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A Enhanced Approach for Identification of Tuberculosis for Chest X-Ray Image using Machine Learning

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Abstract— Lungs are the primary organs affected by the infectious illness tuberculosis (TB). Mycobacterium tuberculosis, often known as Mtb, is the bacterium that causes tuberculosis. When a person speaks, spits, coughs, or breathes in, active tuberculosis can quickly spread through the air. Early TB diagnosis takes some time. Early detection of the bacilli allows for straightforward therapy. Chest X-ray images, sputum images, computer-assisted identification, feature selection, neural networks, and active contour technologies are used to diagnose human tuberculosis. Even when several approaches are used in conjunction, a more accurate early TB diagnosis can still be made. Worldwide, this leads to a large number of fatalities. An efficient technology known as the Deep Learning approach is used to diagnose tuberculosis microorganisms. Because this technology outperforms the present methods for early TB diagnosis, Despite the fact that death cannot be prevented, it is possible to lessen its effects.

Keywords- Chest X-ray;Mycobacterium Tuberculosis; Deep Learning; U-Net.

I. INTRODUCTION

History of medicine first made reference to tuberculosis in the 17th century. The spreading nature of tuberculosis is sensed by GirolamoTracastoro as early as 1546 by inquire into the patient's bed sheets and cloths which contains the contagious particles. An English physician, Benjamin Marten found that the tuberculosis is caused by "minute living creatures" in 1720.National Jewish Health is first hospital developed to help the needy who are affected by tuberculosis and in 20th century it emerged as TB care center and focus on inventing drugs for varieties of tuberculosis.

The Genexpert test is used to detect the TB bacteria in DNARifampicin resistance is also tested for using this method. The Cartridge Based Nucleic Acid Amplification Test (CB-NAAT) is the term used in India to refer to the Genexpert test. This test is a [21] molecular test which takes sputum sample as an input and produce result within 2 hours. Genexpert test was first introduced in the year of 2004 by Foundation for Innovative New Diagnostics and completed in the year of 2008. The WHO highly recommended this test for the Multi-Drug Resistance tuberculosis and HIV associated tuberculosis which provides the new hope for the millions of people.

On 26 September 2018, The United Nations hosted a high-level debate on tuberculosis as part of "An Urgent Global Response to a Global Epidemic.". The goal[20] of the meeting is to end the tuberculosis epidemic by 2030. Ministers made new commitments to end tuberculosis at Delhi in March 2018. The death rate of tuberculosis has reducing from 23% to 16% in 2017. The overall reduction [27] in tuberculosis death rate since 2000 – 2017 is 42%. The fast reduction of morality rate are in

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European and South-East Asia Region. In general, the new TB cases has been reduced but not to achieve first milestone of the End TB Strategy.

In treatment of tuberculosis, there is lot of space occurred in the estimated number of new cases and the actual number of cases. India, Indonesia and Nigeria are the top three countries which has highest number of gaps in tuberculosis treatment of 3.6 million cases. An [22] immediate action need to be taken against the quality of diagnosis and Multi-Drug Resistance to control the rate of morality.

In the world's population, about one-quarter of people are affected by latent tuberculosis. The tuberculosis is classified into two types where the initial stage is known as latent TB and the next is Active TB. The people with latent tuberculosis do not become sick and they are[23] not capable to scatter the disease to another person's but it is important to treat the persons who are affected to stop the development of TB bacilli. It has been estimated that about 2 billion[24] people have affected by latent tuberculosis. The active tuberculosis is another type of tuberculosis where the people affected by it, need to take long treatment and can spread the disease via coughing or sneezing. The peoples with active tuberculosis need to take several medicines so that they can stop the growth of antibiotic resistance.

Initially, the patients are treated with thebacillus Calmette-Guerin (BCG) antibiotic vaccine to stop spreading bacilli. The common test taken to detect the tuberculosis is skin test, blood test, imaging test, and sputum test. Purified protein derivative (PPD)tuberculin is injected into the person’s skin and check the swelling in the injection site after 48 hours. The skin test also produces a false test report then the blood test is used to confirm tuberculosis. When the cough becomes severe the[25] doctor recommends the patient to take Chest X-Ray. If the doctor found the symptoms of tuberculosis bacilli then sputum image test[4] is taken to confirm the stage of tuberculosis. Based on the level of bacterial infection, the treatment for the patients will be proceeding.

