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# DETECTION OF TUBERCULOSIS USING OPTIMIZED DEEP LEARNING APPROACH WITH ENHANCED SELECTIVE MEDIAN (ESMF) FILTER

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**ABSTRACT**

*Millions of individuals worldwide are afflicted by the infectious disease Tuberculosis (TB), which is critical. For prompt treatment and disease control, it is crucial to identify TB early and precisely from lung imaging. To increase accuracy and reliability, we present a comprehensive strategy for tuberculosis detection, segmentation, feature extraction, and classification in this study. Using a variety of filters including Median, Bilateral, Wiener and ESMF (Enhanced Selective Median Filter), first pre-process lung picture. These filters efficiently lower background noise and improve image quality, enabling more precise TB detection. The ESM Filter has higher noise reduction abilities because it was created primarily to preserve edges while smoothing. Then apply the SCA (Sine-Cosine Algorithm) to segment images after image pre-processing and use the AlexNet structure because of its outstanding performance in image classification tasks to categorize and extract the pertinent characteristics from the TB-infected regions. To increase detection accuracy, BOA (Butterfly Optimization Algorithm) fine-tunes the ESMF and SCA settings. From the result obtained its proved that proposed work produces PSNR of 42.38, SSIM of 0.999, MSE of 0.000121, Accuracy of 91.90%, Specificity of 90.91% and Sensitivity of 83.97%. The tool used for execution is python.*

**Keywords: -** Tuberculosis Classification, Filtering, Segmentation, Feature Extraction, Accuracy, Disease Detection

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## I INTRODUCTION

Mycobacterium tuberculosis, which causes TB, is a chronic infectious illness that affects numerous organs, the most prevalent of which is the lungs. Infection from tuberculosis expeller is an unavoidable source of infection, and TB patients frequently share a history of contact with the disease. Because Mycobacterium TB can be suspended in the nucleus of droplets released by patients who cough or sneeze, and since it can spread to healthy persons when breathed, Mycobacterium TB travels mostly through the air[1]. With millions of new cases reported each year, tuberculosis (TB) remains a significant threat to world health. Effective TB management and containment depend on early and precise diagnoses. The study of lung pictures from medical imaging, in particular, is crucial for TB screening.

Before COVID-19, TB was the main infectious cause of mortality across the globe, and chest radiography is crucial in the early detection and following diagnosis of individuals with this illness. The typical experts' reading exhibits significant within- and between-observer variability, which shows low reader dependability. Several initiatives have been undertaken to solve the shortcomings of human interpretation of chest radiographs for TB diagnosis using a variety of AI (Artificial Intelligence) based algorithms[2].

Our study's main goal is to increase the reliability and accuracy of TB detection and categorization, which will help medical professionals make better clinical judgments. We have developed a multi-stage method to accomplish this, with each stage being tuned for maximum efficiency. The method includes image pre-processing, segmentation, feature extraction, and classification.

The remaining part of the article is divided into the following sections: The second section provides a summary of the latest studies on TB detection. The significance of filtering and deep learning concepts in the identification and categorization of TB is illustrated in Section 3. The suggested DB detection system's process flow is shown in Section 4. In Section 5, the effectiveness of the suggested detection model is evaluated based on its accuracy, sensitivity, and specificity. The current investigation and its future path are concluded in section six.

## II RELATED WORKS

In underdeveloped nations, TB is a dangerous illness that spreads through close contact or the air. Despite its danger, TB can be caught early using effective methods, which can save the lives of those suffering from it. The best screening method for finding pulmonary problems is a chest X-ray. However, it takes radiologists with extensive experience to examine the X-ray images and find anomalies. As a result, AI methods are put to use to assist radiologists in making an accurate determination of TB disease in its early stages. Suliman Mohamed Fati et al., (2022) concentrates on using CNN and ANN, two AI approaches for identifying TB. Additionally, this study offers two distinct methods, each with two systems, for diagnosing TB using two datasets. The first method combines Res-Net-50 and GoogLeNet methods from two CNN models. The approach uses the PCA (Principle Component Analysis) algorithm to lower the dimensionality of the data before the classification stage to retrieve deep characteristics. The SVM method is then employed to accurately classify facts. When using X-ray pictures from both databases to diagnose TB, the suggested hybrid technique produced better results. The second method, in contrast, employs ANN (Artificial Neural Networks) relying on the combined features obtained from ResNet-50 and GoogleNet models and integrates them with the attributes obtained from the GLCM (Gray level co-occurrence matrix), DWT (Discrete Wavelet Transform), and LBP (Local Binary Pattern) methods. For the two datasets related to TB, ANN produced superior results[3].

To avoid sickness, reduce mortality risk, and slow down transfer to other individuals, early identification of TB is a crucial and difficult undertaking. The chest X-ray (CXR), which is affordable and widely available in most nations, is the preferred method for lung disease monitoring in medical centers. However radiologists must manually review CXR pictures, which places a significant strain on them and increases inter-observer variability. Therefore, it is difficult for researchers to recommend a CAD (Computer Aided Diagnosis) system that is both affordable and precise for diagnosing TB. In this study, Ahmed Iqbal et al., (2022) proposed TBXNet, a simple and effective DL (Deep Learning) network that can correctly categorize an immense amount of TB CXR images The network is built around five dual convolutional blocks, each with different filter sizes (32, 64, 128, 256, or 512). In the network's fusion layer, the dual convolution blocks are fused with a trained layer. Additionally, the fusion layer receives pre-trained information from the pre-trained layer. On Dataset A and Dataset B, the recommended TBXNet has a precision of 98.98% and 99.17% respectively[4].

