RESEARCH ARTICLE

Stochastic Learning-Based Artificial Neural Network Model for an Automatic Tuberculosis Detection System Using Chest X-Ray Images

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ABSTRACT Tuberculosis (TB) is still one of the most serious health issues today with a high fatality rate. While attempts are being made to make primary diagnosis more reliable and accessible in places with high tuberculosis rates, Chest X-rays has become a popular source. However, specialist radiologists are required for the screening process, which could be a challenge in developing countries. For early diagnosis of tuberculosis utilizing CXR images, a complete automatic system of tuberculosis detection can decrease the need for trained staff. Various deep learning and machine learning technologies have been introduced in recent years for examining digital chest radiographs for TB-related variances with the goal of reducing inter-class reader variability and reproducibility, as well as providing radiologic services in areas where radiologists are not available. Tuberculosis is sometimes misclassified as other conditions with similar radiographic patterns as a result of CXR images, resulting in inefficient therapy. The current approach, however, is limited to Computer-Aided Detection (CAD), which has only been evaluated with non-deep learning models. Deep neural networks open potentially new avenues for tuberculosis treatment. There are no peer-reviewed studies comparing the effectiveness of various deep learning systems in detecting TB anomalies, and none compare multiple deep learning systems with human readers. In this paper, the aim of the proposed method is to develop an efficient tuberculosis detection system based on stochastic learning with artificial neural network (ANN) model by random variations using Chest X-ray images. This approach can able to incorporate random functions into the network, either by assigning stochastic transfer functions to the network or by assigning stochastic weights to the network. This proposed method is to learn features from CXR images and optimize the parameters of an ANN model by randomly mixing the training dataset before each iteration, resulting in varied ordering of model parameter updates. Furthermore, in a neural network, model weights are frequently initialized at a random beginning point. By focusing on randomness functions with optimization, the proposed technique achieved great accuracy. The motivation of the proposed method is to detect abnormalities in CXR with the different levels of complexity of TB by strong or weak evidence with different deep geometric contexts such as shape, size, cavitation, and density. ANN's primary benefit is extracting hidden linear and non-linear inter-relationships of high-dimensional and complex data. The proposed method was systematically tested with the Shenzhen and Montgomery datasets using metrics such as sensitivity, specificity, and accuracy, and it was discovered that the proposed method attained better accuracy when compared to state-of-the-art methods. The proposed method shows an improved efficiency with sensitivity of 96.12%, specificity of 98.01%, accuracy 98.45% and F-Score 95.88% respectively.

I. INTRODUCTION

Tuberculosis (TB) is a long-lasting and infectious disease that primarily affects the poor and requires extensive treatment. Tuberculosis affects ten million people each year. TB kills 1.5 million people per year despite being a preventable and treatable disease [1]. After tuberculosis enter the body, the time it takes to develop disease and the likelihood of having the disease varies from person to person. The sickness is especially likely to affect people who have low body resistance and small children. The sickness can manifest itself immediately after contracting the bacterium or decades later [2]. The disease's symptoms are usually minor at first and gradually worsen with time. As a result, a lot of people put off seeing a doctor. The condition is suspected based on the patient's complaints and results on a chest X-ray. In suspected tuberculosis cases, the bacillus must be seen under a microscope and cultured in growth medium for a definite diagnosis [3], [4]. In the laboratory, sputum or, in rare cases, additional samples acquired from the patient are evaluated, and a definitive diagnosis is made.

Several research have recently been published to assist clinicians with decision-support systems and disease diagnosis. Expert systems and various AI techniques for categorization systems in medical diagnostics are increasingly becoming more prevalent in these studies. Artificial diagnostic systems have been used for tuberculosis diagnosis, as they have for other clinical diagnosis issues. There are a variety of machine learning models that use various methodologies and algorithms to predict TB. The dataset will be taught in two ways: supervised learning, which uses a labelled set of training data, and unsupervised learning, which uses an unlabelled dataset.

Various Deep Learning and Machine Learning technologies have been introduced in recent years for examining digital chest radiographs for TB-related variances with the goal of reducing inter-class reader variability and reproducibility, as well as providing radiologic services in areas where radiologists are not available. Tuberculosis is sometimes misclassified as other conditions with similar radiographic patterns as a result of CXR images, resulting in inefficient therapy. The current approach, however, is limited to CAD, which has only been evaluated with non-Deep Learning models. Deep neural networks open potentially new avenues for tuberculosis treatment. There are no peer-reviewed studies comparing the effectiveness of various deep learning systems in detecting TB anomalies, and none compare multiple deep learning systems with human readers. In this paper, the aim of the proposed method is to develop an efficient tuberculosis detection system based on stochastic learning with artificial neural network (ANN) model by random variations using Chest X-ray images. This approach can able to incorporate random functions into the network, either by assigning stochastic transfer functions to the network or by assigning stochastic

weights to the network. The proposed method learnt features from CXR images and optimised the parameters of an ANN model by randomly mixing the training dataset before each iteration, resulting in varied ordering of model parameter updates. Furthermore, in a neural network, model weights are frequently initialised at a random beginning point. The motivation of the proposed method is to detect abnormalities in CXR with the different levels of complexity of TB by strong or weak evidence with different deep geometric contexts such as shape, size, cavitation, and density. These anomalies may indicate TB, but usually are unable to confirm the diagnosis. ANN's primary benefit is extracting hidden linear and non-linear relationships of high-dimensional and complex data. The proposed method accomplished high accuracy by focusing on randomness functions with optimization. The proposed method was systematically tested with the Shenzhen and Montgomery datasets using metrics such as sensitivity, specificity, and accuracy, and it was discovered that the proposed method attained better accuracy when compared to state-of-the-art methods. The proposed method shows an improved efficiency with sensitivity of 96.12%, specificity of 98.01%, accuracy 98.45% and F-score 95.88% respectively. Model dataset images from Shenzhen and Montgomery are shown in Figure 1.