Isoniazid and rifampin [26]is a common drug used to prevent active tuberculosis. These two antibiotics are recommended to take for six months. Pyrazinamide and Ethambutol are additional antibiotics combined with the above antibiotics for the first two months. In most of the cases, people feel better after taking medicine for three weeks. These antibiotics also give rise to side effects[28] like nerve damage and blur vision. The vitamin tablets are given along the antibiotics to reduce the risk. Recently, When the compound is coincidence with isoniazid, it can kill the bacteria that cause tuberculosis.In default all the medical image obtained will have the impurities in them. The acquired image is initially pre-processed and it is through the filters to remove the noise from the image. After eliminating the impurities the image undergoes segmentation process to extract the some information from the image.

The proposed system is trained and tested using this set and the accuracy of the system is checked before the implementation. InMontgomery County X-ray Set, 80 x-rays which has combination of both normal and abnormal is used for training the deep learning system and remaining 74 x-rays are used for testing the performance of the deep learning system. After segmentation process the image is given to the proposed system to predict where primary tuberculosis or secondary tuberculosis and based upon the prediction the treatment is done to the patient.

II. RELATED WORK

Diagnosis of tuberculosis worsens when the organism develops treatment resistance. Though it doesn't always yield the best findings, computed tomography image analysis is a popular technique for locating drug-resistant TB. This results in the Deep Transfer Learning technique being used to classify the TB CT images [1]. The VGG16 is used to train the deep transfer network, and user votes are used to tag photos. Although the slide processing precision (at 59.86%) is less exact than previous methods, the 3D tuberculosis drug resistance performance has improved.

Stefan Jaeger et colleagues [2] and created a system employing image analysis and machine learning methods that can tell the difference between drug-sensitive and drug-resistant tuberculosis in a patient's chest X-ray. Several classifiers are used to extract the properties. Artificial Neural Network (ANN) beats all other classifiers, as evidenced by AUC values of 66% in the second experiment and 65% in the first trial. Problems arise when a deep learning network does not train on larger training sets.

TB bacilli are automatically and highly sensitively detected in a microscope field view using a Deep Neural Network-based technique [3]. This technique uses sputum as its input and outputs the suspected location of Mycobacterium TB bacilli.This technique, which was created to address the issue of medication resistance when treating tuberculosis, achieves 83.78% recall when detecting tuberculosis bacilli in test images. A tiny dataset was used to train the system.

Patients who have tuberculosis typically receive subpar care that has negative side effects. SAS software was used by D. Menzies, et al. in [4] to help medical personnel recognize and treat tuberculosis. The rifampin group had a higher treatment rate than the isoniazid group in the study, which had 6800 patients from nine different countries and utilized the medicine isoniazid. A higher percentage of cases are treated and there is more safety when tuberculosis is prevented proactively.

The Adaptive Neuro-Fuzzy Inference System [5] is a method for determining the various stages of tuberculosis. An intelligent system was created to recognize tuberculosis based on the standards set by the experts. In this technique, all scalar data are converted to fuzzy values in order to detect irregularities. The output errors are reduced by employing the back propagation strategy. The lengthy and expensive process of training the intelligent system that establishes the levels of TB places a restriction on the system.

Classification of tuberculosis lesions is still a problem due to poor image classification and segmentation techniques. In [6], the Conventional neural network is used to classify the images. For the algorithms they used to classify the photos, they chose CapsNet, AlexNet, and VGG-16. CapsNet performs better than Alexnet and VCG-16 when categorising variation occurrences outside of the training dataset, according to the system's output.

Ilena, et al. [7] used a Using chest x-ray images, a computer-aided diagnostic (CAD) system will assist medical professionals in promptly identifying tuberculosis.. This automatic CADx technology assists the physician and radiologist more accurately. Nodules can be both located and made more obvious by technology. A sensitivity, specificity, and accuracy of 66.67%, 86%, and 76%, respectively, are the results produced by the proposed system. Improved picture categorization based on recovered properties is required for better classification.

This problem needs to be resolved because the manual tube rculosis diagnosis method frequently predicts the wrong thing.I n this investigation, we use the Canny edge detector and Rando m Forest classification [8].The detection of tuberculosis bacilli by DIP produces superior results when compared to the "Auto matic identification of tuberculosis, Mycobacterium" paper.The amount of bacilli in the sample has an impact on the outcomes.

In order to classify data with the CAD system and diagnose tuberculosis, Rahul Hooda et al. created a prospective deep learning system[9]. The chest X-ray image is divided into normal and pathological by this deep learning algorithm. The standard neural network, created with seven layers, accurately categorizes a picture as belonging to the TB positive or negative class. Adam optimizer, momentum optimizer, and stochastic gradient descent (SGD) optimizer performance of three classifiers are compared. The validation accuracy of the Adam classifier is 82.09%, and the total accuracy is 94.7%.