TB is one of the main causes of death globally. It may still be decreased if recognized and treated promptly. Normally, the Ziehl-Neelsen method is used to diagnose TB, and a human professional examines it under an optical microscope to discover tuberculosis bacilli. Because this process takes time, a computerized bacilli identification system speeds up the diagnosing process. Zulfiqar Ahmad Khan et al., (2020) created an autonomous TB bacilli separation technique in this study. The source picture is first preprocessed by using AMD (Adaptive mean filter) to eliminate impulsive noise and power law transformation to improve the image before converting the color space from RGB value to HSV. Because every component is segregated in the HSV color space, it is more suited for image processing. Following that, they used a multi-level thresholding method to appropriately separate each bacillus in the input sample, improving accuracy by 2.13% when compared with existing methods[5].

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TB is one of the leading causes of death worldwide. Mycobacterium tuberculosis causes the disease, which damages the lungs. Forecasting and correctly identifying TB is a major issue in the field of medicine. The medical treatment procedure also differs from one individual to the next, as some patients establish resistance to medications. Through the help of ML algorithms, physicians can be assisted in diagnosing and providing appropriate treatment, as well as making faster and better decisions. Akshita Tiwari et al., (2019) examine the numerous causes and signs associated with TB and how, in recent years, precise and rapid prognosis and diagnostics studies have been conducted using ML techniques[6].

TB is a transmissible illness that has been a huge threat to human health around the world, killing millions of people each year. Early detection and treatment pave the way for the patient's complete wellness. CAD has proven a promising option for the detection of TB. Many CAD methods based on ML have been employed for the detection of TB in the AI domain, resulting in a revival of AI in the field of medicine. DL, a major area of AI, opens up more possibilities for identifying fatal TB. Manisha Singh et al., (2022) focus on the limits of traditional TB diagnoses and provide a comprehensive discussion of several ML techniques and their uses in TB detection[7].

## III SIGNIFICANCE OF FILTERS AND DEEP LEARNING IN TB DETECTION

Filters and DL are important in TB prediction, especially in the analysis of medical images and diagnostic support models.

**Extracting Features:** Convolutional filters are good in gathering pertinent features from medical pictures such as chest X-rays and CT scans. Filters can detect certain patterns and irregularities linked with TB, such as nodules, cavities, and infiltrations, in TB prognosis.

D**imension Reduction:** Many layers and variables are frequently used in DL models, resulting in high-dimensional feature spaces. Filters aid in lowering the dimensionality of these spaces while keeping critical information, making big medical imaging datasets practically possible.

**Improved Accuracy:** When paired with proper filters and structures, DL models have exhibited excellent TB recognition precision. They are capable of identifying subtle and complicated abnormalities in medical scans that human radiologists may miss, resulting in better more precise diagnoses.

**Automation:** Filters and DL can help to automate the tuberculosis prediction process, lowering the strain on healthcare staff and speeding up identification. This is especially useful in areas with a scarcity of qualified radiologists or where tuberculosis is common.

**Early Warning:** In the beginning stages, when symptoms are mild or absent, tuberculosis can be difficult to identify. Filters and DL can aid in the early identification of TB by detecting minor symptoms of the disease in medical imaging, allowing for immediate treatment and minimizing the spread of the illness.

Filters, segmentation, feature extraction, and DL techniques are critical in TB prediction because they enable the development of precise, effective, and scalable diagnostic systems that can help healthcare practitioners detect and manage TB early. Their capacity to identify significant characteristics and handle enormous amounts of medical picture data makes them indispensable in combating this global health threat.

## IV PROPOSED WORK

The following is the method for detecting tuberculosis in lung pictures using the Median, Bilateral, Wiener, and ESMF filters, followed by segmentation using the SCA, feature extraction, classification using the AlexNet framework, and optimization with BOA:

**Data Collection:** To efficiently conduct TB detection research, a comprehensive dataset of lung pictures was obtained, including samples from both TB-infected individuals and those with healthy lungs. Furthermore, the images were scaled and standardized to ensure consistent resolution, which is critical for maintaining data integrity and facilitating proper analysis.

**Image Preprocessing using Filtering:** Use various filtering algorithms for denoising images. According to the specific needs and features of the images, the Median Filter, Bilateral Filter, Wiener Filter, or ESMF are used to effectively minimize noise and improve image quality.

### Median Filter (MF)

The median of n observations $X_i, i = 1, \ldots. n$ is indicated by $\mathrm{med}(x_i)$ and it is calculated as follows:

$$\mathrm{med}(x_i) = \begin{cases} x_{(v+1)} & n = 2v+1 \\ \frac{1}{2}(x_{(v)} + x_{(v+1)} & n = 2v \end{cases} \quad -------- (1)$$

$x_i$ represents the $i^{th}$ order statistic. The equation (1) for an odd n will be utilized extensively in the sections that follow.

