning of the experiments, lipid inclusions in the adrenal glands in all the laying hens were identified both in the lumen of the blood vessels and in the form of separate lumps in the perivascular space. The lipids were placed the most densely in the adrenal cortex [Fig. 2a, 2b]. Sixty days after the beginning of the experiments, large lipid inclusions in both the cortical and medullary substances of the adrenal glands were found in the laying hens in the reference group [Fig. 2c, 2d]. By the end of the experiments, a decrease in the number and size of lipid inclusions in the perivascular space was observed in the adrenal glands of the experimental laying hens. Lipids were mainly detected in the adrenal cortex [Fig. 2e]. In all the experimental laying hens, disruption of fats metabolism was observed, which was manifested by the deposition of lipids in the lumen of blood vessels. For instance, in the laying hens in the experimental group, a decrease in the number of lipid inclusions in the perivascular space was noted along with an increase in their number in the lumen of the blood vessels. These changes were manifested in the adrenal cortex [Fig. 2f].

At the end of the experiments, only single lipid inclusions in the perivascular space and blood vessels of the adrenal medulla were detected in the laying hens in the experimental group [Fig. 2g].

CONCLUSION

The use of the coniferous feed additive promotes the development of an adaptive response in the laying hens with nonspecific stress syndrome. Coniferous feed additive allows improving the general condition of laying hens in case of nonspecific stress syndrome. By the 60th day of administering the coniferous feed additive, the birds showed an adequate reaction to each other, their appetite improved, and the egg productivity increased. The use of a coniferous feed additive has a positive effect on the morphofunctional state of the adrenal glands of laying hens in case of nonspecific stress syndrome. The number of chromaffin cells and lipid inclusions in the adrenal glands decreases, which is evidence of a decrease in glucorticoids. The research results have demonstrated that administering the coniferous feed additive to laying hens allows normalizing their general condition in case of nonspecific stress syndrome. Evaluation of the clinical status of the experimental bird after 60 days of using the coniferous feed additive indicated

a decrease in signs of arousal and aggression. Laying hens calmly accepted food without fighting for the feeding front. An increase in egg productivity and egg quality was noted.

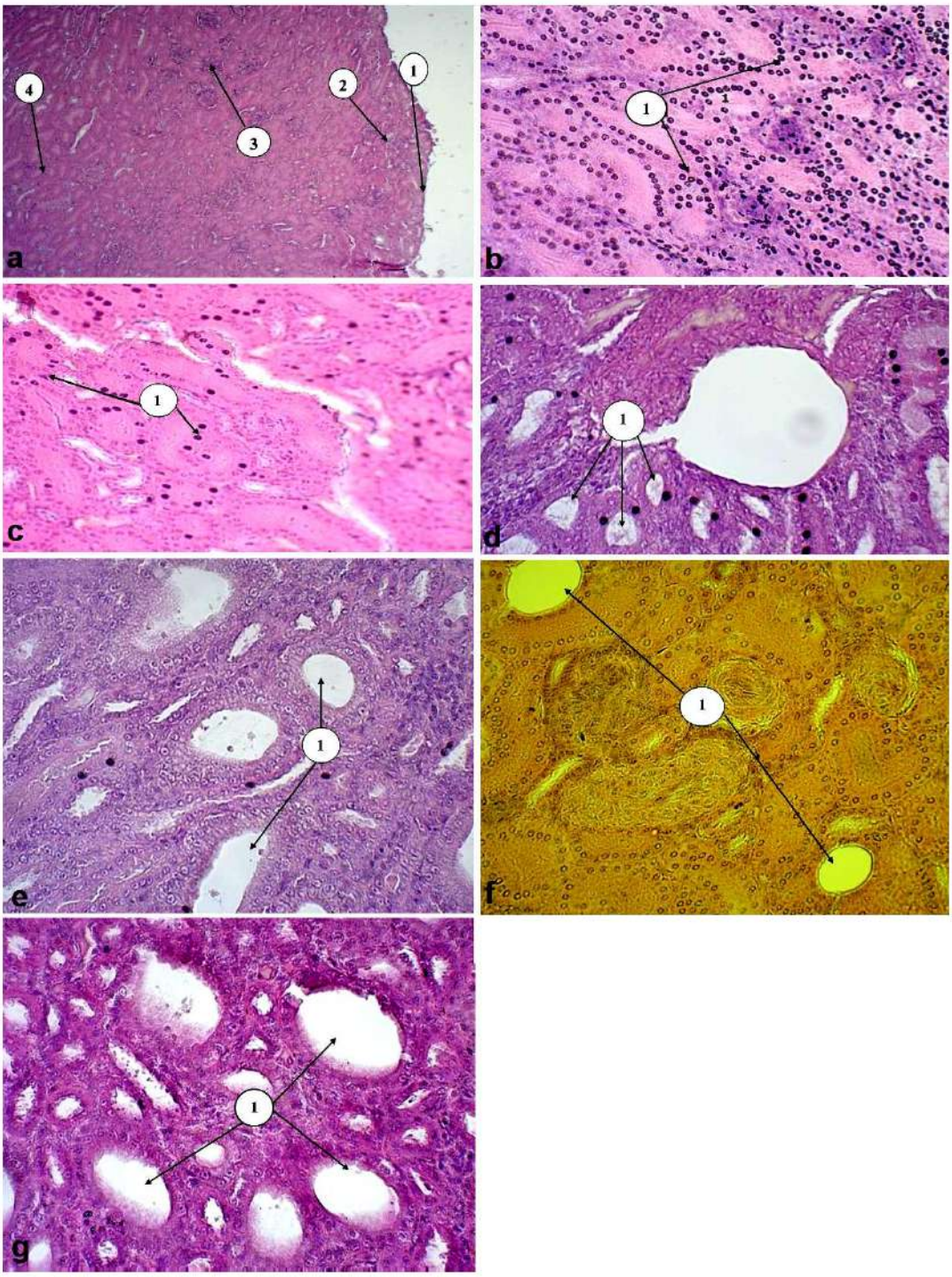

Fig. 1: Staining with hematoxylin and eosin. a) The adrenal gland of an experimental laying hen. Magnification x40, (1 — adrenal capsule, 2 — subcapsular zone, 3 —chromaffinocytes, and 4 — the inner zone of the interrenal tissues). **b)** The adrenal gland of an experimental laying hen at the beginning of the experiments. Magnification: x100, (1 — chromaffinocytes). **c)** The adrenal gland of an experimental laying hen 60 days after the beginning of the experiments. Magnification: x100, (1 — single chromaffinocytes). **d)** The adrenal gland of an experimental laying hen at the beginning of the experiments. Magnification: x100 (1 – light vacuoles of dissolved lipids). **e)** The adrenal gland of an experimental laying hen at the beginning of the experiments. Magnification: x100 (1 — light vacuoles of dissolved lipid inclusions in the adrenal cortex). **f)** The adrenal gland of an experimental laying hen 60 days after the beginning of the experiments. Magnification: x40 (1 — light vacuoles of dissolved lipid inclusions). **g)** The adrenal gland of a reference laying hen 60 days after the beginning of the experiments. Magnification: x100 (1 — light vacuoles of dissolved lipid inclusions).

