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Enhancing Tuberculosis Detection: A Review of Optimization Algorithms in Medical Imaging

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Abstract: Tuberculosis (TB) remains a major global health challenge, causing approximately 1.5 million deaths annually and affecting over 10.6 million people worldwide as of 2021. In countries like South Africa, TB remains a leading cause of mortality. Caused by *Mycobacterium tuberculosis*, the disease primarily affects the lungs but can spread to other organs. Early and accurate diagnosis is crucial to reduce transmission and mortality rates.

This review focuses on the role of optimization algorithms in enhancing machine learning (ML) and deep learning (DL) models for TB detection in medical imaging. It explores chest X-rays (CXR) images as the main diagnostic imaging data, while emphasizing the use of these optimization algorithms for image segmentation, feature selection, and hyperparameter tuning.

This study evaluates the performance of seven optimization algorithms in improving TB detection accuracy: genetic algorithm (GA), surrogate algorithm, particle swarm optimization (PSO), pattern search (PS), particle swarm optimization with pattern search (PSOPS), genetic algorithm with pattern search (GAPS), and firefly algorithm.

The algorithms were implemented using data from chest X-ray images. The results indicate that the top three performing algorithms are PSOPS (accuracy 78%, recall 80%, and specificity 78%), surrogate (accuracy 72%, recall 86%, and specificity 68%), and GAPS (accuracy 62%, recall 91%, and specificity 55%), based on comparisons with the ground truth image.

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The experiments and review in this study offer valuable insights for researchers and practitioners while identifying opportunities for future research. These insights can guide practitioners in choosing suitable optimization algorithms for TB detection, improving accuracy, efficiency, and scalability. Such improvements could enhance diagnostics, enabling early detection and intervention and thereby reducing the global TB burden.

Keywords: **Tuberculosis detection, optimization algorithms, machine learning, deep learning, image segmentation, feature selection.**

1. Introduction

Tuberculosis (TB) is a contagious and potentially life-threatening infectious disease caused by the bacterium *Mycobacterium TB* (WHO, 2024; Kefan et al., 2023; Bagcchi, 2023; Lopez-Lopez et al., 2021; Joel et al., 2021). Despite significant advances in medical science, TB remains one of the top 10 causes of death globally (Joel et al., 2021), with approximately 1.5 million deaths and 10.6 million new cases reported in 2021 alone (WHO, 2024). The disease predominantly affects the lungs (pulmonary TB) but can also impact other parts of the body (extrapulmonary TB), leading to severe health complications if not detected and treated early. TB is primarily transmitted through airborne particles released when an infected individual coughs, sneezes, or talks. While many exposed individuals develop latent TB, where the bacteria remain inactive, about 5-10% progress to active TB disease, particularly those with weakened immune systems.

Drug-resistant strains of TB, including multidrug-resistant TB (MDR-TB) and extensively drug-resistant TB (XDR-TB) (Shleider Carnero Canales et al., 2023; Seung et al., 2015), further complicate treatment and highlight the need for early and accurate diagnosis. Early detection of TB is critical for reducing transmission, improving patient outcomes, and decreasing mortality rates (Mohammed et al., 2023; Sava et al., 2023; Perez-Siguas et al., 2023). Accurate and timely diagnosis enables prompt treatment (Kale et al., 2022), limiting the spread of infection and preventing complications (Perez-Siguas et al., 2023). Traditional diagnostic methods (Shivakumar & Shettigar, 2022), such as sputum smear microscopy, chest radiography, and culture tests, remain widely used but often suffer from limitations, including low sensitivity, long turnaround times, and dependence on skilled personnel. Advancements in molecular diagnostics (Zhang et al., 2023; Fu et al., 2023; Yang et al., 2023; Liu et al., 2022; Shivakumar & Shettigar, 2022; Pai et al., 2023), like nucleic acid amplification tests (e.g., GeneXpert) and whole-genome sequencing (WGS), have improved diagnostic accuracy. Non-invasive techniques, such as chest X-rays (CXR) and computed tomography (CT) scans, play a vital role in TB screening, particularly in resource-limited settings (Liu et al., 2023b).

However, interpreting medical images can be subjective and prone to inter-observer variability, leading to misdiagnosis and delayed treatment. The integration of machine learning (ML) and deep learning (DL) techniques in medical imaging has revolutionized TB diagnosis by enabling automated, accurate, and rapid detection (Boyina et al., 2024; Nath et al., 2024; Flores et al., 2024; Hansun et al., 2023; Tummalapalli et al., 2023; Ma et al., 2023; Urooj et al., 2022). These models can analyze complex imaging data, identify patterns indicative of TB, and assist radiologists in decision-making. However, the performance of ML and DL models, in most cases, heavily relies on effective image segmentation, feature selection, or/and hyperparameter tuning. Optimization algorithms play a crucial role in this regard, as they enhance the accuracy and efficiency of these models.

Several related reviews in the literature, though not focused on TB detection, have explored the use of optimization algorithms - including evolutionary, meta-heuristic, and swarm intelligence techniques - in various aspects of medical image analysis. These applications include image segmentation (Kaur & Singh, 2023; Khin et al., 2020; Houssein et al., 2024), feature selection (Allam & Nandhini, 2017; Riaz et al., 2022), and image processing or analysis (Kaur & Singh, 2023; Xu et al., 2023; Kumar et al., 2021; Singh, 2023). These algorithms help overcome challenges such as data variability, limited training datasets, and the complexity of medical images. However, specific reviews on the use of optimization algorithms for TB detection and the stages at which they are applied appear to be lacking in the literature. This gap highlights the need for the present study and the contribution it aims to make.

The remainder of this paper is organized as follows. Section 2 outlines the research objectives and the corresponding research questions. Section 3 discusses the role of medical imaging in TB diagnosis and the challenges associated with it, highlighting the necessity of optimization algorithms. In Section 4, we review various optimization algorithms used in TB detection. Specifically, the review is categorized into three areas - image segmentation, feature selection, and hyperparameter tuning - where optimization algorithms have been applied. Section 5 presents the results of clustering-based segmentation using seven optimization algorithms. Finally, Section 6 concludes the study with key remarks and directions for future research.

2. Research Objectives and Questions

This review aims to explore the application of optimization algorithms in enhancing ML and DL models for TB detection in medical imaging. The specific objectives are:

Objective 1: To review various optimization algorithms used in TB detection, focusing on image segmentation, feature selection, and hyperparameter tuning, as the specific context in which these algorithms can be utilized in a ML workflow. This objective is addressed in Sections 3 and 4.

Objective 2: To compare the performance of different optimization techniques within the context of image segmentation. This objective is addressed in Section 5.

Objective 3: To identify emerging trends and potential future research directions in the application of optimization algorithms for TB diagnosis. This objective is addressed in Section 6.

The following research questions guide this review:

Question 1: Which optimization algorithms are commonly used to enhance ML and DL models for TB detection in medical imaging, within the context of image segmentation, feature selection, and hyperparameter tuning?

Question 2: How do different optimization algorithms compare in terms of performance and efficiency?

Question 3: What are the potential future research directions for improving TB detection using optimization algorithms?

By addressing these questions, this review aims to provide valuable insights for researchers, practitioners, and decision-makers involved in TB detection and medical imaging, ultimately contributing to improved diagnostic methods and better patient outcomes.

