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Artificial Intelligence based Deep Architecture for Tuberculosis Detection

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ABSTRACT
Artificial Intelligence-based system for Tuberculosis (TB) detection has been proposed in this work. TB detection in the early stage can help in mitigating the effects in organ damage of kidneys, liver, spine, and brain, thus reducing human deaths. Manual diagnostic through radiologists can be misdiagnosis due to human error. Designing an artificial intelligence-based decision support system can help in the accurate prediction of TB through lung Chest X-ray (CXR) image. In the proposed work, five different kinds of image enhancement techniques were applied to the publicly available image dataset. The dataset is balanced using a data balancing approach with eight different kinds of data augmentation applied. Six different modified network architectures of Convolutional Neural Network(CNN) is utilised. Comparative Studies of five image enhancement techniques in behaviour response with CNN architectures are evaluated for best performance. The obtained result showed Gamma corrected image with Modified ChexNet performed the best with 96.3% accuracy, 95.3%precision and 97% recall.

KEYWORDS
P AI, TB, CXR, CNN, accuracy, recall, precision

1. INTRODUCTION

Tuberculosis (TB) is a contagious disease caused due by respiratory infection by “Mycobacterium Tuberculosis”, which affects the lung lining immensely [1]. According to World Health Organisation (WHO) reports, TB is the thirteenth leading cause of fatality across the world. TB is highly infectious and placed in the second precedence after Coronavirus [2].

Antibiotics can help to cure the disease, but detection in the later stage TB can enter the bloodstream to affect the spine, brain, and kidney.[3] In order to mitigate the effects of the disease the chances of affecting the organs and reducing fatality requires “Early detection” of the disease. For early detection of TB, a standardized screening high-quality laboratory is required, which is not a “feasible solution” for people living in developing countries like Bangladesh, Nepal, India, and Sri Lanka. To solve the “feasibility” issue screening of “Chest X-rays” becomes a proper diagnostic to detect the disease. Manual screening diagnosis through radiologists can create “errors”, due to misdiagnosis [4]. In order to solve the problems of “misdiagnosis due to human error and misdiagnosis as well as predictability, Artificial Intelligence-based technology can play important role in designing “Decision Support Systems” or “Computer-Aided Design System” to support the medical diagnosis process [5].

Moreover, it is important to note the cost-effectiveness of Chest X-ray images in comparison to radiography diagnosis. Chest X-ray images can help to design DSS-based systems for the detection of pneumonia and other lung disorders [6].

Furthermore, DSS-based systems help researchers for better crafting for “medical images” than hand-crafted features, especially for DSS based on deep-learning architecture. Deep-Learning based architecture like Convolutional Neural Networks (CNN), filters of CNN can help to distinguish features of “medical images” accurately [7].

To capture accurate features from CNN, researchers try to increase layers of convolution layer in “depth-wise”, or “length-wise”. In the case of increment layers, it becomes very impossible to train the model. Different pre-trained networks of CNN can be found useful in vanishing gradient problem which uses approach transfer learning-based approach for feature extraction and transfer learning [8]. CNNs are commonly applied to medical image processing. The working functionality of CNN depends on datasets of images of “low quality” or “blurry images” still a cause of concern for better feature extraction.

Image Enhancement Techniques play a crucial role in the development of remote sensing, microscope imaging, medical image analysis, etc. Image Enhancement techniques applied on images such as wavelet transformation, de-noising algorithms, filtering, etc find a good purpose for enhancement. In relation to medical images, geometric features of corners, ridges and edges play important roles as “feature functionalities” for the purpose. Approaches for enhancement enhance the “predictability” of the machine learning algorithm [9].

A lot of research work has been proposed from the last twenty years in “Image Enhancement” Techniques for enhancing classification models. The adaptive Histogram Equalisation Technique proposed by Arun et.al. [13] can help in image quality enhancement. Hasiken et.al. [10] utilized the theory of fuzzy set theory for better image enhancement for minimum processing time. Selvi et.al. [11] designed image enhancement techniques for fingerprint analysis. Bi and multi-histogram were proposed by Mohammad et.al. [12] for the preservation of natural and brightness of the image. In paper [14], histogram techniques were applied on Chest X-ray images to check applicability on Artificial Intelligence or not. A 3-channel approach using Contrast Limited Adaptive Histogram Equalisation, original and image complementation outstands in the detection of Covid-19from Severe Acute Respiratory Syndrome(SARS) and Middle East Respiratory Syndrome(MERS) and achieved a sensitivity of 93.1% [15]. Histogram Equalisation (HE) for enhancement techniques for Covid-19 from CXR.A patch-based CNN with trainable parameters for Covid-19 detection and 92.5% sensitivity [16]. VGG-based network utilizing a new three-channel approach and histogram equalization by CXR images of size 8474 Covid-19 images. Two sets of filtered images in a three-channel approach from original and enhanced images with 94.5% accuracy for Covid-19 images [17].