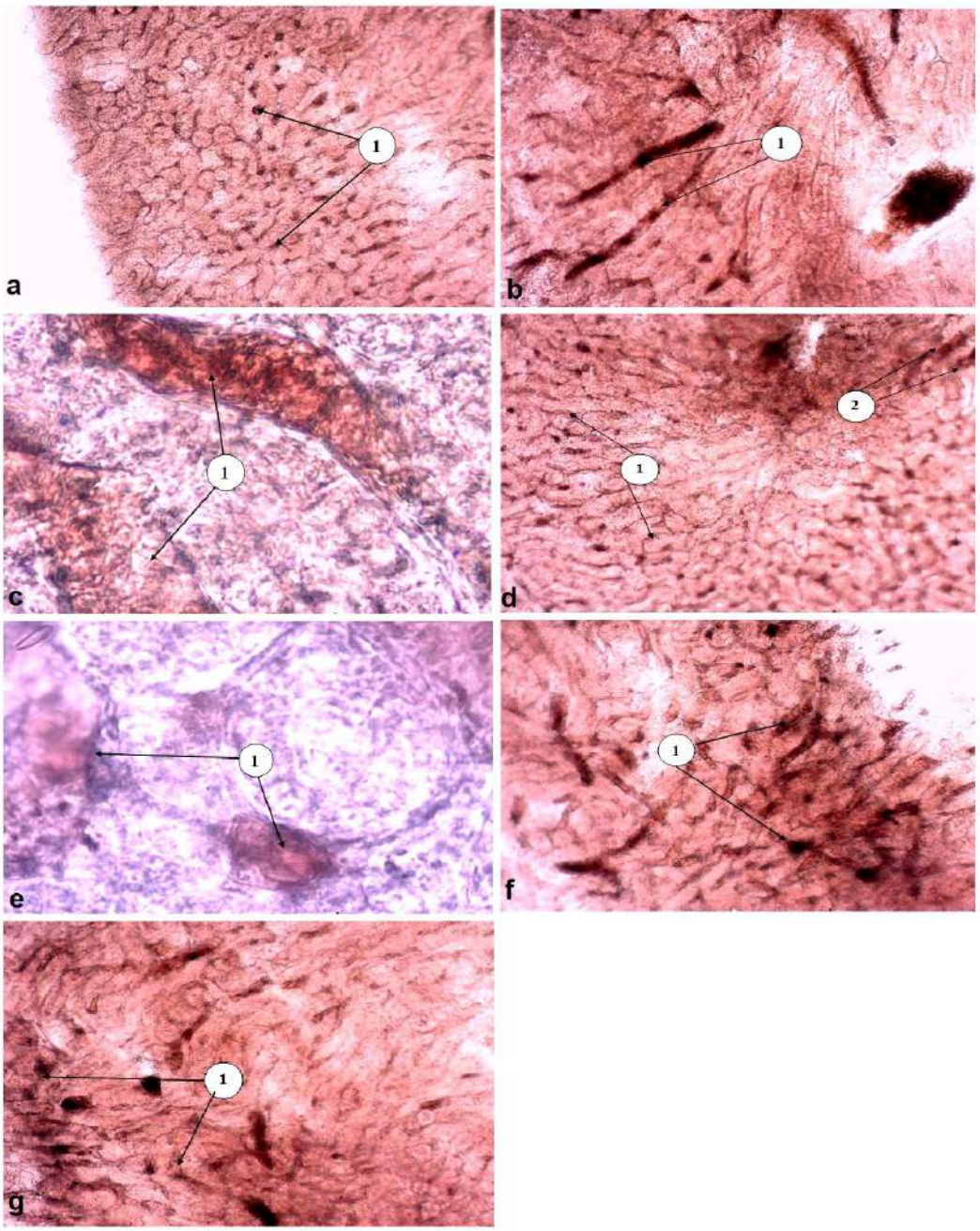

Fig. 2: Staining with Sudan III. a) The adrenal gland of an experimental laying hen 30 days after the beginning of the experiments. Magnification x10 (1 — lipid inclusions in the adrenal cortex). **b)** The adrenal gland of an experimental laying hen 30 days after the beginning of the experiments. Magnification x100 (1 — lipid deposits in the vessels of the adrenal cortex). **c)** The adrenal gland of a reference laying hen 60 days after the beginning of the experiments. Magnification x100 (1 — lipid inclusions in the adrenal cortex). **d)** The adrenal gland of a reference laying hen 60 days after the beginning of the experiments. Magnification x40 (1 — lipids in the adrenal cortex; 2 — lipids in the blood vessels of the adrenal medulla). **e)** The adrenal gland of an experimental laying hen 60 days after the beginning of the experiments. Magnification x100 (1 — lipid inclusions in the adrenal cortex). **f)** The adrenal gland of an experimental laying hen 60 days after the beginning of the experiments. Magnification x40 (1 — lipids in the vessels of the adrenal cortex). **g)** The adrenal gland of an experimental laying hen 60 days after the beginning of the experiments. Magnification x40 (1 — lipid inclusions in the adrenal medulla).

When assessing the morphological structure of the adrenal glands after 60 days of administering the coniferous feed additive, a decrease in the number of chromaffinocytes as well as their redistribution were revealed. At the beginning of the experiments, they were located both in the medulla and in the adrenal cortex. By the end of the experiments, most of the chromaffin cells were found in the adrenal medulla. Important changes were observed in relation to lipid inclusions in the adrenal glands. When stained with hematoxylin and eosin, they were white vacuoles, while staining with Sudan III revealed them as yellow-red inclusions. At the beginning of the experiments, lipid inclusions were detected in the adrenal medulla and cortex. After 60 days of using the coniferous feed additive, lipid inclusions were detected in the cortex in

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large quantities, and only single lipid inclusions were found in the medulla. A decrease in the number of lipid inclusions may indicate the normalization of the production of glucocorticoids of steroid nature.

CONFLICT OF INTEREST

The authors declare no competing interests in relation to the work.

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None.

FINANCIAL DISCLOSURE

None.