3. Medical Imaging and Optimization Algorithms in Tuberculosis Detection

3.1 Role of Medical Imaging in Tuberculosis Diagnosis

Medical imaging (De Backer et al., 2006; Bhalla et al., 2015; Aggarwal et al., 2021) plays a pivotal role in the diagnosis of TB, particularly because TB can present with non-specific clinical and radiological features that resemble other diseases. Traditional methods for diagnosis - such as the tuberculin test, blood test, and microscopic slide sputum smear test - encounter obstacles arising from a range of factors such as limited sensitivity, the necessity for toxic chemical reagents, and the demand for skilled clinicians (Ibrahim et al., 2023). The imaging methods utilized for the diagnosis and evaluation of TB encompass chest radiography (CXR), ultrasound, computed tomography (CT), and magnetic resonance imaging (MRI).

Concepcion et al. (2023) observed that CXR represents the customary preliminary imaging modality for assessing children suspected of TB, owing to its extensive accessibility and efficacy in identifying pulmonary TB and lymphadenopathy. A list of TB CXR datasets is provided in Appendix A. More can be found in Santosh et al. (2022). Ultrasound may be employed where accessible, especially in regions with limited resources. CT and MRI constitute more sophisticated imaging methodologies that are generally held in reserve for intricate cases and are commonly accessible in well-resourced areas or tertiary facilities due to their higher cost.

Alshoabi et al. (2022) presented a comprehensive pictorial examination of the radiological patterns connected with TB, underscoring the capacity of the disease to imitate other benign or malignant conditions and the significance of imaging in its diagnosis. The study accentuated the role of medical imaging, such as CT and MRI, in identifying TB in various organs, including the lungs, peritoneum, and brain.

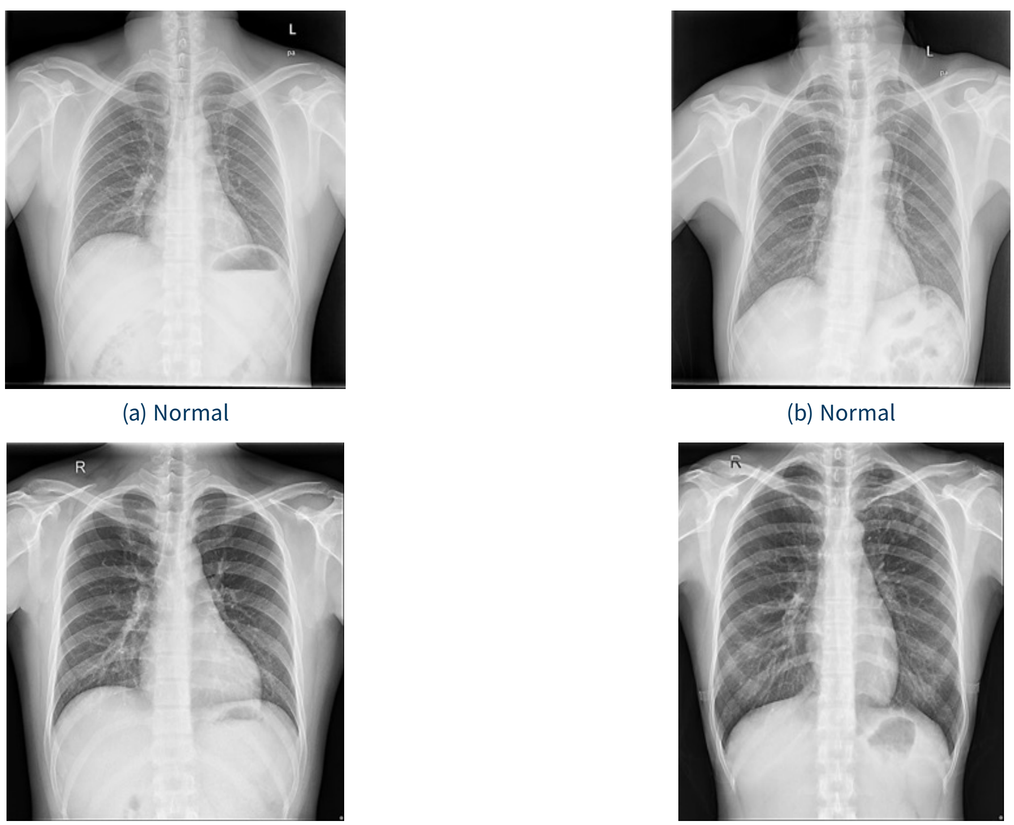
Regarding the drawbacks, Nel et al. (2022) observed that chest imaging, while being useful in the diagnosis of pulmonary TB (PTB), is associated with several constraints. CXR, which is commonly employed, often yields non-specific findings that can be interpreted differently by various observers, consequently resulting in substantial inter- and intra-observer variability. This implies that two distinct physicians might interpret the same X-ray differently, thereby complicating the diagnosis.

Furthermore, even though other imaging modalities such as ultrasound, CT, and MRI can offer more comprehensive information, they also possess their own limitations. These limitations may include restricted accessibility in specific regions, elevated costs, and the necessity for specialized equipment and trained personnel to interpret the findings. These factors can render it difficult to solely rely on imaging as a definitive means of diagnosing PTB, particularly in resource-constrained settings where access to such technologies may not be readily available.

However, the imaging manifestations of TB can differ between children and adults, thus posing challenges to diagnosis. Despite the limitations, medical imaging plays an essential role in the diagnosis of TB, particularly in cases wherein microbiological confirmation is difficult to obtain. Figure 1 shows two samples each from the Shenzhen CXR image dataset (Jaeger et al., 2014) representing normal and TB cases.

3.2 Challenges

The detection of TB from medical images presents several challenges. One significant challenge is the high volume of TB cases, which can overwhelm medical experts, making the process of analyzing microscopic slides and CXR images tedious and prone to misdiagnosis (Ibrahim et al., 2023). Another issue is the low sensitivity of existing assays, which complicates the interpretation of results obtained from these laboratory procedures. This is particularly problematic in underdeveloped countries and remote areas where there is a scarcity of adequate testing materials (Ibrahim et al., 2023). Another challenge is the reliance on medical imaging for TB diagnosis, which requires high accuracy, sensitivity, and specificity, and this can be difficult to achieve without the aid of advanced



(a) Normal (b) Normal

(c) TB (d) TB

Figure 1. Samples of chest X-rays.

computational tools like AI-driven models (Ibrahim et al., 2023; Liu et al., 2023b; Hossain et al., 2023; Lewis et al., 2021; Cevik, 2020).

Another challenge in detecting TB from medical images, specifically CXR, is the difficulty for radiologists in differentiating TB from lung cancer, as both conditions can appear similar on imaging (Hossain et al., 2023). This similarity can lead to diagnostic errors. An additional challenge is the availability of CT scans, which are often not accessible in low-resource environments and can be difficult to obtain for critically ill patients (Lewis et al., 2021; Cevik, 2020). CT scans provide a detailed, three-dimensional view of the lungs, which is crucial for accurate TB detection. However, in their absence, clinicians often must rely on X-ray images, which are more widely available and inexpensive but offer a simpler, two-dimensional image. This limitation can make it challenging to accurately identify and evaluate the infectious disease processes, as X-rays may not provide sufficient detail to distinguish TB from other pulmonary conditions.