Khuzi et al. [18] uses a feature of pixel information from grey-level co-occurrence matrix (GLCM) and then used it for TB detection from mammographic images. Jaeger et al. [19] proposed DSS-based Tb-based screening from Chest X-ray by using local binary pattern (LBP) and hessian shape features from CXR images with Support Vector Machines as a classifier. With recent developments in deep architecture learning techniques as such CNN for disease detection, a number of state of art techniques are proposed in TB detection. Hooda et al. [20] used CXR images for deep learning architecture for TB and non-TB classes. Evalgelista et al. [21] designed CADx using deep architecture using CNN for CXR Tb detection for accuracy of 88.76% from three combined datasets. Also, testing them ensemble methods of learnings. Pasa et al. [22] used a deep CNN utilising shortcut connection, though results not appreciable saliency maps generated shows unique features. Nguyen et al. [23] utilized ensemble methods to use pre-trained networks such as ResNet-50, DenseNet-121, Inception, VGG16, VGG19 for binary classes of TB detection on two datasets. Rajpurkar et al. [24] utilised a CNN architecture 121 layers deep and the model tested on the National Institutes of Health(NIH) CXR dataset for ten different lung diseases.

The main contribution of the paper is illustrated as:

1.Five different image enhancement techniques are experimented on the dataset.

2.Six different deep CNN architecture applied with network modification is utilized

3.Data Balancing approach of balancing between classes is proposed.

4. Study relies to compare and evaluate best image enhancement technique on best network performer for best classification strategy.

The manuscript is divided into different sections. Section 2 contains a detailed study on pre-trained models, image enhancement techniques. Section 3 contains the dataset description, data balancing approach, data pre-processing , data augmentation with results and comparative study of experimentation applied. Section 4 contains conclusion.

2. BACKGROUND

CNNs have outperformed than traditional machine learning paradigm. The network extracts differential and important features of the image. Transfer-based learning paradigms have been successfully incorporated in various areas; CNN utilizes feature extraction to the small datasets [9].

2.1 Architecture Deployment

For TB detection, six pre-trained networks were used as such as two Residual Networks variants, DenseNet201, InceptionV3, CheXNet were used in this literature. Residual Networks with different variants utilize the problem-solving of vanishing gradients and degradation approach of residual learning rather than features.

Dense Convolutional Network (DenseNet) utilizes a smaller number of parameters and doesn't learn from "redundant feature maps", like conventional CNN. DenseNet directly accesses the "input image" and gradient loss function. CheXNet is CNN with 121 layers deep trained on the largest Chest X-ray 14, which contains 100,000 frontal view Chest X-ray images of 14 diseases.

Inception-V3 is a specialized CNN, that makes changes through label smoothening, with 7*7 convolutions, and the classifier propagates through the network (batch normalization applied along with side head). The network is scaled with computation through aggressive regularisation and factorized convolutions.

2.1.1 Modification in Pre-trained Networks Fully Connected layers with modified CNN layer

In a pre-trained network architecture, the fully connected layers are used as classification layers. The last fully connected neural network are replaced with modified layers of CNN for better classification predictability of the model depicted in Figure.1. The modified CNN layers are arranged in sequence of precedence of GlobalMaxPooling2D [9], Dense [9], Dropout [9], Dense. GlobalMaxPooling2D layer is beneficial for getting more basic convolutional architecture for the categorization of classes. It aids in avoiding the problem of "overfitting" as it lacks parameters. Moreover, this layer takes summation of spatial features resulting in input regularization and optimized confidence maps. The Dropout and Dense layers are similar as in Base architecture development.

