ISSN: 0976-3104
SPECIAL ISSUE: Emerging Technologies in Networking and Security (ETNS)
Rao and Rao.

ARTICLE OPEN ACCESS

A FUSION TECHNIQUE TO CLASSIFY GLAUCOMA FROM FUNDUS IMAGES

M Nageswara Rao[1*], M Venu Gopala Rao[2]

[1]Research scholar, Dept. E.C.E, K L University, INDIA
[2]Dept.of E.C.E, K L University, INDIA

ABSTRACT

Glaucoma is a common cause of blindness and it is increasingly becoming more severe when taking into consideration the aging population. As the dead retinal nerve fibres are not healable, earlier detection as well as prevention of glaucoma is crucial. Resilient and automatic mass-screening will assist in the extension of symptoms-free life for the patients. A new automatic appearance-based glaucoma classification system which does not rely on segmentation-based measures is suggested here. It employs image fusion, which refers to the procedure of fusing images obtained from various sources for acquiring improved situational awareness. The goal of fusion of source images is the combination of highly relevant data from sources into one composite image. Genetic Algorithm (GA) is utilized for features selection. Features extraction methods utilized are Discrete Wavelet Transform (DWT) utilized for multiresolution fusion as well as Local Binary Patterns (LBP) for texture features. Outcomes prove that the suggested model attains excellent glaucoma classification.

Published on: 2nd -December-2016

KEY WORDS

Glaucoma, Image Fusion, Wavelet Transform, Local Binary Patterns (LBP), Genetic Algorithm (GA), Random Forest (RF), Bagging and Boosting

***Corresponding author: Email:** nagmedikonda@gmail.com

INTRODUCTION

Glaucoma is a common cause of blindness amongst retinal diseases with 13% of the cases getting affected. The changes happen in retinal structure that gradually results in loss of peripheral vision and in the end leads to blindness if it is not treated in time. No cure is present for Glaucoma, however, its earlier detection as well as treatment helps in preventing loss of vision. Because the procedure of manual diagnosis is expensive as well as error-prone, effort has been made toward automated detection of Glaucoma in its earlier stage [1].

Glaucoma refers to a set of eye diseases that are related to concurrent functional failures in visual field. Changes in structure are symptomized by a slow diminishing neuro-retinal rim denoting degeneration of axons as well as astrocytes of the Optic Nerve. Because any lost capacity of the optic nerve is not recoverable, earlier detection as well as care is crucial for patients to retain their vision.

Two major kinds of Glaucoma include: 1) Primary Open Angle Glaucoma (POAG) as well as (ii) Angle Closure Glaucoma (ACG). The former progresses in a slow manner and at times without any significant loss in vision for several years. Treatment involves medication if an early diagnosis is made. The latter requires surgery as a small portion of the outer edge of the iris is to be removed.

In latest studies, a lot effort has been put into automatic diagnosis of glaucoma on the basis of computer vision. The structure of glaucoma analysis systems is dependent on the types of image cue and image modality utilized. Amongst structural image cues learnt for diagnosing glaucoma, cues based on optic discs as well as cups are significant. Optic discs are situated near ganglion nerve fibres congregating in the retina. Optic cup is where the depression occurs in the optic disc from where the fibre comes out of the retina through the Optic Nerve Head (ONH). The borders of the cup and disc structures are required to be found since it helps the assessment of glaucoma cues like disc and cup asymmetry and high Cup-to-Disc Ratio (CDR), described as the ratio between vertical cup diameter to vertical disc diameter. Value of CDR is assessed by planimetry from color fundus images after outlining the optic discs and cups physically. As the process of manual annotation of cup and disc for every image involves

THE IIOAB JOURNAL ISSN: 0976-3104

more labour and time, this work proposes automation through computer vision methods to segment the cups and discs from fundus images.

The term Fundus refers to the part of the organ opposite to the opening. The image [Figure 1] below shows the interior surface of the eye which includes retinal blood vessel, macula, fovea, optic disc as well as cup. Different factors from the image are required to be analysed to figure out the glaucoma disorders. ONH, CDR, rim disc ratio as well as Retinal Nerve Fibre Layer Height (RNFLH) are few of the significant factors in the assessment of ONH as well as Retinal Nerve Fibre Layer (RNFL). As glaucoma has impact on the optic disc as well as cup by converting the cup to disc ratio as well as rim to disk ratio, appropriate segmenting of the characteristics is necessary for detecting glaucoma [2].

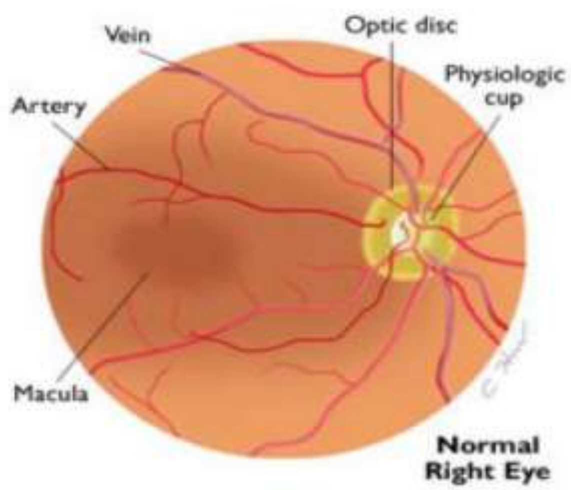

Fig: 1. Left Retinal Color Fundus Image

………..

Colour Fundus Imaging (CFI) is a modality through which glaucoma may be evaluated. It has also grown into a recommended modality for wide-scale screening of retinal diseases and moreover it has been already used for huge-scale screening of diabetic retinopathy. With this technology, fundus image can be acquired in a non-invasive way that is best suited to huge-scale screenings In these programmes, automatic system determines any symptoms of doubt which indicate the presence of a disease and this improves effectiveness as only those images that contain those symptoms need ophthalmologist's attention. Many efforts had been made for automatic detection of glaucoma from a 3-D image. But, due to the high cost, this facility is not available at basic health care centres and hence could not be used properly for wide screening.

Combining multiple images' information of one scene is known as Image fusion where the images are obtained from various sensors, captured at various timings, and have various spatial or spectral features. The aim of this fusion is the retaining of the beneficial feature of every image. Because of the existing multi-sensor data in various fields, researchers are more focussed towards image fusion for its application in several fields. For instance, in multi-focus imaging, one or more objects might be focused in a certain image, however other objects in the scene might be focused on in another image. For remotely sensed images, few have excellent spectral data while the others have excellent geometric resolution.

