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A Systematic Review of the Accuracy of Machine Learning Models for Diagnosing Pulmonary Tuberculosis: Implications for Nursing Practice and Implementation

Kewalin Pongsuwun[1] | Wimolrat Puwarawuttipanit[1] | Sunisa Nguantad[2] | Benjakarn Samart[3] | Udsaneyaporn Pollayut[4] | Pham Thi Thanh Phuong[5] | Suebsarn Ruksakulpiwat[1]

[1]Department of Medical Nursing, Faculty of Nursing, Mahidol University, Bangkok, Thailand | [2]Department of Nursing Siriraj Hospital, Faculty of Medicine Siriraj Hospital, Mahidol University, Bangkok, Thailand | [3]Lerdsin Hospital, Bangkok, Thailand | [4]Department of Medical and Surgical Nursing Kuakarun, Faculty of Nursing, Navamindradhiraj University, Bangkok, Thailand | [5]Faculty of Nursing, Hai Duong Medical Technical University, Hai Duong city, Hai Duong, Vietnam

Correspondence: Suebsarn Ruksakulpiwat (suebsarn25@gmail.com)

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ABSTRACT

This systematic review evaluates the application of machine learning (ML) models for diagnosing pulmonary tuberculosis and their potential to inform nursing practice and implementation strategies. Studies published between 2019 and 2024 were systematically identified through searches in Scopus, PubMed, Medline, ScienceDirect, CINAHL Plus with Full Text, Clinical Key, Ovid, EMBASE, and Web of Science. The review adhered to PRISMA guidelines, with rigorous inclusion and exclusion criteria applied. A total of 734 records were retrieved, with 18 duplicates removed, leaving 716 articles for screening. Of these, 699 did not meet the inclusion criteria. Full-text review of 17 articles excluded five studies, resulting in 12 studies included in the final analysis. The synthesis revealed five key diagnostic features commonly utilized in ML models: chest x-rays, computed tomography scans, sputum smear images, human exhaled breath, and personal information. Among 13 identified ML algorithms, convolutional neural networks were the most frequently employed due to their superior performance in analyzing imaging data. These findings emphasize the transformative potential of ML technologies to enhance early tuberculosis diagnosis, optimize nursing practice, and improve clinical outcomes.

1 | Background

Tuberculosis (TB) is an infectious disease caused by the bacterium *Mycobacterium tuberculosis*, primarily affecting the lungs. It spreads through the air when individuals with pulmonary TB cough, sneeze, or spit, and inhaling even a small number of these germs can result in infection (WHO 2024a). The global incidence of TB declined from 2000 to 2021; however, differences in TB risk factors persist across countries and regions (Bai and Ameyaw 2024). In 2023, a worldwide total of 10.8 million people developed TB, with 1.09 million deaths reported. Of all documented TB cases, 6.1% involved individuals living with HIV. The majority of cases were concentrated in the WHO region of South-East Asia (45%), followed by Africa (24%) and the Western Pacific (17%). Smaller shares were observed in the Eastern Mediterranean (8.6%), the Americas (3.2%), and Europe (2.1%) (WHO 2024b).

Abbreviations: AI, artificial intelligence; CAD4TB, computer-aided detection for tuberculosis; CNN, convolutional neural network; CR, chest radiograph; CT, computed tomography; CXR, chest x-ray; GFNN, Gaussian-fuzzy-neural network; ML, machine learning; PLS-DA, partial least squares discriminant analysis; PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses; qXR, qure artificial intelligence for chest x-ray; SVM, support vector machine; TB, tuberculosis.

Summary

- Machine learning models, particularly those utilizing imaging-based features such as chest x-rays and CT scans, have demonstrated high diagnostic accuracy for pulmonary tuberculosis, with convolutional neural networks being the most effective algorithms for analyzing imaging data.
- The integration of multimodal approaches, combining imaging, clinical, and demographic data, expands diagnostic possibilities and presents practical solutions for addressing diagnostic challenges in resource-constrained settings.
- AI-driven diagnostic tools provide nurses and healthcare providers with enhanced capabilities for early detection, potentially reducing tuberculosis transmission rates and improving patient outcomes. However, further research is essential to develop and validate implementation strategies tailored to diverse healthcare environments.