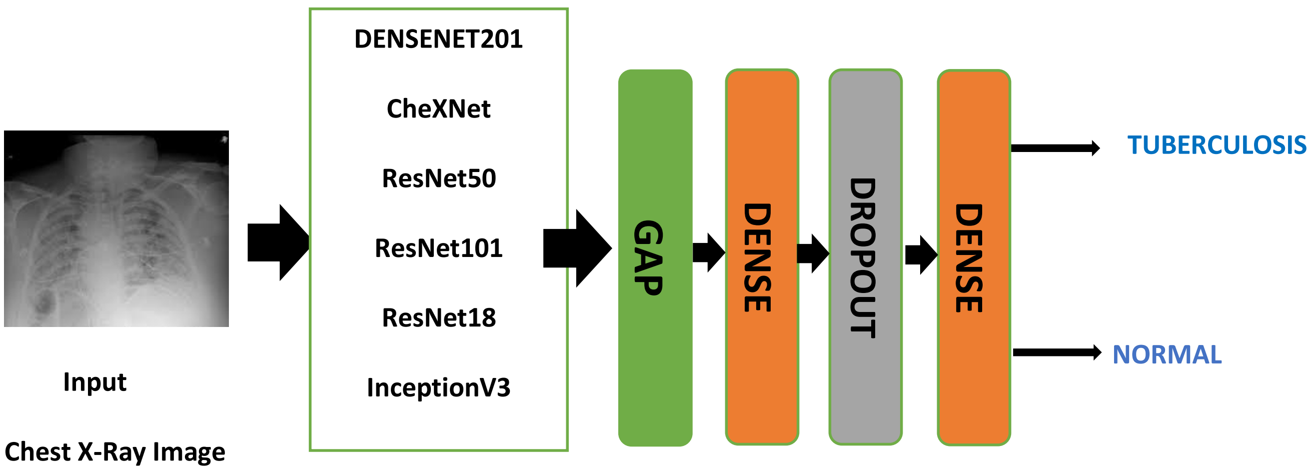


Fig. 1 The flow work for CNN designing of pre-trained transfer learning approach with fully connected replaced with GAP (Global Average Pooling), Dense layer, Dropout layer and Dense layer in sequence to give output as two binary classes TB.

2.2 Image Enhancement Techniques

Image Enhancement Techniques is a crucial stage for image-processing technique, which holds the "key information" of the image and removes or reduces the unwanted information of the image. In this, we deployed five different enhancement strategies in this research. In the following section, these image enhancement techniques will be briefly introduced:

2.2.1 Historgram Equalisation

Histogram Equalisation motives to distribute the grey level in the image. Each level of gray is distributed dark and light contrast distribution for image enhancement." Skewness" is strong for getting insights into the darkness and lightness of the image. For even and desired distribution of the image, re-distribution of the dark end, which makes feature clear visibility. Histogram of the image with range between 0 to L-1 discontinuous function is given by equation as:

$$h(r)_k = n_k \quad (1)$$

Where, r_k is the intensity value at kth value, n_k is piels of the image at intensity r_k .Pixel normalisation is the basic agenda used for image. M*N image is assumed , histogram is normalised through r_k occurrence in the image.

2.2.2. Contrast Limited Adaptive Histogram Equalisation (CLAHE)

The improved version of Histogram Equalisation is Adaptive Histogram Equalisation. Adaptive Histogram Equalisation (AHE) uses the HE technique over the small region(patches), thus improving the small region of the image and contrast betterment. This technique improves the regional contrast and preserves edges with adaption in the local pixel rather than global pixel adaption. AHE could make the noise appear more than the actual image noise. Contrast Limited Adaptive Histogram(CLAHE) gives the natural appearance than HE. CLAHE uses the same technique as AHE but a threshold parameter is used.

The image is converted to HSV from RGB format as HSV is more sensitive to human eyes. The component HSV value is processed by CLAHE (no effect on hue and saturation). Cropping of histogram and re-distribution of gray-level is done to cropped pixels. Each pixel value is reduced to a user-selectable range. Finally, the HSV image is transformed back to RGB colour space.

2.2.3. Gamma correction

Linear Operations of scalar addition, subtraction, and multiplication are applied on pixel level for image normalization. Non-linear Operations on pixels are performed by Gamma correction. Internal mapping between pixel and gamma according to the relationship between values. If pixel value P is represented by [0,255] range and Ω is angl , τ is set value for gamma , x is the gray scale value of the pixel.
Let's assume xm be the middle value point of range 0 to 255. Linear mapping from P to Ω is illustrated as:

$$\varphi: P \rightarrow \Omega, \Omega = \{\omega|\omega = \varphi(x)\}, \varphi(x) = \frac{\pi x}{2xm} \quad (2)$$

Mapping Ω to τ is defined as:

$$h: \Omega \rightarrow \tau, \tau = \{y|y = h(x)\} \quad (3)$$

$$h(x) = 1 + f_1(x) \quad (4)$$

$$f_1(x) = \text{acos}\,(\emptyset(x)) \quad (5)$$

Where 'a' lies in range of 0 to 1.

2.2.4. Balance Contrast Enhancement Technique (BCET)

BCET is strategized for balance contrast for compressing or expanding the image regardless of alteration of histogram pattern. The parabolic function is applied to the image. The parabolic form of function is defined as:

$$Y = a(x - b)^2 + c \tag{6}$$

$$b = \frac{h^2(E-L) - s(H-L) + l^2(H-E)}{2[h(E-L) - e(H-L) + H - E)} \tag{7}$$

$$a = \frac{H-L}{(h-l)(h+l-2b)} \tag{8}$$

$$c = L - a(l - b)^2 \tag{9}$$

Here, in equation(6) a,b, and c are the coefficients obtained from the equation by utilizing minimum, maximum, and mean using input and output image values, ‘I’ is the minimum value of the image, ‘e’ is the mean of the input image, ‘h’ maximum value of input image, ‘L’ is the minimum value of output image, ‘E’ is the mean of the output image and ‘H’ is the maximum value of output image.