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ARTICLE

EFFECTS OF NOISE POLLUTION ON ANGER AND SMOKING ADDICTION IN COLLEGE STUDENTS

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ABSTRACT

A common phenomenon observed in our daily lives, noise leads to both auditory and non-auditory health problems. In addition to workplace environments where people often develop noise-induced hearing loss, noise may frequently lead to hearing loss in our everyday lives, too. Also, it is proven that too much exposure to noise combined with other variables has a triggering effect. Furthermore, there is a meaningful relationship between smoking and anger, and increase in anger symptoms is observed in smokers during their deprivation periods. In this research, in order to measure the anger variable, The State-Trait Anger and Anger Expression Scale and in order to measure smoking Fagerström Test for Nicotine Dependence Scale were used. In order to measure the noise intensity, CESVA DC 311 model T240385 serial numbered devices were used in 8 different spots. The research took place and was evaluated in Okan University and 473 individuals participated the research. Considering this research, the correlation between noise levels and anger and smoking addiction was tested while studying the relationship of these variables on college students' group. According to the results of the study, noise was found to be significantly and positively correlated with the trait, state, outraged and hated anger. However, there is significant positive correlation between trait anger and nicotine addiction in the smoking group. Mean scores for the trait, state, outraged, and hated anger were found higher among smoking addicts when compared to non-smokers. On the other hand, the mean scores for controlled anger were higher among non-smokers.

KEY WORDS
Noise, anger, smoking addiction, education, demographic characteristics

INTRODUCTION

All over the World, the cities face the problem of noise pollution. While noise can be defined as undesired sound, all the sounds except those in workplaces can be called environmental noise. As a type of air pollution, environmental noise pollution poses threat to people's health. Noise pollution becomes more dangerous day by day due to population growth, urbanization, and various noise sources. Noise pollution will continuously increase due to the improvements in highways, railways, and airways which are the biggest sources of environmental noise pollution [1]. The relationship between anger and noise depends on some psychopathologic characteristics such as one's age, gender, and how sensitive that person is to noise. In previous research, the correlation between noise sensitivity and anger was found higher among the group aged from 17 to 20 than that of the younger group aged between 14 and 16. Although anger is expressed similarly by women and men, men's anger is often higher than that of women [2].

Negative circumstances such as noisy environments the people are exposed to may cause the person to get angry and show aggression [3-5]. Anger is a human emotion depending on psychological and physical factors and it has evolved as a part of the "Fight or Flight" mechanism along with the human being. Anger helps us to recognize when others misbehave us, and we try to correct the misbehavior through our anger. It is a normal emotion and may also be useful. It is not the emotion itself, but its effect on our feelings and behaviors that may raise problems for us and the people around us. Anger makes the person uncomfortable because it increases the epinephrine level which in turn accelerates the heartbeats, causes the person to breathe excessively, sweat, and get nervous. The individual might feel stronger, resolute, and even untouchable. Those with anger might not feel pain. On the other hand, anger might also makes the individual feel desperate and daunted [6]. Every emotion is associated with a specific core-relational-theme. Anger means that someone is confronted with a demeaning offence; anxiety means that someone is confronted with an uncertain situation or an existential threat, disgust means that someone is taking in or being too close to an indigestible object or idea [7].

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It is estimated that 1,3 billion people are smoking all over the world today. 4,9 million people are dying every year due to nicotine consumption and if it continues this way, this number will probably increase up to 10 million in 2020, and 70 percent of those 10 billion is estimated to include people from developing countries. In addition to health problems arising from tobacco consumption and environmental cigarette smoke exposure, cigarette addiction is also accepted as a disease according to the International Classification of Diseases (ICD-10). Nicotine addiction requires regular treatment because it is a chronic disease and relapses.

There are significant relationships between anger and many aspects of smoking. Symptoms of anger are observed to decrease after the person smokes [8] Those smokers who show constant anger tend to smoke to be able to cope with anger [9]. When anger is considered, cigarette addicts are more vulnerable compared to non-smokers or those who do not smoke continuously [10]. Zvolensky and Hawkins [9] found that there was a relationship between anger and failure to quit smoking. Anger is accepted as a predictor variable as to the reason why the addiction relapses in the cessation process. Another study revealed that

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those cigarette addicts who have excessive anger have much more difficulty in quitting and they often tend to restart smoking one week later. The results of the research conducted by Kerrin et al. [11] also confirmed those findings. It was found that people who experienced an increase in their anger symptoms one week after quitting smoking showed a tendency to resume smoking compared to those who did not experience an increase. It was suggested that anger management interventions could help the cessation process. The literature review unveiled the limited number of research conducted on the relationship between noise, anger, and smoking addiction. Taking this into account, the study aims to examine the effect of noise, an environmental factor, on anger and cigarette addiction.

MATERIALS AND METHODS

The present study has been conducted in a correlational and comparative design. In this study two different questionnaires were used in order to obtain data from participants. The questionnaires are The State-Trait Anger, Anger Expression Scale and Fagerström Test for Nicotine Dependence. In order to measure the noise intensity, CESVA DC 311 model T240385 serial numbered devices were used in 8 different spots. The testing and data collection phases were conducted under Istanbul Okan University's permission and participants were given informed consent form to confirm their volunteering.

Participants

The present study has been conducted in a correlational and comparative design. Participants are 473 students from Istanbul Okan University. The participants were selected using convenient sampling technique. Participants of the study consisted of N=172 male Mage=22.95; SD=3.889) and N=301 Female (Mage=21.02; SD=2.818). Totally N=473 participants (Mage=21.72; SD=3.375) were attended the research [Table 1]. Participants of the study consisted of N=169 smoker Mage=22.25; SD=2.566) and N=304 nonsmoker (Mage=21.42; SD=3.721).

Measures

State-Trait Anger Scale (STAS) is a 20-item scale, with half the items proposed to measure state anger and the other half trait anger. The STAS asks individuals to respond according to how they feel right at the moment, or at a particular time. The requires individuals had to respond according to how they generally feel or react [12].

The Anger Expression (AX) is a 20-item scale, with eight items measuring Anger/In (AXI), eight items measuring Anger/Out (AXO), and four items tentatively measuring a third construct, Anger/ Control (AXCON) [13].

The Fagerström Test for Nicotine Dependence is a standard instrument for assessing the intensity of physical addiction to nicotine. The test was designed to provide an ordinal measure of nicotine dependence related to cigarette smoking. It contains six items that evaluate the quantity of cigarette consumption, the compulsion to use, and dependence. In scoring the Fagerstrom Test for Nicotine Dependence, yes/no items are scored from 0 to 1 and multiple-choice items are scored from 0 to 3. The items are summed to yield a total score of 0-10. The higher the total Fagerström score, the more intense is the patient's physical dependence on nicotine [14].

Procedures

During sample gathering from locations with high noise intensity, students who share same environment were requested to fill in the questioners and the noise analysis gathered in the end is shown in [Table 1]. The unfinished surveys were not included in research and the results were calculated with Statistical Package for the Social Sciences Version 25 (SPSS).