Within the field of bio-medical imaging, two extensively utilised modalities are viz., the Magnetic Resonance Imaging (MRI) as well as the Computed Tomography (CT) scan do not reveal similar information on the structure of brain. CT scan is best suited to take the image of hard tissues or bone structures whereas MR imaging is best for the soft brain tissues which helps to detect diseases that affect the skull base. As the required information cannot be received through a single image, these images are complementary.

By fusing the images the best features of individual image are obtained. The integration of these features is a huge advantage. The primary stage in image fusion is registering of the image that brings the constituent images to general coordinate system, because image fusion is useful only if common objects in image have similar geometrical configuration with regard to size, region as well as orientation. This can also be named as the pre-processing stage. Next, the images are put together to form a single image with a careful selection of various features taken from various images.

Fusion technique includes a simple technique of pixel averaging to even more complex techniques like principal component analysis and wavelet transform fusion. Various methods for fusing the image can be differentiated based on whether image fusion occurs in the spatial domain or transformed to another domain.

In this work, various feature extraction, feature selection and classifier techniques are proposed. And image fusion in Glaucoma is discussed. Section 2 reviews associated literature review. Section 3 describes methods applied and Section 4 details experimental result. Section 5 includes conclusion of the paper.

RELATED WORK

Xu et al., [3] presents an unsupervised technique to segment optic cups in fundus images to detect glaucoma with no use of extra training images. The method adopts the super pixel framework and domain prior wherein the super pixel task of classification is designed as a Low-Rank Representation (LRR) problem along with an effective closed-form solution. Moreover, the author develops an appropriate scheme for automatic selection of the key criteria in LRR and obtains the end results for every image. Assessed on the common ORIGA dataset, the result shows that the method achieved optimal performance in comparison to existing methods.

Niwas et al., [4] suggests the discriminate features are chosen by various feature selection protocols to detect Primary Angle-Closure Glaucoma (PACG) on the basis of Anterior Segment Optical Coherence Tomography (AS-OCT) images. A new condition was recommended for further selection of more dependable attributes. The method depends on the selection of top-ranking attributes in every algorithm and the ranking combination to select the best feature.

Guo et al., [5] presents an analysis of fundus images based in a computer aided system to automate the classification and grading of cataract that is extremely helpful for reducing the workload of experienced ophthalmologists as well as assist cataract patients in developing regions to detect the disease in time receive treatment from health care providers. The wavelet transform as well as sketch based method are examined for extracting the best suited feature to classify and grade the condition of cataract from the fundus image.

Raja & Gangatharan [6] presents an automatic technique to detect glaucoma from the fundus image with the help of hyper-analytic wavelet transform. Enhancing the directional selectivity and preservation of the information on phase is done with the image hyper-analytic wavelet transform. Prior to the transforming, the required pre-processing steps like gray scale conversion as well as equalization of histogram are executed. Next the magnitude as well as phase spectra of the image are assessed. This confirmed that the accuracy of classification was increased by 5 %.

Niwas et al., [7] focuses on the application of repetitive features to diagnose complicated diseases like Angle-Closure Glaucoma (ACG) with the use of anterior segment optical coherence tomography image. Supervised [Minimum Redundancy Maximum Relevance (MRMR)] as well as unsupervised algorithms for [Laplacian score (L-score)] features selection are investigated with various ACG methods. The total accuracy has proven the utility of repetitive attributes by L-score technique in enhanced ACG diagnosis as opposed to minimally redundant attributes by MRMR technique.

Gupta & Awasthi [8] presents image fusion technique which provides optimal result with Discrete Wave Packet Decomposition (DWPT) as well as optimizes results with GA and then compared them with Intensity Hue Saturation (IHS) utilized to fuse the images. Finally the performance of proposed technique is assessed with its mean, standard deviation, entropy, variance, mutual information, Peak Signal to Noise Ratio (PSNR) as well as structure similitude.

Bock et al., [9] suggested an innovative automatic system for detecting glaucoma which functions with affordable as well as typically utilized digitized colourful fundus image. After the pre-processing step particular to glaucoma, various general types of features are compressed with appearance oriented dimension reduction techniques. Consequently, a probabilistic two-stage classification strategy merges the feature kinds for extracting the new Glaucoma Risk Index (GRI) which exhibits a remarkable performance on detecting glaucoma. With sample group of 575 fundus images, 80 % classification accuracy is attained in the five fold cross validation setup. The GRI achieves 88 % of competitive Area under ROC (AUC) in comparison to existing topography oriented glaucoma probability score of scanning laser tomography with AUC of 87 %.

METHODOLOGY

In this section, feature extraction based wavelet transform and LBP are described. Feature selection based GA is discussed. The RF, bagging and boosting classifiers are described.

FEATURE EXTRACTION

Feature extraction is a crucial step in fusing images. In the process of extracting features the raw image is transformed into frequency domain as well as sampling with wavelet transform function. Texture values of features extracted in horizontally, vertically and diagonal transform vector forms are provided by wavelet transform function. Merging these texture values, a feature matrix is created. Value of integer wavelet transform function is used for the feature extraction. Integer wavelet transform function

THE IIOAB JOURNAL ISSN: 0976-3104

refers to a family of wavelet transform functions. The values of transforms usually produce the values of filter in whole number [10].

WAVELET TRANSFORM

Wavelet coefficient measured by a wavelet transform represents modification in the time series at a specific resolution. With consideration of the time series at different resolutions one can filter out and perform processing of actual features of the image. The term wavelet thresholding is described as disintegration of the data or the image into wavelet coefficient when compared to the detail coefficient with the given threshold value, and diminishing the coefficient near to zero to remove the impact of features in the given data. From the altered coefficients, the image is rebuilt. This procedure is also called as inverse discrete wavelets transform. At the time of thresholding, a wavelet coefficient is compared against given threshold and is marked as zero if the magnitude is lesser than the given threshold; or else it is maintained or it is changed as per the threshold rule. Threshold differentiates the coefficients because of feature containing significant information on signals. Choosing the appropriate threshold is most important because it has significant role in the elimination of features as fusing of images result in sharpness reduced images otherwise known as smoothed images.