A system is created by Jaime Melendez et al. [10] to solve the manual labeling issue.The technology utilized to address this issue includes chest radiography, multiple-instance learning (MIL), and computer-aided detection (CAD). This method requires less labeling details than the conventional supervised CAD method because they are only needed during optimization. The system's performance, however, hasn't much improved over the earlier approach.

Tuberculosis diagnosis is still difficult, and people with the disease have high mortality rates when they go untreated and without a diagnosis. The generated feature vectors are classified into normal or abnormal, i.e., whether the CXR is impacted by Tb or not, using the K-means algorithm, the region expanding method, and the active contour segmentation techniques [11]. Since the algorithm does not improve upon the previous system.

The ensemble learning approach is utilized in [12] to address several lung problems. The supervised subsystem, which recognizes texture, shape, and localized anomalies, yields numerous subscores that are combined to create the CAD system. In comparison to an unbiased human observer, the system's overall performance is comparable. Certain kinds of irregularities are still ignored by the system because it combines several detectors. The system's adaptability is minimal.

A neural network approach for diagnosing drug-resistant tuberculosis was created by L.H.R.A. Evora et al. Based on the patients' historical characteristics for diagnosing tuberculosis, the decision support system was created. The patients are divided into groups[13] according to their treatment resistance using feed-forward multilayer perceptrons (MLP). Clinical results for the diagnosis of tuberculosis suggest that this method can be used to assess patients' resistant TB. Costly and with a low sensitivity in the event of smear-negative TB, an expert MTB RIF approach should be avoided.

A drug-resistant organism develops as a result of subpar medical care, which also causes treatment to fail. In order to close this knowledge gap, an ontology system is created [14]. Sub-Saharan Africa is where the ontology was primarily established. For the purpose of diagnosing tuberculosis, decision networks and knowledge engineering techniques are employed. Beyond what can be rationalized by a single human expert, the ontology has the ability to advance our understanding of adherent behavior. In terms of probabilistic representation, the existing technique has drawbacks.

Tuberculosis screening is important for the detection of tuberculosis which has several difficulties. In [21], Ramya.R, Srinivasababu. P used a lung tumour extracting[15] the lung region using edge detection. The binary classifier is used to separate the pathological from the normal X-Ray images using a set of textures and shapes. The technology is currently used in Kenya as a part of a mobile system in remote locations. The accuracy of the system depends on binary large object analysis for weak edge pixel detection.

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Adaptive signal processing techniques are used in [16] to automatically segment bacilli in ziehl-neelsen sputum stained images. ZN-image noise is first decreased with a mean filter, then the image is improved with brightness and contrast modifications, and finally the image is subjected to a threshold from which the image is directly identified. Using pixels feature vectors, the problem with traditional segmentation is resolved. The diagnosis of tuberculosis can be made promptly and precisely using an adaptive filter, it can be concluded.

Since it is more challenging to automatically distinguish the location of the lungs for identification of lesions, SemaCandemir, et al. [23] developed a Chest X-ray imaging system to segment the lung to find the lesions. The overlap measure showed a 95.4% accuracy when[17] comparing experimental findings to the industry standard for expert segmentation. For segmenting and studying the lung, a number of state-of-the-art techniques have been established. [24] discusses the difficulties in treating tuberculosis in HIV/AIDS patients. Using the graph cut segmentation method, the lung region is retrieved.Before classifying the lung as diseased or normal, the approach computes numerous form, edge, and texture attributes. For the first set (78.3% accurate), the system's area under the receiver operating characteristic (AUC) curve was 87% together with a second set that has an AUC of 90% (84% accuracy).

Circularity, compactness, eccentricity, and tortuosity characteristics are inputs utilized by Riries Rulaningtyas et al. [19] to train a neural network that divides images into normal and pathological ones using the back propagation approach. The neural network uses a single hidden layer yields a 20 node hidden layer, 0.05 learning rate, and 0.9 momentum rate with a mean square error of 0.000368 and zero error classification for fresh data input.

III. PROPOSED SYSTEM DESIGN

Approach is implemented based on the framework designed for the earlier detection of tuberculosis. Based upon the framework, initially a chest x-ray is taken as an input image. The obtained image is pre-processed out to enhance the quality of the image to get the accurate result where the pre-processing is done using various filter to check which filter produces better image enhancement. After the image enhancement, the processed image undergone to segmentation process. The segmentation process is used to chunk the image into several parts or to simplify the image and to obtain some useful information from the image. By segmenting the image, the infection level of the tuberculosis bacilli is identified. Then the image is moved to the deep learning system to predict the stage of tuberculosis. The system is trained with the available database of the patients and the trained system is tested to check the accuracy of the system and the proposed system is used to find the whether it is primary tuberculosis or secondary tuberculosis.