Table 1: Noise decibels of locations where participants filled questionnaires

Locations	Decibels	N	%
Social Sciences Faculty Building	56.80	46	9.7
Medicine III Floor Building	60.50	39	8.2
Medicine I Floor Building	62.00	49	10.4
Medicine IV Floor Building	64.80	56	11.8
Medicine II Floor Building	67.50	66	14.0
Wellness Center Building	74.70	58	12.3
Starbucks indoor Building	78.00	63	13.3
Engineering Faculty Building	80.00	96	20.3
Total		473	100.0

RESULTS AND DISCUSSION

Correlation between State-Trait Anger Scale and Nicotine Addiction Scale is shown in [Table 2]. Pearson's correlation revealed that there was significant, positive correlation between trait anger and nicotine addiction in the smoking group ($r(169)=.315$; $p<.01$). Pearson's correlation revealed that there was significant, negative correlation between controlled anger and nicotine addiction in the smoking group

(r(169)=-.186; p<.05). Pearson's correlation revealed that there was significant, positive correlation between outraged anger and nicotine addiction in the smoking group (r(169)=.213; p<.01).

Table 2: Pearson correlation between State-Trait Anger Scale and Nicotine Addiction Scale

Smoker		Trait Anger	State Anger	Controlled Anger	Outraged Anger	Hated Anger
Yes n=169	Trait Anger					
Yes n=169	State Anger	r.300** p.000				
Yes n=169	Controlled Anger	r-.309** p.000	r.459** p.000			
Yes n=169	Outraged Anger	r.708** p.000	r.432** p.000	r-.275* p.000		
Yes n=169	Hated Anger	r.452** p.000	r.735** p.000	r.092 p.235	r.506** p.000	
Yes n=169	Nicotine Addiction	**r.315** p.000**	r-.007 p.925	**r-.186* p.016**	**r.213** p.006**	r.142 p.065
No n=304	Trait Anger					
No n=304	State Anger	r.142* p.013				
No n=304	Controlled Anger	r-.491** p.000	r.338** p.000			
No n=304	Outraged Anger	r.656**	r.323**	r-.444**		

Other significant correlations are in between subscales of State-Trait Anger Scale. [Table 3] shows mean scores of State-Trait Anger Scale according to smoker-nonsmoker and results of independent samples t test. Trait anger levels of participants according to smoking were compared using independent samples t test. This revealed that the mean trait anger scores of smoker participants (M=22.83; SD=5.718) was significantly higher than nonsmoker participants (M=20.60; SD=5.373) [t=4.220; p<.05].

State anger levels of participants according to smoking were compared using independent samples t test. This revealed that the mean scores of state anger were not significantly different according to smoking. Controlled anger levels of participants according to smoking were compared using independent samples t test. This revealed that the mean scores of controlled anger were not significantly different according to smoking. Outraged anger levels of participants according to smoking were compared using independent samples t test. This revealed that the mean outraged anger scores of smoker participants (M=17.93; SD=4.477) was significantly higher than nonsmoker participants (M=15.85; SD=3.944) [t=5.057; p<.05]. Hated anger levels of participants according to smoking were compared using independent samples t test. This revealed that the mean hated anger scores of smoker participants (M=17.13; SD=4.278) was significantly higher than nonsmoker participants (M=15.95; SD=4.130) [t=2.947; p<.05].

Table 3: Means scores of State-Trait Anger Scale according to smoker-nonsmoker and results of independent samples t test

	Smoker	N	M	SD	t	p
Trait Anger	Yes No	169 304	22.83 20.60	5.718 5.373	4.220	**.000**
State Anger	Yes No	169 304	22.89 22.19	4.118 3.741	1.872	.062
Controlled Anger	Yes No	169 304	20.53 21.41	4.782 4.849	-1.918	.056
Outraged Anger	Yes No	169 304	17.93 15.85	4.477 3.944	5.057	**.000**
Hated Anger	Yes No	169 304	17.13 15.95	4.278 4.130	2.947	**.003**

State-Trait Anger Scale and Nicotine Addiction Scale mean scores shown in [Table 4], according to locations where participants filled the questionnaires and results of one-way ANOVA. As it shown in [Table 4] all locations have different noise levels. A significant difference was found among university students' main scores of trait anger according to the locations where they filled the questionnaires [F (7-465) =6.498; p=.000]. The results of the Tukey test conducted to determine the source of the difference indicated that trait anger levels of students at Engineering faculty (M=22.22) were significantly higher than those of students on the 2nd floor of Medicine Faculty (M=19.85) (p=.034). Trait anger levels of students at Coffee Shop (M=23.92) were found to be significantly higher than those of students at Social Sciences Faculty building (M=19.85) (p=.003), those of students on the 2nd floor of Medicine Faculty M=19.85) (p=.000), those of students on the 3rd floor of Medicine Faculty(M=19.51) (p=.002) and those of students on the 4th floor of Medicine Faculty (M=19.70) (p=.001). Trait anger levels of students on the top floor of wellness center (M=23.19) were found to be significantly higher than those of students at Social Sciences Faculty building (M=19.85) (p=.037), those of students on 2nd floor of Medicine Faculty (M=19.85)

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(p=.004), those of students on the 3rd floor of Medicine Faculty (M=19.51) (p=.023) and those of students on the 4th floor of Medicine Faculty (M=19.70) (p=.013).

Table 4: Means scores of State-Trait Anger Scale and Nicotine Addiction Scale according to locations where participants filled the questionnaires and results of independent samples t-test