A signal analysis technique identical to image pyramid is the discrete wavelet transform. The major distinction is that the image pyramid leads to a complete collection of transform coefficients, whereas the wavelet transform leads to a non-redundant image representation. The discrete 2D wavelet transform is calculated by the recursive use of low pass as well as high pass filter in every direction of the input image after which sub-sampling is done. One of the key limitations of the wavelet transform while used for fusing of image is its common shift dependency which means that an easy shift of the input signal leads to absolutely different transform coefficient. This leads to inconsistent image fusion when brought up in image sequence fusion. To defeat this limitation of shift dependency the input image must be split into the shift invariant representations. [Figure 2] shows the wavelet based image fusion.

The segmentation of image is done by horizontal and vertical straight line and this indicates the first-order of DWT, with the given image being divided into four sections as LL1, LH1, HL1 and HH1. Common image fusion process with DWT:

Step 1: Implementation of Discrete Wavelet Transform on all source images for creating wavelet lower decomposition.

Step 2: Fusion of every decomposition stage with various fusion rules such as simple average, simple maximum, simple minimum, etc.

Step 3: Execute Inverse Discrete Wavelet Transform on fused decomposed level, for rebuilding of fused end image F.

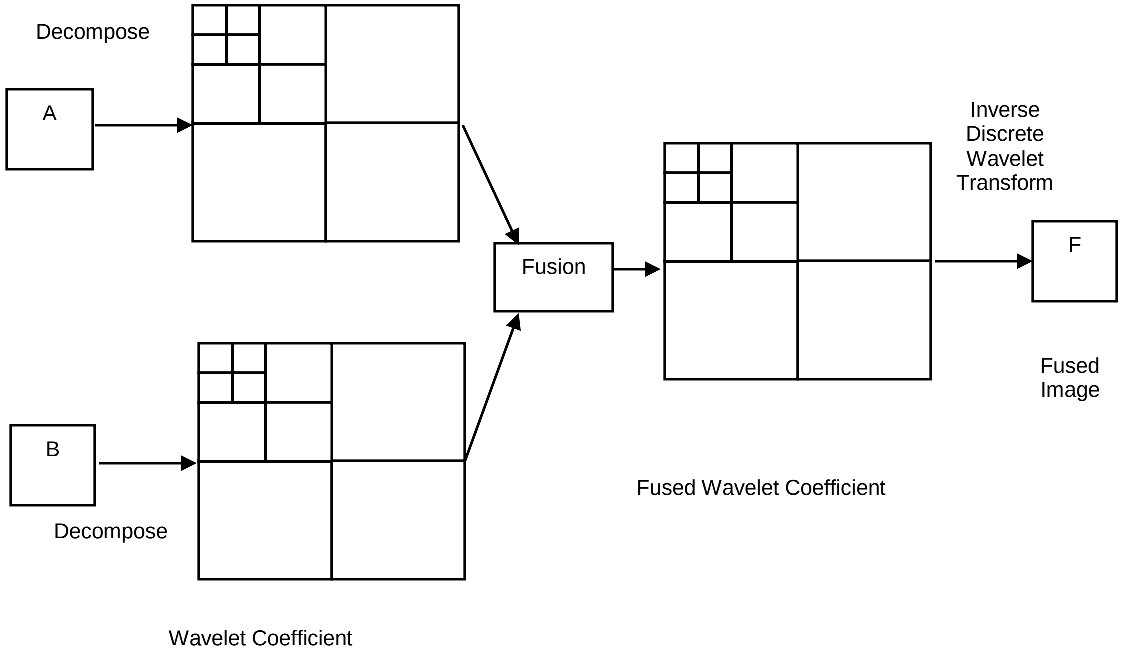

Fig: 2. Wavelet Based Image Fusion

………..

Two major group of transforms, continuous and discrete. Of specific attention is the DWT that is a spatial-frequency decomposition which will provide a flexible multi-resolution image analysis. In single dimension (1-D) the principle notion of the DWT is for representing the signal as a superposition of wavelet. Assume that a discrete signal is denoted by *f* (*t*), then the wavelet decomposition is given as in equation (1) [11]:

$$f(t) = \sum_{m,n} C_{m,n} \psi_{m,n}(t), \qquad (1)$$

Where $\psi_{m,n}(t) = 2^{-m/2} \psi\left[2^{-m} t - n\right]$, *m* and *n* represent integers. There exists a special choice of ψ so that $\Psi_{m,n}(t)$ comprises an ortho-normal basis, therefore the wavelet transform coefficient can be got by the computation:

$$C_{m.n} = \left\langle f, \psi_{m,n} \right\rangle = \int \psi_{m,n}(t) f(t) dt \qquad (2)$$

To build a multi-resolution analysis, a scaling function φ is required along with the expanded and translated version of it $\phi_{m,n}(t) = 2^{-m/2} \phi\left[2^{-m} t - n\right]$. As per the features of the scale space spanned by φ and ψ the signal *f* (*t*) can be decomposed in its coarse component and detail of different sizes by projection onto the respective space. Hence for finding such decomposition in an explicit manner, additional coefficient $a_{m,n}$, is needed at every scale. At every scale $a_{m,n}$, and $a_{m-1,n}$, describes the estimates of the function *f* at resolution 2^m and at the coarser resolution 2^{m-1} correspondingly, where the coefficient $C_{m,n}$, describes the loss of information while moving from an estimation to other. To acquire the coefficient $C_{m,n}$, and $a_{m,n}$, at every scale and position, a scaling function is required that is like equation (2). The approximation coefficient and wavelet coefficient can be got:

$$a_{m,n} = \sum_{k} h_{2n-k} a_{m-1,k}, \qquad (3)$$

$$C_{m,n} = \sum_{k} g_{2n-k} a_{m-1,k}, \qquad (4)$$

h_n is a low pass FIR filter whereas g_n is associated high pass FIR filter. In order to rebuild the actual signal the analysis filter can be chosen from a bi-orthogonal set that has an associated collection of synthesis filters. The synthesis filters *h*~ and *g*~ could be utilized for appropriate reconstruction of the signal with the rebuilding equation

$$a_{m-1,1}(f) = \sum_{n} \left[\tilde{h}_{2n-1} a_{m,n}(f) + \tilde{h}_{2n-1} C_{m,n}(f) \right] \qquad (5)$$

Equations (3) and (4) are applied by filtering as well as down sampling. Conversely, equation (5) is applied by initial up sampling as well as consequent filtering

LOCAL BINARY PATTERNS (LBP)

The actual LBP operators label the pixel of one image by decimal number known as LBP code that encodes the local structure around every pixel. It continues like this as shown in **[Figure- 4]**. It compares every pixel with its eight neighbours in a 3x3 neighbourhood by deducting the center pixel value; The finalised negative value is coded with 0 and the rest with 1; Through the clock wise concatenation of all the binary codes a binary number is obtained and its corresponding decimal value is applied for labelling. The derived binary numbers are referred to as LBP codes [12].