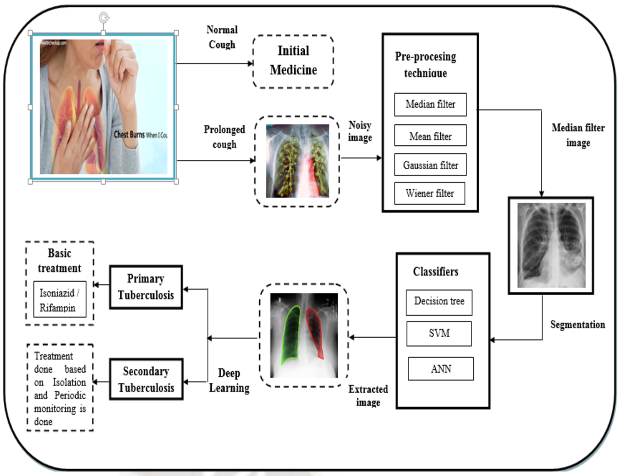

Figure 1. Proposed System Framework

Figure.1 explains the system's intended general structure. With the aid of their doctor's experience, patients are currently diagnosed with either a typical cold, a cough, or tuberculosis (TB). But generally speaking, not every circumstance necessitates this tactic. In order to predict an accurate and straightforward diagnosis given by physicians at an early stage, researchers have developed a number of models. As a result, the suggested system structure gives major weight to early TB diagnosis. Sputum imaging and chest X-ray imaging are often the two methods used to diagnose tuberculosis. A chest x-ray is the most cost-effective option for a simple diagnosis, according to the poll, as opposed to the latter, which necessitates the use of a high resolution microscope for greater clarity.

From the final image, performance metrics are performed to evaluate the accuracy. The metrics are accuracy, Specificity and sensitivity. These metrics performance is made between existing system and proposed system and concluding that the proposed system is more accurate than the existing system. Using the values, Primary and Secondary tuberculosis is identified. Incase if primary tuberculosis occurred the basic treatment is given to the patient and for the secondary tuberculosis, treatment is done based on the isolation condition. The proposed system implementation is carried out in the following manner. The first step in implement is image acquisition followed by Pre-processing, Segmentation, Deep learning and finally the tuberculosis is detected. shows what are steps followed in the proposed system and how the work carry on from one step to another steps.

A. Image Acquisition

Image acquisition is the beginning in the work process. The action of retrieving an image from the source is called image acquisition. Images are produced by combination of illumination

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source and reflection of the energy by the element to be captured. Based upon the nature of illumination the sensor is used to sense the image and transfer it into digital image.

Figure 2. Image Obtained from Montgomery Set

The figure 2 is the input image of the patient who age is 40 yrs. and has extensive cavity TB smear and culture positive involving LUL lungula and some areas in right lung as well but had previously normal CXR (1Y ago) but positive TST and contact with active case taken from the set.

B. *Preprocessing*

Pre-processing is defined as a process of enhancing the image to extract the required features exactly. The main aim of image preprocessing is to eliminate the impurities from the obtained image. It is important to removal the unwanted impurities in the images so that the information from the image can be obtained effectively. The medical image contains lot of noise which is acquire from the CAD system and by processing the image all the impurities are removed and can be applied to upcoming processes like feature extraction and segmentation, etc. In general, picture preparation can be done in one of the ways listed below. Image resampling is Resampling of image is the process of resizing of the image pixel by defining the dimensions of the image where increasing an image is referred to as "up sampling" and reducing an image is referred to as "down sampling. "A low-intensity image is transformed into a high-intensity image, and vice versa, by the process of enhancing contrast. It is an artistic method that highlights certain elements of the image.

C. *Converting Color Image into Gray Scale Image*

The Grayscale image contains only the shades of black and white color where the RGB image contains three layers of images which has separate layer for every color. The conversion of colored image to achromatic is important because color image needs 8 bit for every single color, so to store red, blue and green color it takes 3*8 = 24 bits to store a single image whereas the grayscale image takes only 8 bits to store a single image. It is difficult to process the RGB image than the grayscale image becomes the intensity of the pixel in high in RGB image, so the conversion of color image to grayscale image becomes needy in image processing. It is also easier to extract features of an image.