The input-output relationship of a one-dimensional type median filter of dimensions $n = 2v + 1$ is as follows:

$$y_i = med\,(x_{i-v},\ldots \mathrm{x_i},\ldots . x_{i+v}) \quad i \in Z -------(2)$$

It takes the sequence $\mathrm{x_i i} \in \mathrm{Z}$ as input and outputs the sequence $\mathrm{y_i}$, i.e. Z. (2) is also known as the moving median or the running median.

$$y_{ij} = med\,\{x_{i+r,j+s}\,;\,(r,s) \in A\}\,(i,j) \in Z^2 -----(3)$$

The filter window is a set $\mathrm{A} \subseteq \mathrm{Z}^2$ that specifies a neighborhood of the center pixel $(\mathrm{i,j})$[9].

**Bilateral Filter (BF)**

A bilateral filter smooths images and reduces noise while keeping edges. Gaussian blurring can be expressed mathematically as follows:

$$\mathrm{GB}\,[\mathrm{I}]_{\mathrm{p}} = \sum_{\mathrm{q} \in \mathrm{S}} \mathrm{G}_{\sigma}\,(\|\mathrm{p} = \mathrm{q}\|\mathrm{I_q} ------(4)$$

The outcome GB $[\mathrm{I}]_{\mathrm{p}}$ at pixel p is shown above, and the RHS is effectively a total of all pixels q weighted by the Gaussian method.is the pixel q intensity. The bilateral filter is defined as follows.

$$\mathrm{BF}\,[\mathrm{I}]_{\mathrm{p}} = \frac{1}{\mathrm{W_p}} \sum_{\mathrm{q} \in \mathrm{S}} \mathrm{G}\sigma_{\mathrm{s}}\,(\|\mathrm{p} - \mathrm{q}\|\,\mathrm{G}\,\sigma_{\mathrm{r}}(|\mathrm{I_p} - \mathrm{I_q}|\mathrm{I_q} ------(5)$$

Here $\frac{1}{\mathrm{W_p}}$ indicates the Normalization Factor, $\mathrm{G}\,\sigma_{\mathrm{r}}(|\mathrm{I_p} - \mathrm{I_q}|)$ represents Range Weight and $(\mathrm{G}\,\sigma_{\mathrm{s}}\|\mathrm{p} - \mathrm{q}\|$ denotes Space weight

The normalization element and range weight are additional terms added to the prior formula in this case. $\sigma_{\mathrm{s}}$ denotes the kernel's spatial extent, i.e. the size of the neighborhood, and $\sigma_{\mathrm{r}}$ indicates an edge's lowest amplitude. It assures that only pixels with intensity levels identical to the center pixel are evaluated for blurring while maintaining sharp intensity fluctuations. The sharper the edge, the lesser the value of $\sigma_{\mathrm{r}}$. The formula leads to a Gaussian blur $\sigma_{\mathrm{r}}$ as it approaches infinity[10].

**Wiener Filter (WF)**

Wiener filtering achieves the best equilibrium among inverse filtering and noise smoothing. It eliminates the additive noise while also inverting the blurring. It reduces the overall MSE during the inverse filtering and noise smoothing processes. Wiener filtering approximates the original image linearly. A stochastic foundation underpins the technique. According to the orthogonality concept, the Wiener filter in the Fourier domain can be stated simply as follows[11].

$$W(f_1, f_2) = \frac{H * (f_1, f_2)\, S_{xx}(f_1, f_2)}{|H(f_1, f_2)|^2 S_{xx}(f_1, f_2) + S_{\eta\eta}(f_1, f_2)} ------(6)$$

Here $S_{xx}(f_1, f_2)$ and $S_{\eta\eta}(f_1, f_2)$ are the power spectra of the initial picture and additive noise and are the blur filter. The Wiener filter includes two distinct parts: an inverse filtering part and a noise smoothing part. It not only deconvolves the signal using inverse filtering, but it also reduces noise using a compression process.

## Enhanced Selective Median Filter (ESMF)

Various sorts of noise signals can taint medical images, lowering their quality; as a result, it's crucial to lessen the impact of noises. The basic objectives of image de-noising are to suppress noise signals while maintaining the relevant information in the images, such as edges, diminutive structures, texture details, etc. In this module, an Enhanced Selective Median filter has been presented to reduce noise in chest X-ray images.

***Algorithm 1:*** *Enhanced Selective Median filter*
*Step 1: Set the maximum window size, Wmax = 39×39.*
*Step 2: If any pixel is discovered to be a noisy, then initialize the present filtering window size 3 × 3 surrounding the noisy pixel*
*Step 3: Count the number of non-noisy pixels in the 3 × 3 neighborhood of each noisy pixel discovered in the present filtering window.*
*Step 4: If it discovers at least one or two non-noisy pixels in the present filtering window, it replaces the noisy pixel with the median of those closest non-noisy pixels and proceeds to step 7.*
*Step 5: If no non-noisy pixels are present in the present filtering window, step 3 is followed by a 2x window size increase.*
*Step 6: If the window size is greater than Wmax, replace the noisy pixel with the median value of maximum window.*
*Step 7: Process the subsequent noisy pixel.*

## Image Segmentation Using SCA

To improve the efficiency of the SCA or segmentation of images, start by setting up its attributes and fine-tuning them to the assignment at hand. Construct a function with objective characteristics that will be used as a quantitative metric to assess the quality and accuracy of the segmentation findings, to make sure the algorithm creates exact delineations of TB-affected patches in lung pictures.