THE IIOAB JOURNAL ISSN: 0976-3104

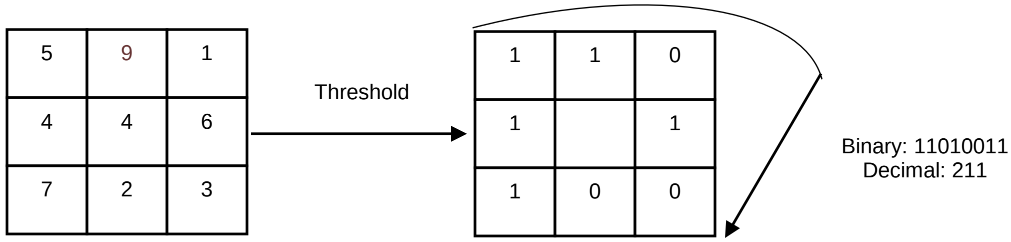

Fig: 2. An example of the basic LBP operator

……..

The drawback of the base LBP operator is that its small 3x3 neighbourhood may not obtain dominant attributes in the large-scale structures. To handle with textures at various scales, the operator generalizes later to utilize neighbourhood of various sizes. A local neighbourhood is referred to a collection of sampling points spaced even on a circle that is at the centre of the pixel to be labelled, as well as the sampling point which does not fall among the pixels are interpolated with bilinear interpolation and hence allows for any radius and any quantity of neighbourhood sampling points.

Mathematically, given a pixel at (x_c, y_c), the result LBP is shown in decimal form as equation (6):

$$LBP_{P,R}(x_c, y_c) = \sum_{P=0}^{P-1} s(i_p - i_c)2^P \qquad (6)$$

i_c and i_p are corresponding gray-level value of the central pixel whereas P surrounding pixel in the circle neighbourhood with a radius R, and function s(x) is defined in equation (7):

$$s(x) = \begin{cases} 1 & if \ \ x \geq 0 \\ 0 & if \ \ x < 0 \end{cases} \qquad (7)$$

With the above description, the principle LBP operator is invariant to monotonic gray-scale transformation protecting pixel intensity order in the local neighbourhood. The LBP histogram label estimated over an area is utilized as a descriptor of texture. The operators $LBP_{(P,R)}$ produce 2^P various output values, relating to 2^P distinct binary pattern constructed by P pixels in the neighbourhood.

FEATURE SELECTION

The process of feature selection may be taken as the process of finding and eliminating non-relevant, repetitive and random class co-related attributes. The feature selection problem is NP-hard. Hence the best solution is not assured to be found unless thorough search in the feature space is executed. Evolutionary algorithm such as GA has been extensively used for feature selection. GA is a random search method with the ability to explore effectively in large search space that is normally needed in case of selecting the attribute. Moreover, GA performs a global search whereas many other search algorithms perform local search. GA is a search algorithm which owes its inspiration to the idea of natural selection. The principle notion is the evolving of a populace of individuals, where every individual solution is a candidate solution for a given issue. Feature selection methods contain potential advantages such as: 1) Reduces the quantity of training data required for achieving learning, 2) Creates training model with enhanced accuracy on prediction, 3) Learned knowledge is more compact, simpler and easier to interpret, 4) Learning requires reduced execution time, and 5) Decreases storage requirement [13].

GENETIC ALGORITHM (GA)

GA Optimization is performed by natural genetic substance exchange between the parents. Offspring is produced from parent gene. Offspring's fitness is assessed. Breeding is permitted only between the fittest individuals. GA is utilized in various areas like optimization of function, authenticating and controlling systems, processing of image, controller parameter optimization, multi-objective optimization, etc.

GA manipulates a populace of possible solutions for the issue to be addressed. Normally every solution is encoded as a binary string which is equal to the genetic substance of an individual in nature. All solutions are related to fitness values that reflect its goodness in comparison with another solution in the populace. Individual solution's fitness value and the survival chance and reproduction in the subsequent generation are directly proportional. Recombining of genetic substance in genetic algorithm is replicated by a crossover technique that will exchange parts among the strings. One more operation named mutation leads to sporadic and random bit alteration in string. Mutations have direct similarity in environment and play the roles of developing lost genetic substance. GA has application in many areas which includes image processing [14].

GA algorithm has a coding strategy and selection, crossover and mutation operator. An object is encoded with a classical binary code in the coding scheme. Roulette wheel method is applied for selection operator. In crossover step, single-point crossover produces new unit by swapping parts from the parent string at various crossover points. In binary coding, mutation operates by changing 0 to 1, or from 1 to 0. The crossover rate and mutation rate are pre-defined. GA has different phases progressing to a specified number of generations. This research focuses on, the chromosome that is coded in binary string bit with its size respective to the features and feature *i* is selected and is denoted by '1 or not by '0'. **[Figure- 5]** is a GA encoded sequential representation.

