Fuzzy Bat Algorithm based Segmentation and Mean Weight Convolution Neural Network (MWCNN) Classification for Lung Images

P. Dhanalakshmi and Dr.G. Satyavathy

Abstract---*One of the biggest causes of non-accidental death is cancer. Globally, lung cancer has been confirmed to be the leading cause of death from cancer in men and women. The risk of death can be minimized with an initial diagnosis, so that the doctors may give the necessary care within a prescribed period. It was a challenging effort to locate the region of the field in Enhanced Particle Swarm Optimization Kernel Support Vector Machine (EPSOKSVM). The Fuzzy Bat Algorithm (FBA) with Mean Weight Convolution Neural Network (MWCNN) algorithm is proposed to settle this issue, in favour of identifying a area of Region of Interest (RoI) in the lung images in order to increase the certainty of classification. Medical images are decomposed into several layers in the proposed study to derive detailed visual information from various levels of scale. By using FBA, the lung images are then subdivided to identify RoI . With FBA objective fitness function, the interval between cancer and non-cancer areas are determined. Through the optimization process the fitness value is determined, and then the RoI area is segmented. Then, the non-negative sparse coding features acquired in various scales are incorporated to create a multi-scale function as the ultimate depiction for a medical image. Using, Mean weight computation and Average pooling function for the LIDC-IDRI database, MWCNN algorithm is used to achieve better results of classification certainty. The research findings reveal that the proposed FBA with MWCNN algorithm produces better results in the lung classification in terms of precision, recall, accuracy and F - measure values.*

Keywords---*Lung Cancer, Multi-Scale Decomposition, Non-Negative Sparse Coding, Fuzzy Bat Algorithm (FBA), Mean Weight Convolution Neural Network (MWCNN) Classifier, and Classification.*

I. INTRODUCTION

Digital image technology is expeditiously evolving and is multidisciplinary, incorporating information from various disciplines to build a framework. It is being used in various fields of human practices such as electronics, chemistry, biology, medicine, health and criminology, industrialization and investigation [1]. Image processing is a kind of signal processing for which an image is provided as input, and the output may either be an image or a series of attributes that is associated to the image. Major approaches of image processing consider the image as a two-dimensional signal where a human being is engaged in the visual loop [2].In developing countries, Lung cancer is one of the extremely devastating illness, with a fatality rate of 19.4% [3]. Imaging methods like, chest X-ray, Magnetic Resonance Imaging (MRI) and Computed Tomography (CT), are used for initial diagnosis of lung tumors. A Diagnosis is segregating tumor into a non-cancerous (benign) or cancerous tumor (malignant). The probability of

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recovery at the advanced stage is weaker as contrasted with diagnosed in initial stage of the disease, in terms of medication and way of living to endure cancer therapy. Physical analysis and diagnostic framework can be significantly improved with the execution of image processing techniques [4]. Anyhow, correct segmentation of the images, is an essential move in the identification of lung cancer. Image segmentation is the mechanism by which digital images are divided into several segments and used to distinguish entities (or other similar details in a picture). The segmentation motive is to facilitate (or) alter the interpretation of an image in a more realistic way and accessible. The precise segmentation of medical image is a predictive component, in the diagnosis of lung cancer. Physical segregation of the lung nodules from a CT image is a difficult, meanwhile necessary task. An automated segmentation process is adopted in order to separate lung nodules from CT images provided, that the specifications are appropriately defined [5].In order to reduce false-positive results, several procedures [6] are being used to generate automated identification and analysis of the lung nodule. A complete automated procedure is developed that enables identifying and segregating a tumor, if it is present in a series of lung CT scan [7]. It also presents valuable observation of the identified tumor, such as its estimated volume, position of the nucleus, etc. The strategy offers a one-touch solution that analyzes entire CT images of a single patient in a single action. It enables to reduce the physical effort of going through every CT slice and to equipping tumor detection quicker and more precise. Custom image processing and segregation procedures are being used to identify and fragment tumor region from CT scan.

In the modern medical age, categorization and characterization of lung cancer medication approaches remain crucial. Image recognition methodologies and machine learning algorithms are evolved to identify the stages of lung cancer. Convolutional Neural Networks (CNNs) paradigm is getting familiar in pattern recognition and computer vision research due to its encouraging result in producing high-level image descriptions [8]. A modern deep learning system to know high-level image representation is used to reach high classification precision with minimum variance in binary classification tasks for medical images. Using convolution layers CNN multiplies the weights of the same kernel over the whole input volume for each kernel, which may reduce the effects of the classification. The input image changes the object a bit to identify it, network behaviors won't change due to max pooling and the network will spot the object yet. The procedure mentioned above is unexceptional as max-pooling lacks useful insight and does not encode parallel spatial relationships among features. Therefore, CNN is uneven on huge input data transformations. To resolve these problems, each input sample is given a mean weight value and max-pooling is interchanged by average pooling function. There are various strategies, but segmentation accuracy of lung cancer is not considerably assured. The current methods have disadvantages in locating the Region of interest (RoI), and the complete precision of the method is diminished. A Fuzzy Bat Algorithm with Mean-Weight Convolution Neural Network (FBA+MWCNN) is speculated to upgrade the outcomes of segmentation and categorization to conquer the aforementioned challenge. The aim of this study is decomposition into multiple-scale layers, segmentation using FBA and classification of lung cancer by MWCNN for segmented image. The suggested approach offers very specific segmentation and classification outcomes for the provided dataset.