The following is a summary of our contribution to the paper:

- The goal of the proposed method is to create an effective tuberculosis detection system using random variations and stochastic learning with an artificial neural network (ANN) model.
- The proposed method is to reduce the different levels of complexity of TB by strong or weak evidence with different deep geometric context such as shape, size, cavitation, and density. ANN's primary benefit is extracting hidden linear and non-linear interrelationships of high-dimensional and complex data.
- It achieves great accuracy by focusing on randomness functions and stochastic learning optimization.

The rest of this paper is organized as follows. Section 2 gives Related Work on using various AI techniques for Tuberculosis Detection System. Section 3 gives proposed method for TB Detection System. Section 4 Discuss with Performance evaluation for TB detection system. Section 5 our conclusion is specified.

II. RELATED WORKS

Cao et al. [4] has developed large-scale, well-annotated, and real world X-ray image dataset for automated tuberculosis screening and also focused on building effective and economical computer models that classify images into distinct categories of TB symptoms using deep CNN model. To identify masses from mammograms, The GLCM with texture based descriptor on the spatial connection between different
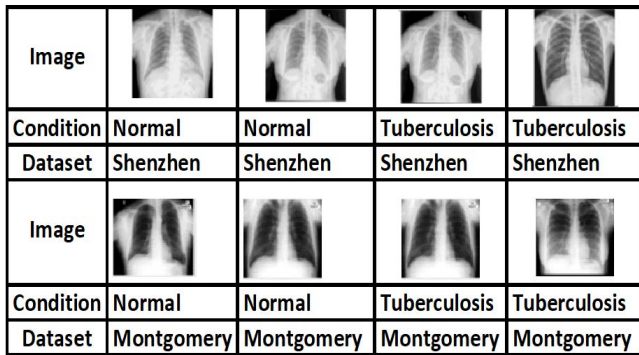
Image				
Condition	Normal	Normal	Tuberculosis	Tuberculosis
Dataset	Shenzhen	Shenzhen	Shenzhen	Shenzhen
Image				
Condition	Normal	Normal	Tuberculosis	Tuberculosis
Dataset	Montgomery	Montgomery	Montgomery	Montgomery

FIGURE 1. Model dataset images from Shenzhen and Montgomery [27].

pixel pairs, was employed by Khuzi *et al.* [5]. Jaeger *et al.* [6] suggested an automatic TB detection method that computed low-level features such as shape-based and texture-based descriptors from Chest X-Rays images using a LBP. The collected features are put into a binary classifier on two smaller datasets to produce with following accuracy of each dataset of 78.3% and 80%, respectively. Anthimopoulos *et al.* [7] constructed a deep learning with CNN architecture and utilised it to diagnose pulmonary lung problems using CT scans, providing a higher-compactness resolution image of lung components in 2D or 3D formats, in comparison to CXRs. Interestingly, their suggested model can distinguish six different lung disease presentations as well as healthy instances with a shown accuracy of >80%. The transferability and generalizability of proposed model needs further evaluated, given the dataset employed in their investigation was confined to only 120 CT images.

A CAD approach for diagnosing tuberculosis was developed by Song *et al.* [8] in 2010. Using the original dataset of 100 photos, that system was able to achieve an accuracy of 85%. By incorporating image manipulation techniques including texture analysis and masking, Jaeger *et al.* [9] built a TB detection pipeline using the dataset of 138 Chest X-rays investigated. The algorithm was able to reach an accuracy of 83%. Vajda *et al.* [26] developed a TB detection that emphases on lung field segmentation with Shenzhen dataset, resulting in an algorithm correctness of 95.6% and an AUC of 0.99. Melendez *et al.* [10] integrated the CAD4TB algorithm's score, which is based on imaging findings, with 12 clinical characteristics to assess the effectiveness of the CAD4diagnostic TB in conjunction with clinical data. The AUC of the CAD4TB algorithm is 0.84 with a specificity of 95% and a sensitivity of 49% indicating that the algorithm was improving. Murphy *et al.* [11] created a deep learning CAD4TB model that trained 500 tagged CXRs images and achieved specificity and sensitivity of 98% and 90%, respectively. For tuberculosis detection, Asha *et al.* [12] built a hybrid model that used k-means and other classification methods and achieved a 98.7% accuracy rate.

From CXR image, deep learning creates hierarchical characteristics automatically. High-level features are derived from low-level features. Deep learning's ability to learn high-level characteristics was found to give better categorization results [13]. A complete automated frontal chest radiograph screening system that can detect TB-infected lungs has been demonstrated [14]. This approach starts with an atlas-based lung segmentation algorithm before extracting user specified data like shape and curvature descriptor histograms or hessian matrix eigenvalues. The same task may be accomplished with a simple CNN [15]. Another CNN-based algorithm [4] was developed to categorise different forms of TB symptoms. An automatic detection system using deep learning method for TB classification was developed [16]. There are 27 layers in the deep CNN employed in this technique, with 12 residual connections. For training and testing, six datasets were employed. It consistently outperforms physicians and thoracic radiologists in detecting tuberculosis on chest x-rays.