2.2.5 Image Complement

Inversion of image technique is used to complement zero with one and one with zero, so black and white are reversed in the binary image. In the eight-bit gray level image, 255 is subtracted from the original pixel intensity, the difference is the pixel value for a new image. After complement operation, lighter spots turn darker and darker turns lighter. The mathematical computation is as follows:

$$y = 255 - x \tag{10}$$

Here in equation (10),x and y are the pixel intensity value for the original image and transformed image. The complemented image shows the region of interest lungs area lighter and bones darker. This is standard procedure used by radiologists which helps in deep architecture development for better classification. Histogram of the inverted image is the flipped copy of original image.

2.3 Visualisation Techniques

Visualization tools emergence led to a diverse increase in CNN functionality and logical work-base behind the networks. The decision-making capacity of CNN has awarded a great pace in better visual representation of objects. The reasoning behind each event prospers the effectiveness of each model that is easily decipherable by human minds resulting in the trustworthiness of CNN. Grad CAM,Smooth Grad, Grad CAM++, ScoreCAM,etc are some of the visualisation techniques. In this research work, Score CAM has a promising performance.

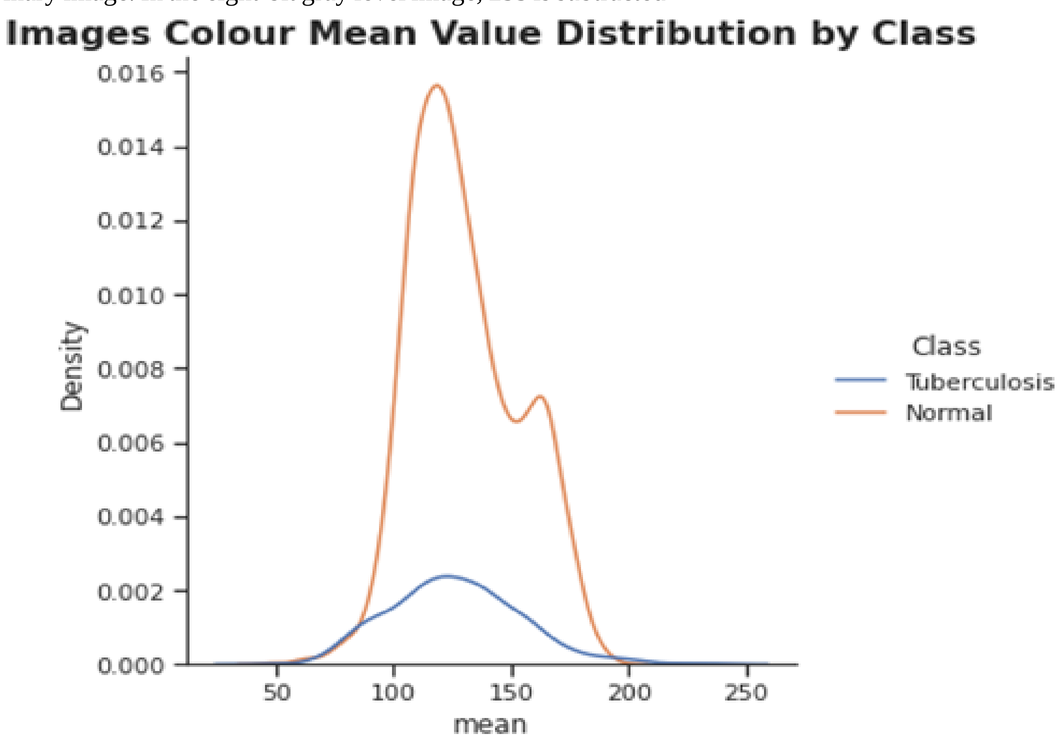


Fig. 2 Mean Versus Density plot for TB and Normal class.