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II. LITERATURE REVIEW

Xiao et al[9] proposed settling down the issue of inadequate segmentation of the pulmonary juxtapleural nodules and inefficient segmentation. This research used a programmed system to incorporate the process of threshold iteration to divide the lung parenchyma images and the technique of fractal geometry to identify depression boundaries. The system consists an advanced convex hull rectification to accomplish the perfect lung parenchyma segmentation. The findings of the evaluation ensure that the procedure will precisely and effectively divide of the juxtapleural lung parenchymal images. The conventional quantitative analysis is used to assess the effects of the experiment and has not been tested in the Computer-Aided Design (CAD) process.

Dandıl[10] suggested pipeline which is of four phases. CT images are improved in pre-processing stages, and volumes of the lungs are extracted from the image using a novel approach, which is known as Lung Volume Extraction Technique (LUVEM). The candidate nodules are calculated in the detection phase as per the Circular Hough Transform (CHT) process. Then, Self-Organizing Maps (SOMs) segregate the lung nodules. Energy, shape, intensity, texture, and combined features are used for extraction of the feature in the computation process of the feature, in which the Primary Component Analysis (PCA) is used in the step of feature reduction. Benign and malignant nodules are identified by Probabilistic Neural Network (PNN) in the final phase. Owing to the various datasets, nodule types, sizes and testing processes, it is difficult to equate previously documented CAD structures.

Papyan et al [11] was inspired by the use of the multi-scale predicted patch log-likelihood by limiting it to the basic Gaussian scenario. For additional improvement and development, the patches by analyzing a multi-scale prior. The algorithm applies precisely the same before various scale patches are pulled out from the target image. Though, the entire patches handled are of the same size, their footprint differs in the endpoint image according to sub-sampling. The system is intended to overcome another shortcoming in patch-based restoration algorithms-the reality is that a prior local (patch-based) acts as a basis for a global stochastic phenomenon.

Fenwa et al [12] addressed the efficiency of the Artificial Neural Network (ANN) and Support Vector Machine (SVM) classifiers on obtained datasets of cancer. A quick and efficient procedure is suggested for identifying lung nodules and distinguishing the images of cancer from all other lung diseases such as, tuberculosis is immediately required as the occurrence of lung cancer has increased significantly in recent years and identification in initial stage can save lots of human lives year after year. Practicing time of the neural network has to be assured.

Shi et al[13] recommended a innovative CNN methodology for recognizing nodules in CT images of the Lung. Here then, Two 2.5-dimensional CNN architectures, two 3-dimensional CNN architectures, a 3-dimensional CNN architecture with patch position information, a 3-dimensional CNN architecture with fixed space transformation, and a 3-dimensional CNN architecture with a 3-dimensional space transformer network module were studied and compared. Evaluations reveal that the 2.5-dimentional CNN architecture, which has separate CNN modules worked better for the slices of every view than the model that used one CNN module for all views. Among all strategies, the 3-dimentional CNN architecture with limited parameters performed in perfect manner. Accelerate the process of developing a new defined medical dataset intended for further research work.

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Nasrullah et al[14] suggested a framework based on extreme learning for an automatic diagnosis of lung cancer. The experimental method has operated in several phases on 3D lung CT scanning images to identify and assess the nodules' malignancy. Taking into account the 3D characteristic of the lung CT data and the briefness of the mixed link network (MixNet), two deep 3D faster Region-CNN (R-CNN) and U-Net encoder-decoder with MixNet were built to find and recognize the characteristics of the lung nodule. The gradient boosting system (GBM) with 3D MixNet has been suggested for classification of the nodules. The suggested method was validated on 1200 images gathered from the Lung Image Database Consortium image collection (LIDC-IDRI), including 3250 nodules, using statistical tests.

III. PROPOSED METHODOLOGY

The Fuzzy Bat Algorithm (FBA) with Mean Weight Convolution Neural Network (MWCNN) approach is proposed in this research to continue improving the segmentation of the lung cancer and classification for the image dataset of LIDC-IDRI. The proposed method comprises three major stages of multi-scale layer decomposition, segmentation using FBA, and classification using MWCNN. Figure 1 represents the Architectural diagram for the proposed process.