	Locations	dB	N	M	SD	F	P	Tukey
Trait Anger	Engineering Faculty	80	96	22.22	5.753	6.498	.000	Eng>Med 2nd p=.034
	Starbucks indoor	78	63	23.92	6.086			Star. in>SSFB p=.003
	Social Sciences F.	56.8	46	19.85	4.402			Star. in>Med 2nd p=.000
	Medicine Faculty 1st	62	49	21.90	5.026			Star. in>Med 3rd p=.002
	Medicine 2nd floor	67.5	66	19.48	4.598			Star. in>Med 4th p=.001
	Wellness Center	74.7	58	23.19	5.859			Wellness>SSFB p=.037
	Medicine 3rd floor	60.5	39	19.51	5.572			Wellness>Med 2nd p=.004
	Medicine 4th floor	64.8	56	19.70	5.092			Wellness>Med 3rd p=.023
								Wellness>Med 4th p=.013
State Anger	Engineering Faculty	80	96	23.30	4.089	4.247	.000	Eng>Med 2nd p=.002
	Starbucks indoor	78	63	22.79	3.575			Eng>Med 3rd p=.045
	Social Sciences F.	56.8	46	22.50	3.613			Med 1st Med 2nd p=.002
	Medicine Faculty 1st	62	49	23.80	3.867			Med 1st> Med 3rd p=.021
	Medicine 2nd floor	67.5	66	20.91	3.185			
	Wellness Center	74.7	58	22.76	4.485			
	Medicine 3rd floor	60.5	39	21.08	3.520			
	Medicine 4th floor	64.8	56	21.75	3.694			
Controlled Anger	Engineering Faculty	80	96	21.73	4.671	1.592	.136	
	Starbucks indoor	78	63	20.02	5.191			
	Social Sciences F.	56.8	46	21.67	4.854			
	Medicine Faculty 1st	62	49	20.65	4.265			
	Medicine 2nd floor	67.5	66	20.94	4.813			
	Wellness Center	74.7	58	20.09	5.266			
	Medicine 3rd floor	60.5	39	21.54	5.041			
	Medicine 4th floor	64.8	56	22.07	4.398			
Outraged Anger	Engineering Faculty	80	96	17.40	4.450	5.446	.000	Eng> Med 2nd p=.001
	Starbucks indoor	78	63	17.51	4.119			Star in > Med 2nd p=.003
	Social Sciences F.	56.8	46	15.76	3.695			Med 1st Med 2nd p=.002
	Medicine Faculty 1st	62	49	17.82	4.290			Wellness>Med 2nd p=.001
	Medicine 2nd floor	67.5	66	14.68	3.235			
	Wellness Center	74.7	58	17.78	4.896			
	Medicine 3rd floor	60.5	39	15.56	4.147			
	Medicine 4th floor	64.8	56	15.52	3.751			
Hated Anger	Engineering Faculty	80	96	17.00	4.114	7.640	.000	Eng>Med 2nd p=.002
	Starbucks indoor	78	63	16.68	3.885			Eng> Med 3rd p=.010
	Social Sciences F.	56.8	46	16.52	3.811			Star. In>Med 2nd p=.035
	Medicine Faculty 1st	62	49	18.35	4.562			Med 1st>Med 2nd p=.000
	Medicine 2nd floor	67.5	66	14.44	3.474			Med 1st>Med 3rd p=.000
	Wellness Center	74.7	58	17.91	4.236			Med 1st>Med 4thp=.002
	Medicine 3rd floor	60.5	39	14.28	3.727			Wellness>Med 2nd p=.000
	Medicine 4th floor	64.8	56	15.21	4.259			Wellness>Med 3rd p=.000
								Wellness>Med 4th p=.009
Nicotine Addiction	Engineering Faculty	80	52	3.17	2.595	.683	.686	
	Starbucks indoor	78	24	3.04	2.710			
	Social Sciences F.	56.8	13	2.62	2.181			
	Medicine Faculty 1st	62	16	3.44	2.851			
	Medicine 2nd floor	67.5	12	3.58	3.343			
	Wellness Center	74.7	39	3.28	2.752			
	Medicine 3rd floor	60.5	6	1.33	1.751			
	Medicine 4th floor	64.8	7	2.14	2.610			

A significant difference was found among university students' main scores of state anger according to the locations where they filled the questionnaires [F (7-465) = 4.247; p=.000]. The results of the Tukey test conducted to determine the source of the difference indicated that state anger levels of students at Engineering faculty (M=23.30) were significantly higher than those of students on the 2nd floor of Medicine Faculty (M=20.91) (p=.002) and those of students on the 3rd floor of Medicine Faculty (M=21.08) (p=.045). State anger levels of students on the 1st floor of Medicine Faculty (M=23.80) were found to be significantly higher than those of students on the 2nd floor of Medicine Faculty (M=20.91) (p=.002) and those of students on the 3rd floor of Medicine Faculty (M=21.08) (p=.021).

A significant difference was found among university students' main scores of outraged anger according to the locations where they filled the questionnaires [F (7-465) = 5.446; p=.000]. The results of the Tukey test conducted to determine the source of the difference indicated that outraged anger levels of students at Engineering faculty (M=17.40) were significantly higher than those of students on the 2nd floor of Medicine Faculty (M=14.68). Outraged anger levels of students at Coffee Shop (M=17.51) were found to be significantly higher than those of students on the 2nd floor of Medicine Faculty (M=14.68) (p=.003). Outraged anger levels of students on the 1st floor of Medicine Faculty (M=17.82) were found to be significantly higher than those of students on the 2nd floor of Medicine Faculty (14.68) (p=.002). Outraged anger levels of students on the top floor of wellness center (M=17.78) were found to be significantly higher than those of students on the 2nd floor of Medicine Faculty (M=14.68) (p=.001).

A significant difference was found among university students' main scores of hated anger according to the locations where they filled the questionnaires [F (7-465) = 7.640; p=.000]. The results of the Tukey test conducted to determine the source of the difference indicated that hated anger levels of students at Engineering faculty (M=17.00) were significantly higher than those of students on the 2nd floor of Medicine Faculty (M=14.44) (p=.002) and those of students on the 3rd floor of Medicine Faculty (M=14.28) (p=.010). Hated anger levels of students at Coffee Shop (M=16.68) were found to be significantly higher than those of students on the 2nd floor of Medicine Faculty (M=14.44) (p=.035). Hated anger levels of students on the 1st floor of Medicine Faculty (M=18.35) were found to be significantly higher than those of students on the 2nd floor of Medicine Faculty (M=14.44) (p=.000), those of students on the 3rd floor of Medicine Faculty (M=14.28) (p=.000) and those of students on the 4th floor of Medicine Faculty (15.21) (p=.002). Hated anger levels of students on the top floor of wellness center (M=17.91) were found to be significantly higher than those of students on the 2nd floor of Medicine Faculty (M=14.44) (p=.000), those of students on the 3rd floor of Medicine Faculty (M=14.28) (p=.000) and those of students on the 4th floor of Medicine Faculty (15.21) (p=.009).

Correlation between State-Trait Anger, Nicotine Addiction and Level of Noise shown in [Table 5]. Pearson's correlation revealed that there was significant, positive correlation between trait anger and level of noise (r(473)=.223; p<.01). Pearson's correlation revealed that there was significant, positive correlation between state anger and level of noise (r(473)=.099; p<.05). Pearson's correlation revealed that there was significant, positive correlation between outraged anger and level of noise (r(473)=.158; p<.01). Pearson's correlation revealed that there was significant, positive correlation between hated anger and level of noise (r(473)=.107; p<.05). There was no significant correlation between controlled anger and noise and also there were no significant correlation between nicotine addiction and noise.