TB causes significant social and economic challenges for individuals and households, impacting family and community relationships, contributing to financial strain and food insecurity, and worsening the health of the affected individuals (Meghji et al. 2021; Nhassengo et al. 2024; WHO 2024c). To combat this disease, the World Health Organization (WHO) introduced the End TB Strategy (World Health Organization 2015). However, given the current pace of decline in TB incidence, achieving the WHO's goal of eradicating the TB pandemic by 2030 remains a considerable challenge.

Over the past decades, TB diagnostics have advanced significantly, transitioning from traditional culture-based methods to faster, more accurate, and less labor-intensive tests. These include immune-based diagnostics, x-rays, clinical symptom assessment, cough detection, and molecular techniques such as phenotypic and genotypic methods, next-generation sequencing, and both sputum- and non-sputum-based molecular diagnostic approaches (Kontsevaya et al. 2024).

Machine learning (ML), a subset of artificial intelligence (AI), involves algorithms that enable computers to learn from data and make decisions without explicit programming. AI has emerged as a powerful tool with extensive applications across healthcare, where ML techniques, such as supervised learning, unsupervised learning, and neural networks, are being used to analyze complex medical data, including diagnostic imaging and patient outcomes (Shaheen 2021; Santamato et al. 2024). This growing adoption of AI technologies in healthcare highlights their potential to significantly transform diagnostic practices, providing faster and more accurate results, which is especially relevant for conditions like pulmonary TB. The integration of AI in healthcare can enhance disease diagnosis, optimize treatment selection, improve clinical laboratory testing, and assist clinicians in decision-making (Alowais et al. 2023). AI has been applied in various diagnostics, such as neural network algorithms for diagnosing ischemic stroke (Ruksakulpiwat et al. 2023), digital platforms for skin disease diagnosis (Aboulmira et al. 2024), automated analysis of slit-lamp images for eye diseases (Yonehara et al. 2025), and AI-driven volume analysis for early Alzheimer's disease detection (Salokhiddinov and Pirnazarov 2023).

The potential of AI in pulmonary TB management is vast, offering promising opportunities to enhance patient care. Recent studies have shown that AI can effectively diagnose TB, such as the use of autofluorescence spectroscopy of blood plasma combined with an artificial neural network algorithm for rapid detection of latent and active TB (Yue et al. 2024). Employing a combination of diagnostic methods and incorporating advanced techniques provides the most effective outcomes for diagnosing TB. Improving test quality, accessibility, and the integration of advanced technologies can enhance the sensitivity, efficiency, and accuracy of TB diagnosis (Zaporojan et al. 2024).

For nurses, the implications of these advancements are profound. The incorporation of ML and AI-based diagnostic tools in clinical practice can empower nurses to make timely, accurate assessments and treatment decisions. This can lead to better patient management, reduced transmission rates, and improved health outcomes. Nurses play a vital role in patient education, monitoring, and the application of clinical data to guide patient care. AI-powered diagnostic tools can support nurses by providing comprehensive insights, streamlining diagnostic processes, and enhancing decision-making capabilities, ultimately improving patient care quality.

ML models demonstrate significant potential for enhancing the accuracy of pulmonary TB diagnosis, offering innovative tools to support clinical decision-making and improve patient outcomes. This systematic review evaluates the effectiveness and reliability of ML-based classification methods for pulmonary TB diagnosis. Accordingly, we aim to systematically review the evidence on the application of these methods in improving diagnostic accuracy for pulmonary TB.

2 | Objective

To systematically review and synthesize existing evidence on the application of ML-based methods for diagnosing pulmonary TB, with the aim of guiding implications for nursing practice and implementation.