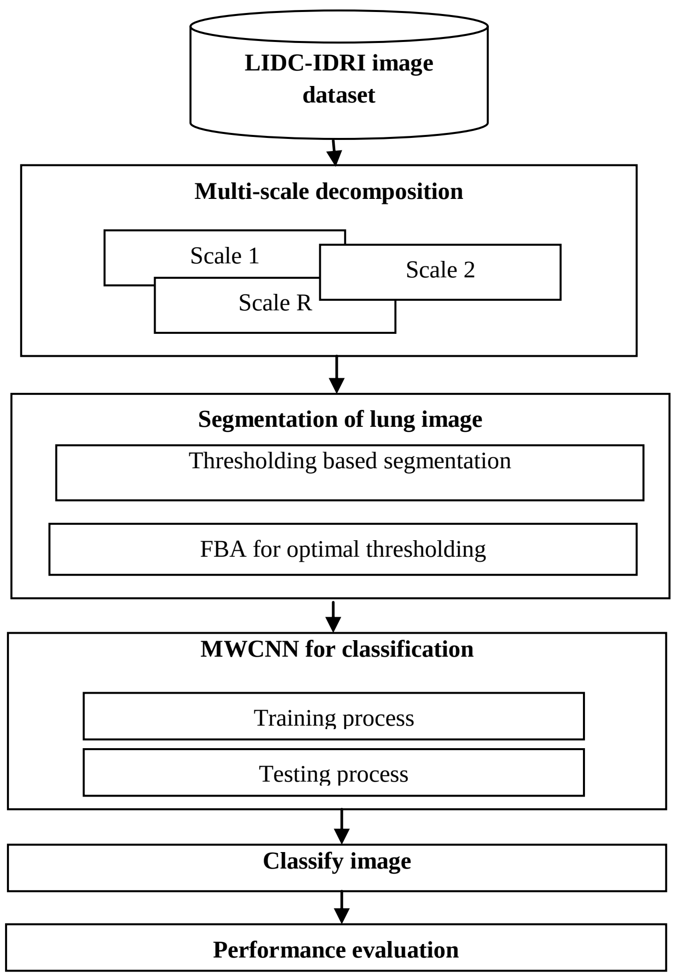

Figure 1: Overall Block Diagram of the Proposed System

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3.1 Decomposition of Images into Multiple Scale Layers

The images are disintegrated into multiple-scale layers. Based on the spatial scale, this multi-scale imaged is integration enables details to be derived and boosting of fine-scale features. Scale-space is known as a scale parameter in the process of image processing and modeling, which obtains a multi-scale spatial depiction of the original image by repeatedly modifying this scale parameter [15]. This research, applies the Gaussian function to accomplish multi-scale transformation of medical images. It uses Gaussian filters to smooth out images, assuming that I(x, y) stands for the input image, the smoothened images L(x, y, σ)is attained by the convolution of input image I(x, y) and Gaussian function G(x,y,σ) in the following way

$$L(x,y,\sigma) = I(x,y) * G(x,y,\sigma) \qquad (1)$$

Where * is the convolution operation and Gaussian function is described as

$$G(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} (2)$$

Where $'\sigma'$ is the variance. We receive images on a rough scale to do down-sampling. Medical images are disintegrated to multi-scale image layers $L = \{L_1, L_2, \ldots, L_R\}$ repeating the cycle R times and R suggests image layers. The information and noises in the image are omitted and suppressed after convoluting original images according to equation (1). Thus the essential visual characteristics that are distinct are obtained in a multi-scale transformation.

3.2 Segmentation using FBA

In this part, Fuzzy Bat Algorithm (FBA) based segmentation is performed for the identification of RoI area within lung images. The first step in the CAD picture of the lung CT is to segment the region of interest and then examine each section acquired individually for a diagnostic tumor, cancer, node detection or other pathology. It is a simpler approach, as with the segmentation process the region used to determine the right diagnosis is becoming lesser. Then the radiologist will concentrate only on relevant data within the particular area. Effective lung segmentation technique tends to improve the precision and maximize confidence level in decision making of recognition method of every lung anomaly[9].

Optimal thresholding is the first step of image thresholding. A lung CT image comprises two major classes of pixels: pixels of high intensity located in the body, and pixels of low intensity located in the lung. Because of the significant variation in severity within these two classes, thresholding results in a successful separation. As this algorithm deals with lung images, this iterative method determines a threshold value such that the two classes of pixels are properly segregated. It functions as follows: Let Th_i be the threshold value at step i and t_b, t_n be the average body pixel intensity value, t_b higher than Th_i, and t_n lower than Th_i intensity. The threshold for step i + 1 is: $Th_i+1=(t_b+t_n)/2$. This process is repeated until convergence. The earlier threshold Th0 is fixed at 120 which is the gray median level. When convergence is attained, the threshold value of the image is Th_k. Each pixel with a magnitude greater than Th_k is set to 0, pixels belong to the body and all other pixels are set to 1 which belongs to the surrounding air. The Fuzzy Bat Algorithm (FBA) is now implemented reliably in the automated selection of the 'Th_i' threshold to segment the Region of interest (RoI).