D. *Segmentation*

Image segmentation is the process of breaking up a single image into several images. As a result of segmentation, which makes it simpler to comprehend the characteristics of each component, the process of recognizing lesions can be made simpler given the high degree of variation in medical images. The process that needs to be followed is semantic segmentation, which produces categorization for the relevant use-case. As shown in [13], semantic segmentation uses the deep learning technique and provides the dataset with the best intersection-over-union score of 0.87 Image segmentation is becoming a procedure that is more relevant in various sectors since deep learning and semantic segmentation [14] work together to achieve the necessary results. Where segmentation helps create a reliable perception of the thing. Therefore, it can be stated that the semantic segmentation technique is the most useful when combined with deep learning. A judgment or category is given to each pixel value in an input image during the semantic segmentation process.

E. *Classification*

In general, the procedure for training and evaluating the system based on particular parameters is called image classification. In training, a collection of photographs is utilized as input, and one image is distinguished from another using the features of the other images. Following the training phase, the system performs testing, during which it uses the attributes of the given image to determine the exact outcome. The different classifiers employed include.

F. *Support Vector Machine*

The kernel trick is used by a machine learning algorithm to translate the data. The ideal boundary is discovered using the data. The main drawback of support vector machines is that they were designed primarily for processing numerical linearly separable data, which makes them a machine learning approach.

G. *Randam Forest*

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H. *U-NET*

Semantic segmentation can be effectively handled Using U-Net innovation. Along with Constriction, Bottleneck, and Development Segments, U-Net includes the Convolution Operation, Max Pooling, ReLU Activation, Concatenation, and Up Sampling Layers. Four constrained squares make up the compression portion of the model. Each withdrawal square

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applies two 3X3 convolution ReLu layers and a 2X2 max pooling after receiving data. For each pooling layer, there should be twice as many highlights maps. Two 2X2 up convolution layers and two 3X3 convolution layers make up the bottleneck layer. The developing region's extension barriers each have two 3X3 Conv layers and a 2X2 up sampling layer. A hyperlink is also included. A 1X1 Conv layer is used in the final phase to create an equal number of highlight maps to the appropriate number of yield pieces. For each pixel in the image, U-net employs a deficit work. This makes finding certain cells on the division map easier. After Softmax has been applied to each pixel, a bad luck work is added. As a result, the division problem is changed into a grouping problem because we are compelled to give each pixel a class in order to categories it.

IV. RESULT AND DISCUSSION

The different methods for Pre-processing are employed and the performance are calibrated using the measured values.

A. Datasets Used

The X-ray machine at Shenzhen Hospital For the purpose of this data collection, These X-ray images were obtained by Shenzhen No. 3 Hospital in Guangdong province, China. X-rays were obtained by Shenzhen Hospital in accordance with standard medical procedures. JPEG-formatted photos are included in the bundle. 336 abnormal x-rays and 326 abnormal x-rays both exhibit various TB symptoms. Each category is described in detail in the sample datasets that are provided below as an illustration of the datasets mentioned above.

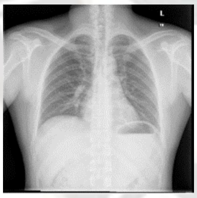

Figure 3. Class 0 Input Image

The aforementioned image depicts lung and chest inflammation and exhibits symptoms of congestion brought on by the common cold, however it cannot be used to rule out tuberculosis and instead identifies a possible point of causality leading to TB.

Figure 4. Class 1 Input Image

A right upper lobe infiltrative lesion and cavitation visible on the chest X-ray are compatible with tuberculosis and its progression. But it has not yet fully manifested the full impact of the disease in its advanced form.

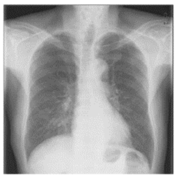

Figure 5. Class 2 Input Image

An advanced type of tuberculosis is genitourinary TB, as shown in the figure above. Kidney infection can be the cause of pyelonephritis, which manifests as pyuria (sterile pyuria), which lacks the typical urine pathogens on routine culture.

B. Performance Evaluation of Filters

To obtain an accurate result in image processing, it is crucial to remove the image's noise. By eliminating the image's contaminants, it can be used for other operations like segmentation, feature extraction, and texture analysis. Filtering methods are used to eliminate the noise from the image. Time domain and frequency domain are two different types of filtering algorithms. The main tool for enhancing and restoring images is the linear filter. The several types of filters include the Gabor, Weiner, Mean, Gaussian, and Median filters. Peak signal-to-noise (PSNR) ratio is used to assess how well a filtering approach performs. The MSE value ought to be reduced in order to have a low degree of picture mistake. It is necessary to first determine the mean-square error before calculating the PSNR value. The input image given to the MATLAB is shown below which is resized to 950 x 950 pixels of size. Based upon the MSE and PSNR value, the accuracy of the filters is computed.