Additionally, the quality of computer-aided TB diagnosis is affected by the inherent properties of CXR images, such as the bilateral symmetry of the human thorax, which is not always strictly adhered to in the images (Liu et al., 2023b). This variability can make it difficult for computer-aided systems to learn discriminative features necessary for accurate TB area detection. The use of machine learning and deep learning, including convolutional neural networks (CNNs) and transfer learning techniques, for the classification of TB from medical images is a promising approach to address these challenges, but it necessitates rigorous validation to ensure reliable performance (Ibrahim et al., 2023). Some studies have argued that machine learning (ML) and/or deep learning (DL) models can detect TB comparably to, or even better than, a human specialist (Boyina et al., 2024; Nath et al., 2024; Flores et al., 2024; Hansun et al., 2023; Tummalapalli et al., 2023; Ma et al., 2023; Urooj et al., 2022).

However, developing these models requires access to large and diverse datasets to train the algorithms effectively, which can be a challenge (Liu et al., 2023b; Ibrahim et al., 2023, Hossain et al., 2023; Cevik, 2020). To overcome this challenge, there is a need (1) to use synthetic data (McDuff et al., 2023; Chen et al., 2021; Khosravi et al., 2024; Rashidi et al., 2022; Yu et al., 2023; Riegler et al., 2015), and/or (2) to use ML/DL tools that are able to work with smaller data sets (Huang et al., 2022; Liu et al., 2023a; Gozes & Greenspan, 2019; Ramdan et al., 2020; Hall et al., 2020; An et al., 2021).

The ML and DL methodologies utilized for TB detection include, as part of the workflow, the use of optimization algorithms. Optimization algorithms (Yang, 2020; AB Wahab et al., 2015) are mathematical methods utilized to determine the most optimal solution for a specific problem by minimizing or maximizing an objective function. These algorithms find extensive application across diverse domains including machine learning, data science, engineering, and operations research, aiming to enhance the efficacy of models, systems, or processes. It is observed from the literature that optimization algorithms have been used in the literature in three sections of TB detection from X-rays or CT scan images. The three sections are as follows - image segmentation, feature selection and hyperparameters tuning of the classifier or model. Figure 2 shows this process of detecting TB from CXR and the sections that the optimization algorithms had been used in the literature.

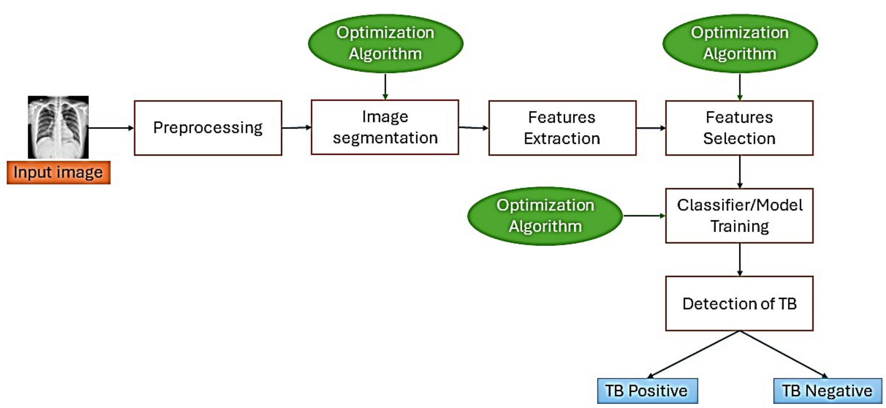


Figure 2. The Process of tuberculosis detection and stages where optimization algorithms had been used.

The optimization algorithms have the objective of extracting the most optimal features from images related to TB, and they also strive to choose the best hyperparameters for classifiers (Hrizi et al., 2022). By utilizing optimization techniques such as genetic algorithms (GA), particle swarm optimization (PSO), ant colony optimization (ACO) and others, it is possible to minimize the number of characteristics extracted while simultaneously increasing the accuracy rate (Manivannan & Sathiamoorthy, 2023b). Furthermore, optimization algorithms aid in optimizing the weighting parameters of deep learning models (Simi Margarat et al., 2022; Manivannan & Sathiamoorthy, 2023b) with the aim of improving classification accuracy. The use of these optimization algorithms enables the creation of more dependable and efficient systems for TB detection, thereby reducing the requirement for expert intervention, improving the screening process, and ultimately enhancing the overall performance of TB detection models (Urooj et al., 2022). In addition, the use of optimization algorithms in TB detection helps to overcome the challenges of time-consuming and subjective CXR interpretation (Escorcia-Gutierrez et al., 2023).

4. Review of Optimization Algorithms Used in TB Detection

Detecting TB in medical images frequently requires the utilization of different optimization algorithms to improve the accuracy and effectiveness of the detection procedure. Optimization algorithms have been extensively studied and used as part of the workflow for the purpose of detecting TB in medical images. In this section, we review some of the optimization algorithms that have been used in different ways as part of the TB detection process, as illustrated in Figure 2. The uses are classified into three sections - image segmentation, feature selection, and hyperparameter tuning of the classifier or model.

Table 1 provides an overview of the eligibility criteria used, information sources, search strategy, and study selection process. Additionally, we present a PRISMA

Table 1. Method for the Literature Selected.

Items	**Descriptions**
Eligibility Criteria	**Inclusion:** Studies employing optimization algorithms or evolutionary algorithms or meta-heuristics algorithms to enhance TB detection in medical imaging either by image segmentation or feature selection or hyperparameter tuning of the model/classifier. **Exclusion:** Non-English articles, Studies without empirical results, Studies without TB disease, Reviews, Studies without the use of optimization algorithms, Studies using the class of gradient-based optimization.
Information Sources	**Databases:** Google Scholar, PubMed, EBSCOS. **Time Frame:** Studies Published between 2010 and 2024.
Search Strategy	**Keywords:** “Tuberculosis detection” “medical imaging” “machine learning” “deep learrning” “optimization algorithms” “evolutionary algorithms” “meta-heuristics algorithms” **Boolean Operators:** AND, OR, NOT to refine searches.
Study Selection	- Initial screening based on titles and abstracts. - Full-text assessment for eligibility. - Discrepancies resolved by consensus.

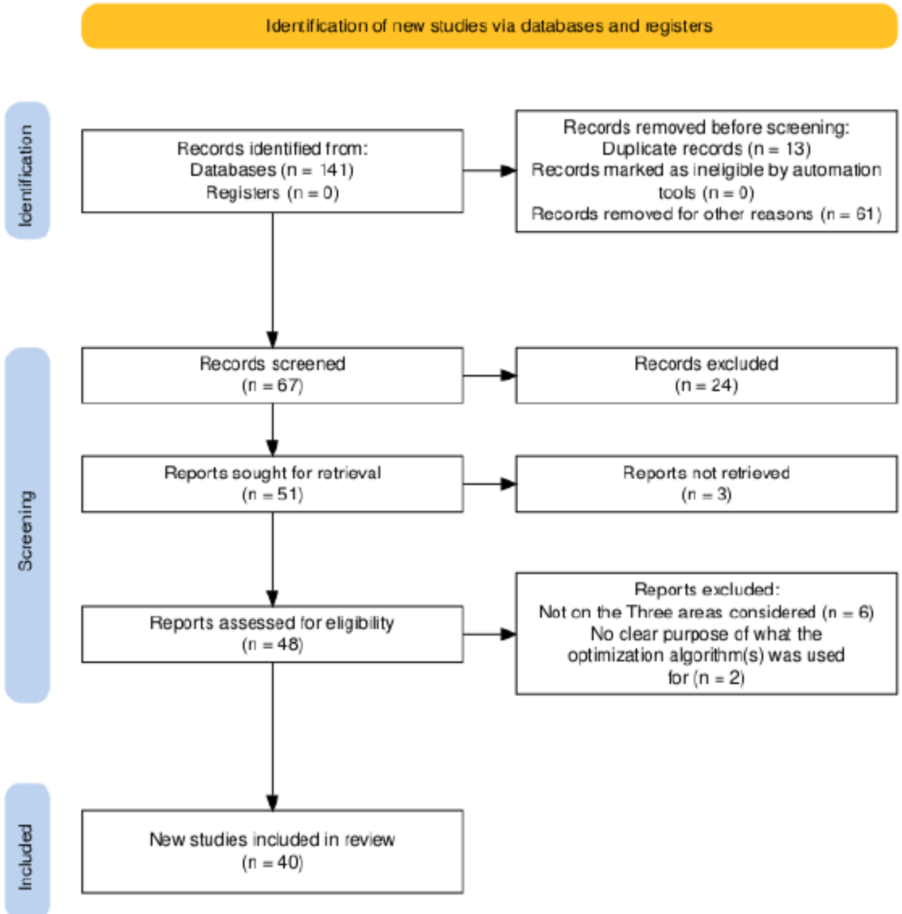


Figure 3. PRISMA Flow Diagram.