The SCA method begins by initializing a population X, which has m people and each individual has n dimensions. Each individual is evaluated using the fitness function, and the best individual region among all current individuals is chosen. The procedure then iterates for the specified number of times. The individual's region is modified over the iteration. The procedure for updating is as follows:

$$X_i^{i+1} \begin{cases} X_i^t + r_1 \times \sin(r_2) \times |r_3 \times P_b^t - X_i^t,\ r_4 < 0.5,| \\ X_i^t + r_1 \times \cos(r_2) \times |r_3 \times P_b^t - X_i^t,\ r_4 \geq 0.5,| \end{cases} \text{------------(7)}$$

Here $X_i^t$ indicates the location of the $i^{th}(i = 1,2 \ldots m)$ individual in $i^{th}$ time process; $r_2 \epsilon [0,2\pi], r_3 \epsilon [0,2]$ *and* $r_4 \epsilon [0,1]$ are the three various random values. $P_b^t$ denotes the best position of the individual after the iteration t. $r_1$ denotes the control attribute, which balances the algorithm's exploitation phases. The changed equation is:

$$r_1 = a - a\frac{t}{T} \text{------------(8)}$$

Here a denotes the constant value, t indicates the actual count of present iterations, and T is the highest value of the iterations[12].

**Feature Extraction and Classification**

Extract characteristics of segmented groups after the process of segmentation. First, set up the AlexNet DL model to accurately categorize lung pictures in our image categorization pipeline. Following that, divide the dataset into discrete subsets for training, validation, and testing, allowing us to reliably assess the efficacy of the model. After the data split, train the AlexNet model with the characteristics gathered from the training set and continuously fine-tune the variables with the validation set to obtain optimal performance when classification. This extensive methodology assures that our TB detection system is accurate and reliable.

Alexnet is made up of eight levels. The first five layers are convolutional, and the last three are completely linked. There are some 'layers' in between termed pooling and activation. AlexNet receives a 256 X 256 RGB image as input. This means that all images in the training set and all test images must be 256 X256 pixels in size. If the input image is grayscale, it is transformed to RGB by reproducing the single way to produce a three-channel RGB image. To feed the first layer of AlexNet[13], random crops of size 227 X 227 were created from among the 256 X 256 images.

**Optimization with BOA**

Use the BOA, a nature-inspired optimization method, to improve the effectiveness of our TB detection system. The goal function encapsulates the optimization of critical

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components inside our workflow, such as the ESMF, SCA, and even AlexNet DL model hyperparameters like the learning rate and size of the batch. By incorporating BOA into this workflow, it is possible to consistently fine-tune these variables, thereby increasing the accuracy of TB identification. This continual tuning procedure guarantees that our technology reaches its maximum ability in discriminating TB-affected areas from healthy lung tissues, ultimately boosting diagnostic precision and assisting in early intervention.

The scent of the butterfly is described as an indicator of the physical power of the stimulus[14].

$$f_i = c\, I^a, i = 1,2,\ldots\ldots NP ---------- (8)$$

Here $f_i$ denotes the fragrance of the butterflies, $c$ indicates the modality of the sensory value, I describes the intensity of the stimulus, a indicates the exponent of the power value ranges from 0 to 1, and the $NP$ describes the actual butterflies quantity. The arithmetical representation of the BOA is described as the following formula:

$$X_i^{t+1} = X_i^t + (r^2 \times X_{best}^t - X_i^t) \times f_i -------- (9)$$

$$X_i^{t+1} = X_i^t + (r^2 \times X_j^t - X_k^t) \times f_i -------- (10)$$

Here $X_i^t$ position of $i^{th}$ butterfly in the iteration of i, $X_{best}^t$ indicates the global value of the optimal individual, r $\in(0,1)$ is the random type value, and $X_j^t$ and $X_k^t$ represents the $j^{th}$ and $k^{th}$ individual selected randomly. BOA concepts process two kin of search approach while the process of searching.

## V RESULTS AND DISCUSSION

This section displays the results of this tuberculosis detection system, which combines techniques such as denoising, segmentation, feature extraction, deep learning with the AlexNet framework, and optimization via the BOA.

## EVALUATION METRICS

Assessing the effectiveness of image filters such as Median, Bilateral, Wiener, and ESMF in tuberculosis illness identification from lung imaging is critical. Image quality measurements commonly employed for this purpose include the Peak Signal-to-Noise Ratio (PSNR), the Structural Similarity Index (SSIM), and the Mean Squared Error (MSE).

### PSNR Analysis

PSNR quantifies the quality of images by dividing the maximum possible power of a signal by the power of corrupting noise. The signal-to-noise ratio (SNR) is the relationship of the signal-to-noise control in a gathered visual signal.

$$SNR == 10\log_{10}\left(\frac{P_s}{P_n}\right)^2 = 10\log_{10}\left(\frac{A_{signal}}{A_{noise}}\right)^2 ------(11)$$

Where $P_s, P_n, A_{signal}$, and $A_{noise}$ stand for, respectively, signal power, power of the noise, amplitude of the signal, and noise power.