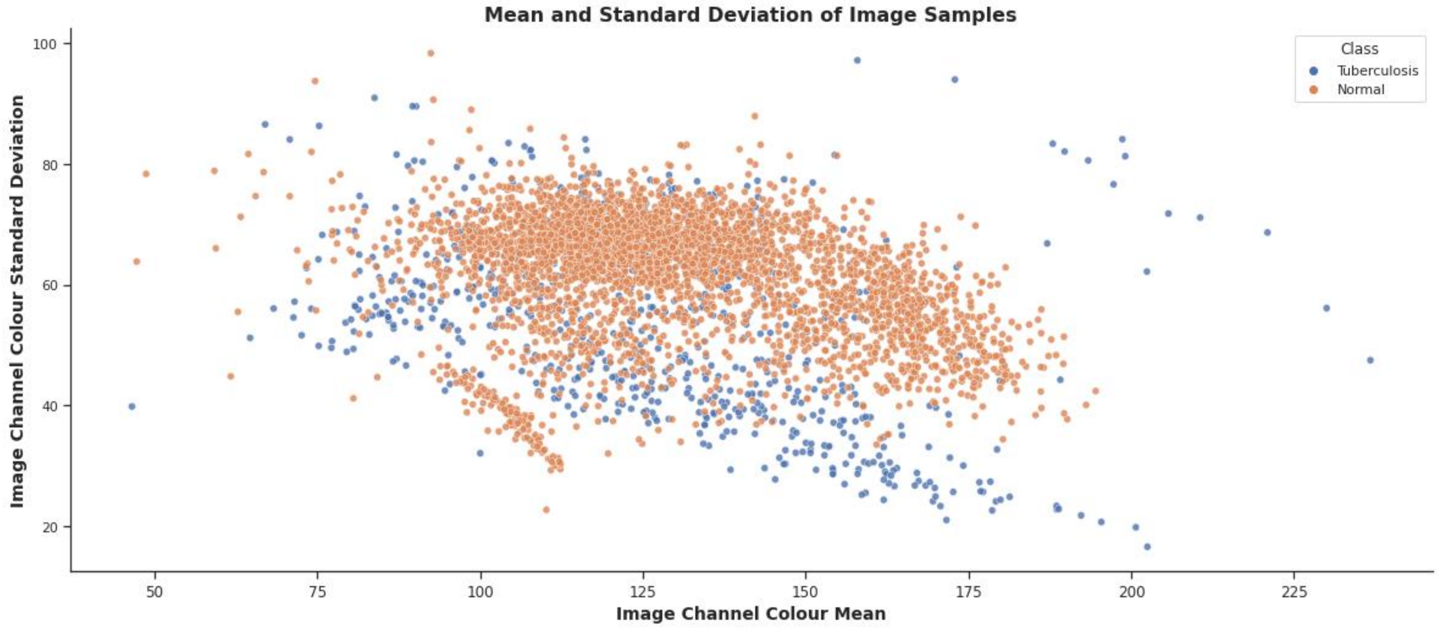
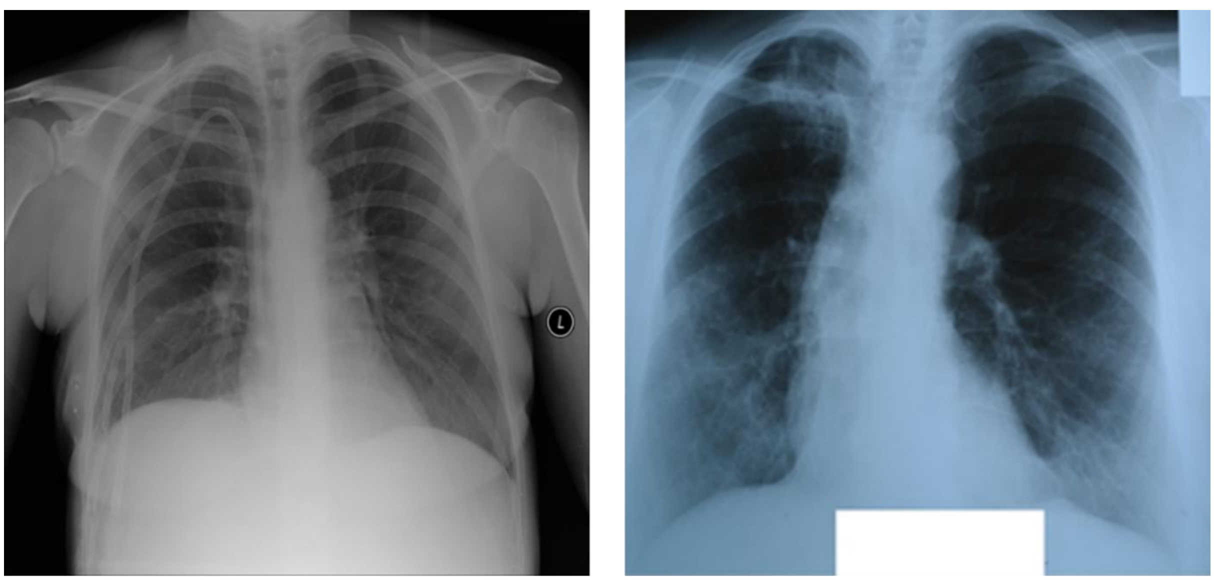


Fig. 3 Image Colour Channel per class



(a) (b)

Fig. 4 (a). Normal CXR (b). TB

3. EXPERIMENTS AND RESULTS

Experiments were performed on Google Collaboratory Pro with Tensorflow, Keras, Pandas, and Numpy,etc libraries to support the work. Python is used as a script.