Figure 6. Resized Input Image for Preprocessing

The figure 6 is the resized image used for filtering purpose. In this image, the various filter are applied to check the efficiency with which filters that successfully cut down noise perform. The following are the images produced by the filters: the input image (a), the Median filter (b), the Gaussian filter (c), and the Wiener filter (d).

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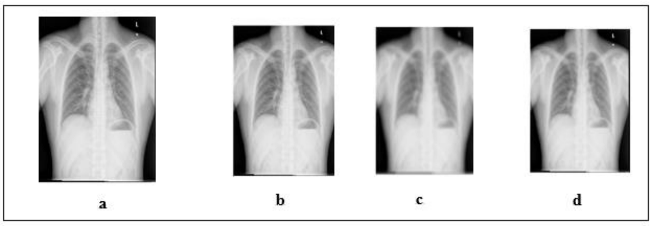

Figure 7. Denoised Output for Class 0 Image

The results of several filters applied to the class 0 image are shown in figure 7. Class 0 image a and various filtered output images b, c, and d are shown in the image above.

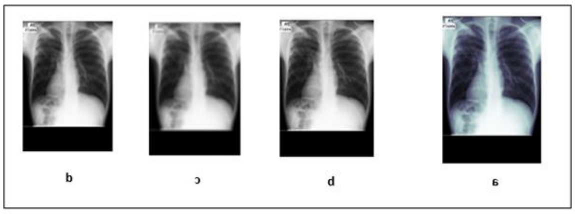

Figure 8. Denoised Output for Class 1 Image

Figure 8 displays the results of several filters used on the class 1 image. A is the class 1 image in the aforementioned image, while b, c, and d are various filtered output images.

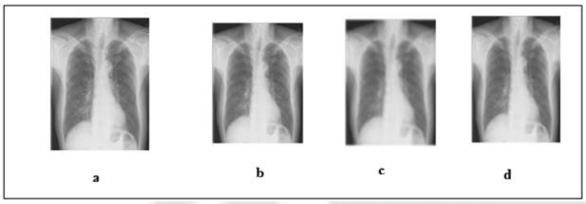

Figure 9. Denoised Output for Class 2 Image

Figure 9 displays the results of several filters used on the class 2 image. The class 2 image is shown in image a, and the filtered output images are shown in images b, c, and d.

C. Performance Comparsion of Filters using MSE Value

The performance of the filters is now calculated using the Mean-square error value computed using the MATLAB. The table6.1 show the comparison of various filters used to reduce the noises in the acquired image.

TABLE I. MSE VALUE COMPARISON OF PERFORMANCE

Types of Filters	Images		
	Class 0	Class 1	Class 2
Median Filter	97.63	92.48	88.57
Gaussian Filter	85.14	83.46	87.61
Wiener Filter	92.58	97.51	94.83

The bar chart is drawn using the MSE values in the table 1 and shows the performance of filters in graphical manner.

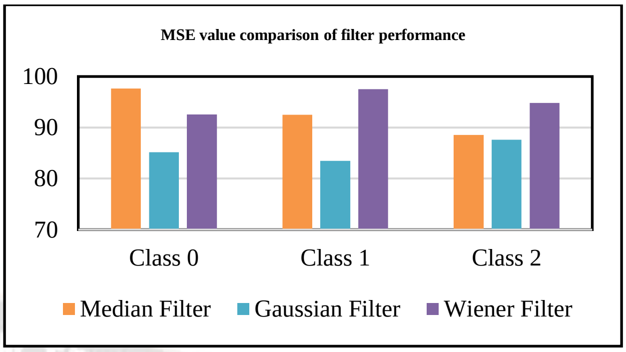

Figure 10. Comparison of Filters Using MSE Values

D. Performance Comparsion of Filters Using PSNR Value

Table 2 shows the performance utilizing the values after the median, Gaussian, and Wiener filters' MSE values for different forms of noise are used to calculate the PSNR value.

TABLE II. PSNR VALUE COMPARISON OF FILTER PERFORMANCE

Types of Filters	Images		
	Class 0	Class 1	Class 2
Median Filter	93.21	81.75	74.15
Gaussian Filter	86.74	82.61	91.14
Wiener Filter	91.54	91.20	91.02

The bar chart is drawn using the PSNR values in the table 2 and shows the performance of filters in graphical manner.