Where $P_s, P_n, A_{signal}$, and $A_{noise}$ describe signal power, noise power, signal amplitude, and noise power, in that order. For PSNR, the numerator of equation (11) is the square of the signal's peak value, and the denominator is the MSE. The peak difference between the original and filtered images is calculated in terms of PSNR. The PSNR is a typical method for expressing the MSE in image processing. The PSNR of the recreated and original images is

$$PSNR\,(I,J) = 10\log_{10}\frac{R^2}{MSE(I,J)} -------- (12)$$

R indicates the maximum suitable pixel value.

**Table 1: PSNR Analysis of ESMF Filter with Other Existing Filters**

| No of Images | Median Filter | Bilateral Filter | Wiener Filter | ESMF Filter |
|---|---|---|---|---|
| 1 | 18.27 | 27.33 | 30.53 | 42.38 |
| 2 | 16.52 | 25.48 | 32.62 | 41.83 |
| 3 | 17.59 | 20.63 | 31.73 | 40.63 |
| 4 | 20.73 | 24.72 | 29.43 | 39.08 |

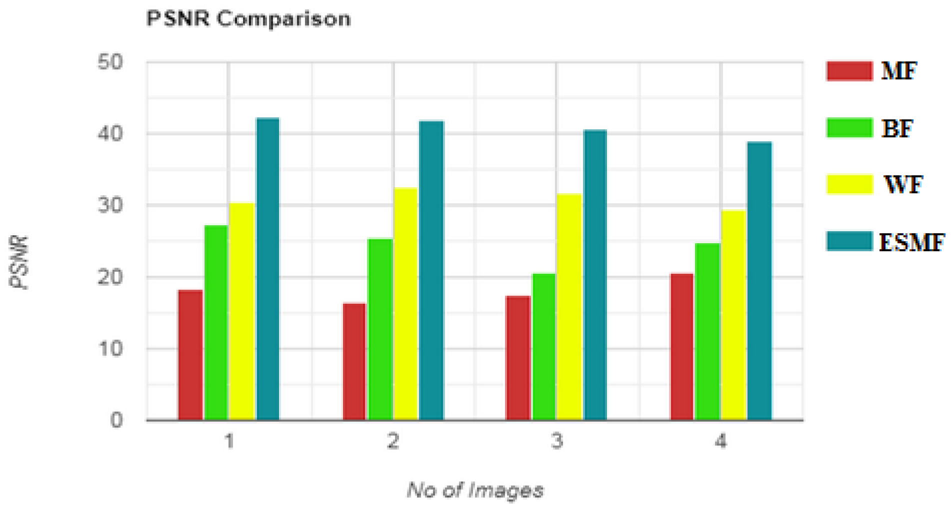


**Fig 1: PSNR Analysis of ESMF Filter with Other Existing Filters Graph**

PSNR produced by proposed ESMF is 39 to 43 which is very high compared with MF is 17 to 21, BF is 20 to 2 and WF is 29 to 32. From the results we can prove that PSNR of ESMF Filter is very high that other filters.

**Structural Similarity Index (SSIM) Analysis**

SSIM is a metric that determines how similar two pictures are to one another. The SSIM index is determined on various windows within a picture. The distance around two windows of equal size N X N is between x and y.

$$\mathrm{SSIM}(x,y) = \frac{\left(2\mu_x\mu_y + c_1\right)(2\sigma_{xy} + c_2)}{\left(\mu_x^2 + \mu_y^2 + c_1\right)(\sigma_x^2 + \sigma_y^2 + c_2)} - - - - - - - - (13)$$

From the equation 13, $\mu_x$ indicates the mean value of x, $\mu_y$ describes the average value of y, $\sigma_x^2$ represents the adjustment value of x, $\sigma_y^2$ represents the altered value of y, and $\sigma_{xy}$ indicates the covariance data of x value and y value.

$c_1 = (k_1L)^2, c_2 = (k_2L)^2$ are the two variables to steady the separation by a pathetic denominator, anywhere L indicates the rate of progressive pixel value.

**Table 2: SSIM Analysis of ESMF Filter with Other Existing Filters**

| No of Images | Median Filter | Bilateral Filter | Wiener Filter | ESMF Filter |
|---|---|---|---|---|
| 1 | 0.791 | 0.898 | 0.991 | 0.999 |
| 2 | 0.764 | 0.990 | 0.992 | 0.998 |

| | | | | |
|---|---|---|---|---|
| 3 | 0.792 | 0.887 | 0.992 | 0.997 |
| 4 | 0.823 | 0.884 | 0.994 | 0.997 |