flow diagram (Haddaway et al., 2022) (see Figure 3) that illustrates the flow of information through the phases of this review. A total of 141 articles were retrieved from the databases. Among these, 13 were duplicates, and 61 did not fit the scope of this review (e.g., studies focused on gradient descent optimization, those that did not use an optimization algorithm, and review articles). This reduced the number of articles to be screened to 67. Of these 67 articles, 24 were excluded because the optimization algorithm used was not applied to TB images. This left 51 articles for retrieval. However, 3 of these 51 could not be accessed in full, reducing the number of articles assessed for eligibility to 48. Among these, 6 did not fall within the three areas considered, and 2 lacked a clear explanation of how the optimization algorithm(s) were used.

4.1 Image Segmentation

Image segmentation (Kaur & Kaur, 2014; Saini & Arora, 2014) is the process of simplifying and analyzing images by separating them into different segments based on the characteristics of each pixel in the image. Each pixel in an image is assigned a label and pixels having the same label share some properties. Image segmentation is an important process because it allows for further analysis of the specific image regions. It also enables object detection and recognition in images (Van de Sande et al., 2011; Roth & Ommer, 2006; Bhogal & Devendran 2022; Wang et al., 2019).

Several studies have explored optimization algorithms for image segmentation in TB detection. (Yuliansyah et al., 2020) combined PSO with Fuzzy C-Means (FCM) and a Wiener filter to improve lung X-ray segmentation, achieving 88.57% accuracy, 90% sensitivity, 85% specificity, 93.75% precision, but struggling with abnormalities near the lung edges. Priya (2022b) used ACO with morphological operations for bacilli detection in TB sputum smears, enhancing edge preservation and segmentation efficiency.

Lul et al. (2020) integrated ACO with snake algorithms for lung CT segmentation, improving focal zone detection with reduced processing time. Ayas et al. (2015) applied the firefly algorithm for microscopic TB image segmentation, optimizing threshold values and achieving over 96% accuracy. These methods demonstrate the potential of optimization algorithms in enhancing TB diagnostic imaging.

Table 2 presents various optimization algorithms utilized in the literature for image segmentation in TB detection, along with their performance, comparison methods, and the datasets used in the studies.

4.2 Feature Selection

Feature selection (Bolon-Canedo & Remeseiro, 2020; Remeseiro & Bolon-Canedo, 2019; Agrawal & Chandra, 2015) is the process of choosing the best set of features in an image that will allow for optimized models in the classification of the image. Most optimization algorithms are a type of evolutionary algorithm that can be used to optimize complex problems by simulating the process of natural selection (Joel et al., 2022). In the context of TB detection, optimization algorithms could potentially be employed to optimize the feature selection process for machine learning models that are used to identify TB in medical images.

Hrizi et al. (2022) developed an optimized machine learning model for TB diagnosis, using a genetic algorithm (GA) to select texture features and optimize SVM hyperparameters. Their approach, tested on the Image (CLEF, 2020) TB dataset, achieved a mean accuracy of 84%, outperforming KNN (82%) and LDA (82%). Osman

Table 2. Section 1 – Image Segmentation.

Reference Papers	Optimization Algorithms	Performance	Comparison	Dataset Used
Priya (2022b)	hybrid-ACO	Improved image enhancement, preservation of more edges and object shape retention.	ACO	Sputum smear images
Lu et al. (2020)	ACO	Improved segmented image and shorter time taken	Traditional ACO	Some lung CT scans images
Ayas et al. (2015)	Firefly Algorithm	Sensitivity – (99.47%, 96.86%) Specificity – (91.18%, 96.18%) Accuracy – (97.58%, 96.16%)	N/A	Six different set of microscopic images
Priya (2022a)	hybrid-ACO and hybrid-PSO	Improved image enhancement, preservation of more edges and object shape retention.	ACO and PSO	Sputum smear images
Pushparani et al. (2016)	PSO	AUC 94% Accuracy 95%	Results in (Van Ginneken et al., 2002; Arzhaeva et al., 2009)	Chest X-rays images
Sugirtha and Murugesan (2017)	PSO	Eccentricity and Axis length ratio	Existing results (No Reference)	Sputum smear images
Askarali and Fredrik (2024)	Crow search and rider Optimization	Sensitivity – 88% Specificity – 88% Accuracy – 86%	DCNN, NN, and ROA-DCNN	Spinal cord images
Passanna et al. (2022)	PSO	Accuracy - 90%	None	Chest X-rays images
Vaiyapuri and Alaska (2020)	Whale Optimization (WOA)	Feature Similarity (CT: 0.974, MR: 0.978) Dice (CT: 0.973, MR: 0.963) Feature of merits (CT: 0.831, MR: 0.883)	Adaptive KM, Fuzzy KM, PSO-KM, GA-KM	CT and MR images (Menze et al., 2025)
Jaszcz et al. (2022)	Red Fox Heuristic Optimization Algorithm (RFOA)	Accuracy 97.2% Jaccard index 94.35% Dice coefficient 97.1%	U-NET, ACO, and Modified U-NET	Chest X-rays images (Paul, 2019)

et al. (2010) combined GA with a neural network (GA-NN) for TB detection in Ziehl-Neelsen stained images, achieving 89.64% accuracy with two input features, surpassing a standard NN (88.57%) with seven input features.

Kanesamoorthy and Dissanayake (2021) used GA for feature selection in TB treatment failure prediction, reducing features from 35 to 20. An SVM with a linear kernel performed best with 67% accuracy, 50% precision, and a 57% F1-score. Win et al. (2020) applied PSO for feature selection in TB detection from chest X-rays, achieving 92.5% accuracy on the Montgomery dataset and 95.5% on the Shenzhen dataset. Fonseca et al. (2022) employed Local Binary Patterns and Monarch Butterfly Optimization for feature selection, with KNN achieving 90.33% accuracy and 92.41% AUC, supporting IoT-based TB diagnosis. Li et al. (2022) introduced bGACO-SVM for feature selection, integrating an improved ACO algorithm with SVM for TB pleural effusion diagnosis. It outperformed six other methods, achieving 96.57% accuracy, 96.91% specificity, and an MCC of 0.9366.

Tables 3 and 4 present various optimization algorithms used in the literature for feature selection in TB detection, along with their performance, comparison methods, and the datasets used in the studies.

Table 3. Section 2 – Feature Selection.