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Bat algorithm is operated using bat's echolocation behavior [16]. Echolocation requires transmission of a heavy sound pulse and monitors closely to the echo that comes back from the objects. Bat used this specific point to spot its prey and omit obstacles in its way. Bats are capable of producing a large sound and monitoring to the echo response for the intent of bouncing back from nearby objects to detect their preys. This pulse reaction can be translated to frequency and made valuable feedback.

The fitness values are determined to validate RoI segmentation depending on the bats' behaviour. The movements of the simulated bats is provided by updating their velocity and location using the following equations (3-5):

$$f_i = f_{min} + (f_{min} - f_{max})\beta \quad (3)$$

$$v_i^j = v_i^j(t-1) + \left[\hat{x}^j - x_i^j(t-1)f_i\right] (4)$$

$$x_i^j(t) = x_i^j(t-1) + v_i^j(t) (5)$$

Where e$f_{min}, f_{max}$are the lowest and highest frequencies respectively, 'β' refers to the random number created used to monitor pace and range of motion of the bats[17]. The variable x $\hat{x}^j$ describes the existing perfect global RoI position (solution) for the intensity j judgment, which is obtained by evaluating all the solutions given by the m bats. It has idealized certain rules for modeling this algorithm, as follows:

1. Each of the bats use echolocation to perceive the range within the points and they even "understand" in some mysterious way the contrast between food/prey and environmental barriers;
2. A bat b_i fly continuously with acceleration $v_i$with a fixed frequency$f_{\min}$ at position x_i, differing wavelength λ and loudness A_0 to hunt for prey. They will alter the wavelength (or frequency) of their emitted pulses spontaneously and change the pulse emission rate r $\in [0, 1]$ based on the vicinity of their aim
3. Even though the sound level may differ in several aspects, the loudness is expected to range from a broad (positive) $A_0$to a minimal static level Am_i

The characteristics of RoI are segmented as follows, by means of Fuzzy bat optimization:

Objective function f(x), x = (x_1, ..., x_n).

Initialize the bat population x_i and v_i, i = 1, 2, ...,.

Determine pulse frequency $f_i$at x_i, ∀i = 1, 2,...,.m

Initialize pulse rates r_i and the loudness A_i, i = 1, 2,...,.m

1. Input as LIDC-IDRIdatabase images
2. While t<T
3. For each bat b_i(Region of points), do
4. Create new solutions using eq. (3), (4) and (5)
5. If rand>r_i, then
6. Do segmentation
    6.1. Optimal thresholding with threshold
    6.2. Execute RoI region identification
    6.3. Uncover the RoI characteristics through thresholding using objective function
    6.4. Choose an efficient threshold solution from the range of threshold
    6.5. Create local solution among the best solution
7. If rand<A_i and f(x_i)<f(x') then
    7.1. Allow the new threshold
    7.2. Increase r_i and decrease A_i

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8. End if
9. Repeat fuzzy bat for parameter tuning from step 2
10. Rate the bats and discover the existing best x'

Firstly, the primary position x_i, velocity v_i and frequency f_i are activated for each bat b_i. For each time step t, being T the highest number of repetitions. The lung image is provided as data, and pulse frequency is utilized to execute the inadequate attributes. The appropriate fitness value is optimally determined by the use of objective function. One of the existing proper solutions is chosen and a new solution is created for each bat that agrees the demand. Step 2 shall be repeated until the maximum iterations are conducted. The ending iteration of the algorithm contains the properly-modified process which grants the best solution. Evaluate the objective function . Creating a fresh population is by upgrading the method of frequencies, accelerations and solutions .Typically in the bat algorithm, frameworks such as wavelength λ, loudness (volume) A_0, minimum frequency and maximum frequency are modified by experimentation. In the present process an execution of a fuzzy program is provided which is responsible for dynamically setting each of these parameters to enhance the accomplishment of the algorithm to achieve extreme efficiency.

a. Mean Weight Convolution Neural Network (MWCNN)Algorithm For Classification

In this segment, Mean Weight Convolution Neural Network (MWCNN) classifier is suggested to manage the dataset of the LIDC-IDRI lung image. It is widely recognized that the more aspects being incorporated into a neural network, the more information machine will adopt from this in order to attain the better results [18]. The overall framework of this MWCNN classifier with their inputs and outputs is shown in the figure 2.