Table 5: Pearson correlation between State-Trait Anger, Nicotine Addiction and Level of Noise

	Level of Noise
Trait Anger	**r.223**** **p.000**
State Anger	**r.099*** **p.032**
Controlled Anger	r-.043 p.345
Outraged Anger	**r.158**** **p.001**
Hated Anger	**r.107*** **p.020**
Nicotine Addiction	r.065 p.400
*p<.05; **p<.01	

Acting as a stressor, noise can result in anger. The findings of a study conducted by Iwata [15] revealed that those with a high level of noise sensitivity show more remarkable symptoms of anger. Another research carried out by Ramirez et al. [2] found that psychobiological factors, such as age, were also important variables determining the relationship between anger and noise. According to the results of this study, the relationship between noise sensitivity and anger was higher among older participants. As the literature review shows, there is a positive correlation between anger and noise, and according to the literature, the higher the noise level, the higher the anger level.

Although the literature review reveals a good number of studies regarding the relationship between smoking behavior and anger, the significance of the current study stems from the fact that there is no specific study on university students. In a study conducted in this area, a positive relationship was found between the number of cigarettes consumed daily and the level of trait anger [16]. In a study by Eiden et al. [10], smokers were found to be associated with higher levels of anger than those who did not smoke continuously or did not smoke at all. In another study, decreases in anger symptoms were observed in smokers in the period after smoking [8].

For the research done in Iran by Alimohammadi et al. [17], 250 workers in a car manufactory, noise pollution and their exposure to noise were examined. The most striking and significant correlation variable was anger. This proves us that our research touches an aspect that is in every part of life for different age and profession groups.

CONCLUSION

In this study, the effects of noise pollution on anger and cigarette addiction were examined on university students. The following results can be predicted from this study: The higher the noise level, the higher the anger level. While trait, state, outraged, and hated anger were found positively correlated with noise, no correlation was found between controlled anger and noise. There is a positive and significant relationship between nicotine addiction and anger. People with high anger levels also show addiction to nicotine. Nicotine addicts have a higher average of trait, hated, and outraged anger than non-smokers, while their controlled anger averages are lower.

In light of research's results, difference in student behavior under noise pollution was observed and its effects on anger are correlated with smoking. This research will provide basis for future research: Lack of research in this topic (especially in Turkey sample) unfortunately shows us that the interest in this topic is insufficient. Usage of different inventory in future researches (State anxiety, State stress) is one of the key factors for improving the study.

CONFLICT OF INTEREST

There is no conflict of interest.

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None.

FINANCIAL DISCLOSURE
None.

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ARTICLE

EFFECTS OF NOISE POLLUTION ON ATTENTION DEFICIT AND HYPERACTIVITY DISORDER IN COLLEGE STUDENTS

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ABSTRACT

Attention Deficit Hyperactivity Disorder (ADHD) springs in childhood and is described with behaviors like impulsivity, inattention, struggling with paying attention and hyperactivity. Causes can be various such as inheritance, neurological/neuropsychological or environmental. People get affected not only psychologically, but also physiologically. Noisy environments usually affect people with ADHD as well. The inattention symptoms of ADHD become clearer as the noise gets louder. The relation between ADHD and noise is aimed to be studied in this research. 622 individuals participated in the research in Istanbul Okan University. CESVA DC 311 model device was used in 8 different places in order to measure noise levels in the first part of the survey. Next, in order to study the relation between ADHD and noise, Adult Self-Report scale was used on students. The analysis indicated that average of impulsivity and hyperactivity of participants in Humanities and Social Sciences Faculty is much lower than those in Wellness Center. A significant difference in ADHD total point average was found. By Tukey test, the origin of difference was analyzed, and it was observed that total average points of participants in Humanities and Social Sciences Faculty was significantly lower than those in Wellness Center. According to unpaired T-test data in demographic parameter studies, no significant difference between these parameters and ADHD points was found.

KEY WORDS
ADHD, noise pollution, location, decibel, health

INTRODUCTION

Known as a common disorder among children, adolescents and adults, Attention Deficit and Hyperactivity Disorder (ADHD) shows some persistent indications such as impulsivity, excessive hyperactivity, inattentiveness and difficulty in maintaining concentration. The disorder can begin in early childhood and the symptoms may last a lifetime [1]. While symptoms of ADHD are most obvious in childhood, the symptoms begin to decrease with age and are replaced by internal restlessness in adolescence. Similar symptoms appear in adulthood such as internal unrest, distractibility, impatience and planning difficulties [2].

ADHD increases over years and ADHD prevalence rates vary among children, adolescents and adults. ADHD prevalence is between 7.8 % and 9.5 % among children; between 5.9% and 7.1% among adolescents; and between 1.2% and 7.3% among adults. As for university students this rate is proven to be 2% worldwide while it is reported to be 6.1% among university students studying in Turkey [3][4][5]. The parents need to be aware of the situations regarding the behavioral characteristics of children diagnosed with ADHD and the kind of arrangements they need to do in their house. The teachers also need to obtain the necessary information in order to make arrangements in the classroom considering the characteristics of children with ADHD, in case they have problems in obeying the classroom rules, make mistakes because of their attention deficit or experience problems in participating in the games or other classroom activities [6]. In the treatment of ADHD, along with the individual treatments offered to the child, the child should be evaluated together with the family members as a whole, and his/her parents, especially the mother, should be subjected to psychological examination and, if necessary, they should be provided appropriate treatment [7]. ADHD is a complicated and multifaceted syndrome and there is a very large literature regarding its causes, biological sub-structures and its impact on the individual and the community [8]. Literature review shows that ADHD may develop out of various factors. Those can be classified into inheritance-related factors, neurological / neuropsychological factors and environmental factors. Most of the studies conducted on the field of genetics refer to genetic factors as the key determinants of ADHD symptoms [9, 10]. These studies suggest that ADHD might be influenced by some hereditary variables which may also change phenotype of ADHD. ADHD or a similar phenotype is more commonly seen in children born with extreme low weight and premature [11]. However, genetics is not the only factor responsible for ADHD. Environmental factors also have important effects on the emergence of ADHD and interaction of environmental and genetic factors significantly contribute to ADHD. Exposure to toxic metals such as lead, mercury and manganese contribute to ADHD development. Exposure to nicotine or alcohol especially in fetal period may also increase the risk. ADHD is also linked to social and economic disadvantage. That is to say, ADHD develops more within families with low socioeconomic status. Many studies show that environmental factors are consistent in terms of time and countries [12-14].