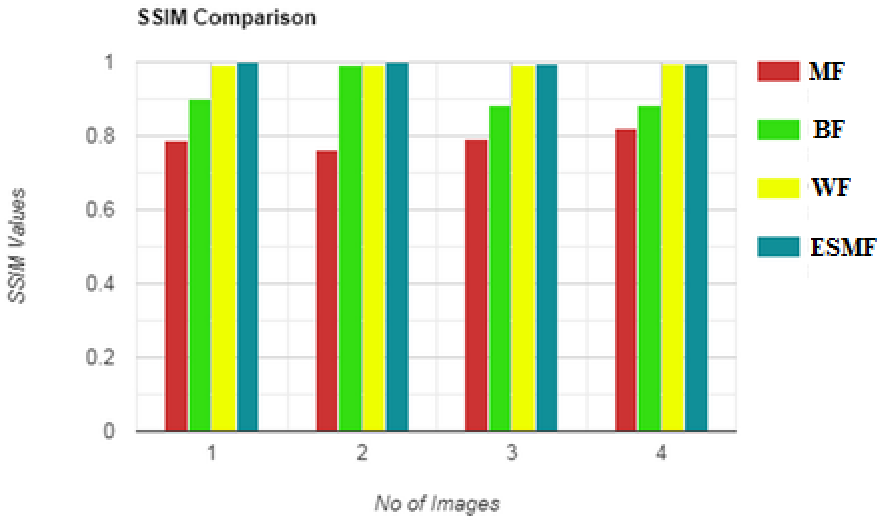


**Fig 2: SSIM Analysis of ESMF Filter with Other Existing Filters Graph**

The SSIM of proposed ESMF is 0.997 to 0.999 which is very high compared with MF is 0.764 to 0.823, BF is 0.884 to 0.990 and WF is 0.991 to 0.994.From the results we can prove that SSIM of ESMF Filter is very high that other filters.

**MSE Analysis**

MSE calculates the average squared discrepancy between two pictures' pixel values. Lower MSE values suggest that the filtered image and the initial image are more similar. The MSE is commonly used to assess error sensitivity and the separation of dual signals. MSE is defined as the four-sided difference between important pixels in the pixel values of the two images.

In MSE, the signal for error $e_i = a_i - b_i$ is expressed by the variation between two discrete image signals of a specific length N, and, a and b, where $a_i$ and $b_i$indicate the values of the $i^{th}$ pixels in a and b, and signifies the total number of pixels in the given photos. The MSE of these dual signals is,

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(a_i - b_i)^2 --------- (14)$$

The gray image is indicated as I and the J represents the filtered picture. MSE among the two various images I and J is

$$\mathrm{MSE}(\mathrm{I},\mathrm{J}) = \frac{1}{\mathrm{M} * \mathrm{N}} \sum_{c=1}^{M} \sum_{d=1}^{N} (\mathrm{I}(c,d) - \mathrm{J}(c,d))^2 ------(15)$$

Here $\mathrm{M} * \mathrm{N}$ denotes the size of the image, $\mathrm{I}(c,d) - \mathrm{J}(c, \text{and } d)$ represent the intensity value of the specific and recreated pixel image.

**Table 3: MSE Analysis of ESMF Filter with Other Existing Filters**

| No of Images | Median Filter | Bilateral Filter | Wiener Filter | ESMF Filter |
|---|---|---|---|---|
| 1 | 0.000150 | 0.000159 | 0.001193 | 0.000121 |
| 2 | 0.000452 | 0.000504 | 0.000973 | 0.000244 |
| 3 | 0.000589 | 0.000544 | 0.001070 | 0.000504 |
| 4 | 0.000160 | 0.000162 | 0.001085 | 0.000142 |

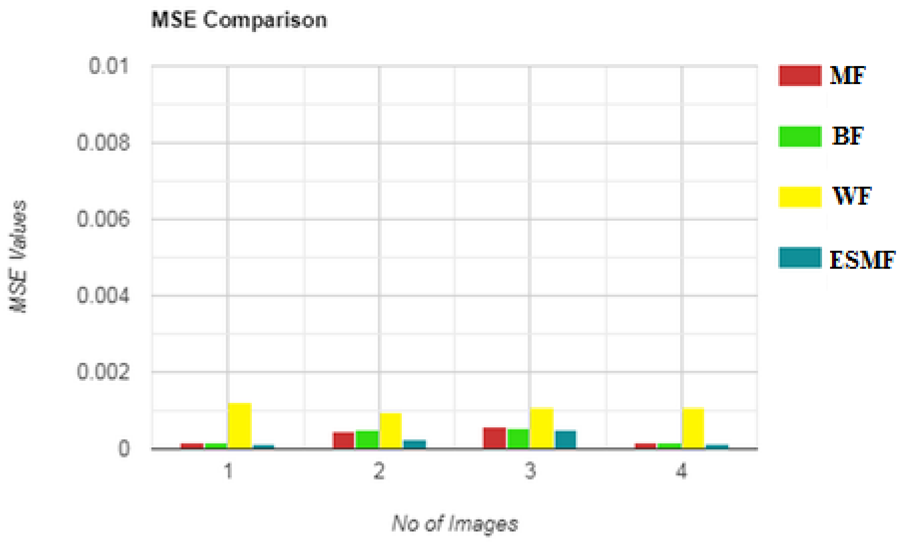


**Fig 3: MSE Analysis of ESMF Filter with Other Existing Filters Graph**

From the results we can prove that MSE of ESMF Filter is 0.000121 to 0.000504 very low compared with MF is 0.000150 to 0.000589, BF is 0.000159 to 0.000544 and WF is 0.000973 to 0.001193. Lower MSE means higher the performance.