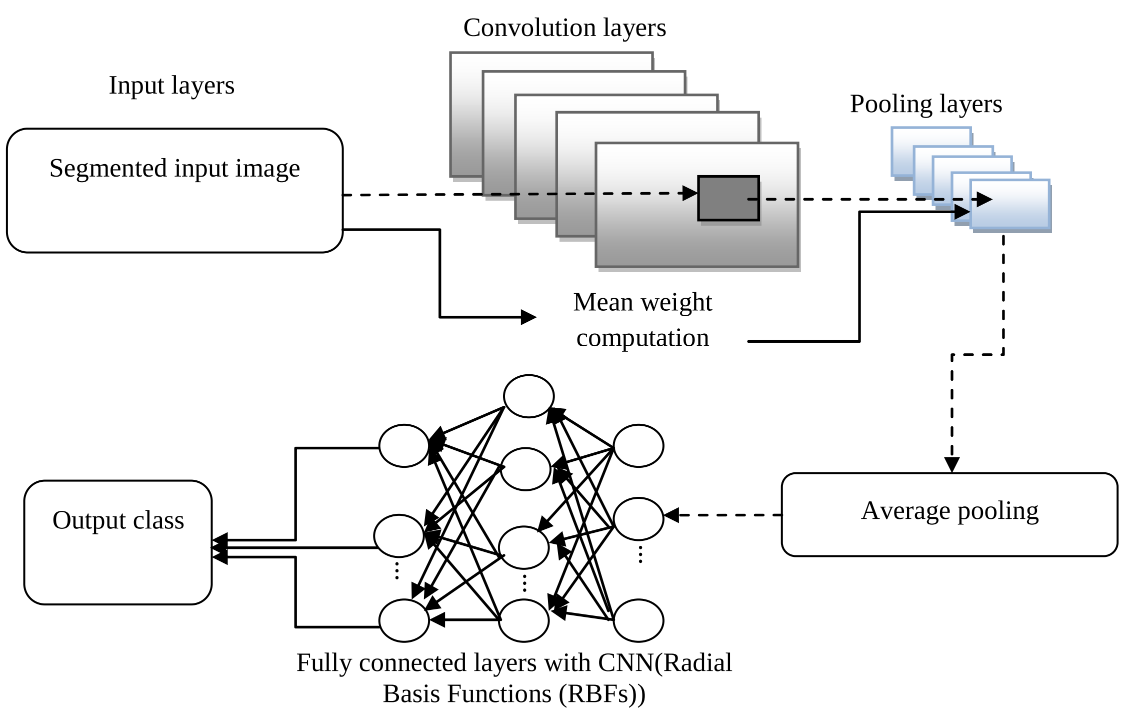

Figure 2: Proposed Mean Weight Convolution Neural Network (MWCNN) Architecture

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Input layers: Input layer gets fragmented image of lung from training image and converts the data into a coherent form to transmit the data precisely to the adjacent layer.

Convolutional Layers: The convolutional layers perform as feature extractors and hence they study the object descriptions of their lung images data, which is segmented. In the convolutional layers the neurons are organized into feature maps. Every neuron in a function map has a accessible region, which is linked to a neuronal neighbourhood in the prior layer through a series of trainable mean weights, also known as a filter bank [19]. To arrive a new feature map, inputs are combined with the observed weights and the results are delivered through a non-linear activation function. The weights of the entire neurons inside a feature map are forced to be equal; nevertheless, various feature maps inside the same convolutional layer have contrasting weights such that multiple features at each location can be extracted [19]. More precisely, the k^{th} output factor Y_k can be determined as

$$Y_k = f(C_k * x * m_{WE})(6)$$

Whereas, segmented input image is marked with x, the convolutional filter accompanied to the k^{th} feature map is marked with C_k; the multiplication symbol in this instance corresponds to the 2D convolutional operator used to determine the filter model's inner product at each position of the fragmented input image; and f(•) describes the nonlinear activation function [20]. Nonlinear activation methods enable nonlinear extraction. Currently, the Rectified Linear Units (ReLUs)[21] used in this work. In equation (7), the mean weight value is determined for each fragmented input image 'x'. Various Random weight values (w_i,i=1... n) are provided for every segmented image as input. The mean value is then determined to those random weight values and the final mean is multiplied to the fragmented input image.

$$m_{WE} = \frac{W}{\sum_{i=1}^{n} w_i}(7)$$

Where Wrefers to the weight of the single image, $w_i$refersto the random weights.