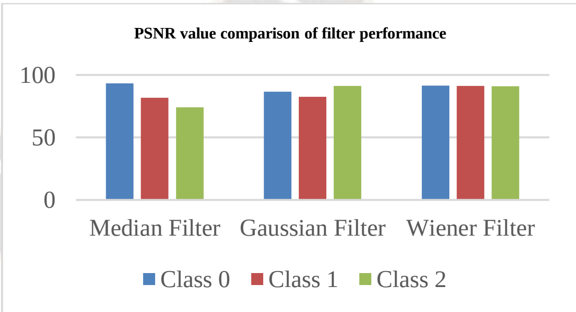

Figure 11. Comparison of Filters Using MSE Values

E. Performance Comparsion of Filters Using Accuracy Value

By using the PSNR value the accuracy of the filters are computed. The table 3 shows the accuracy comparison of various filters.

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TABLE III. ACCURACY OF FILTERS

Types of filters	Accuracy (%)
Median Filter	98.45%
Gaussian Filter	90.02%
Wiener Filter	69.98%

The bar chart is drawn using the accuracy values in the table 3 and shows the performance of filters in graphical manner.

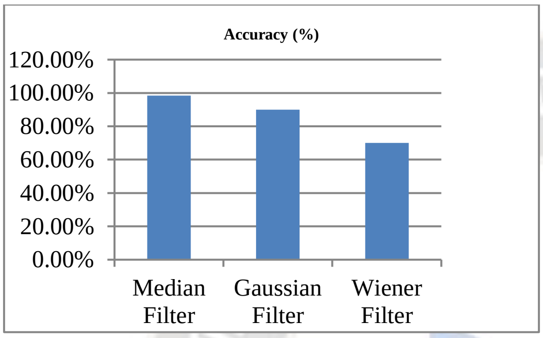

Figure 12. Accuracy of filters

From the figure 12 it is concluded that the median filters has good accuracy in removing the noise compared to all other types of filter. So, we can use the median filter for image preprocessing in general.

F. Segmentation

To separate the afflicted lesions from the lungs, semantic segmentation is performed. All three of the different input image types (classes 0, 1, and 2) have been segmented. The three classes of input photos are displayed below in the table along with the segmented versions of each class.

TABLE IV. SEGMENTED IMAGES AND THEIR ACCURACY, SPECIFICITY AND SENSITIVITY

Class	Input Image	Filtered Image	Segmented Image	Specificity	Sensitivity	Accuracy
0				92%	93%	98.5%
1				94%	86%	98.5%
2				94%	82%	99%

G. Classification

The mappings used to characterize the outcomes in each of the models are presented in help make the conclusion on the models' accuracy more apparent. The precision and recall are evaluated using the measurements presented in the confusion matrix.

H. SVM

For every image in the dataset, the confusion matrix values were calculated using the Support Vector Machine algorithm and are shown in table 5. The SVM's performance is exceedingly poor as evidenced by the algorithm's higher false-positive rate in predicting tuberculosis across all three classes.

TABLE V. PERFORMANCE OF SVM IN ALL THREE CLASSES

CLASSES	TP	TN	FP	FN
0	136	132	37	21
1	73	77	13	17
2	47	51	28	30

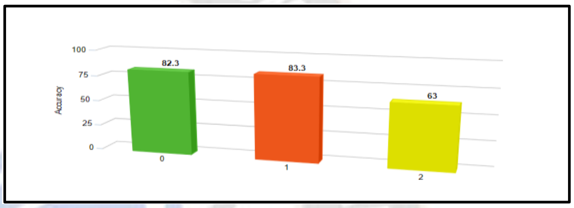

Figure 12. Accuracy chat for SVM method

The Support vector machine's effectiveness for each of the three classes is depicted in the above figure. Class 2 has a lower accuracy rate than classes 0 and 1, which lowers the performance rate of the SVM approach. Class 0 and class 1 accuracy rates are both above 80%.

I. Random Forest

The confusion matrix values for each image in the dataset that were acquired using the Random Forest technique are shown in table 6. A low performance of the random forest is determined by the algorithm's false rate in predicting tuberculosis across all three classes. Random forest approach has a lower false rate than SVM prediction.