TB detection using pulmonary images. The categorization results are often evaluated using the aforementioned methods based on three main performance metrics: accuracy, sensitivity, and specificity.

**Accuracy Analysis**

The overall reliability of the classification findings is measured by accuracy. It is determined as the proportion of properly identified samples (both true positives and true negatives) to the total sample count. A classification system with high accuracy is sturdy and reliable.

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$$\text{Accuracy} = (\text{Number of Exact Assessments})/\text{Total Number of All Assessments}$$

**Table 4: Accuracy by AlexNet+BOA, GoogleNet+BOA and ResNet+BOA**

| No of Images | ResNet+BOA Accuracy % | GoogleNet+BOA Accuracy % | AlexNet+BOA Accuracy % |
|---|---|---|---|
| 1 | 86.47 | 88.74 | 89.22 |
| 2 | 86.92 | 88.94 | 90.17 |
| 3 | 87.98 | 89.13 | 90.67 |
| 4 | 88.07 | 89.57 | 91.52 |
| 5 | 88.59 | 89.95 | 91.90 |

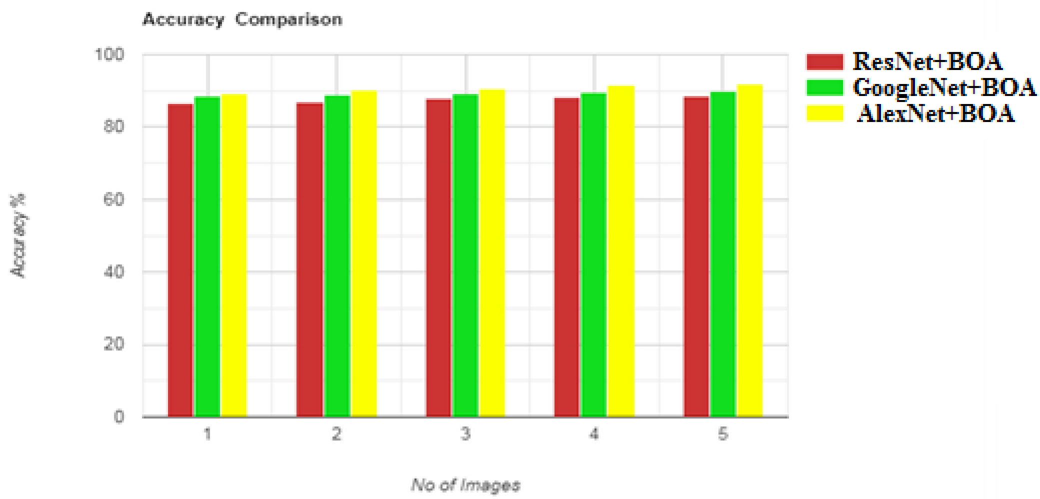


**Fig 4: Accuracy by AlexNet+BOA, GoogleNet+BOA and ResNet+BOA Graph**

The above Table 4 and Fig 4 represent Accuracy obtained by AlexNet+BOA, GoogleNet+BOA and ResNet+BOA. From the results its proved that AlexNet+BOA produces accuracy ranges from 89 % to 92 % which is higher than ResNet+BOA ranging from 86 % to 88 % and GoogleNet+BOA ranging from 88 % to 90 % respectively.

**Sensitivity Analysis**

Sensitivity assesses the system's capacity to correctly detect TB-infected regions among the total number of TB-infected regions. It is determined by dividing the number of true positives by the total number of true positives and false negatives. The high sensitivity value suggests that the system has been successful in detecting tuberculosis patients, reducing false negatives, and preventing missed diagnoses.

$$\text{Sensitivity} = (\text{Number of True Positive Assessment}) / (\text{Number of All Positive Assessment})$$

**Table 5: Sensitivity by AlexNet+BOA, GoogleNet+BOA and ResNet+BOA**

| No of Images | ResNet+BOA Sensitivity % | GoogleNet+BOA Sensitivity % | AlexNet+BOA Sensitivity % |
|---|---|---|---|
| 10 | 79.17 | 81.09 | 82.59 |
| 20 | 79.60 | 81.38 | 82.97 |
| 30 | 80.18 | 81.99 | 83.12 |
| 40 | 80.39 | 82.14 | 83.67 |
| 50 | 80.57 | 82.52 | 83.97 |