3 | Methods

3.1 | Identify Relevant Studies

In this systematic review, we adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al. 2021) to detail the processes of literature identification, screening, exclusion, and inclusion. A systematic search was conducted across nine electronic databases—Scopus, PubMed, Medline, ScienceDirect, CINAHL Plus with Full Text, Clinical Key, Ovid, EMBASE, and Web of Science—to identify studies published between 2019 and 2024 that evaluated ML-based classification systems for diagnosing pulmonary TB. The timeframe from 2019 to 2024 was selected to ensure the inclusion

TABLE 1 | Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
• Studies included adults with Pulmonary tuberculosis (18 years or older) • The studies aimed to apply machine learning for the diagnosis of tuberculosis patient • Studies published in the English language • Studies published between 2019 and 2024 • Accessibility of the full text of articles in detail	• All types of reviews, unpublished master's theses, and doctoral dissertations without the peer review process • Involve animal sample • Conference proceedings, abstracts, protocol, letter to the editor, brief report, or statement paper

of the most recent advancements in ML technologies, especially those applied in healthcare. Over the past 5 years, substantial developments and innovations in ML for disease diagnosis, including TB, have occurred. This period captures the rapid evolution of these technologies, making studies from this timeframe particularly pertinent to our review. Boolean phrases were used to combine search terms such as "Tuberculosis Patient," "Artificial Intelligence," "Diagnosis," and "Accuracy." To supplement the database search, the reference lists of included studies were manually reviewed to identify additional relevant literature. All references were systematically managed using EndNote for organization and subsequent analysis.

3.2 | Study Selection

Titles and abstracts were initially reviewed to identify potential studies meeting the eligibility criteria. Subsequently, the full texts of selected studies were assessed to ascertain their relevance to the review's objectives. Inclusion criteria were then applied to ensure that only studies relevant to our research question were included, while exclusion criteria were employed to eliminate literature not aligned with the scope of the review (Table 1).

3.3 | Quality Assessment

The purpose of the quality assessment is to appraise the methodological soundness of each study and examine how effectively it has mitigated potential biases in its design, implementation, and analysis. In this review, two independent researchers evaluated the methodological quality of the selected studies using the Joanna Briggs Institute (JBI) critical appraisal tools, which are tailored for use in systematic reviews (JBI 2024).

3.4 | Data Extraction

The standardized chart for data extraction (Table S1) developed for this review included the following data for each study: References, Published year, Country, Settings, Target population, Study design, Sample size (*n*), Age of participants (mean ± SD), Quality assessment, Purpose of Study, Main Outcome (Accuracy diagnosis in TB patient), Algorithms, Features, and Implications/Suggestions.

3.5 | Data Synthesis

In this review, we utilized the convergent integrated analysis framework outlined by the JBI for systematic reviews to synthesize data from the selected studies (Moola et al. 2017). This approach focused on extracting overarching themes by examining both shared and differing elements within the primary findings. Furthermore, sub-themes were developed to emphasize nuanced details of the results, aligning with methodologies frequently employed in qualitative thematic analysis.

4 | Results

4.1 | Search Results

An initial literature search identified 734 articles, with 82 retrieved from Clinical Key, 34 from Web of Science, 176 from PubMed and Medline, 189 from ScienceDirect, 16 from CINAHL Plus with Full Text, 204 from Scopus, 24 from Ovid, and 9 from EMBASE. No additional records were identified from other sources. After removing duplicates, 716 unique references were screened. Of these, 699 were excluded based on the inclusion and exclusion criteria during the title and abstract screening phase. This process left 17 articles for full-text review, during which 5 were excluded for reasons including publication before 2013, a lack of relevance to ML in TB diagnosis, being reviews or mini-reviews, or unavailability of the full text. Ultimately, 12 articles were included for final screening and quality appraisal. The literature retrieval process followed PRISMA guidelines, as in Figure 1.