Researchers conducted over the last ten years suggest that cognitive factors may also lead to ADHD. ADHD is attributed to low level of cognitive control. Attention is one of the cognitive factors and it has three aspects which are directing attention, drawing attention and vigilance. Among those only vigilance is associated with ADHD. In order to fully understand whether a person has ADHD or not, it is important to make accurate definitions of the typical parameters such as inattention, impulsivity and hyperactivity, and to identify how inappropriate the person performs those behaviors in relation with his/her developmental

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age [15]. Symptoms given under the title of "inattention" are inappropriate for one's developmental level and impair social activities. Inattention symptoms given under that title are being indifferent details, committing incautious errors during activities, inability to concentrate while working on something, failing to follow given instructions and fulfill ordinary daily responsibilities, difficulty in planning work and activities, being distracted easily with external stimulus and memory impairment about daily activities. These symptoms are more persistent with respect to other ADHD symptoms and they are experienced more frequently. As like inattention symptoms, the symptoms given under the title of "excessive hyperactivity" are also inappropriate for one's developmental age and they lead to negative results in social activities. However, those do not stem from a hostile attitude, resistance or being unable to understand the instructions. Symptoms like making continuous hand or foot movements, not sitting on a seat when he/she is supposed to do so, running or climbing improperly, inability to get involved in leisure activities, often being "on the go", talking excessively or interrupting others are also important for the understanding of hyperactivity and impulsiveness [2, 16]. Literature review show that among the adults who have developed ADHD in childhood and still hold symptoms, inattention symptoms appear more obvious with respect to hyperactivity/impulsivity symptoms [17]. These symptoms cause the individuals to have numerous social and academic problems. The difficulties a child who has ADHD may encounter within her/his own house are not obeying rules, not being able to adapt to mealtime or sleep time, having frequent conflict with siblings, and not being able to complete homework without parents. On the other hand, these problems turn into concentration problems, inappropriate behaviors and inappropriate words in the classroom [18].

Noise is defined as unwanted sound. Environmental noise consists of all the unwanted sounds in our communities except that which originates in the workplace. Environmental noise pollution, a form of air pollution, is a threat to health and well-being. It is more severe and widespread than ever before, and it will continue to increase in magnitude and severity because of population growth, urbanization, and the associated growth in the use of increasingly powerful, varied, and highly mobile sources of noise [19]. Based on the literature review, positive correlation was found between noise and noise sensitivity. Individuals with ADHD are usually sensitive to high sounds. Noise pollution causes impairment in short term memory and distraction. Because, when an individual with ADHD is exposed to noise, he/she feels in a constant state of danger, thus focusing on the noise and keeping it at the center of his/her focus. Research shows that individuals with ADHD have short-term memory capacity and they tend to be distracted more than others who do not have ADHD symptoms. Research findings also suggest that as the noise pollution increases, inattention-related symptoms of ADHD also increase. Recent studies revealed that high level noise might have long-term effects on preterm infants' auditory system. Preterm infants exposed to such noise have a high risk of ADHD.

MATERIALS AND METHODS

This study aims to examine how ADHD is related to noise, which is an environmental factor having a crucial function in ADHD phenomenon. In line with this purpose, the study was conducted on 622 students studying at Okan University. Data collection was conducted in two steps. First, noise level was measured at 8 different locations in Okan University with the use of Cesva DC311 model device with T240385 serial number. Sound measurements have been made at a variety of locations in Okan University by a field specialist via a sound level meter. The testing and data collection phases were conducted under Istanbul Okan University's permission and participants were given informed consent form to confirm their volunteering.

Participants

The original sample consisted of 622 students studying at Okan University. But 4 participants were not included in the study because their forms were uncompleted, and 5 participants were excluded because they were not within the age group specified for the sample of the study. Finally, the sample included 613 participants: 379 female and 234 males. They are aged between 18 and 25, and their mean age is 20.90±1.78.

Measures

Demographic data such as age, gender, university, faculty, department, grade and cumulative grade point average were obtained via Personal Information Forms.

Developed by World Health Organization (WHO), Adult attention deficit and hyperactivity disorder self-report scale (ASRS); [20] consists of 18 questions. Each question requires the participants to answer the frequency of having a specific ADHD symptom in the last six months. The questions are divided into two sub-scales. 9 questions are related to inattention and the other 9 questions are related to hyperactivity/impulsivity. 1st, 2nd, 3rd, 4th, 7th, 8th, 9th, 10th, and 11th questions are categorized under the inattention subscale (F1) while 5th, 6th, 11th, 12th, 13th, 14th, 15th, 16th, 17th and 18th questions are categorized under the hyperactivity/impulsivity subscale (F2). ASRS is a four-point Likert type scale including options like never (0), rarely (1), sometimes (2), often (3), and very often (4). If the sum score in either F1 subscale or F2 subscale is calculated between 17 and 23 the person is classified having "likely" ADHD, while individuals with scores of 24 and over are classified having "highly likely" ADHD. Six of the 18 questions constitute the A part of the form. "Stepwise logistic regression" proved that part A is a better predictor of ADHD [21] [22].

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Procedures

Data were collected at different indoor and outdoor locations such as faculties, coffee houses all having different noise levels. It was stated that the participation in the survey was entirely voluntary, and students who did not want to participate were not included. Participants were informed about the research in advance, and then their consent for participant was taken through informed consent form. Subsequently, participants were asked to fill in personal information forms and scales that were in the content of the work. The application lasted about 10 minutes. Sound measurements have been made at a variety of locations in Istanbul Okan University by a field specialist via a sound level meter. Below, you can see decibel intervals with respect to participants' locations.

Table 1: Decibel intervals with respect to participants' locations

Locations		Decibels
Location 1	Social Sciences Faculty Building	44
Location 2	Engineering Faculty Building	56.8
Location 3	Faculty of Medicine 2nd floor	60.9
Location 4	Faculty of Medicine 4th floor	64
Location 5	Starbucks outdoor Building	68.5
Location 6	Faculty of Medicine 3rd floor	69
Location 7	Starbucks indoor Building	72.9
Location 8	Wellness Center Building	82

Data analysis

Data was analyzed on the SPSS (Statistical Package for Social Sciences). The analysis involved the use of One-Way Analysis of Variance (ANOVA) which is implemented for the aim of comparing variation among more than two groups and Tukey test which is a multiple comparison test as well as descriptive statistics (mean, standard deviation, frequency). Significance was found $p<0.05$ and $p<0.01$ as shown in tables regarding analysis.

RESULTS AND DISCUSSION

The present research has been conducted with 613 university students as study subjects, with 61.83% (n=379) females and 38.17% (n=234) males studying at different faculties in Istanbul Okan University. The participants are aged between 18 and 25, and their mean age is 20.90±1.78. [Table 2] presents participants' demographic information.