Ensemble learning occurs when more than one model is utilised to create a prediction. Ensemble decreases the variance of forecasts, resulting in more accurate predictions than a single model. The three models in the ensemble, which is known as the RID network, are Inception-ResNet, ResNet, and DenseNet. SVM was utilised as a classifier, and the representations were used as feature descriptors [17]. Researchers used an ensemble learning-based three deep neural network prototype fused at the feature level to classify tuberculosis [18]. To categorise TB, researchers employed a combination of three deep learning based conventional architectures: GoogleNet, ResNet, and AlexNet [19]. Simple linear averaging was used to build the ensemble models, which averaged the probability projections provided by the individual models. Reference [20] Used pre-trained models such as GoogLeNet and AlexNet to classify pulmonary tuberculosis, and found that the pre-trained model was more accurate. To ensemble these models, they used weighted average of each representation's likelihood scores. For TB detection, a study published in [21] and [22] used pre-trained CNN classifiers, which were then ensemble using majority voting. Filho *et al.* [28] used public CRX databases to experiment with traditional CNN architectures in order to develop a tool for diagnosing tuberculosis in CRX images. Sathitratanacheewin *et al.* [29] has developed a DCNN model for TB detection system. The DCCN model had an AUC of 0.9845 and 0.8502 for detecting TB in the training and intramural test sets, respectively, using the Shenzhen hospital database. A hybrid technique that integrates the first statistical computerised detection method with Neural Networks was created by Norval *et al.* [30]. The simulations made use of 406 normal images and 394 aberrant images in total. The simulation results revealed that combining a clipped region of interest with contrast enhancement yielded the best results. When the CRX images are further improved utilizing the hybrid technique, even greater results are attained. Barros *et al.* [31] has suggested the forecast of the likelihood of death from tuberculosis, so assisting in the TB prognosis and therapy decision-making process. The data set had 36,228 records and 130 fields in its original

form, but it had missing, incomplete, or erroneous data. SVM, RF, and NN are three machine learning models suggested and analysed by Hussain *et al.* [32]. The 4213 entries in their data set, which came from an unknown facility, represented completed treatments 64.37 % of the time. The metrics of accuracy, precision, sensitivity, and specificity were used to compare the models, and the outcome predicted by the models is treatment completion. The RF model had the highest accuracy (76.32%), while the SVM scored best in terms of precision (73.05%), specificity (73.05%), and sensitivity (95.71%). The highest sensitivity was reached by the NN (68.5%). To classify unfavorable outcomes, Killian *et al.* [33] employed an Indian database of 16,975 patient records. Death, treatment failure, loss to follow-up, and not being examined were all lumped together in the same category. Unfavorable outcomes were categorised by Killian *et al.* [33] using data from 16,975 patient records in an Indian data set. They regarded loss to follow-up, treatment failure, and death as belonging to the same class but not being examined.They proposed the deep learning based LSTM Real-time Adherence Predictor model and compared it to an RF model. The AUROC of LEAP was 0.743, while the RF was 0.722. For TB detection systems using CXR images, Faruk *et al.* [34] constructed four different deep neural networks, including MobileNetV2, nceptionResNetV2, Xception, and InceptionV3. The transfer learning method was utilised to train and estimate a TB detection system model, which is provided good accuracy.

Lin *et al.* [35] proposed an adaptive attention network (AANet) for extract the specific radiographic results of COVID-19 from the diseased areas with various sizes and appearances. The suggested AANet outperforms state-of-the-art approaches, according to this method's tests on a number of open datasets. The research work, which was offered by Bhatt *et al.* [36], largely focuses on the primary taxonomy and several deep CNN architectures. Dey *et al.* [37] have developed the model for screening TB with ensemble algorithms based on the fuzzy integral method using Chest X-ray images. Sanchez *et al.* [38] implemented an adaptation and classification approach to tackle the over-fit issues on a limited Chest x-ray dataset. This approach is utilized CNN method to experiment with different layers for classification and produced 97.78% accuracy.

According to the research, deep learning has been successful in detecting tuberculosis. The features of the original chest x-ray images are extracted in all of the aforementioned works. The majority of studies, however, relied on CNN's automatic extraction of features. Different features should be investigated since the features utilized influence the classifier's performance. For an ensemble binary classifiers to work well, there must be a variety of error rates [23]. In other words, the base classifiers failures should be unrelated. The vast majority of studies simply integrate classifiers that have been trained on related traits. As a result, a reliable tuberculosis diagnosis method is required, which necessitates the use of deep learning and AI.
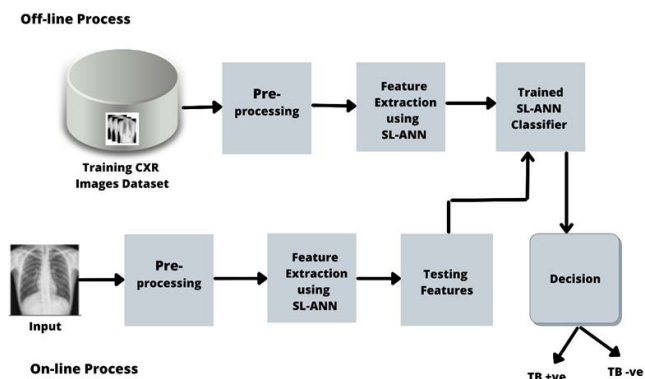

FIGURE 2. Overview of proposed stochastic learning-based artificial neural network (SL-ANN) model for an automatic tuberculosis detection system using chest x-ray images.

III. PROPOSED METHOD

According to the findings of the literature review, new approaches for detecting Tuberculosis must be developed in order to deal with a wide range of variances. The Artificial Neural Network (ANN) model based on Stochastic Learning by random variations with optimization techniques employing Chest X-ray images overcomes this challenge.

This method is intended to improve the robustness of the Tuberculosis detection system using Stochastic Learning-based ANN (SL-ANN) by using random variations with optimised ANN model parameters by randomly mixing the training dataset before each iteration, resulting in different ordering of model parameter updates. Furthermore, in a neural network, model weights are frequently initialised at a random beginning point. The training phase (off-line) and testing phase (on-line) processes of the Stochastic Learning-based Artificial Neural Network (SL-ANN) approach are carried out separately. The off-line technique extracts features for training of Chest x-ray image. The database has its representation. The Testing phase is also follow the same procedure up to feature extraction of the off-line process. Finally applied classification algorithm is to detect whether the given input is TB positive or TB negative. The system overview of the proposed method is shown in Figure 2.