4.2 | Description of Included Studies

In each of the included studies in our review, patients' ages were reported differently, such as mean and standard deviation, range, median, or interquartile range. Furthermore, all included studies involved both male and female participants in their analysis (Table S1). Table 2 shows that the included studies were published in 2024 (n = 2 studies, 16.7%), 2023 (n = 1 study, 8.3%), 2022 (n = 4 studies, 33.3%), 2021 (n = 3 studies, 25.0%), and 2019 (n = 2 studies, 16.7%). The studies were conducted in various countries, including China (n = 3 studies, 25.0%), not a specific country (n = 2 studies, 16.7%), the USA (n = 1 study, 8.3%), Colombia (n = 1 study, 8.3%), India (n = 1 study, 8.3%), Nepal and Cameroon (n = 1 study, 8.3%), South Africa (n = 1 study, 8.3%), a combined US and China sample (n = 1 study, 8.3%), and Saudi Arabia (n = 1 study, 8.3%). One study (8.3%) had a sample size ranging from 50 to 100. Two studies (16.7%) included participants numbering between 101 and 500. Four studies (33.3%) had sample sizes ranging from 501 to 1000. One study (8.3%) had a sample size between 1001 and 2000. Two studies (16.7%) included more than 2000 participants, while two (16.7%) did not specify the sample size. The