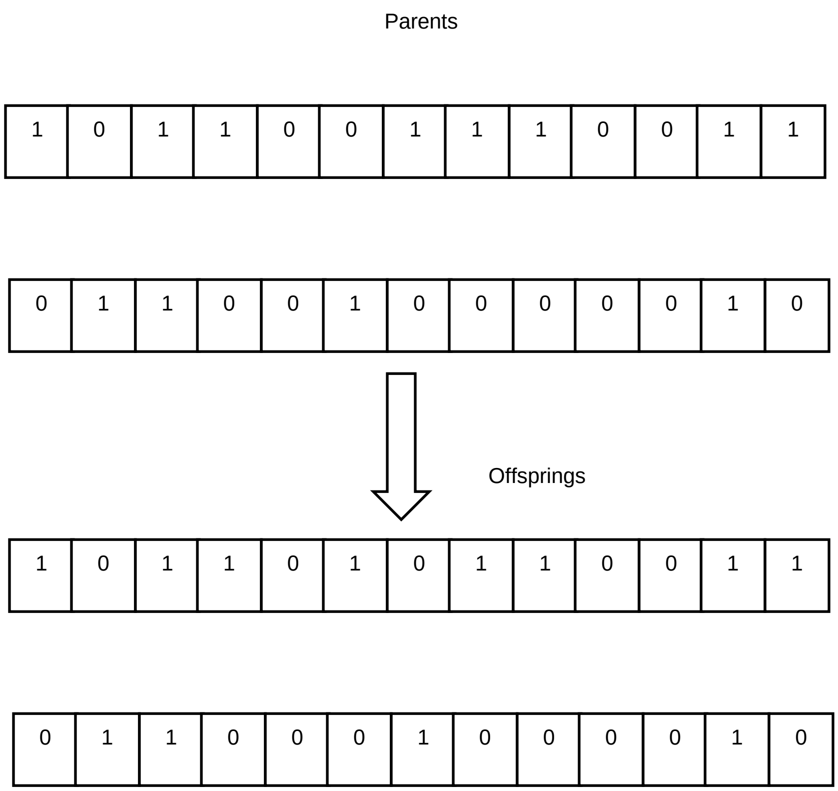

Fig: 3. Example of GA Encoding for feature selection

……

GA is capable of swift and efficient finding of an adequate solution for a difficult problem through probing a search space that is wide and complicated. **[Figure- 6]** shows the GA's flow diagram. Four attributes that helps to describe a GA problem are representation of the potential solution, the fitness function, the genetic operator to assist in identifying the best or near best solution and particular knowledge of problems like variables.

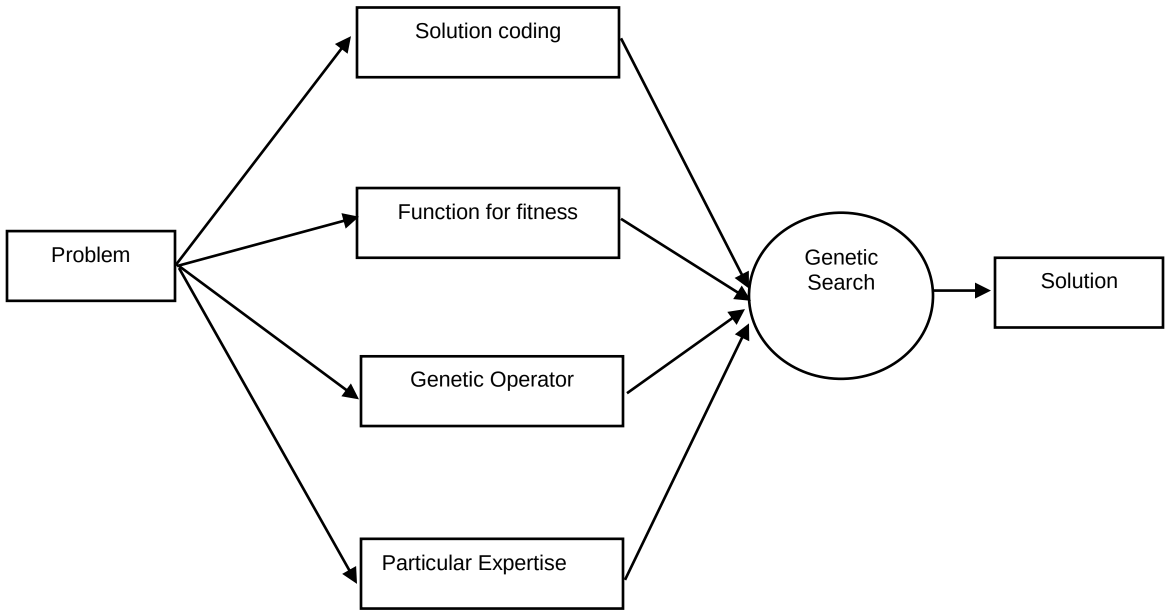

Fig: 4. Flow diagram of GA

GA provides solutions to the given issues through the genetic search part. The four major phases of genetic search are mentioned as:

Initialization: The randomly generated individual candidate solutions form the preliminary population. The size of population is based on the issue but normally comprises several hundred probable solutions which encompass the entire area of possible solutions in the search space.
Evaluation: The fitness function assesses every separate candidate in the populace and assists the procedure of selecting for the subsequent generation that depends on the fitness value.

Selection: A part of the available population is chosen for breeding a novel generation at the time of every subsequent generation. Individual candidate solution's fitness determines the candidate solution selection. Roulette wheel, rank-based, and tournament selection are few of the common selection methods.

Genetic Operator: Crossovers and mutations are two genetic operators which yield the novel populace for the subsequent generation after the selecting of the better individuals. A couple of "parent" solutions are chosen for breeding from the earlier selection pool. A novel solution is developed by generating a "child" solution with crossover and/or mutation. Novel candidate solution is chosen and process proceeds till a novel populace of solutions of proper size is produced.

CLASSIFIERS

Classification refers to a data mining (machine learning) technique applied for prediction of group membership for data examples. Classification is the issue of detection of the class of data using existing known class and this is also known as supervised classification. Hence the requirement is that novel individual item is placed into a group depending on quantitative information on one or more metrics or features, also depending on the learning set which contains the already determined groups. The classification where no expert is available for predicting is known as unsupervised classification. A framework is defined in which the collection of attributes are defined where a number of classifiers and algorithms are also available. This work focuses on the RF, bagging and boosting classifiers.

RANDOM FOREST (RF)

The RF algorithm based image fusion system is where the input image is classified into blocks of size MxN pixels. The input data set is created by the extraction of spatial and frequency domain attributes. At the time of training, RF algorithm employs the feature information to generate the random tree of poor learners for ensemble decision. At the next stage, the prediction of poor learner in the form of decision tree is combined using the majority voting scheme [15].

The advantages of RF method are the generation of different kinds of random tree with decreased variance which means the poor learners. This kind of poor learner is required basically for ensemble. RF-based ensemble method can compensate for the drawback of a tree with the advantage of other. Hence, RF algorithm could efficiently use the diversity of arbitrary trees as opposed to individual methods. RF algorithm arbitrarily creates several tree classifiers and collates the predictions. The tree, thus

THE IIOAB JOURNAL
ISSN: 0976-3104

generated is trained on bootstrap sample of the training data set and utilizes random subsampling of attributes. This scheme provides resilience against excess training and over fitting of inputted data. RF method performs better with high dimensional features space, specifically in a small data set that has a highly complicated structure.