A. PRE-PROCESSING

Two stages of image pre-processing techniques are involved. The image resizing process begins with the first stage. All of the images were reduced to 250 by 250 pixels in size. The canny edge detection algorithm is used in the second stage to find edges. The theory is that Chest X-ray images with tuberculosis can have more uneven edges than normal chest X-ray images, making tuberculosis detection more likely.

A multi-stage technique is used by the canny operator. The CXR image is first smoothed using Gaussian convolution. The first derivative operator is applied the highlighted area of Chest x-ray image for smoothed image with high spatial
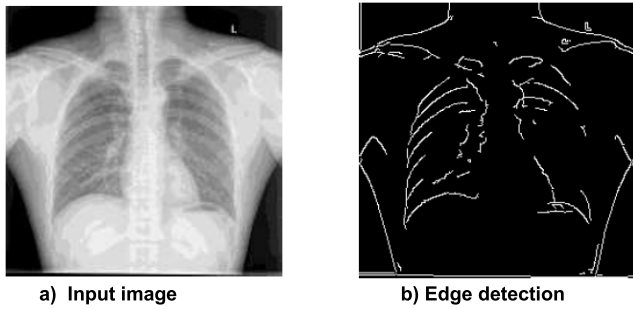
a) Input image   b) Edge detection

FIGURE 3. Pre-processing steps using canny edge detection.

FIGURE 4. General feed-forward based ANN architecture method for tuberculosis detection system using chest x-ray image.

derivate. In the gradient magnitude image, edges were created ridges. Non-maximal suppression is achieved by tracking along the tops of these ridges and set zero to all pixels that are not actually on the ridge top, resulting in a thin line in the output. Two threshold values, T1 and T2, regulate the hysteresis of the tracking process, with T1 > T2. Only at a position higher than T1 on a ridge can tracking begin. After that, tracking remains in both directions until the ridge's height falls below T2. This hysteresis prevents noisy edges from being broken up into many fragments. Figure 3 shows the sample edge detection using canny edge detection technique.

B. FEATURE EXTRACTION BASED ON FEEDFORWARD ARTIFICIAL NEURAL NETWORK (FF-ANN)

After the Pre-processing stage, Artificial Neural Network architecture obtains the process of feature extraction in the Chest x-ray (CXR) images. ANN's primary benefit is extracting hidden linear and non-linear inter-relationships of high-dimensional and complex data. ANN architecture is used Feed-forward neural networks learning technique and also called Multi-layer perceptron (MLP). It consist of input layer, hidden layer, output layer and weights. The four-layer network topology of the feed-forward neural network is denoted by the notation I/H1/H2/O, where I denotes the number of input units, H denotes the hidden units, and O denotes the output units. Furthermore, it adopt that each layer is completely interconnected with the layers above and below, and there is connection from the output of every unit in L_k to the input of every unit in L_{K+1}.

The Multilayer FF-ANN implements a composite function:

$$o = f \text{ composite } (i) \qquad (1)$$

Using p mapping layers in a $p + 1 - layer^2$ FF network yields

$$o = f^{L_p} \left(f^{L_{p-1}} \ldots \left(f^{L_i} (i) \ldots \right) \right) \qquad (2)$$

The overall function for each output unit $o_i = 0, 1, 2, \ldots O$ defined by

$$o_i = f_i^{L_2} \left(f^{L_1} (i) \right) = \sum_{k=1}^{H^i} w_{ik}^{L_1 \to L_2} f_K^{L_i} (i) \qquad (3)$$

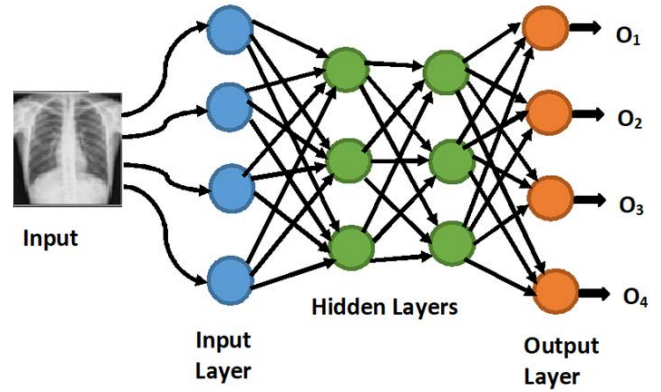Here, the interconnection weight denoted by unit k in L_1 to unit i in L_2 as $w_{ik}^{L_1 \to L_2}$. In the case where the hidden layers have a sigmoidal activation function is denoted f^{sig}, equation (3) becomes

$$o_i^{L_2} = \sum_{k=1}^{H_i} w_{ik}^{L_1 \to L_2} \left\{ f_k^{sig} \left(\sum_{j=1}^{I} w_{ik}^{L_0 \to L_1} i_j \right) \right\} \qquad (4)$$

In this network, data (input) only moves in one direction, via hidden nodes, from input nodes to output nodes. In the network, there are no cycles or loops. The steps for training neural networks are as follows: (i) Set the weights in the hidden units to uniform random values. (ii) Determine the weights of all the output units. When there are a lot of training inputs, it could take quite some time, and learning is slow as a result. To increase speed learning, employ a technique known as stochastic gradient descent. In order to improve the accuracy of these ideas, stochastic gradient descent selects a small number of 'm' training inputs at random. If the sample size is sufficient and the random training inputs $x_1, x_2, \ldots x_3$ are labelled, the following formula is used to get the average value:

$$\frac{\sum_{j=1}^{m} \nabla C_{X_j}}{m} \approx \frac{\sum_x \nabla C_x}{n} = \nabla C \qquad (5)$$

This change allows to reduce the computational load by a significant amount. When stochastic gradient descent is used to solve non-convex loss functions, convergence is not assured and is dependent on the initial parameter values. All weights should be set to modest random values when using feedforward neural networks. Initialize the biases to zero or small positive values.