Pooling Layers: Pooling layers are used in the feature maps to reduce spatial resolution and thereby attain spatial invariance to misrepresentation and translations of inputs [22]. It was popular practice to use average pooling aggregation layers to multiply the average of entire input values, from a specific image neighborhood to the next layer. Nevertheless, in most of the modern research [23], max pooling aggregation layers spread the entire value to the next layer within a responsive field [22]. Max pooling properly chooses the highest entity inside each accessible region, such that

$$Y_{k_{ij}} = \max_{(p,q)\in R_{ij}} x_{kpq}(8)$$

where the result of the pooling process, related with the k^{th} feature map, is indicated by $Y_{k_{ij}}$, x_{kpq} stands for the element at location (p, q) consist of the pooling area i j, that demonstrates a approachable field over the location (i, j) [24]. Figure 3 demonstrates the variation among max pooling and average pooling. A segmented input image of size 4 × 4, a 2 × 2 filter and pace of two is enforced, max pooling outputs the highest value of each 2 × 2 region, At the same time the average pooling gives result of the average rounded integer value of each sub-sampled area. The average pooling method is used in this work for classification.

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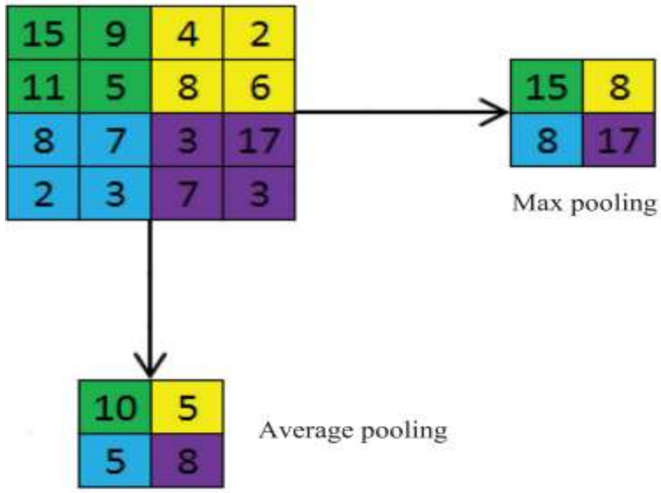


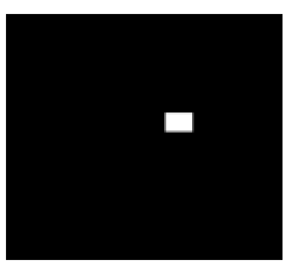
Figure 3: Average (VS) Max Pooling

Fully Connected Layers: Several convolutional and pooling layers are piled on the top of each other to obtain more complex depictions of features while going around the network. The fully connected layers which pursue these layers are perceive these feature representations and operate the process as high-level reasoning[25]. Using the softmax process alongside a CNN [26] is typical for categorization difficulties. Advance performance was obtained by the use of Radial Basic Functions (RBFs), as the classifier on top of the convolutional layer which enhances the categorization reliability.

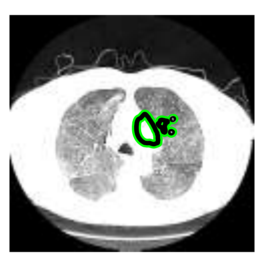
IV. EXPERIMENTAL RESULTS

The output variables are analyzed in this study using FBA with MWCNN, ANN, SVM, and EPSOKSVM. The measures considered are accuracy, recall, precision and F-measure. The series of Lung Image Database Consortium image (LIDC-IDRI) comprises of diagnostic and lung cancer screening thoracic computed tomography (CT) scans with annotated labelled lesions. It is a globally available online resource for the practice and assessment of computer-aided diagnostic (CAD) strategies for the identification and diagnosis of lung cancer. 200 images are used for implementation, from these 150 images are used for training and 50 images are used for testing. LIDC-IDRI-0068 belongs to 3 = malignant metastatic, LIDC-IDRI-0149 belongs to 1=benign or non-malignant disease and LIDC-IDRI-0173 belongs to 0=No disease. These images are collected from https:// wiki.cancerimagingarchive.net /display /Public/LIDC-IDRI [27].