BAGGING

Bagging technique is applied for enhancing the result of machine learning classification algorithms. This approach was designed by Leo Breiman and the name originates from "bootstrap aggregating". If classification is to be done into two potential class, the classification protocol generates a classifier $H : D \rightarrow \{-1,1\}$ based on the training dataset of example descriptions (in the case played by a document collection) D. The bagging approach produces a series of classifiers H_m, m=1,.......,M with regard to alterations of the training dataset. The classifiers are merged into a compound classifier. Predicting the compound classifier is presented as a weighted combination of every single classifier prediction in equation (13):

$$H(d_i) = sign\left(\sum_{m=1}^{M} \alpha_m H_m(d_i)\right) \tag{13}$$

The above stated formula could be understood as a procedure for voting. An instance d_i is sorted to the class which receives major quantity of votes from classifiers. This is the theory of classifier voting. Parameters α_m, m=1,.......,M are decided such that more precise classifier has more effect on the end prediction than low accuracy classifier. The precision of base classifier H_m will be slightly high when compared to a random classification's precision. Hence these classifiers are known as feeble classifiers [16]. If the learning procedure is able to be influenced by the classifier H_m directly, the minimization of classification error by H_m is possible by maintaining parameters α_m as constant.

BOOSTING

The Boosting algorithm applied for classification and regression are AdaBoost and AdaBoost R2 correspondingly. The two algorithms subsequently generate a sequence of neural networks in which the training instances which are incorrectly predicted by the preceding neural networks play more vital role in the training of a latter network. The component prediction is merged through weighted averaging for regression task and weighted voting for classification task in which the weight is decided by the algorithm itself [17].

The AdaBoost algorithm was devised in 1995 by Freund and Schapire, implemented to solve most of the working complexities of previous boosting algorithms which is the objective of this work. Pseudo code for AdaBoost is mentioned in a generic form as given by Schapire and Singer. This algorithm is given a training dataset as input $(x_1, y_1),....,(x_m, y_m)$ where each x_i belongs to certain domain or instance space X, and each label y_i is in a label set Y. For major part of this work, it is supposed that $Y = \{-1,+1\}$. AdaBoost, works with a poor or base learning algorithm iteratively in a sequence three of rounds $t = 1,.....,T$. The major idea of the algorithm is to sustain a distribution or set of weights over the training set. Weights of this distribution on training instance i, on round t is represented as $D_t(i)$. In the beginning, every weight is set as equal but on every round the weight of wrongly classified instance is improved and hence the base learner focuses on the tough instance in the training set.

RESULTS AND DISCUSSION

This section deals with the evaluation of Correlation based Feature Selection (CFS) - RF, CFS -Bagging, CFS -Adaboost, GA - RF, GA -Bagging and GA -Adaboost techniques. 360 normal images as well as 150 Glaucoma images are utilized. The classification accuracy, specificity, sensitivity and F-measure for both abnormal and normal are shown in the **[Table- 1]** and **[Figure- 4 to 7]**. The sample images 7 to 9 are shown in **[Figure- 10 to 13]**.

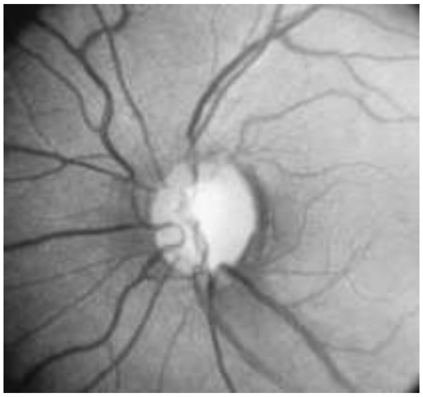

Fig: 5. Sample Image 1

Fig: 6. Sample Image 2

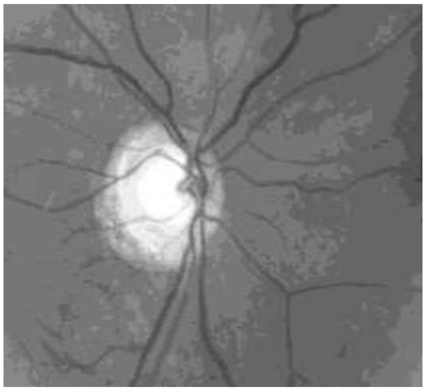

Fig: 7. Sample Image 3

Table: 1. Summary of Results

	CFS - Random forest	CFS - Bagging	CFS - Adaboost	GA - Random forest	GA - Bagging	GA -Adaboost
Classification Accuracy	85.1	87.25	89.02	89.61	90.59	91.18
Specificity for Abnormal	0.8722	0.8944	0.9111	0.9139	0.9194	0.9278
Specificity for Normal	0.8	0.82	0.84	0.8533	0.8733	0.8733
Sensitivity for Abnormal	0.8	0.82	0.84	0.8533	0.8733	0.8733

Sensitivity for Normal	0.8722	0.8944	0.9111	0.9139	0.9194	0.9278
F measure for Abnormal	0.7595	0.791	0.8182	0.8284	0.8452	0.8534
F measure for Normal	0.892	0.9083	0.9213	0.9255	0.9324	0.9369