Reference papers	Optimization Algorithms	Performance	Comparison	Dataset Used
Hrizi et al. (2022)	GA	Mean Accuracy 84%	KNN, CART, NB, LDA, and RF	CT scan images (Clef 2020)
Osman et al. (2010)	GA	Accuracy 89.64%	Deep learning model with manual selection	Tissue slides images
Win et al. (2020)	PSO	Montgomery dataset: Accuracy 92.7% and Shenzhen dataset: Accuracy 92.7%	Results in (Jaeger et al., 2013; Hwang et al., 2016; Lopes & Valiati 2017; Vajda et al. 2018; Karargyris et al., 2016; Islam et al., 2017; Rajaraman et al., 2019; Jemal, 2019; Santosh & Antani, 2017; Pasa et al., 2019)	Chest X-rays images (Jaeger et al. 2014)
Fonseca et al. (2022)	MBO	Accuracy (90.33 ±3.06%) And AUC 92.41%	Result in (Jaeger et al., 2013)	Chest X-rays images (Jaeger et al. 2014)
Mohan et al. (2022)	Seagull Algorithm	Accuracy 98.62% Precision 99.23% Sensitivity 98.00% Specificity 99.24%	Result in (Rahman et al., 2020b)	Chest X-rays images (Rahman et al., 2020b; Rahman et al., 2020a)
Kadry et al. (2022)	SHA	Accuracy 99.22%, Precision 99.33%, Sensitivity 99.11% Specificity 99.33%	Conventional Deep features and the Result in (Rahman et al., 2020b)	Chest X-rays images (Rahman et al., 2020a)
Rajakumar et al. (2021)	Mayfly Algorithm	Accuracy 97.25%, Precision 96.71%, Sensitivity 97.83% Specificity 96.67%	Traditional VGG16, VGG19 and the result in (Rahman et al., 2020b)	Chest X-rays images (Rahman et al., 2020b, Rahman et al., 2020a)
Passanna et al. (2022)	GA	Accuracy 90%	None	Chest X-ray Images
Satheesh and Raj (2017)	Orthogonal Learning PSO (OLPSO)	Sensitivity 89.87% Specificity 82.88%	Results in (Krishnamurthy et al., 2016; Thawkar & Ingolikar, 2017; Rafi & Bharathi, 2016)	CT lung images

Table 4. Section 2 – Feature Selection Continued.

Reference Papers	Optimization Algorithms	Performance	Comparison	Dataset Used
Dhivyaa et al. (2024)	EAMSO: Ensemble of AEO (Artificial Ecosystem-based Optimization), MBO (Monarch butterfly optimization) and Seagull-Algorithm	Accuracy 98.91% Precision 98.87% Recall 96.99% F1-Score 97.92%	AlexNet, DenseNet, VGG-16, XceptionNet, ResNet50, InceptionV3, EfficientNet B4	Chest X-ray images
Gujrathi and Yadav (2024)	Hybrid Binary PSO (HBPSO)	Accuracy 99.73%, Precision 99.72% Recall 99.72% Specificity 99.75% F1-score 99.72%	Results in (Lestari et al., 2023; Gichuhi et al., 2023; Lubis et al., 2021; Ayas and Ekinci 2014; Singh et al., 2022)	Chest X-ray images
Sweetlin et al. (2019)	Cuckoo search algorithm	Accuracy 92.77%	Compare with the one without entropy measure	Lung CT images
Sahlol et al. (2020)	AEO	Shenzhen dataset: Accuracy 90.2% and Dataset 2: Accuracy 94.1%	Results in (Jaeger et al., 2013; Lopes & Valiati 2017; Sivaramakrishnan et al., 2018; Hwang et al., 2016; Kermany et al., 2018)	Chest X-ray images (Jaeger et al. 2014; Kermany et al., 2018)
Kim et al. (2024)	Mayfly Algorithm	Accuracy 98.75% F1 score 98.70% Precision 97.44% Dice 98.75% Jaccard Index 95.33%	Simple CNN, Batch Normalized CNN (BN-CNN), and Dense CNN (DCNN).	Chest X-ray images

4.3 Hyperparameter Tuning of the Classifier or Model

The importance of adjusting certain sets of parameters in machine learning and/or deep learning models (Jafar & Myungho, 2020; Shanmugavadivel et al., 2022; Iqbal et al., 2022) to achieve optimal performance of the models/algorithms cannot be overstated. Hence, the need for optimization algorithms to be used in searching for and identifying the set of parameters in the hyperparameter space of the classifier or model that provides the optimal combination of them on the data within a reasonable amount of time. This control of the learning process by the optimization algorithms has a significant effect on the performance of the models/algorithms.

Akbar et al. (2023) introduced pAtbP-EnC, an ensemble deep learning model optimized/fine-tuned using a genetic algorithm (GA) to enhance anti-tubercular peptide prediction, achieving to 93.91%, and 94.17% accuracy on RD and MD testing datasets, respectively.

Yusoff et al. (2021) proposed a hybrid CNN with an enhanced PSO (ePSO) algorithm for TB classification from CXR images. ePSO optimized/fine-tuned the neural network architecture, balancing exploration and exploitation to minimize loss and maximize accuracy. The proposed model achieved 98% accuracy, precision, recall, and f1-score.

Simi Margarat et al. (2022) employed the Adaptive Monarch Butterfly Optimization (AMBO) algorithm to optimize/fine-tune a Deep Belief Network (DBN) classifier for TB detection, improving accuracy (99.2% on Shenzhen, 98.7% on MC datasets) and reducing error. The DBN-AMBO model demonstrated higher efficiency when compared with other classifiers like Recurrent Neural Network (RNN), CNN, Generative Adversarial Networks (GAN), and a standard DBN.

Manivannan and Sathiamoorthy (2023b) used Harris Hawks Optimization (HHO) to tune the hyperparameters of a GRU-based deep learning model (HHODL-TBC) for TB classification, achieving 99.33% accuracy. The Harris Hawks Optimization (HHO) algorithm is a technique that is inspired by the cooperative behavior and chasing style of Harris' hawks in nature.

Escorcia-Gutierrez et al. (2023) developed WSOD-TL-TBC, utilizing Water Strider Optimization (WSO) to fine-tune LSTM hyperparameters for TB detection, outperforming other deep learning models (such as VGG-16, VGG-19, Inception-V3, Xception, and AlexNet) with 98.9% accuracy, 97.51% sensitivity, 97.51% specificity, and 98.01% f-score.

In Tables 5 and 6, we present various optimization algorithms used in the literature for hyperparameter tuning of models or classifiers in TB detection, along with their performance, comparison methods, and the datasets used in the studies.

Table 5. Section 3 – Hyperparameter Tuning of the Classifier/Model.