C. STOCHASTIC OPTIMIZATION

In this section, the stochastic training algorithm is involved a search for weights using random techniques. Prior to calculating the cost using all the data points in the training set, randomly initialize the weights. Next, calculate the cost by gradient method with respect to the weights. Finally update weights and continues this process until the minimum is

reached. The update is calculated is as follows:

$$w_j = w_j - \alpha \frac{\partial J}{\partial w_j} \qquad (6)$$

For large training set, calculate the cost of a single data point and the accompanying gradient rather than the cost of all the data points. The update is calculated is as follows:

$$for\ i\ in\ range\ (m): \quad w_j = w_j - \alpha \frac{\partial J_i}{\partial w_j} \qquad (7)$$

In this context, the update stages are carried out fast, getting to the minimum in a short period of time. The high dimensionality of weight space in that initial weights $w(0)$ are often randomly generated. Since $w(0)$ provides the starting point. The proposed optimization algorithm has considered for iterative characters. The sequence of solutions $\theta_0, \theta_1, \ldots \theta_k$ is previously appointed and construct the next point is expressed as follows,

$$\theta_{k+1} = \theta_k + r_k \qquad (8)$$

where θ_k is the kth iteration and r_k is the random normal distribution $N(0, \sigma)$. When the new point is accepted, the cost function $J(\theta_{k+1})$ is less than $J(\theta_k)$ otherwise $\theta_{k+1} = \theta_k$. The initial point θ_0 and the variance σ must be determined before the optimization technique. The algorithm of stochastic optimization is as follows:

The uphill and downhill directions of random variants are implemented in the initial modification to the random optimization method. The weight adjustment in the second extension involves a moving statistical bias. This is accomplished by setting the mean of to zero. This method includes a number of qualities that are immediately appealing. Another aspect to consider is that the weight X over which the search must be performed is not always compact. This constraint could be applied at any time; in fact, some weight may need to be arbitrarily large.

IV. EXPERIMENTS
In the experimental part, four metrics were used to evaluate the proposed method performance: sensitivity, specificity, accuracy, and F-Score and also ROC-AUC analysis. The ability of the model to identify positive cases and negative cases are measured by two parameters namely sensitivity and specificity. The accuracy of the model indicates its overall efficiency. In this study, a positive case is represented by TB, while a negative case is represented by non-TB. The Montgomery and Shenzhen datasets [24] are utilised to evaluate the work described in this study. There are 138 images in the Montgomery dataset with 80 images of normal lungs and 58 images of tuberculosis. The Shenzhen dataset contains 662 images, 326 non-TB images and 336 TB images. The overall healthy lung images are 406, while the total number of images of TB-infected lungs is 394. From the selected Chest X-ray images, 80% of them were used for training and 20% for testing.

Algorithm of Stochastic Optimization
Input: Select random point (kth iteration)
Output: Optimised the parameters of an ANN model

---

function Stochastic_Optimization(w)
$X \leftarrow w(0)$; // *Select* $w(0) \in X$;
$k \leftarrow 0$;
//*Let Maximum Number of Iteration (M) allowed*
       while random_vector_Gaussian $(k < N)$ *do*
// $\xi(k)$
           if $X == w(k) + \xi(k)$ *then*
      if $E(w(k) + \xi(k)) < E(w(k))$ *then*
      $w(k+1) = w(k) + \xi(k)$;
        else
              $w(k+1) = w(k)$;
            end
      else
          if $k = M$ *then*
             break;
          else
               $k \rightarrow k+1$;
        end
      end
    next k
return w
// *Modification of Random Optimization, Let* $b(0) = 0$
if $E(w(k) + \xi(k)) < E(w(k))$ *then*
    $w(k+1) = w(k) + \xi(k)$;
    $b(k+1) = k_1\xi(k) + k_2 b(k)$;
else if $E(w(k) + \xi(k)) > E(w(k))$ *then*
      if $E(w(k) - \xi(k)) < E(w(k)$ *then*
      $w(k+1) = w(k) - \xi(k)$;
      $b(k+1) = b(k) + k_3\xi(k)$;
    else
    $w(k+1) = w(k)$;
      $b(k+1) = k_4 b(k)$;
    else
end

A. EXPERIMENTAL SETUP
In the experimental setup, construct the feedforward-based artificial neural network. The activation functions for the hidden layers will be ReLU and sigmoid, respectively. Softmax activation will be included in the final layer. Cross-entropy is used to calculate the error. After initializing the feedforward-based ANN model with sequential modules, used the dense model to add a different layer. There are three parameters defined namely (i) the first parameter is output dimension which defines hidden layer, (ii) The weights that are almost 0 but not 0 are randomly initialised by a uniform function as the second argument, (iii) The third parameter is defined ReLU activation. Finally, add an output layer in the feed-forward ANN structure with two neurons, each one can represent the positive class or negative class. After adding all layers, compile the ANN and add several

TABLE 1. Overall performance of proposed method.

Method	Dataset Used	Sensitivity (%)	Specificity (%)	Accuracy (%)	F-Score (%)
Stochastic Learning Based Artificial Neural Network Model (Proposed Method)	Montgomery + Shenzhen TB Images:58+336 = 394 Non TB Images: 80+326=406	96.12%	98.01%	98.45%	95.88%

TABLE 2. Comparison of average performance measures of the proposed method.

