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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

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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.

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.

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

COMPUTATIONAL BIOLOGY

THE IIOAB JOURNAL

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 x_0 which has been provided with the help of convolutional network. This system is composed with L layers, where every layer executes a non-linear transformation $H_\ell(\cdot)$, where ℓ denotes the layer [14]. $H_l(\cdot)$ 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 $\mathrm{X}\ell$. ResNets. Conventional feed-forward networks link the result of ℓth layer as input to $(\ell+1)^{th}$ layer, that tends to develop transition layer: $\mathrm{x}_l = H_\ell(\mathrm{x}_{l-1})$.

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

$$\mathrm{x}_l = H_\ell(\mathrm{x}_{\ell-1}) + \mathrm{x}_{l-1}. \qquad (1)$$

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 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.

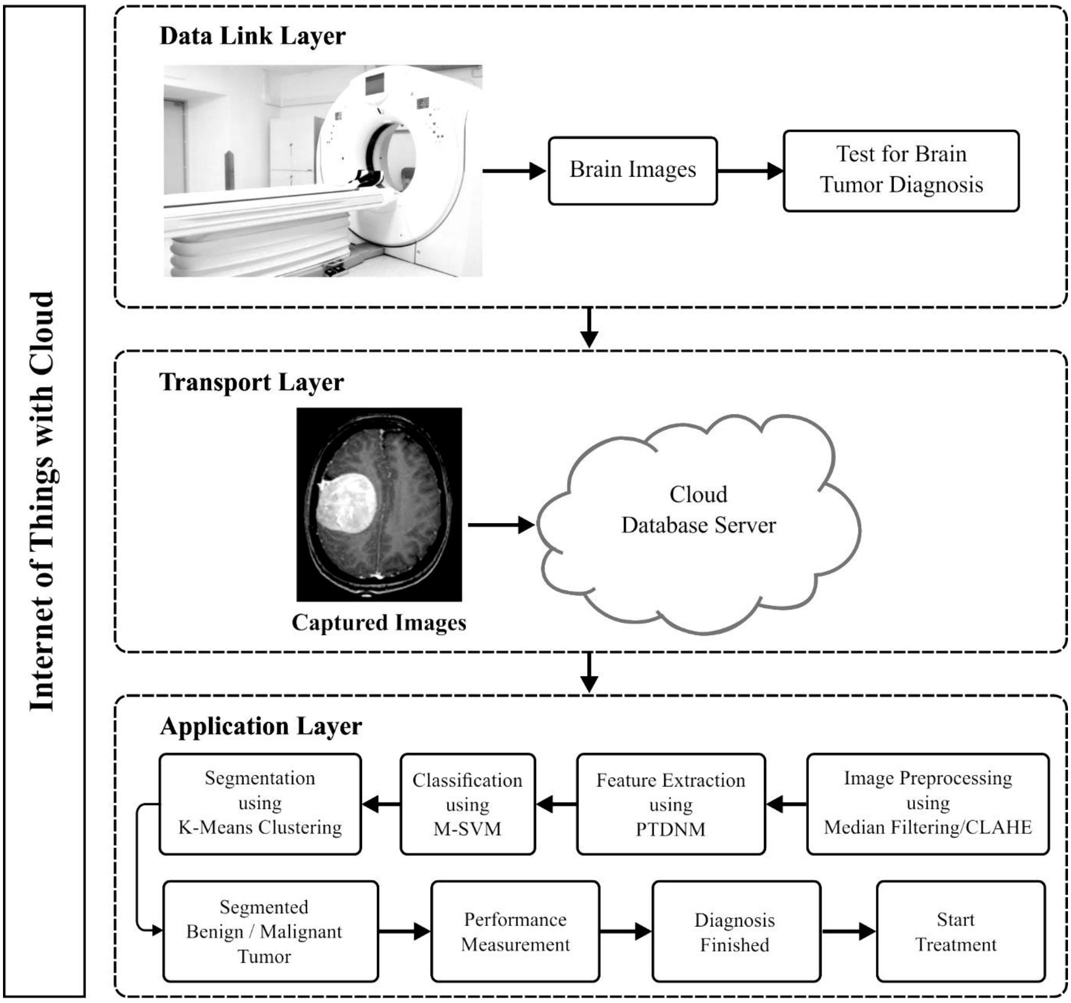

Fig. 1: Overall Process of Proposed ODEN Model

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,

$$b = argmax_{b'}\, \overline{w}^{T}\Phi(\bar{a}, b) \qquad (2)$$

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.

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

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.

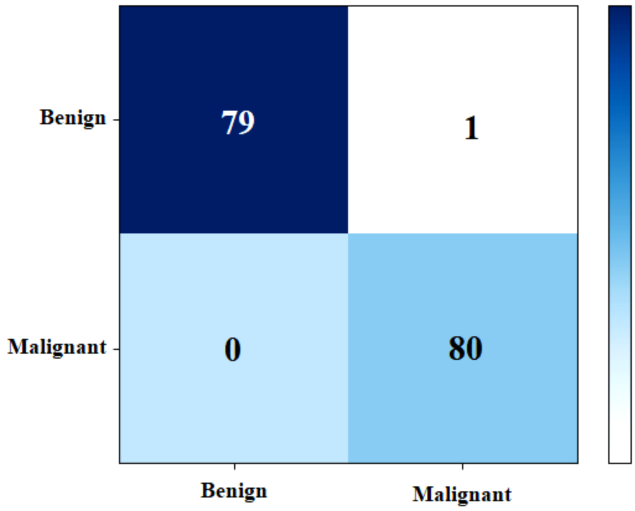

Fig. 2: Confusion Matrix of Proposed ODEN Model

IIOAB JOURNAL
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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.