3.1 X-ray Database

In the proposed work, the tuberculosis dataset is utilized which is available publicly on the Kaggle repository. "Tuberculosis (TB) Chest X-ray Database" [25]. The dataset is binarily classed into TB class and Normal class of lungs CXR images.

3.1.1 Data Balancing Approach

In the deep learning mechanism, training with a larger set is the best criteria, but less availability of image instances per class can generate confusion in classification problems by network architectures. To counter this, a data balancing approach is recommended. In the dataset, the ratio of images of Normal class to TB class is 3500:700, a large difference in ratio of images per class. Approach of data balancing is applied using 1:1 rule. Prior applying 1:1 rule, TB images are duplicated to twice i.e., 700*2=1400 using up-sampling and Normal are down sampled to 1400 images as same as twice TB images.

3.1.2 Dataset Pre-processing and Data Augmentation

CXR images are pre-processed and resized to 299*299 size for pre-trained networks.

3.1.3 Dataset Augmentation

The invariance property of the image can be promisingly classified with CNN. Property of invariance is correlated to viewpoint, illumination, size, and translation. This forms the base of the "augmentation" in the dataset Data Augmentation technique helps in the increment of the relevant image dataset in the dataset. Eight different types of augmentation techniques are used in dataset augmentation [26-30].

3.1.4 Performance Evaluation

The architecture and experiments done are evaluated on basis of the confusion matrix yielding true positives (TP), true negatives (TN), false negatives (FN), false positives (FP).

$$1. Accuracy(A) = \frac{TP+TN}{((TP+FP)+(TN+FN))} \quad (11)$$

$$2. Sensitivity(S) = (TP)/(TP+FN) \quad (12)$$

$$3. Precision(P) = (TP)/(TP+FP) \quad (13)$$

$$4. F1\ Score(F) = (2 * \mathrm{TP})/(2 * \mathrm{TP} + \mathrm{FP} + \mathrm{FN}) \quad (14)$$

$$5. Recall(R) = TP/(TP+FN) \quad (15)$$

The study is carried on datasets classified as "Normal" and "Tuberculosis". Major experiments carried on the study are:

1. Image Enhancement techniques applied on both classes of CXR image-set.

2. Training and testing of original unenhanced TB images and five enhanced image datasets, which are tested on six different networks.

3. The reliability of the architecture verified by ScoreCAM methodology.

The dataset is trained on 80% with 10% cross validation and 10% testing dataset.