Method	Sensitivity (%)	Specificity (%)	Accuracy (%)	F-Score (%)
Automatic Frontal Chest Radiograph Screening Method (AFCRS) (2018) [26]	95.00%	90.00%	97.03%	94.12%
CNN (2019) [14]	94.74%	97.83%	96.63%	93.04%
Ensemble Deep Learning (EDL) (2019) [25]	90.91%	88.64%	89.77%	91.45%
Stochastic Learning Based Artificial Neural Network Model (SL-ANN) (Proposed Method)	96.12%	98.01%	98.45%	95.88%

parameters namely, the optimal number of weights using stochastic learning optimization for randomness functions, loss function, and metrics for accuracy which is used to evaluate by the model. In order to iteratively determine the ideal combination of weights and biases, stochastic learning optimization is used by gradient descent approach. Every sample in the training dataset has its error rate calculated, and the model is updated accordingly. For each set of images and FF-ANN architecture, the learning rate, batch size, and epoch were set to 0.0001, 32 and 100 respectively. The proposed method has been implemented Keras and Tensorflow.

B. PERFORMANCE ANALYSIS

The proposed Tuberculosis Detection System was tested using the benchmark dataset listed in the experiment setup column. The proposed approach stochastic learning based artificial neural network model produces a good result by producing a better sensitivity, specificity, and accuracy. As indicated in Table 1, the tuberculosis detection method has a promising accuracy. Table 1 shows the average of all measures for the tuberculosis detection system with various benchmark datasets. Table 1 shows that the proposed strategy yields promising results for the tuberculosis detection system. Figure 5 depicts the average performance analysis of the suggested stochastic learning based artificial neural network model.
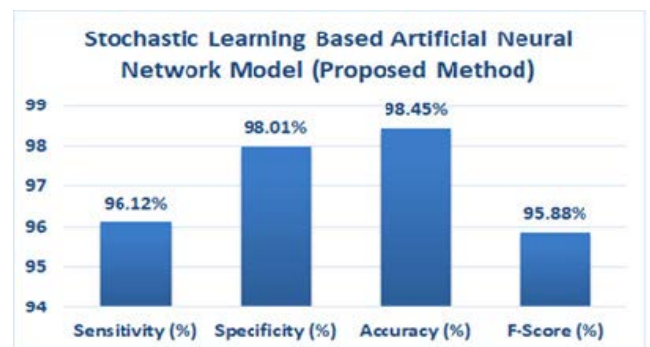

FIGURE 5. Average performance measures of proposed method.

One of the most often used metrics for evaluation is Area Under Curve (AUC) is employed in the proposed system. The AUC metrics used to randomly select positive data points higher than randomly selected negative datapoints. It used two basic terms: (i) True Positive Rate (Sensitivity) (ii) True Negative Rate (Specificity)

(i) True Positive Rate (Sensitivity): True Positive Rate refers to the proportion of positive data points that, when compared to all positive data points, are actually measured as positive.

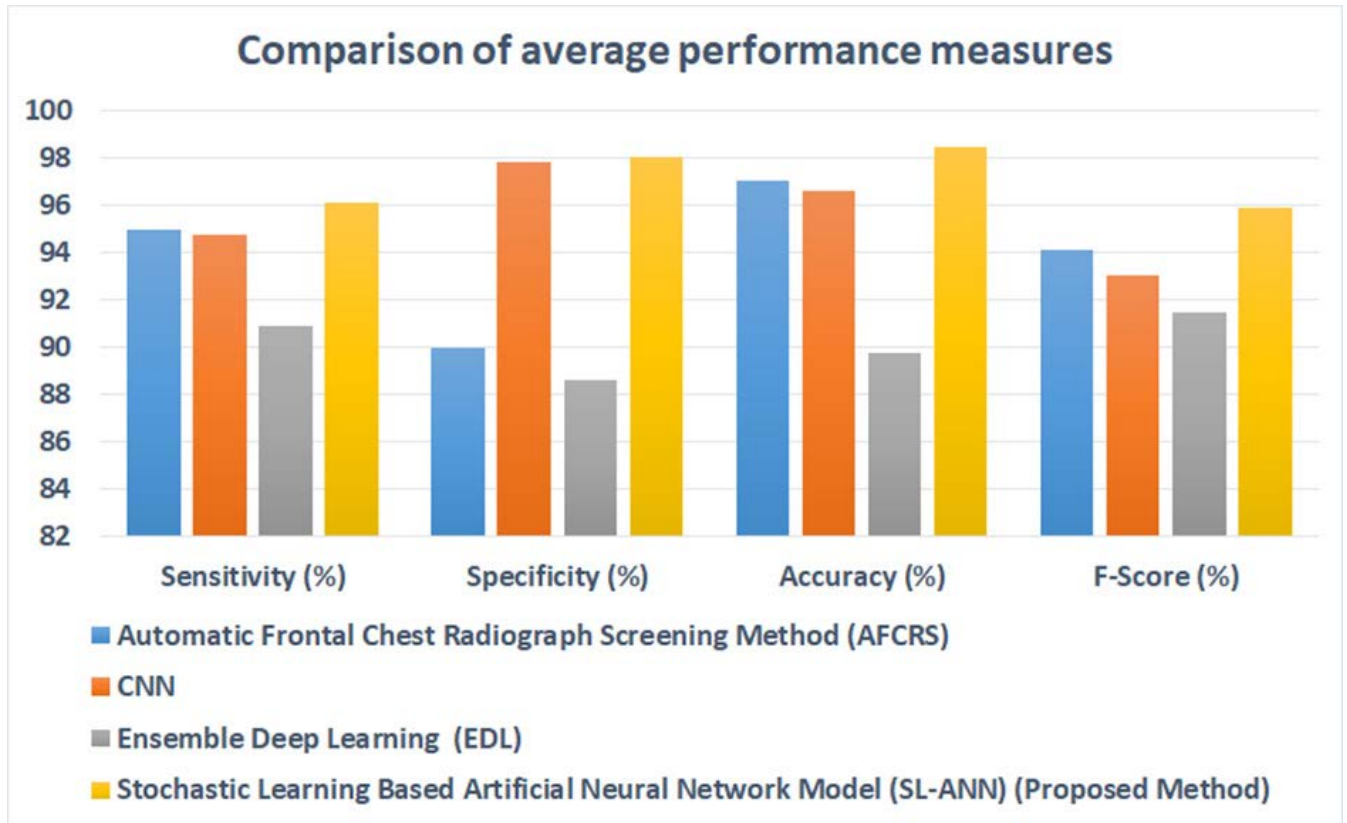$$TruePostiveRate = \frac{TruePostive}{FalseNegative + TruePostive} \quad (9)$$