Reference Papers	Optimization Algorithms	Performance	Comparison	Dataset Used
Urooj et al. (2022)	Stochastic learning optimization	Accuracy 98.45%, Sensitivity 96.12%, Specificity 98.01%, F-Score 95.88%	Results in (Vajda et al., 2018; Hijazi et al., 2019; Lopez-Garnier et al., 2019)	Chest X-rays images (Jaeger et al. 2014)
Hrizi et al. (2022)	GA	Mean Accuracy 84%	KNN, CART, NB, LDA, RF	CT scan images (Clef 2020)
Manivannan and Sathiamoorthy (2023b)	HHO	Precision 98.8%, Recall 98.8%, Accuracy 99.33%, Specificity 98.8%, F1-score 98.8%, and Computational Time 12.10s	ResNetl8, ResNet50, ResNet101, VGG19, InceptionV3, and DenseNet201	Chest X-rays images (Rahman et al. 2021b)
Simi Margarat et al. (2022)	AMBO	Shenzhen Dataset: Accuracy 99.2%, Specificity 99.1%, Recall 95.4%, Precision 97.8% and Montgomery Dataset: Accuracy 98.7%, Specificity 99.4%, Recall 98.9%, Precision 96.6%	RNN, CNN, GAN, DBN-BOA, DBN-EPO, DBN-MBO, and the Results in (Santosh & Antani, 2017; Rahman et al., 2020b; Geetha Pavani et al., 2021; Rahman et al., 2021a)	Chest X-rays images
Jose Escorcia-Gutierrez (2023)	Water Strider Algorithm	Accuracy 98.9%, Specificity 97.51%, Sensitivity 97.51%, F-score 98.01%	VGG16, VGG19, InceptionV3, Xception and AlexNet	Chest X-rays images (Rahman et al. 2021b)
Dasanayaka and Dissanayake (2021)	GA	Accuracy 97.1%, Sensitivity 97.9%, Specificity 96.2%, and Youden's index 94.1%	Results in (Xu et al., 2013; Yang & Song, 2010; Shen et al., 2010)	Chest X-rays images (Jaeger et al. 2014; Johnson et al., 2019)
Maheswari et al. (2024)	Bayesian Optimization	Accuracy 95%, Sensitivity 95%, Specificity 95%, and F1-score 95%, AUC 0.976	Modified DenseNet121 AlexNet, and Results in (Rahman et al., 2020b; Liu et al., 2017; Liu et al., 2022; Tasci et al., 2021)	Chest X-rays images
Khan et al. (2024)	Moth Search Algorithm	Accuracy 99%, Sensitivity 98.56%, Specificity 99%	SVM, Naive Bayes, Logistic Regression	Chest X-rays images
Kumari and Rao (2019)	CBGA	Accuracy 97%, Sensitivity 90%, And Specificity 100%	NN, GA-NN	CT scan images

Table 6. Section 3 – Hyperparameter Tuning of the Classifier/Model Continued.

Reference Papers	Optimization Algorithms	Performance	Comparison	Dataset Used
Ucar (2023)	Bayesian Optimization	Accuracy 99.29%, Sensitivity 99.29% Specificity 99.29%, Precision 99.29% F1-score 99.29%, AUC 99.3%	Results in (Rahman et al., 2020b; Wong et al., 2022)	Chest X-rays images (Rahman et al. 2020b)
Tasci et al. (2021)	Bayesian Optimization	Shenzhen Dataset: Accuracy 97.699% and Montgomery Dataset: Accuracy 97.5%	Result in (Hwang et al., 2016; Lopes & Valiati 2017; Xie et al., 2020; Win et al., 2020; Santosh & Antani, 2017; Rajaraman et al., 2019; Pasa et al., 2019; Ayaz et al., 2021)	Chest X-rays images (Antani, 2014)
Manivannan and Sathiamoorthy (2023a)	POA	Accuracy 98.83%	ResNet-l8, ResNet50, ResNetl01, InceptionV3, VGG19, and DenseNet201	Chest X-rays images (Rahman et al. 2021b)
Singh et al. (2024)	SMRO	Algorithm analysis: Accuracy 93.6%, TPR 90.8%, TNR 89.87% and Technique analysis: Accuracy 94.7%, TPR 93.3%, TNR 90.6%	Algorithm analysis: GWO-DenseNet, WOA-DenseNet, WSO-Densenet, MRA-DenseNet and Technique analysis: FC-SVNN, DNN-SVM, DL, CNN, SMRO-DenseNet (without feature extraction)	Sputum Images (Uddin, 2020)
Roopa and Mamatha (2023)	CLBO	Accuracy 98.90%, TPR 97.60%, TNR 94.60%, PPV 94.60%, NPV 93.30%, F1-score 96.10%	CCNSE, E-TB NET, Ensemble learning, and VGG-UNet	Chest X-rays images (Rahman et al. 2021b)
Guo et al. (2020)	Artificial Bee Colony (ABC) algorithm	Accuracy 98.46%, Recall 97.12%, Specificity 100%, F1-score 98.6%, AUC 0.999	VGG16, VGG19, Inception V3, ResNet34, ResNet50, ResNet101 and Results in (Jaeger et al., 2013; Hwang et al., 2016; Lopes & Valiati, 2017; Lakhani & Sundaram, 2017; Pasa et al. 2019; Rajaraman & Antani, 2020)	Chest X-rays images
Manivannan and Sathiamoorthy (2022)	Whale optimization algorithm	Accuracy 99.0%, Precision 98.64%, Recall 97.74%, Specificity 97.74%, and F-Score 98.18%	ResNet18, ResNet50, ResNet101, VGG19, InceptionV3, and DenseNet201	Chest X-rays images (Rahman et al., 2020b; Rahman et al., 2021b)

5. Image Segmentation Example

5.1 Introduction

In this section, we showcase the results of some clustering-based segmentation performed by seven optimization algorithms - PSO, GA, pattern search (PS), surrogate, particle swarm optimization with pattern search (PSOPS), GA with pattern search (GAPS), and firefly.

Clustering-based segmentation (Coleman & Andrews, 1979; Zou & Liu, 2016; Sathya & Manavalan, 2011; Mittal et al., 2022; Thilagamani & Shanthi, 2011; Lalitha et al., 2013) segments TB images by grouping pixels based on their similarity or proximity. It assigns pixels to different clusters which helps to identify and isolate areas/objects of interest in the TB images. It is a flexible image segmentation technique that can handle complex and variable image backgrounds. It is efficient and allows for further quantitative analysis of the segmented regions produced.

This example was implemented in MATLAB R2022b using some freely available codes (see Selva, 2024a; Selva, 2024b; Mousavi, 2022a; Mousavi, 2022b) that were copied and modified. The TB CXR image used in this example was taken from the dataset (Jaeger et al., 2014) and the corresponding ground truth image was taken from the dataset (Nikhil, 2019).

5.2 Discussion of Results

The time taken by each algorithm is shown in Figure 4. It is observed that for k = 3 and k = 4, PS has the lowest time, followed by the surrogate algorithm. While for k = 5, k = 6 and k = 7 the surrogate algorithm has the lowest duration of time, followed by the PS algorithm. On the other hand, for k = 3 and k = 4 the firefly algorithm has the highest time taken, followed by the GAPS algorithm. However, k = 5, the firefly algorithm still has the highest time taken but it is now followed by GA. For k = 6, GAPS has the highest time taken, followed by GA. And lastly, for k = 7, GA has the highest time taken for the segmentation, followed by the Firefly algorithm.

We also present the accuracy, recall (also called sensitivity), specificity, and precision values of the segmentation as compared to the ground truth. The formulae for these four metrics are given in Equations (1) - (4).

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

$$\text{Sensitivity} = \frac{\text{TN}}{\text{TP+FN}} \quad (2)$$

$$\text{Specificity} = \frac{\text{TP}}{\text{TP+FP}} \quad (3)$$

$$\text{Precision} = \frac{\text{TN}}{\text{TN+FP}} \quad (4)$$

where TP = true positive, FP = false positive, TN - true negative, and FN - false negative.

Figures 5, 6, 7 and 8 show the results of these values when compared to the ground truth image (Nikhil, 2019; Jaeger et al., 2013; Candemir et al., 2013).