Table 2: Demographic Information

Age	Min-Max (Median) Mean±Sd	18-25 (21.5) 20.90±1.78
Gender; n (%)	Female Male	379 (61.83) 234 (38.17)
Level of Income	Low Low-Middle Middle Middle-High High	12 (2,0) 13 (2.2) 282 (46.8) 226 (37.5) 70 (11.6)
Faculty	Faculty of Health Sciences Faculty of Humanities and Social Science Faculty of Business and Administrative Sciences Faculty of Law Faculty of Education Faculty of Architecture School of Applied Sciences Faculty of Fine Arts Faculty of Engineering	267 (43.6) 47 (7.7) 32 (5.2) 71 (11.6) 24 (3.9) 26 (4,2) 38 (6.2) 21 (3.4) 87 (14.2)

Analysis of students' income levels shows that 2% (n=12) of the students have low-income level, 2.2% (n=13) have low-middle income level, 46.8% (n=282) have middle income level, 37.5% (n=226) have middle-high income level and 11.6% (n=70) have high income level.

When the distribution of the students with regard to the faculties they are studying at is examined, we can see that 43.6% (n=267) of the students study at Faculty of Health Sciences; 7.7% (n=47) at Faculty of Humanities and Social Sciences; 5.2% (n=32) at Faculty of Business and Administrative Sciences; 11.6% (n=71) at Faculty of Law; 3.9% (n=24) at Faculty of Education; 6.2% (n=38) at School of Applied Science; 3.4% (n=21) at Faculty of Fine Arts; and 14.2% (n=87) at Faculty of Engineering.

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Table 3: Distribution of Attention Deficit and Hyperactivity Disorder Scores

			Female	Male	Total
ADHD Level	No ADHD	Count % within gender	172 45.4%	123 52.6%	295 48.1%
	Likely ADHD	Count % within gender	158 41.7%	79 33.8%	237 38.7%
	Highly Likely ADHD	Count % within gender	49 12.9%	32 13.7%	81 13.2%
Total		Count % within gender	379 100.0%	234 100.0%	613 100.0%

According to the ADHD scores, 45.4% of the female participants (n=172) have no ADHD; 41.7% (n=158) have likely ADHD; and 12.9% (n=49) have highly likely ADHD. When it comes to male participants' scores, 52.6% (n=123) of the males have no ADHD; 33.8% (n=79) have likely ADHD; and 13.7% (n=32) have highly likely ADHD. Total ADHD scores, on the other hand, show that 48.1% (n=295) of the participants have no ADHD, 38.7% (n=237) have likely ADHD; and 13.2% (n=81) have highly likely ADHD.

Table 4: Analysis of ADHD levels based on gender

	Gender	N	Mean	SD	T	p
Inattention	Female	379	14.34	4.851	.207	.836
	Male	234	14.26	5.318		
Hyperactivity and Impulsivity	Female	379	17.15	5.168	.138	.890
	Male	234	17.09	5.235		
ADHD Total	Female	379	31.49	8.774	.211	.833
	Male	234	31.33	9.478		

Independent T-Test data do not indicate a significant difference between inattention scores based on participants' gender. [t=.207; p>.05]. Likely, results did not reveal a significant difference between hyperactivity and impulsivity scores of females and males. [t=.138; p>.05]. Also, difference between total ADHD scores of males and females was not significant, either.

Table 5: Analysis of ADHD levels based on noise level

Df: 7-605		N	Mean	SD	F	P	Tukey
Hyperactivity and Impulsivity	1	25	14.16	5.022	2.419	.019	8 > 1 p=.010
	2	82	17.48	4.595			
	3	101	16.50	5.157			
	4	27	17.33	4.350			
	5	82	17.54	5.659			
	6	146	16.66	4.693			
	7	40	17.58	5.905			
	8	110	18.19	5.601			
ADHD Total	1	25	25.88	7.870	2.452	.017	8 > 1 p=.008
	2	82	31.99	8.137			
	3	101	29.96	8.872			
	4	27	32.19	7.322			
	5	82	31.83	10.350			
	6	146	31.21	8.150			
	7	40	32.48	10.375			
	8	110	33.05	9.594			
	Total	613	31.43	9.042			

One-way ANOVA calculations indicated a significant difference between the participants' hyperactivity and impulsivity subscale scores with respect to their locations. [F(7-605)=2.419; p<.05]. Tukey test was used in order to identify the reason behind the difference and it was found that hyperactivity and impulsivity average of participants in the 8th Location (Wellness Center) (=18.19) was significantly higher than the average score of participants in the 1st Location (Faculty of Humanities and Social Sciences) (=14.16).

A significant difference was found between participants' total ADHD score averages regarding their locations [F (7-605) =2.452; p<.05]. Tukey test was used in order to identify the reason behind the difference and it was found that Participants in Wellness Center scored meaningfully higher (=33.05) than those in Faculty of Humanities and Social Sciences (=25.88) with regard to total ADHD averages (p=.008).

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According to Bremmer et al. [23], Miedema and Vos [24] and Pelletier et al. [25], noise affects ADHD patients by causing distraction and impairment in short term memory. It is also proposed that individuals are mostly ta risk of experiencing higher level of hyperactivity and higher number of emotional problems in noisy environments. Another study concludes that students with ADHD performed better when they were assigned a work in a silent class environment [26]. A gender-based research has been made in this field and it is found that males experience ADHD more often than females. It is also reported that people having high status jobs are less likely to develop ADHD. In parallel with this claim, another study reports that ADHD is more popular among males on international basis. In addition, ADHD is reported to be more common among those who do not hold a university degree [22]. According to results of other studies, ADHD is influenced by socioeconomic factors, and ADHD patients are also affected by psychosocial and socioeconomic factors such as professional in qualification which emerge as a result of the disorder [28]. In a study, the link between the genes and the effect of socioeconomic factors on ADHD were investigated. The results suggest that low economic level has the ability to affect specific genes that may decrease or increase the possibility of ADHD, although it is not the most important factor leading to ADHD [27]. Another study conducted on children shows that socioeconomic parameters such as education level, welfare level and parenting alone are among the strong determinants of ADHD, and the results show no significant relationship between the gender differences and ADHD [29].

CONCLUSION

In the present study, we detected noise level at a variety of locations in Okan University and then we analyzed the impact of noise on ADHD. According to results, hyperactivity and impulsivity average of participants in Wellness Center was significantly higher than the average score of participants in Faculty of Humanities and Social Sciences. Another significant difference was found between participants' total ADHD score averages in terms of their locations. Participants in Wellness Center scored meaningfully higher than those in Faculty of Humanities and Social Sciences. It is known that social factors and socio-demographic parameters (gender, income status, educational status, etc.) are the ones that significantly affect the level of ADHD among university students. In this regard, this study shows us that the effect of noise pollution on ADHD levels has reached an ignorable level. For prevention and precaution purposes in the future on this topic, diversification of literature has utmost importance. Despite that, because of lack in literature (especially Turkey sample), causes individuals to overlook the significance of this topic.

CONFLICT OF INTEREST
There is no conflict of interest.

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FINANCIAL DISCLOSURE
None.

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