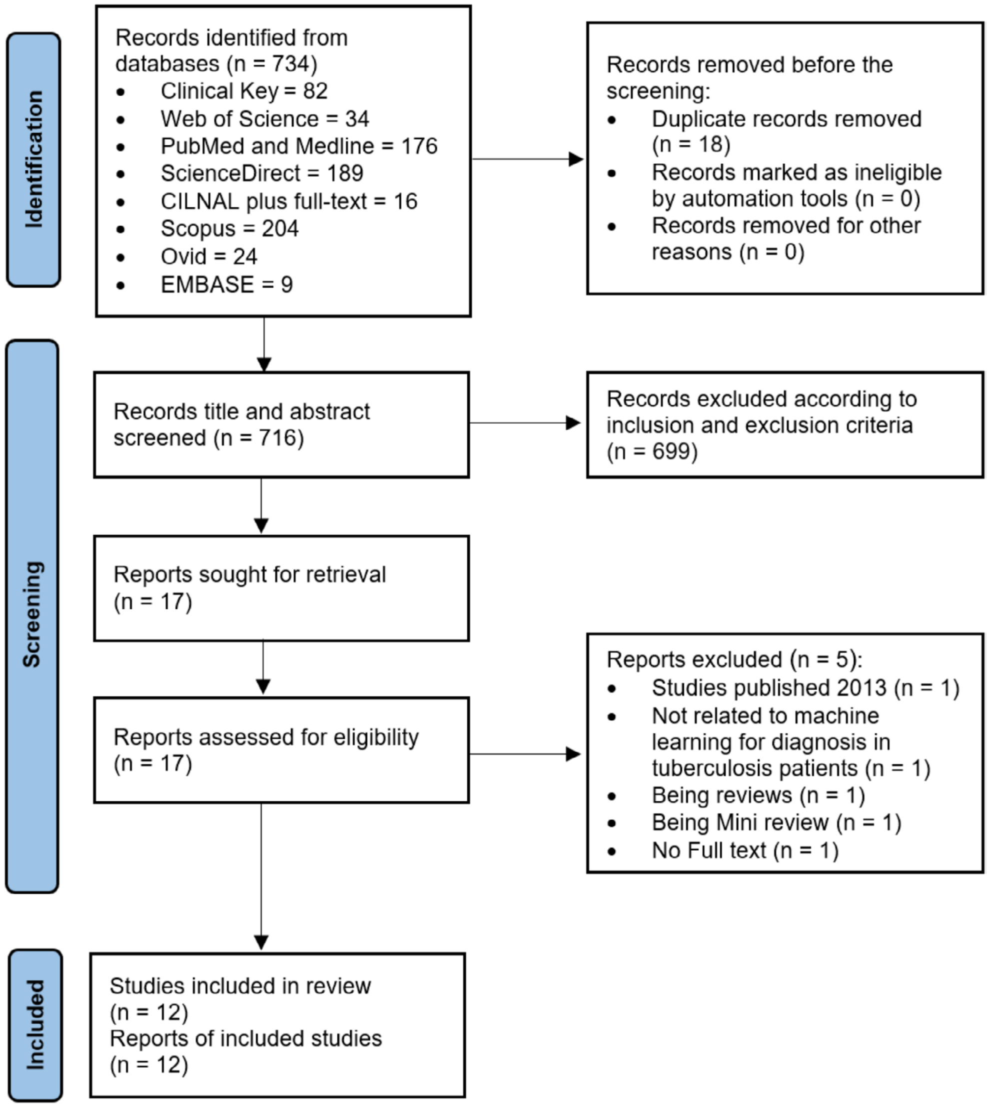

FIGURE 1 | A flow chart diagram displays the selection method of qualified studies. Adapted from Page et al. (2021).

target population for all included studies consisted of patients with pulmonary TB ($n=12$ studies, 100%).

4.3 | Assessment of Methodological Quality

The methodological quality of the included studies was evaluated using the JBI critical appraisal checklist (JBI 2024). The results show that the methodological quality content was reported in the included studies (average of 80.02%). Detailed information regarding the quality assessment for each study can be found in Table S1.

4.4 | Characteristics of Included Studies by Features

Data set, algorithm, and features are considered the architectures of an ML model. Features are essential components of a model, as they demonstrate the correlation between the target variable and the attributes that influence the model's predictions and performance. In the 12 included studies, a total of five main features were reported. Notably, one study may use more than one feature. Chest radiographs (CRs) or chest x-rays (CXRs) were the most commonly included feature in the AI algorithms ($n=5$ studies, 41.5%) (Ejiyi et al. 2024; Han et al. 2022; Nijiati et al. 2021; Qin et al. 2019; Sharma et al. 2021). This was followed by chest computed tomography (CT) scans ($n=4$ studies, 33.3%) (Hrizi et al. 2022; Huang et al. 2023; Yan et al. 2022; Zhang et al. 2024). One study each reported using other features, including information such as sex, age, population type, city location, HIV/AIDS status, and antiretroviral treatment status (8.3%) (Orjuela-Cañón et al. 2022), sputum smear microscopic images (8.3%) (Mithra and Sam Emmanuel 2021), and human exhaled breath (8.3%) (Beccaria et al. 2018). Details of these features can be found in Figure 2.

4.5 | The Optimal Results of Included Studies by the Algorithm

Our study identified 13 different types of AI algorithms that demonstrated effectiveness in diagnosing TB. Table 3 presents the optimal results of the included studies, categorized by algorithm type.

TABLE 2 | The characteristics of the included studies.

Characteristic	Number[a]	Percentage (%)
Publication year		
2024	2	16.7
2023	1	8.3
2022	4	33.3
2021	3	25.0
2019	2	16.7
Country		
China	3	25.0
Not specific	2	16.7
USA	1	8.3
Columbia	1	8.3
India	1	8.3
Nepal and Cameroon	1	8.3
South Africa	1	8.3
US and China	1	8.3
Saudi Arabia	1	8.3
Total sample size (*n*)		
50–100	1	8.3
101–500	2	16.7
501–1000	4	33.3
1001–2000	1	8.3
> 2000	2	16.7
Not applicable	2	16.7
Target population		
Pulmonary tuberculosis	12	100

[a]The number of included studies.