In Figure 5, GA, PS and Firefly obtained their highest accuracy values when k = 3. For PS algorithm, the same accuracy value is obtained for k = 3 and k = 5. GAPS obtained its highest accuracy value when k = 4, while PSO

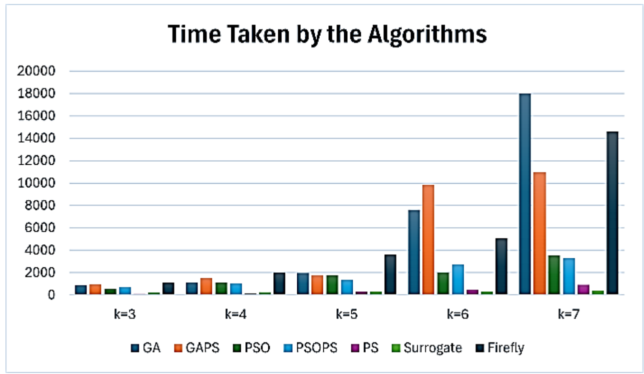


Figure 4. Time taken by the optimization algorithms.

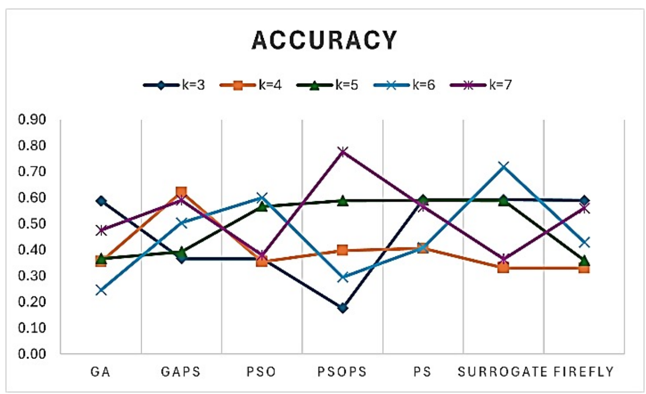


Figure 5. Accuracy values of the segmentation.

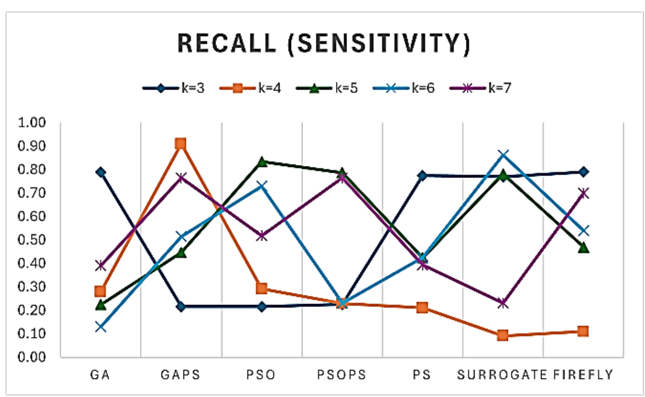


Figure 6. Recall values of the segmentation.

and surrogate algorithms obtained their highest accuracy values when k = 6. And PSOPS obtained its highest accuracy value when k = 7.

However, the highest accuracy value from the experiment is obtained by PSOPS algorithm with a value of 78%, followed by surrogate algorithm with a value of 72%. And then followed by GAPS with an accuracy of 62%.

PSOPS obtained its highest accuracy value when k = 7. However, the highest accuracy value from the experiment was obtained the by PSOPS algorithm with a value of 78%, followed by the surrogate algorithm with a value of 72%. And then followed by GAPS with an accuracy of 62%. In Figure 6, the recall values of the segmentation are observed. Recall, also known as sensitivity, gives the number of positive values that are correctly classified as positive. Hence, recall measures the algorithms' segmentation results in detecting positive samples when compared with the ground truth image. From Figure 6, we observed that GA, PS and firefly algorithms have their highest recall values when k = 3. GAPS has its highest recall value when k = 4. Both PSO and PSOPS have their highest recall values when k = 5. Lastly, the surrogate algorithm has its highest recall value when k = 6. The highest recall value from the experiment was obtained by GAPS with a score of 91%, followed by the surrogate algorithm with a value of 86%, and then followed by PSO with a recall of 83%.

Figure 7 gives the specificity values of the segmentation as compared with the ground truth image. The specificity value shows the ability of algorithms to predict a true negative when compared with the ground truth image. From Figure 7, GA and firefly algorithms have their highest specificity values when k = 3. GAPS has its highest specificity value at k = 4 and k = 7. PSO and surrogate algorithms have their highest specificity values at k = 6, while PSOPS has its highest specificity value at k = 7.

Lastly, PS has its highest specificity value at k = 5. The highest specificity value of the experiment was obtained by PSOPS with a value of 78%, followed by the surrogate algorithm with a value of 68%, and then, by PS with a specificity of 63%. The precision values of the algorithms when compared with the ground truth are given in Figure 8. Precision, also known as the positive predictive value (PPV), is the ratio of the areas in the image that the algorithm correctly classified as positive to the total number of classified positive areas.

From Figure 8, the following algorithms - GA, PS, and firefly - obtained their highest precision value at k = 3. GAPS has its highest precision value at k = 4, PSO has its highest precision value at k = 5 and k = 6, while PSOPS has

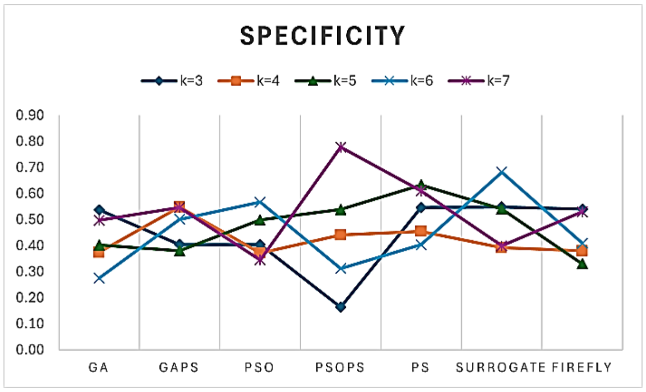


Figure 7. Specificity values of the segmentation.

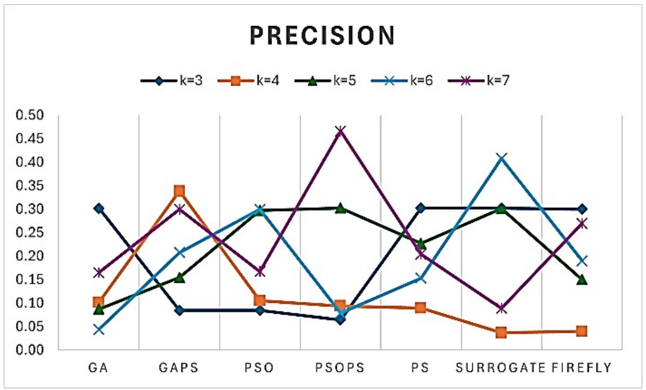


Figure 8. Precision values of the segmentation.

its highest precision value at k = 7. Lastly, the surrogate algorithm has its highest precision value at k = 6. From the experiment, the highest precision value was achieved by PSOPS with a score of 47%, followed by surrogate with a score of 41%. And then, followed by GAPS with a value of 34%.