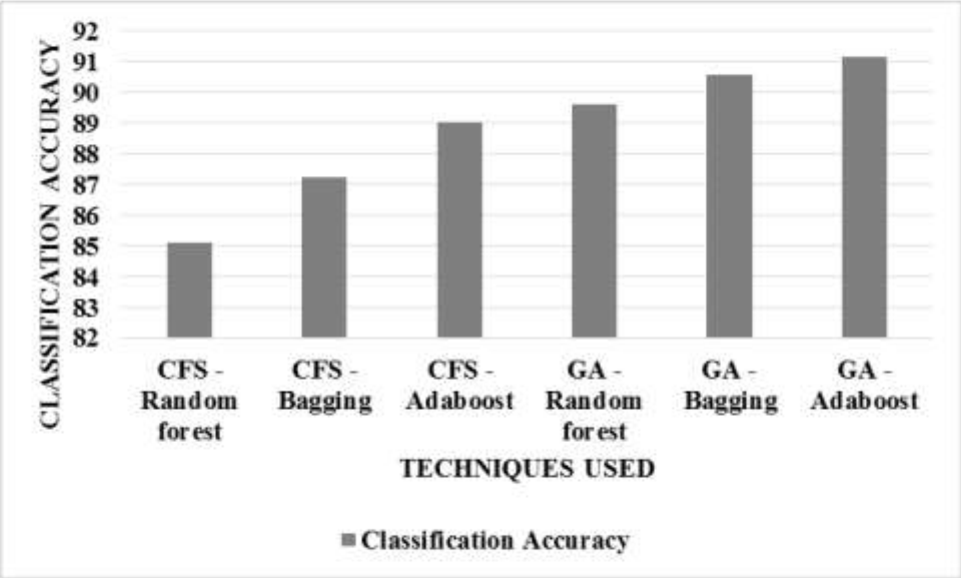

Fig:8 . Classification Accuracy

………

From the **[Figure- 10]**, it can be observed that the GA -Adaboost has higher classification accuracy by 6.89% for CFS - RF, by 4.4% for CFS -Bagging, by 2.39% for CFS -Adaboost, 1.73% for GA - RF and by 0.64% for GA - Bagging.

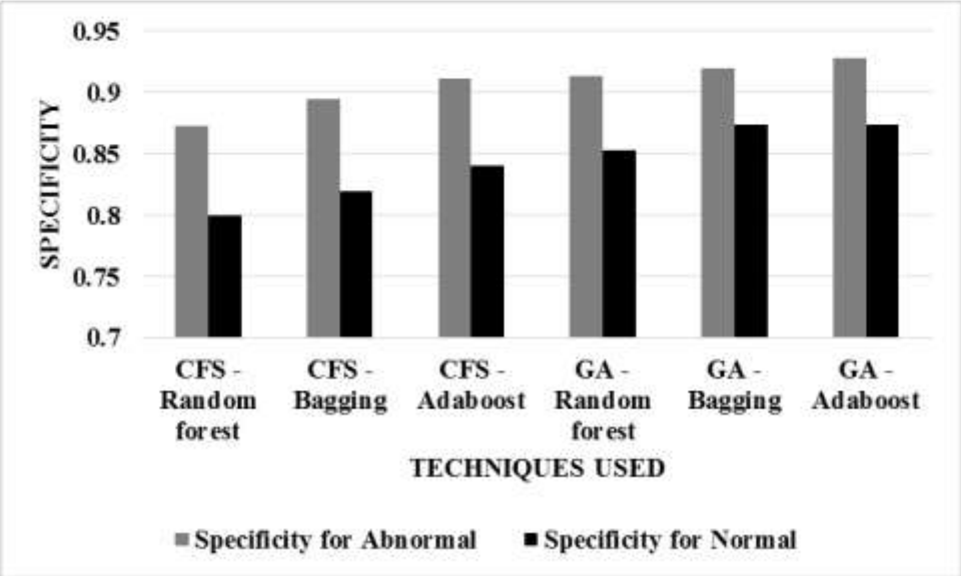

Fig:9. Specificity

………

From the **[Figure- 11]**, it can be observed that the GA -Adaboost has higher specificity for abnormal by 6.17% for CFS - RF, by 3.66% for CFS -Bagging, by 1.81% for CFS -Adaboost, 1.5% for GA - RF and by 0.9% for GA - Bagging. The GA -Adaboost has higher specificity for normal by 8.76% for CFS - RF, by 6.29% for CFS - Bagging, by 3.88% for CFS -Adaboost, 2.31% for GA - RF and by same value for GA -Bagging.

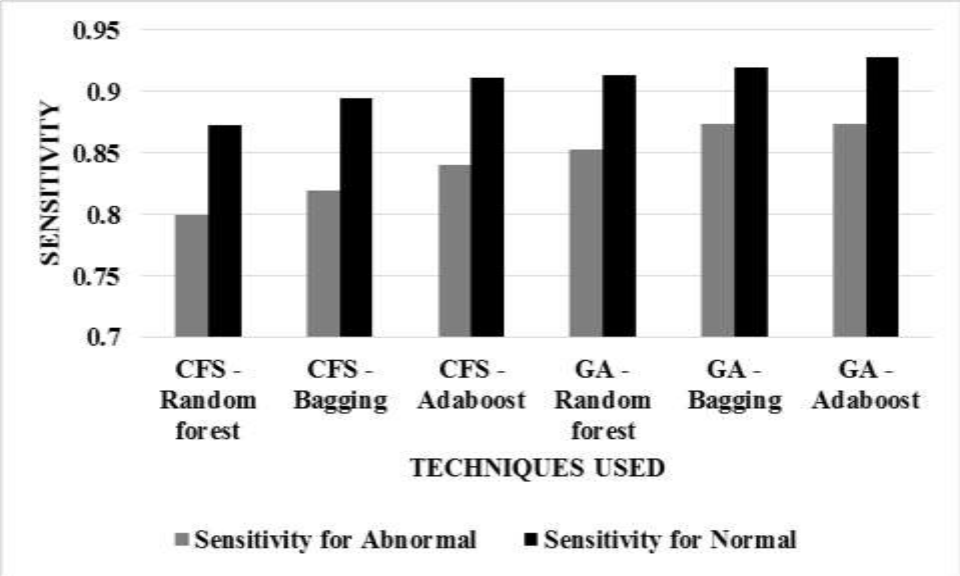

Fig: 10 . Sensitivity

From the [Figure- 12], it can be observed that the GA -Adaboost has higher sensitivity for abnormal by 8.76% for CFS - RF, by 6.29% for CFS -Bagging, by 3.88% for CFS -Adaboost, 2.31% for GA - RF and by same value for GA -Bagging. The GA -Adaboost has higher sensitivity for normal by 6.17% for CFS - RF, by 3.66% for CFS - Bagging, by 1.81% for CFS -Adaboost, 1.5% for GA - RF and by 0.9% for GA -Bagging.