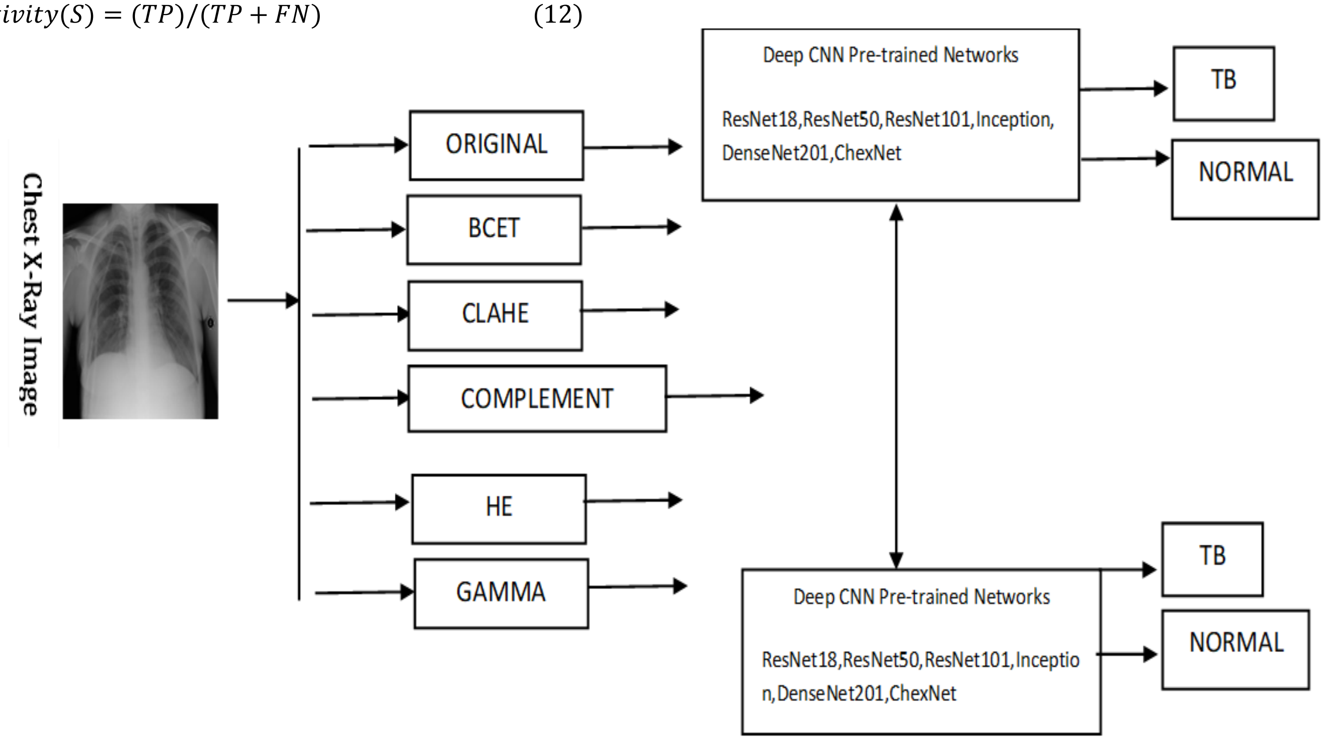


Fig. 5 Block Diagram for System Methodology

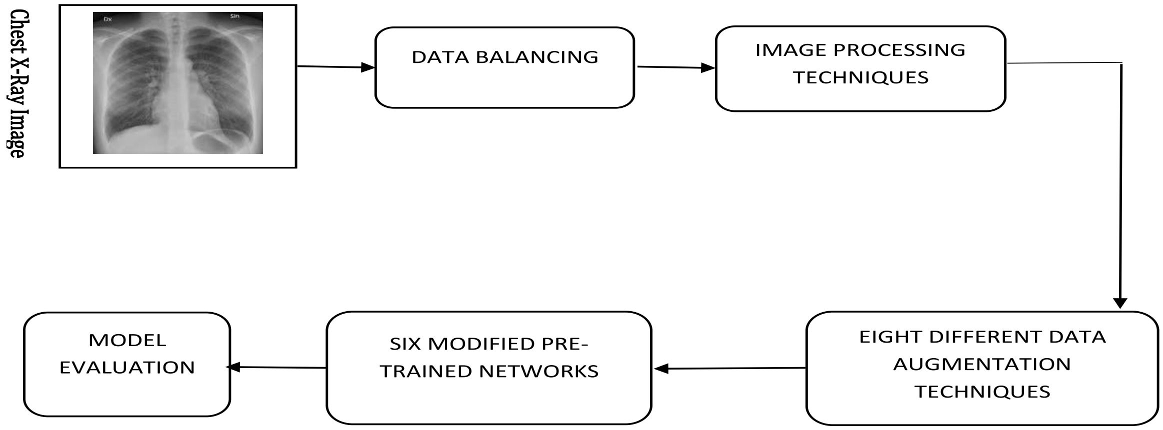


Fig. 6 Flow diagram for proposed work

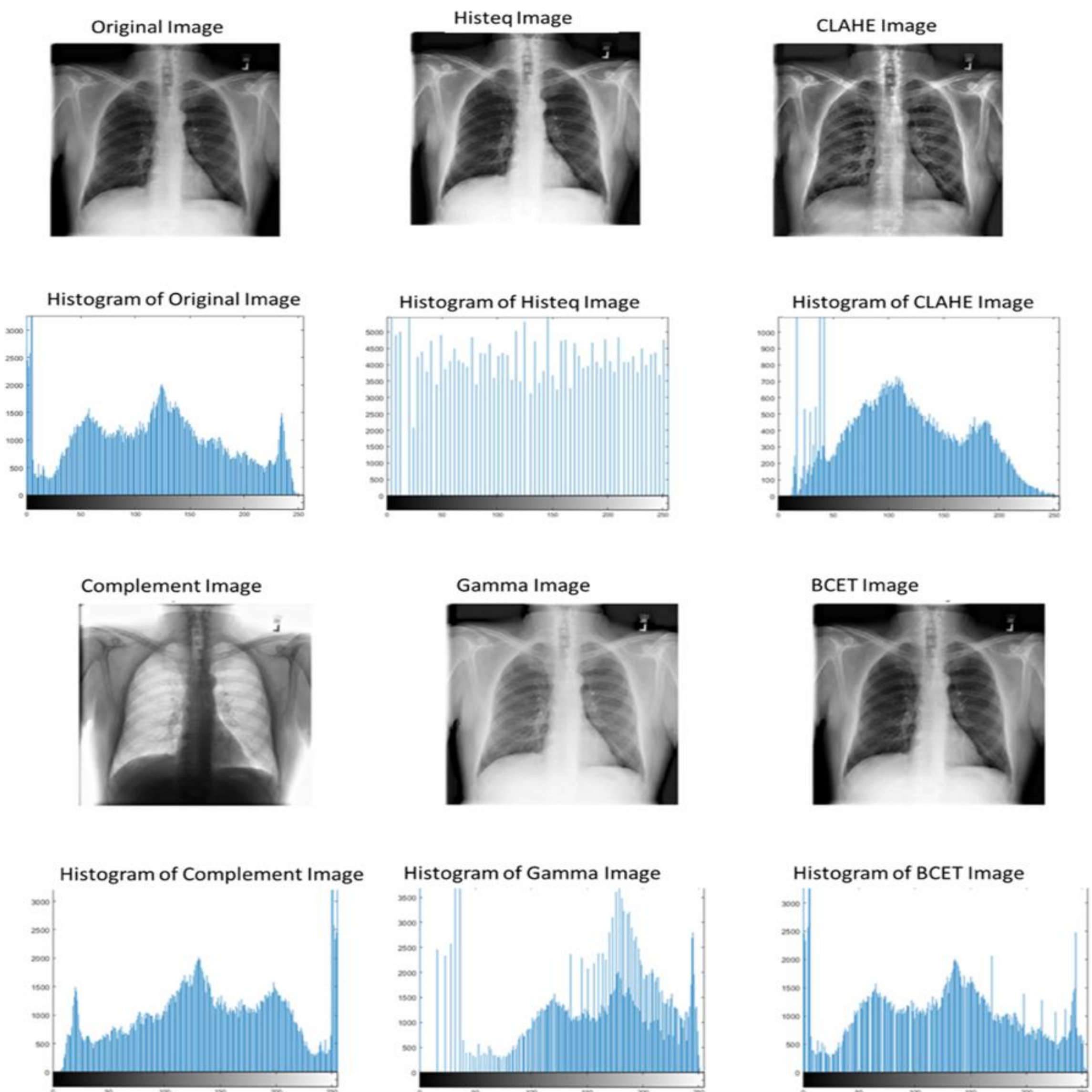


Fig. 7 Histogram for different image enhancement techniques and original dataset.

As shown in Figure (5,6), there six different kinds of experimentations performed on the dataset to classify into binary classes. The experiments performed mainly consist of image datasets as original dataset, HE enhanced image dataset, CLAHE enhanced dataset, BCET enhanced dataset, complement enhanced dataset and Gamma enhanced dataset. The six types of image datasets are fed into deep CNN networks of different variants as in Fig. (5). Comparative study of the best image enhancement technique between two classes are compiled in Table (1,2). Moreover, comparative study of the various CNN models performance is shown in Table(2) between gamma corrected image and original image dataset.

Table. 1 Comparison of the best network for the TB classification using CXR images for different enhancement techniques

Different Enhancement	**Model**	**Average**				
		Accuracy	**Precision**	**Recall**	**F1score**	**Sensitivity**
Original	Modified InceptionV3	93	93	93.42	93.45	95.46
Complement	ModifiedDenseNet201	94.1	94.2	94.1	94.1	95
Histeq	ModifiedChexNet	94.	94.1	94.1	94.1	96
CLAHE	Modified DenseNet	94.0	94.1	94.1	94.07	95.77
Gamma	Modified ChexNet	96.3	95.3	97	96	97.3
BCET	Modified DenseNet	95	95	95	94.4	96.2

Table. 2 Comparison of different models for TB classification using Original and Gamma corrected CXR images

Technique	Network	Average				
		Accuracy	Precision	Recall	F1score	Sensitivity
Original	Modified Resnet18	93.4	93.	93.	93.4	95