Convolutional neural networks (CNNs) were the most commonly used algorithm for TB diagnosis, capable of identifying patterns in CXRs and CT scans ($n=5$ studies, 41.5%) (Ejiyi et al. 2024; Han et al. 2022; Nijiati et al. 2021; Huang et al. 2023; Zhang et al. 2024). Support vector machines (SVMs) were used in four studies ($n=4$ studies, 33.3%) (Sharma et al. 2021; Hrizi et al. 2022; Orjuela-Cañón et al. 2022; Beccaria et al. 2018) and were effective with various features, excluding sputum smear microscopic images. Decision Trees were utilized in two studies ($n=2$ studies, 16.7%) (Sharma et al. 2021; Orjuela-Cañón et al. 2022) and were effective for pattern recognition in CXR.

Random Forests were also used in two studies ($n=2$ studies, 16.7%) and were effective for analyzing human exhaled breath (Orjuela-Cañón et al. 2022; Beccaria et al. 2018). Deep learning was mentioned in one study ($n=1$ study, 8.3%) (Yan et al. 2022) and was used for pattern identification in CT scans. Logistic regression and multilayer perceptrons were each used in one study ($n=1$ study, 8.3%), and both were effective in identifying patterns in information (Orjuela-Cañón et al. 2022). The Naive Bayes algorithm was used in one study ($n=1$ study, 8.3%) and was effective in recognizing patterns in CXR (Sharma et al. 2021).

The computer-aided detection for tuberculosis (CAD4TB), qure artificial intelligence for chest x-ray (qXR), and Lunit INSIGHT (Lunit) algorithms were each used in one study ($n=1$ study, 8.3%) (Qin et al. 2019) and were effective for pattern recognition in CXR. The Gaussian-fuzzy-neural network (GFNN) algorithm, used in one study ($n=1$ study, 8.3%) (Mithra and Sam Emmanuel 2021), was effective for analyzing sputum smear microscopic images. Finally, the partial least squares discriminant analysis (PLS-DA) algorithm was used in one study ($n=1$ study, 8.3%) and was effective in identifying patterns in human exhaled breath (Beccaria et al. 2018).

5 | Discussion

This systematic review identified five main features in ML models for diagnosing pulmonary TB. CRs or CXR were the most frequently used features, reflecting their established role in TB detection. CT scans followed closely, demonstrating their relevance in cases requiring more detailed imaging. Additional features, such as demographic and clinical information, sputum smear microscopic images, and human exhaled breath, highlighted the potential of multimodal approaches to enrich diagnostic accuracy (Biewer et al. 2024; Ketchanji Mougang et al. 2023; Umair et al. 2020).

Among the 13 algorithms identified, CNNs were the most prevalent, showcasing their superior ability to analyze imaging features (Litjens et al. 2017; Rundo and Militello 2024). SVMs were the next most commonly employed, offering versatility across multiple feature types. Traditional methods, such as decision trees and random forests, were also observed, highlighting their continued utility in specific applications. Specialized algorithms like CAD4TB, Lunit INSIGHT, and PLS-DA demonstrated high effectiveness in niche areas such as pattern recognition in CXR and analysis of exhaled breath.

The dominance of imaging features like CRs and CT scans underscores their diagnostic importance in TB management. The preference for CNNs reflects their unparalleled capacity to manage high-dimensional data, particularly in imaging. These results align with the growing reliance on deep learning in medical diagnostics, where algorithms are trained to identify subtle patterns that may escape human observation. According to a recent study, Sarawagi et al. (2024) demonstrated that a CNN model achieved an accuracy of approximately 96.57% in detecting TB from CXR images. Moreover, when comparing this model's performance to various pretrained models, it achieved the highest accuracy. Additionally, Kim et al. conducted training and testing to assess the performance of the TSSG-CNN Model (Tuberculosis Segmentation-Guided Diagnosis) for detecting TB using x-ray images. The study reported an accuracy of 98.75%, underscoring the