(A) Input Image



(B) Segmentation Initialization



(C) Segmented Results

Figure 4(A): Input Sample OF LIDC-IDRI

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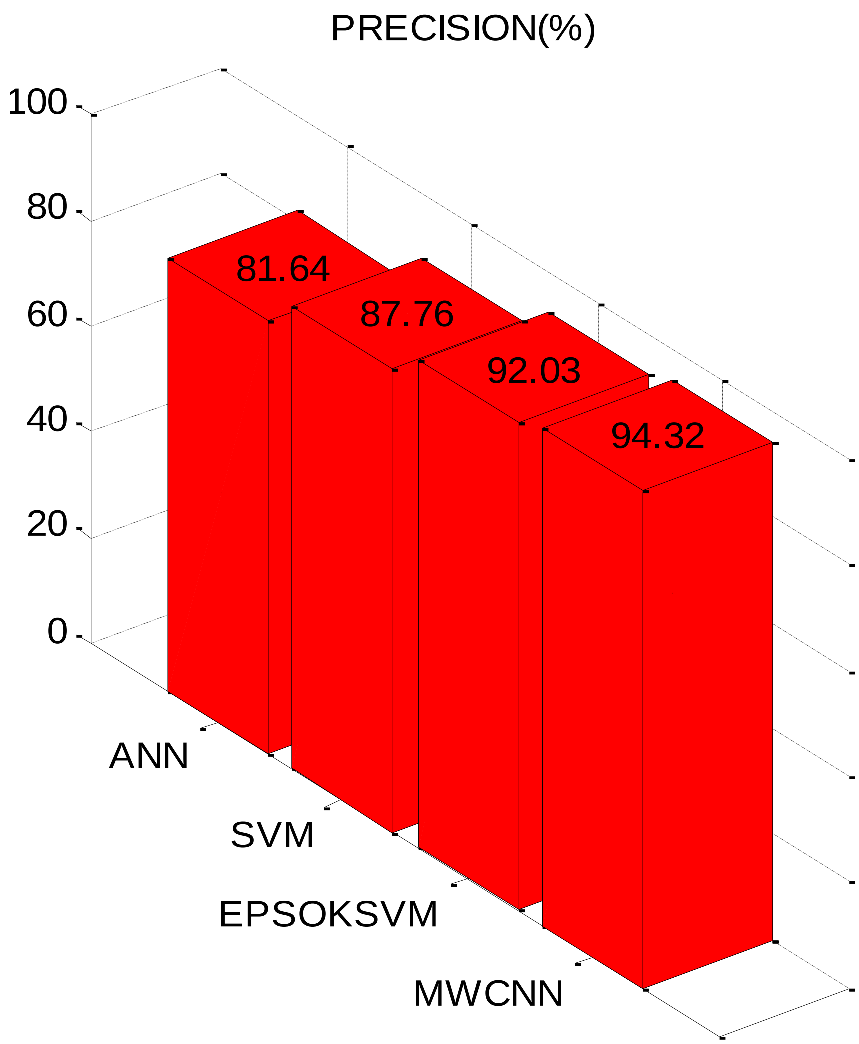
Figure 4 displays the LIDC-IDRI source image and the sample of segmented performance. Figure 4(a) reveals the sample of input image. Figure 4(b) displays the segmentation initialization stage. The segmented findings using the FBA algorithm is presented in Figure 4(c).

Table 1: Result Metrics Comparison with Different Classifiers

METRICS	ANN	SVM	EPSOKSVM	MWCNN
PRECISION (%)	81.64	87.76	92.03	94.32
RECALL (%)	80.55	88.05	91.38	95.00
F-MEASURE (%)	81.09	87.91	91.71	95.00
ACCURACY (%)	80.00	88.18	91.82	94.55
ERROR (%)	20.00	11.82	8.18	5.45



(a) Precision Comparison

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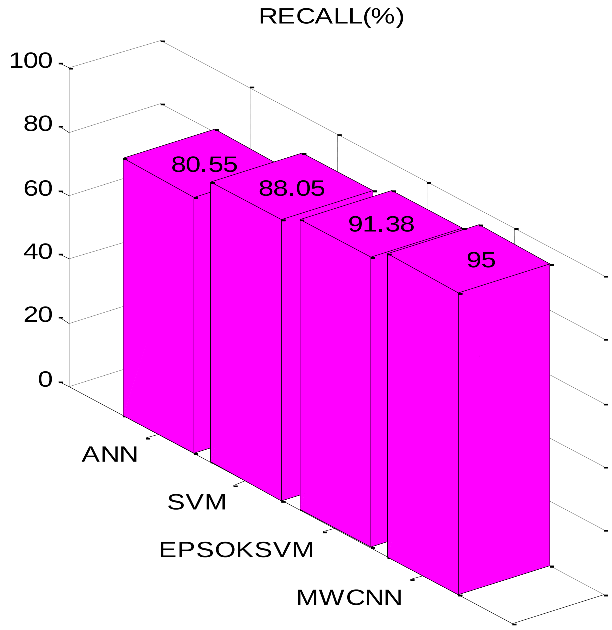
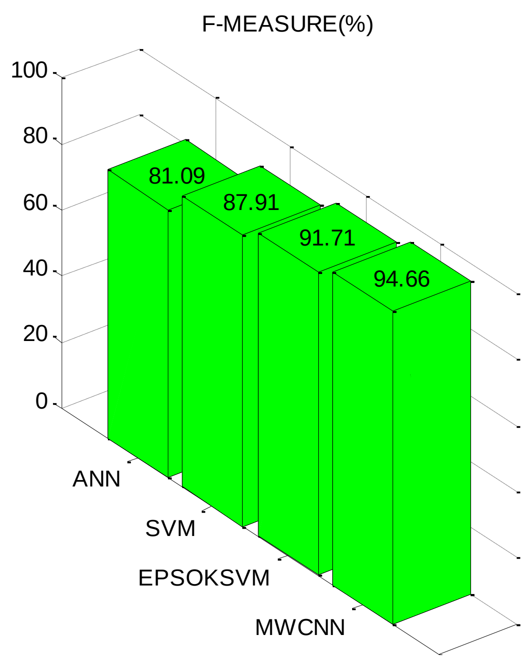