FIGURE 6. Comparison of average performance measures of various tuberculosis detection methods.

(ii) True Negative Rate (Specificity): The percentage of precisely measured negative data points relative to all negative data points is known as the false positive rate.

$$TrueNegativeRate = \frac{TrueNegative}{TrueNegative + FalsePostive} \quad (10)$$

The following metrics also employed in the proposed method, F-Score and accuracy. The F-Score is calculated by the average mean of the precision and recall.

$$F-Score = 2 \times \frac{Precision * Recall}{Precision + Recall} \quad (11)$$

Additionally, accuracy can be measured in terms of positive images and negative images as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (12)$$

The proposed Stochastic Learning Based Artificial Neural Network (SL-ANN) Model is compared with Ensemble Deep Learning [25], CNN [14], and Automatic Frontal Chest Radiograph Screening System [26] in order to show the ability of the proposed technique to Stochastic Learning based optimization in a better way for the detection of tuberculosis system. The proposed system proves clear improvement over

the current approaches due to the Stochastic Learning based optimization technique.

The proposed method outperforms Ensemble Deep Learning [25], CNN [14], and the Automatic Frontal Chest Radiograph Screening System [26] in terms of accuracy. The proposed method shows an improved efficiency with Sensitivity of 96.12%, Specificity of 98.01%, Accuracy of 98.45% and F-Score of 95.88% respectively. The proposed method Stochastic Learning Based Artificial Neural Network Model is compared with Ensemble Deep Learning method, the average measures of sensitivity, specificity, accuracy and F-Score are 90.91%, 88.64%, 89.77% and 91.45% respectively. The CNN method, the average measures of sensitivity, specificity, accuracy and F-Score are 94.74%, 97.83%, 96.63% and 93.04% respectively.

In the Automatic Frontal Chest Radiograph Screening method, the average measures of sensitivity, specificity, accuracy and F-Score are 95.00%, 90.00%, 97.03% and 94.12% respectively. Table 2 and Figure 6 shows a comparison of the proposed method Stochastic Learning-Based Artificial Neural Network Model (SL-ANN) with other existing methods.

Table 2 is used to compute the ROC (Receiver Operating Characteristic) curves and their equivalent AUC (Area Under the Curves), as illustrated in Figure 7. The suggested system outperforms the other techniques in terms of accuracy, and
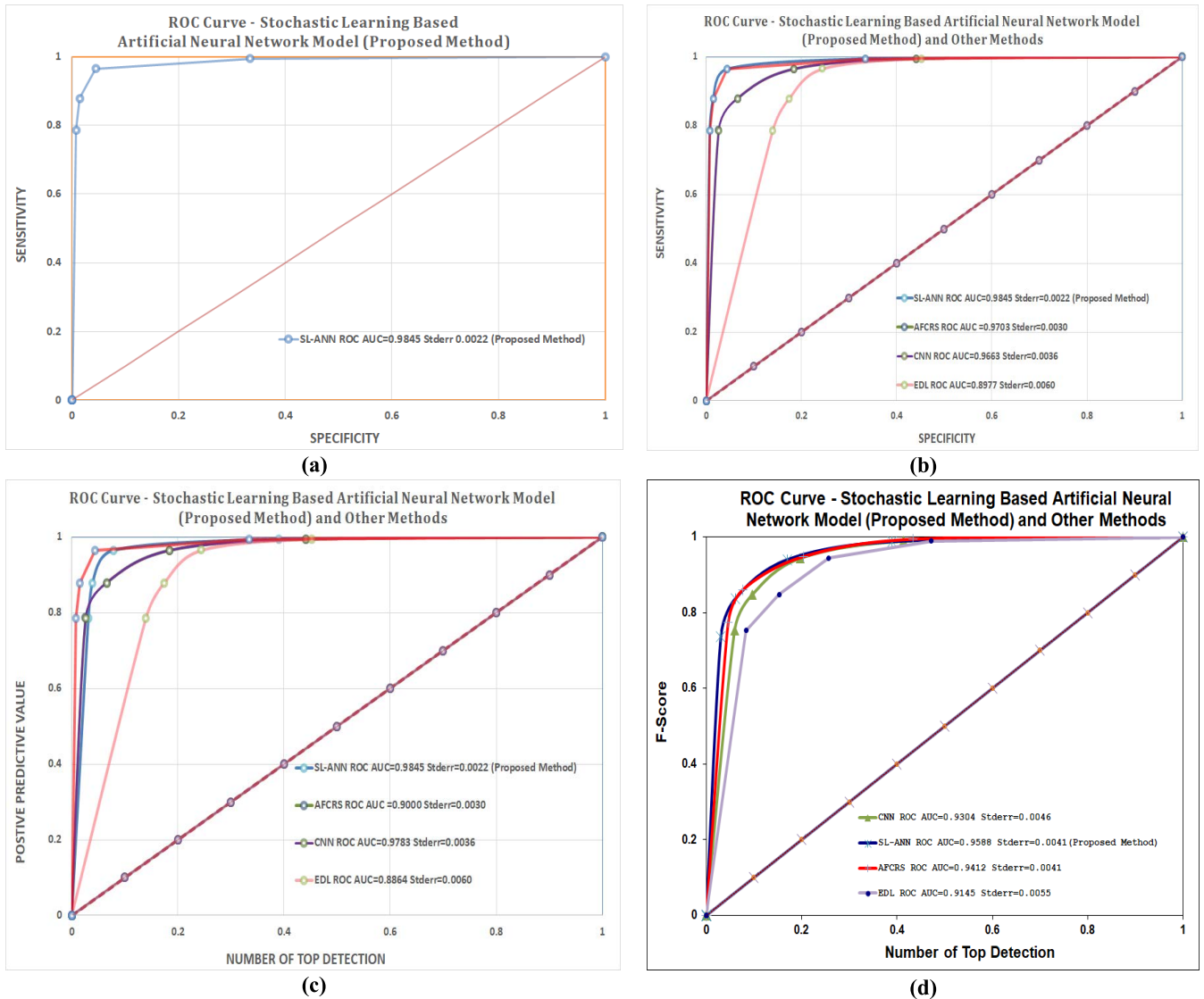
FIGURE 7. ROC-AUC analysis of the proposed method stochastic learning-based Artificial Neural Network Model (SL-ANN) and other existing methods for tuberculosis detection system: a) ROC curve for the SL-ANN Model (ROC-AUC = 0.9845 ± 0.0022). b) Results in terms of sensitivity, specificity, and accuracy compared to the SL-ANN Model and other approaches. C) Results compared to other existing methods and the SL ANN Model in terms of positive predictive value vs top detection rates. d) Results comparing the F-Score Vs. number of top detection for the SL ANN Model and other methods currently in use.