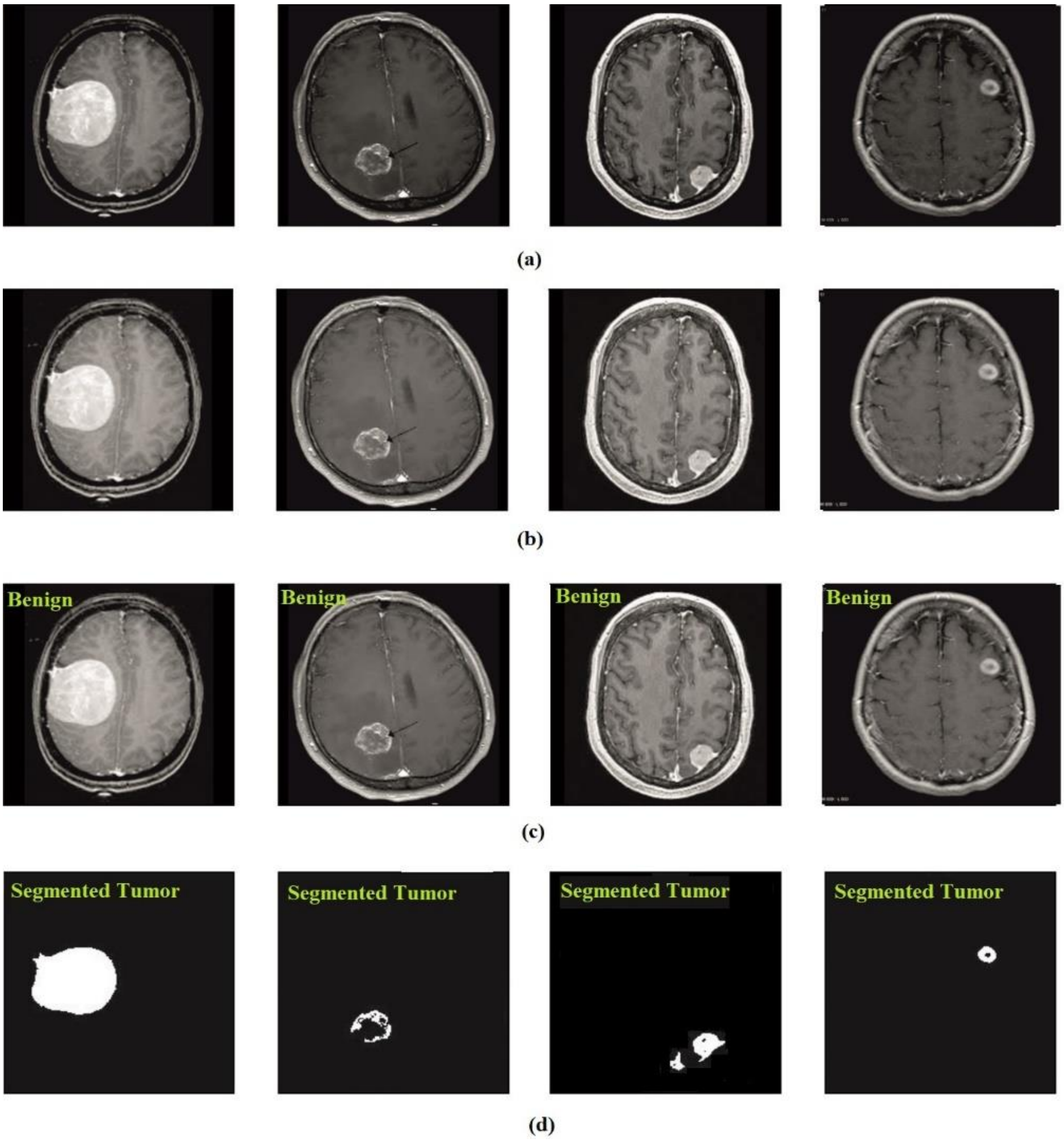

Fig. 3: a. Original Images b. Preprocessed Images c. Classified Images d. Segmented Images

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.

IIOAB JOURNAL
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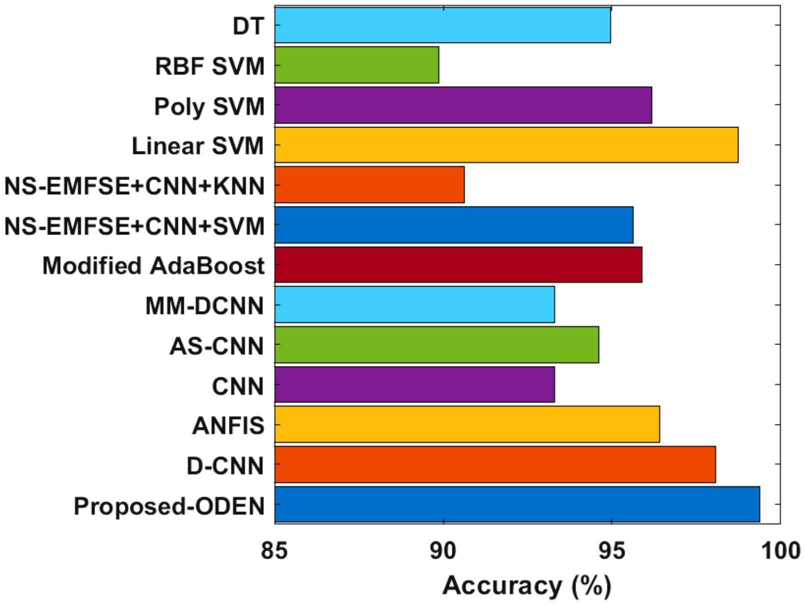

Fig. 4: Accuracy analysis of diverse models

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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FINANCIAL DISCLOSURE

None.

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IIOAB JOURNAL ISSN: 0976-3104

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