	Modified Resnet50	93	93	93	93	95
	Modified Resnet101	93	93	93	93	95.1
	Modified ChexNet	93.2	93	93	93	96
	Modified DenseNet201	93	93	93	92.7	95
	Modified InceptionV3	93.4	93.4	93	93.	95.
Gamma	Modified Resnet18	94.6	95	95	95	96
	Modified Resnet50	95	95	95	94.53	95.81
	Modified Resnet101	94.93	94.94	94.93	94.92	96.2
	Modified ChexNet	96.3	95.3	97	96	97.3
	Modified DenseNet201	95	95	95.05	95	96.6
	Modified InceptionV3	95	94.95	95	94.93	96

Table (1,2) shows the best performing network in different image enhancing techniques. From the table 1 , it is quite evident that Gamma technique is the best technique in classification furthermore it worked best for every network over original image. Furthermore, combination of Gamma enhancement dataset and Modified ChexNet forms best pair for classification with 96.3% accuracy and 97.27% F1 score. CheXNet superior performance in comparison to Modified DenseNet exhibits deep layers are not important factor in performance rather than hyper-parameter tuning is required step.

4. CONCLUSION

The work proposes experimentation on different image enhancement techniques for automatic detection of tuberculosis by utilizing deep CNN with modification in structure. Six different kinds of CNN with modified layers were fed with five image correctors methods to classify into binary classes as Normal and TB. Gamma corrected image with ChexNet performed the best with 96.3% accuracy, 95.3%precision and 97% recall for TB detection. Thus, Artificial Intelligence can aid in designing of systems for proper detection of disease fastly and accurately.

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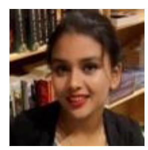

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