TABLE VI. PERFORMANCE OF RANDOM FOREST IN ALL THREE CLASSES

CLASSES	TP	TN	FP	FN
0	144	138	29	16
1	79	84	7	10
2	58	62	17	19

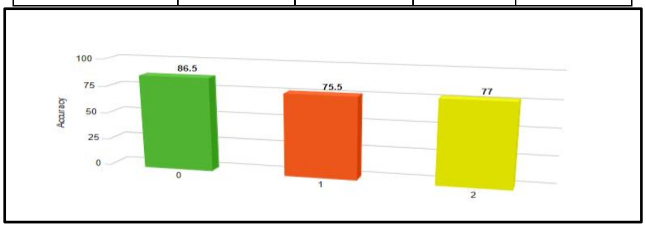

Figure 13. Accuracy chat for Random Forest method

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The accompanying figure displays how well the Random Forest performed for each of the three classes. The accuracy of classes 1 and 2 is below 80%, whereas class 0 accuracy is above 80%, which lowers the performance rate of the Random Forest approach.

J. U-NET

The values for each image in the dataset's confusion matrix, as determined by the U-NET approach, are shown in Table 7. When compared to the predictions of SVM and Random Forest techniques, the U-NET algorithm predicts TB perfectly in each of the three groups.

TABLE VII. PERFORMANCE OF U-NET IN ALL THREE CLASSES

CLASSES	TP	TN	FP	FN
0	160	159	7	0
1	79	98	3	0
2	70	71	15	0

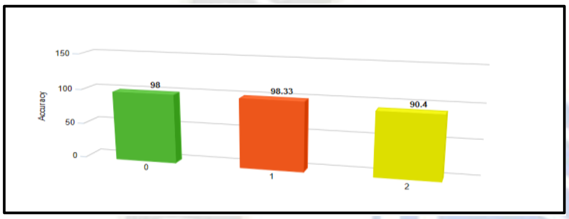

Figure 14. Accuracy chat for U-NET method

The U-NET algorithm's performance for each of the three classes is depicted in the above figure. The accuracy rates for classes 0 and 1 are above 98%, and class 2 is above 90%, demonstrating that the U-NET method performs better than SVM and Random Forest methods.

Using chest x-rays, the system can identify tuberculosis with an accuracy of over 90%, and semantic segmentation performs with superior accuracy of over 98.5%. In comparison to the currently used approaches, the deep learning strategy that was created utilizing semantic segmentation delivers greater accuracy and detects tuberculosis at the very earliest stage [16]. Analysis reveals that the true positives for class 1 for both random forest and UNET remain the same, demonstrating that the UNET algorithm can outperform random forest with little to no further training. Since UNET has 100% accuracy in that spectrum, the false negative rates are nil there.

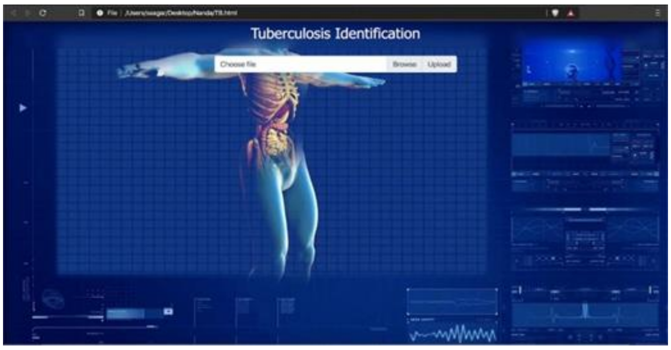

Figure 15. Tuberculosis Detection Web App

A straightforward webapp is shown in figure 16. above and is used to identify tuberculosis. Django was used to create it, and Flask was used to create the container for the model. The x-ray image is accepted in the front by a straightforward user interface (UI), which accepts the.png,.jpeg, and SVG file formats.

V. CONCLUSION

Tuberculosis becomes as a life-and-death disease which plays a major role in the economic growth of the country. So, it is important to step against the impact of tuberculosis in the people using the tools that are available to prevent and treat the tuberculosis. The proposed system will detect the tuberculosis using the deep learning techniques whereas here image pre-processing is concentrated before going to other process like segmentation, feature extraction. The median filter provides a high degree of accuracy, according to the results. The pre-processed image will be used for feature extraction and segmentation tasks in the future. The segmentation technique is used to separate an image into various parts and extract the information that may be useful. There are numerous classifier types used to separate the tuberculosis bacilli from the chest x-ray. The effectiveness of the classifiers is evaluated by comparing their accuracy, sensitivity, and specificity values. In order to determine the type of tuberculosis a patient has, such as primary or secondary tuberculosis, the obtained data is fed into a deep learning model that has been trained to do so.

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