(b) Recall Comparison

Figure 5: Precision and Recall Comparison for Different Classifiers

Figure 5(a), (b) indicates the comparison of two contrasting measure precision and the recall for four specific classifiers Artificial Neural Network (ANN), Support Vector Machine (SVM), Enhanced Particle Swarm Optimization Kernel Support Vector Machine (EPSOKSVM) and Mean Weight Convolution Neural Network (MWCNN)and their performance.. It is determined that the proposed MWCNN classifier offers maximum precision of 94.32% and recall of 95% than the other strategies (Table 1).



(a) F-Measure Comparison

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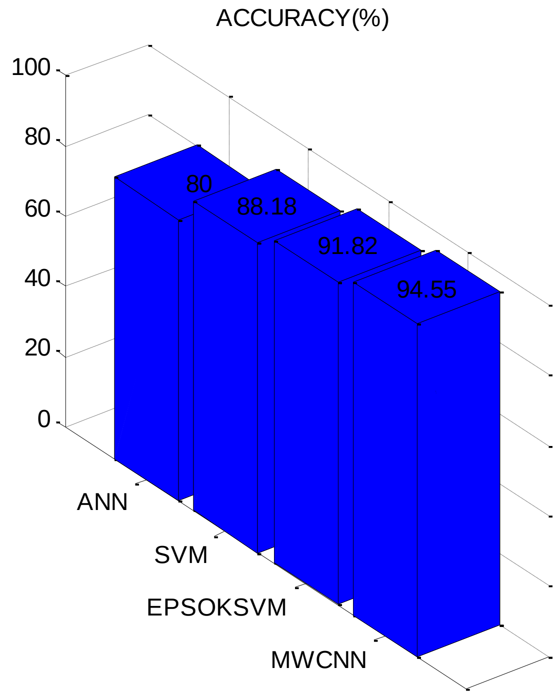

(b) Accuracy Comparison

Figure 6: F-Measure and Accuracy Comparison for Different Classifiers

The four classifiers' F-measure and accuracy comparison are explained in Figure 6. It reveals that the proposed MWCNN classifier offers a higher F-measure and accuracy of 94.66 % and 94.55 %respectively that is greater than the other methods mentioned in Table 1.

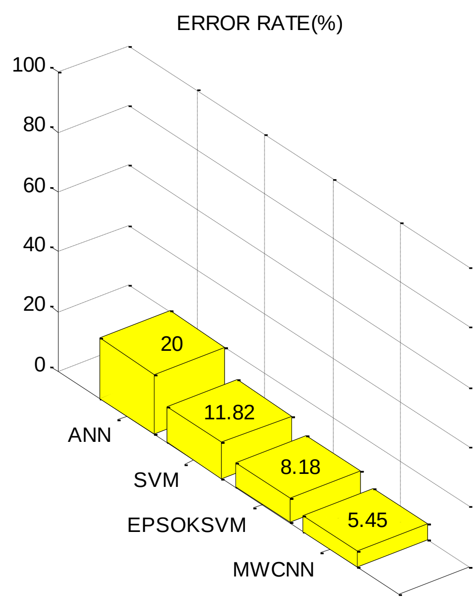

Figure 7: Error Comparison for Different Classifiers

It can be identified from Figure 7 that the error parameter is assessed for four classifiers. The algorithms ANN, SVM, and EPSOKSVM have a increased failure rate of 20.00 %, 11.82 %, and 8.1818 % respectively. The suggested MWCNN algorithm for the LIDC-IDRI lung picture dataset gives a decreased failure rate of 5.45

%(Table 1). The outcome therefore indicates that the proposed MWCNN improves classification efficiency by segmentation of the RoI features in the specified dataset.

V. Conclusion And Future Work

In this research study, Fuzzy Bat Algorithm (FBA) with Mean Weight Convolution Neural Network (MWCNN) algorithm is suggested to remarkably enhance the results of classification accuracy for the specified LIDC-IDRI lung image dataset. Medical images are disintegrated into various layers of scale, hence diverse visual information can be derived from numerous layers of scale. The image segmentation is performed by FBA in the lung images, for the identification of the RoI region. The difference between the cancer and non-cancer areas is determined using an objective function of the FBA. It is inferred that the MWCNN algorithm provides outcomes with better classification certainty. The result concludes that the proposed MWCNN method provides higher accuracy, precision, recall and F-measure values than the existing ANN, SVM and EPSOKSVM algorithms. In future research, optimization based neural network algorithm can be developed for reducing the error rates from the given image database.

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