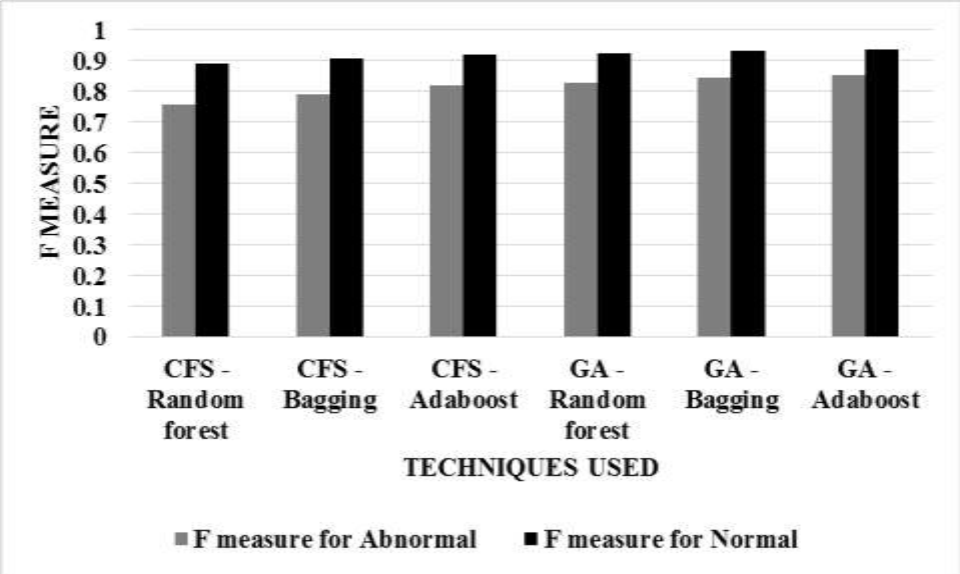

Fig:11. F Measure

From the [Figure- 13], it is observed that GA -Adaboost has greater F measure for abnormal by 11.64% for CFS - RF, by 7.58% for CFS -Bagging, by 4.21% for CFS -Adaboost, 2.97% for GA - RF and by 0.96% for GA - Bagging. The GA -Adaboost has higher F measure for normal by 4.91% for CFS - RF, by 3.09% for CFS - Bagging, by 1.67% for CFS -Adaboost, 1.22% for GA - RF and by 0.48% for GA -Bagging.

CONCLUSION

THE IIOAB JOURNAL
ISSN: 0976-3104

The work provides an innovative automated classification system using digital fundus images. In opposition to traditionally implemented segmentation-based metrics, this is completely data-driven and uses image-based feature which is innovative in the area of glaucoma recognitions. This work evaluated a number of different combinations of image-based features and classifier schemes on a data set of 360 normal images as well as 150 Glaucoma images. Results proved that GA -Adaboost shows higher classification accuracy by 6.89% for CFS -RF, by 4.4% for CFS -Bagging, by 2.39% for CFS -Adaboost, 1.73% for GA - RF and by 0.64% for GA -Bagging.

CONFLICT OF INTEREST

The authors declare no conflict of interests.

ACKNOWLEDGEMENT

None

FINANCIAL DISCLOSURE

The authors report no financial interests or potential conflicts of interest.

REFERENCES

[1] Kumar PSJ, Banerjee MS. [2014] A Survey on Image Processing Techniques for Glaucoma Detection. *International Journal of Advanced Research in Computer Engineering & Technology* (IJARCET), 3.

[2] Deepashri KM, Santhosh K V. [2015] Glaucoma Detection by Image Fusion from Fundus Color Retinal Images: A Review. *International Journal of Control Theory and Applications* 8(3): 1147-1152.

[3] Xu Y, Duan L, Lin S, Chen X, Wong DW K, Wong TY, Liu J. [2014] Optic cup segmentation for glaucoma detection using low-rank superpixel representation. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 788-795). Springer International Publishing.

[4] Niwa SI, Lin W, Bai X, Kwoh CK, Sng CC, Aquino MC, Chew PTK. [2015] Reliable feature selection for automated angle closure glaucoma mechanism detection. *Journal of medical systems*, 39(3): 1-10.

[5] Guo L, Yang JJ, Peng L, Li J, Liang Q. [2015] A computer-aided healthcare system for cataract classification and grading based on fundus image analysis. *Computers in Industry* 69: 72-80.

[6] Raja C, & Gangatharan, N. [2015] Incorporating Phase Information for Efficient Glaucoma Diagnoses Through Hyper-analytic Wavelet Transform. In Proceedings of Fourth International Conference on Soft Computing for Problem Solving (pp. 329-343). Springer India.

[7] Niwas, S. I, Lin, W, Kwoh, C. K, Kuo, C. C. J, Sng, C. C, Aquino, M. C, & Chew, P. T. [2016] Cross-examination for angle-closure glaucoma feature detection. *IEEE journal of biomedical and health informatics* 20(1): 343-354.

[8] Gupta R, Awasthi D. [2014, September] Wave-packet image fusion technique based on genetic algorithm. In Confluence The Next Generation Information Technology Summit (Confluence), 2014 5th International Conference- (pp. 280-285). IEEE.

[9] Bock R, Meier J, Nyúl LG, Hornegger J, Michelson G. [2010] Glaucoma risk index: automated glaucoma detection from color fundus images. Medical image analysis, 14(3), 471-481.

[10] Malviya, P, & Saxena, A. [2014] An Improved Image Fusion Technique based on Texture Feature Optimization using Wavelet Transform and Particle of Swarm Optimization (POS). *International Journal of Computer Applications* 101(6).

[11] Yang Y. [2011] Multiresolution image fusion based on wavelet transform by using a novel technique for selection coefficients. *Journal of Multimedia* 6(1): 91-98.

[12] Wady S H, & Ahmed HO. [2016] Ethnicity Identification based on Fusion Strategy of Local and Global Features *Extraction. Int. J. of Multidisciplinary and Current research*, 4.

[13] Karegowda AG, Jayaram MA, Manjunath AS. [2010] Feature subset selection problem using wrapper approach in supervised learning. *International journal of Computer applications*,1(7):13-17.

[14] Erkanli S, Oguslu E, Li J. [2012] Fusion of visual and thermal images using genetic algorithms. INTECH Open Access Publisher.

[15] Kausar N, Majid, A. [2016] Random forest-based scheme using feature and decision levels information for multi-focus image fusion. Pattern Analysis and Applications 19(1):221-236.

[16] Machová K, Barcak F, Bednár P. [2006] A bagging method using decision trees in the role of base classifiers. Acta Polytechnica Hungarica, 3(2):121-132.

[17] Zhou ZH, Wu J, Tang W. [2002] Ensembling neural networks: many could be better than all. Artificial intelligence 137(1): 239-263.