experimentation shows that the stochastic learning based artificial neural network model (SL-ANN) generates good and comparable outcomes.

The Chest X-ray images are obtained from the Shenzhen and Montgomery datasets, as indicated in Table 2, to estimate the accuracy of each approach. The accuracy of each technique is calculated by dividing the sum of True Positive and True Negative pairings at a specific threshold by the amount of total pairs. Table 2 and Figure 7 present a comparison of each method's average performance parameters of sensitivity, specificity, and accuracy.

The AUC is a measurement of the complete 2D area beneath the entire ROC curve. The likelihood that a classifier would score an arbitrarily selected positive sample higher than an arbitrarily selected negative sample is equal to the AUC of the classifier.

Table 2 is used to compute the ROC curves and their equivalent AUC, as illustrated in Figure 7. Figure 7 (a). Depicts the ROC curve for the proposed Stochastic Learning Based Artificial Neural Network Model (ROC-AUC = 0.9845 ± 0.0022). Figure 7 (b) illustrates the comparison between the SL-ANN Model and other current techniques in terms of sensitivity, specificity, and accuracy values. Figure 7 (c) displays the outcomes using the SL-ANN Model and other current techniques in terms of the number of top detections vs the positive predictive value. Figure 7 (d) displays the findings for the SL-ANN Model and other available methods in terms of F-Score Vs. number of top detection.

During the experiments, it was observed that the SL-ANN model functions effectively works well across various variation of Chest X-rays images in tuberculosis detection system.

It is more robust to method learnt the features from CXR images and optimised the parameters of an ANN model by randomly mixing the training dataset before each iteration, resulting in varied ordering of model parameter updates. By focusing on randomness functions with optimization, the proposed technique achieved great accuracy when compared to the existing approaches.

V. CONCLUSION

In this paper, the Tuberculosis diagnosis system is built on a Stochastic Learning based Artificial Neural Network (SL-ANN) model with random variations using chest X-ray images. This proposed method is incorporated random functions into the neural network, either by assigned stochastic transfer functions to the network or by assigned stochastic weights to the network. This proposed method learnt the features from CXR images and optimised the parameters of an ANN model by randomly mixing the training dataset before each iteration, resulting in varied ordering of model parameter updates. By focusing on randomness functions with optimization, the proposed technique achieved great accuracy. The proposed method was thoroughly tested with the Shenzhen and Montgomery datasets using metrics such as sensitivity, specificity, and accuracy, and it was discovered that the proposed method attained better accuracy when compared to state-of-the-art methods. The results of the proposed approach show a clear enhancement over the Ensemble Deep Learning [25], CNN [14], and Automatic Frontal Chest Radiograph Screening System [26]. The proposed approach shows an improved efficiency with sensitivity of 96.12%, specificity of 98.01%, accuracy 98.45% and F-Score 95.88% respectively. The proposed method SL-ANN Model is compared with Ensemble Deep Learning method, the average measures of sensitivity, specificity, accuracy and F-Score are 90.91%, 88.64%, 89.77% and 91.45% respectively. The CNN method, the average measures of sensitivity, specificity, accuracy and F-Score are 94.74%, 97.83%, 96.63% and 93.04% respectively. In the Automatic Frontal Chest Radiograph Screening method, the average measures of sensitivity, specificity, accuracy and F-Score are 95.00%, 90.00%, 97.03% and 94.12% respectively. Future work may focus on the medical community would benefit greatly from immediate identification, distinction of proportion of disease evolution, and multi-class classification. It can be extended to the development of the mobile device deployment tends to be both cost-effective and time-saving.

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