Table 7 gives an overview of the best values of the four metrics used. From the table, the PSOPS algorithm, with k = 7, obtained the highest accuracy, specificity, and precision values. However, the recall value was slightly lower than the top three. The surrogate algorithm, with k = 6, had consistently maintained its second position as observed from the table. The GAPS, with k = 4 had the third best accuracy value, the first best recall value, and the third best precision value. The PSO (with k = 5) and

Table 7. Overview of the optimization algorithm performances.

Performances	Accuracy	Recall	Specificity	Precision
1st	PSOPS	GAPS	PSOPS	PSOPS
2nd	Surrogate	Surrogate	Surrogate	Surrogate
3rd	GAPS	PSO	PS	GAPS

PS (with k = 5) algorithms had the third best recall and specificity values, respectively.

The original image used and the ground truth image are shown in Figure 9. The results of the segmentations done by the algorithms, as listed in Table 7, are shown in Figure 10 and 11. The best three algorithms as observed from the experiments are PSOPS, surrogate and GAPS. To rank the performances of these algorithms, based on the number of times they appear in the top three and the time taken for these algorithms to achieve the observed values, the best performing algorithms, in descending order are surrogate, PSOPS, and GAPS.

Figure 9. Original X-ray image (left) and the ground truth image (Nikhil, 2019).

Figure 10. Image segmentation by PSOPS, surrogate and GAPS algorithms.

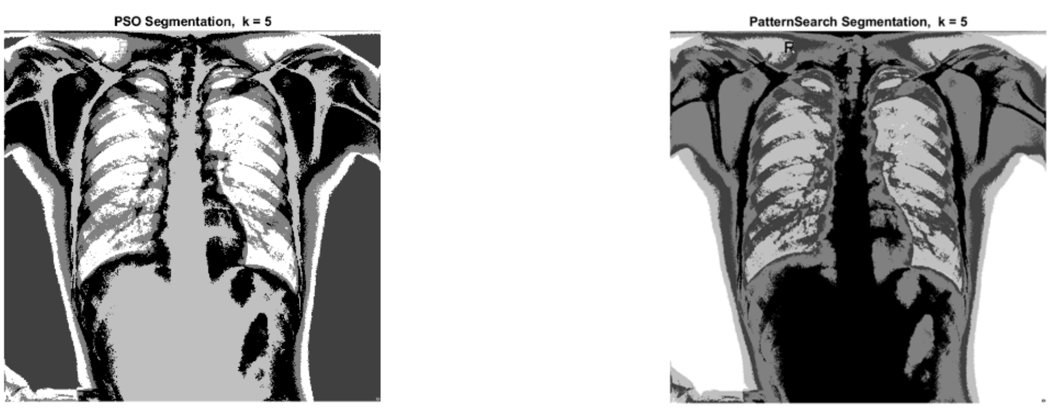


Figure 11. Image segmentation by PSO and PS Algorithms.

6. Conclusions and Future Directions

This study reviewed some optimization algorithms currently employed in the process of detecting TB in medical images. The review indicated that the two optimization algorithms most used for image segmentation are ACO and PSO, whereas for feature selection they are GA and PSO, and lastly, in the case of tuning the hyperparameters of DL models, they are GA and Bayesian optimization. Objective 1 is hereby addressed in that section.

Objective 2 was addressed by considering an illustrative example using clustering-based segmentation on a TB image where we implemented PSO, GA, PS, surrogate, PSOPS, GAPS and the firefly algorithm. We utilized these algorithms to segment the original TB image, without the use of either a classifier or a deep learning model. The results indicated that the following optimization algorithms - surrogate algorithm, PSOPS and GAPS - were most appropriate. As observed from the results (see Table 7), the hybridization of PSO and PS (called PSOPS) performed better than PSO or PS used separately. Also, the hybridization of GA and PS (called GAPS) performed better than GA or PS used separately. In so doing, we have illustrated in this instance that the hybridization of algorithms could provide better performance and hence should also be considered.

The review and the results of this study have given insight into some future directions that research in this area could take, which allowed us to address objective 3. Firstly, most of the comparisons done in the literature are those in which a methodology employing an optimization approach is compared to methodologies that do not; see, for example, the studies in (Osman et al., 2010; Kanesamoorthy & Dissanayake, 2021; Elveren & Yumusak, 2011; Yusoff et al., 2021; Sugirtha & Murugesan, 2017; Priya, 2022b; Simi Margarat et al., 2022). This provides limited insight into the actual performance of different optimization algorithms. We argue that it is necessary to compare different optimization algorithms within specific problem contexts to determine which algorithm performs better on a particular dataset for TB detection or diagnosis. The article (Anu Priya et al., 2021) is one such example, where the authors compared three machine learning optimization algorithms (namely SGD, Adam, and RMSprop).

However, the study was excluded from this review because these algorithms belong to the gradient-descent class, which explores the search space using the gradient of the objective function. A broader study is needed to compare different evolutionary or metaheuristic algorithms.

Secondly, since DL is one of the state-of-the-art tools for researchers in medical imaging, it is important that a thorough analysis of appropriate optimization algorithms be conducted for use in the hyperparameter tuning of these DL models. This can be done through a rigorous comparison of the performances of a variety of optimization algorithms. Lastly, while some studies (Priya, 2022a; Askarali & Fredrik, 2024; Singh et al., 2024) in this review employed hybrid optimization algorithms, more research is still necessary in this aspect, given the variety of hybrid methods available. The performance of hybridized optimization algorithms could be considered as a means of improving current classifiers or DL models for TB detection.

Regarding the limitations of this study, we primarily concentrate on evolutionary and meta-heuristic optimization algorithms in the stages of TB detection, with limited references to traditional gradient descent-based methods. This focus restricts the scope of this review in comparing the performance of a broader range of optimization techniques in TB detection. Also, this review largely emphasizes CXR images, with minimal coverage of other imaging modalities such as CT scans, sputum smear images, and microscopic slide images. This focus may overlook insights from diverse imaging techniques that could enhance TB detection. Future research could include other imaging modalities in TB diagnosis/detection.

In conclusion, we hope practitioners can utilize the insights from this study to select the most suitable optimization algorithm for tasks such as image segmentation, feature selection, and hyperparameter tuning, depending on their specific requirements. By integrating these optimization techniques into their workflows, researchers and healthcare professionals can develop more accurate, efficient, and scalable TB detection systems. Researchers and clinicians can use these recommendations to design more comprehensive studies and validate the effectiveness of different optimization approaches in real-world clinical settings. This will not only enhance diagnostic capabilities but also help reduce the global burden of TB by enabling early detection and timely intervention.

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Conflict of Interest

The authors declare that they have no conflicts of interest to disclose.

Appendix A.

CXR Image datasets for tuberculosis detection

- Tuberculosis chest X-rays (Shenzhen): https://www.kaggle.com/datasets/raddar/tuberculosis-chest-xrays-shenzhen
- Tuberculosis chest X-rays (Montgomery): https://www.kaggle.com/datasets/raddar/tuberculosis-chest-xrays-montgomery
- ImageCLEF 2020: https://www.imageclef.org/datasets
- Chest X-ray dataset for lung segmentation: https://data.mendeley.com/datasets/8gf9vpkhgy/2
- TB Portals: https://tbportals.niaid.nih.gov/download-data
- TB chest X-ray database: https://ieee-dataport.org/documents/tuberculosis-tb-chest-x-ray-database#files
- TBX 11: https://gts.ai/dataset-download/tbx-11/
- TBImages Place: https://www.tbimages.ufam.edu.br/
- TB and pneumonia chest X-ray datasets: https://github.com/vbookshelf/List-of-TB-and-Pneumonia-Datasets

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