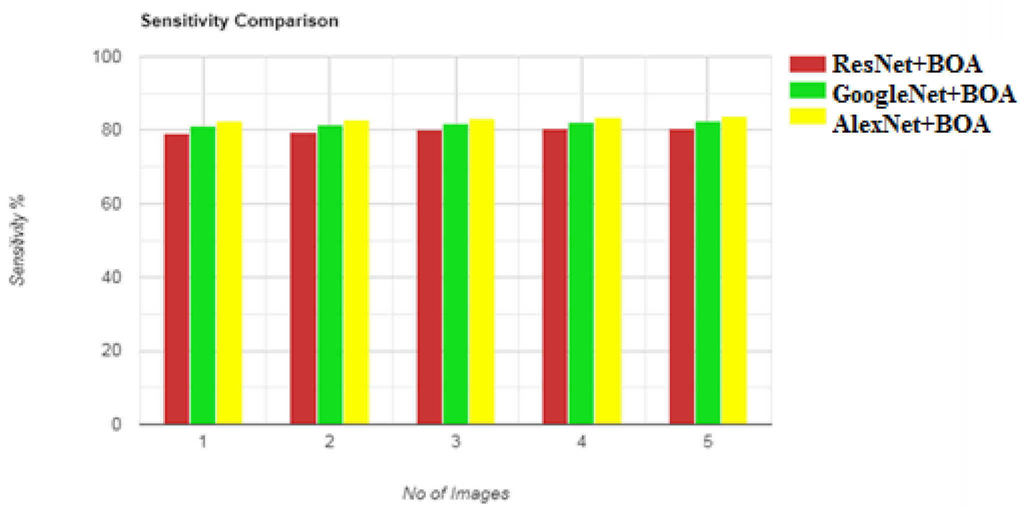


**Fig 5: Sensitivity by AlexNet+BOA, GoogleNet+BOA and ResNet+BOA Graph**

The above Table 5 and Fig 5 represent Sensitivity obtained by AlexNet+BOA, GoogleNet+BOA and ResNet+BOA. From the results it’s proved that AlexNet+BOA produces Sensitivity ranges from 82 % to 84 % which is higher than ResNet+BOA are ranging from 79 % to 81 % and GoogleNet+BOA ranging from 81 % to 83 % respectively.

**Specificity Analysis**

Specificity assesses the system's ability to correctly identify healthy regions among a total number of healthy regions.

$$\text{Specificity} = (\text{Number of Negative Assessment}) / (\text{Number of All Negative Assessment})$$

**Table 6: Specificity by AlexNet+BOA, GoogleNet+BOA and ResNet+BOA**

| No of Images | ResNet+BOA Specificity % | GoogleNet+BOA Specificity % | AlexNet+BOA Specificity % |
|---|---|---|---|
| 10 | 84.92 | 86.93 | 88.67 |
| 20 | 85.34 | 87.19 | 89.58 |
| 30 | 85.66 | 87.44 | 89.99 |
| 40 | 86.14 | 88.12 | 90.27 |
| 50 | 86.56 | 88.56 | 90.91 |

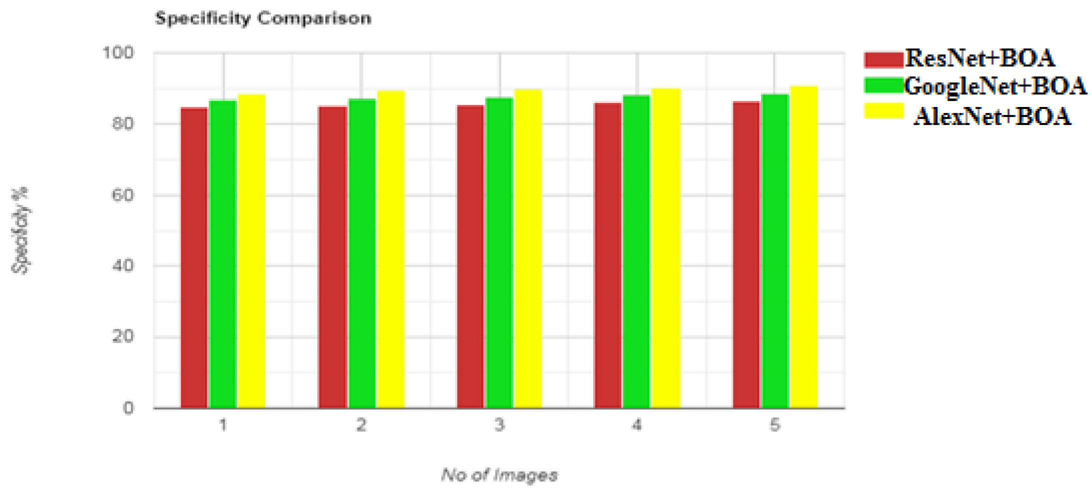


**Fig 6: Specificity by AlexNet+BOA, GoogleNet+BOA and ResNet+BOA Graph**

The above Table 6 and Fig 6 represent Specificity obtained by AlexNet+BOA, GoogleNet+BOA and ResNet+BOA. From the results it's proved that AlexNet+BOA produces Specificity ranges from 88 % to 91 % which is higher than ResNet+BOA are ranging from 86 % to 89 % and GoogleNet+BOA ranging from 88 % to 90 % respectively.

## VI CONCLUSION AND FUTURE WORK

In conclusion, this extensive tuberculosis detection framework outperformed conventional techniques by incorporating a suite of image filters (Median, Bilateral, Wiener, and ESMF), precise segmentation via the SCA, feature extraction, and classification via the AlexNet framework, and optimization via the BOA. The findings, which were analyzed based on accuracy, sensitivity, and specificity, show that our method is robust and reliable in correctly determining TB-infected locations while minimizing both false negatives and false positives. This integrated method has a lot of potential for enhancing TB detection from lung pictures, which could lead to timely interventions, improved patient outcomes, and better healthcare delivery in the field of pulmonary medicine.

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