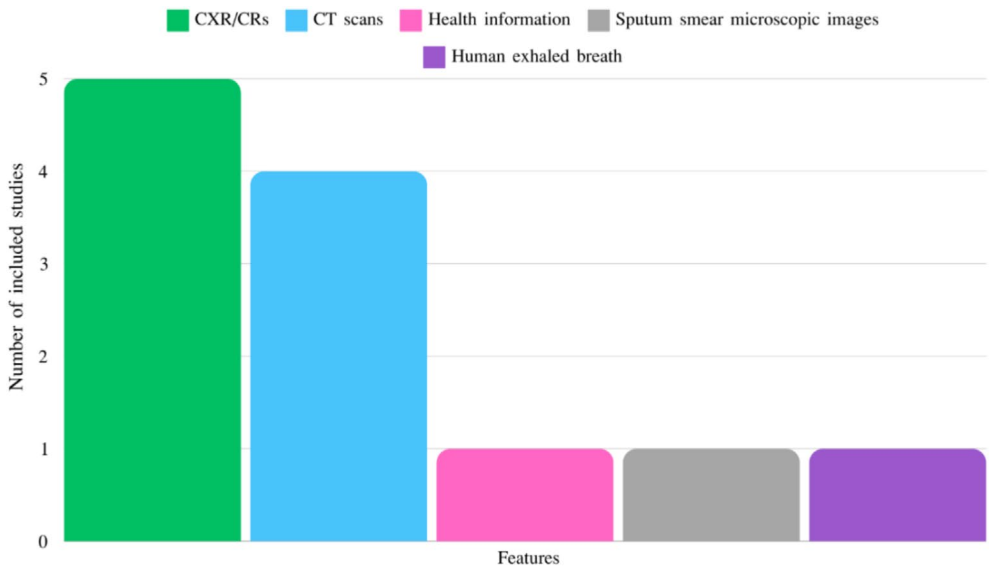

FIGURE 2 | The number of included studies by features. CR, chest radiographs; CT scan, computed tomography scan; CXR, chest x-ray.

model's potential as an effective tool for accurate and early TB diagnosis (Kim et al. 2024).

The inclusion of nonimaging features, such as demographic and clinical data, broadens the scope of TB diagnostics. This multimodal approach underscores the need for models that consider patient-specific factors, especially in settings where imaging may not be readily available. For example, the use of algorithms to analyze human exhaled breath or sputum smear microscopic images points to alternative diagnostic pathways that could complement traditional methods, especially in resource-limited environments (Orjuela-Cañón et al. 2022; Mithra and Sam Emmanuel 2021; Beccaria et al. 2018).

Consistent with previous studies, the application of wearable technology involves using AI to develop anomaly detection models based on deviations in physiological characteristics. Placing medical devices on various body parts can improve measurement accuracy for specific physiological indicators. Metrics such as heart rate, respiratory rate, oxygen saturation, temperature, sleep patterns, physical activity, and coughing are analyzed for biosignal abnormalities using wearable sensors. Especially, cough symptoms can be utilized by AI algorithms to identify and diagnose various known diseases, including pneumonia, asthma, TB, COVID-19, pertussis, and other respiratory conditions (Alqudaihi et al. 2021; Cheong et al. 2022). In addition, using AI can serve as a valuable support system for detecting stained TB bacilli through digital slides. Research indicates that AI achieved a sensitivity of 97.94% and a specificity of 83.65%, assisting in clinical decision-making and reducing the likelihood of missed diagnoses (Xiong et al. 2018).

Further, AI-based analysis of exhaled breath or detection of volatile organic compounds (VOCs) has emerged as a valuable tool for disease diagnosis, offering a noninvasive and real-time detection approach in various physiological environments. Recent studies have identified specific VOCs as biomarkers for respiratory conditions and infectious diseases, including pulmonary TB and COVID-19 infection (Chen et al. 2021; Bellarmino et al. 2024). These advancements demonstrate the transformative potential of ML in enhancing diagnostic accuracy and accessibility, particularly in resource-limited settings. By integrating these technologies into clinical workflows, healthcare professionals, including nurses, can leverage data-driven insights to improve early detection, optimize treatment strategies, and ultimately reduce the global burden of TB. This systematic review underscores the need for continued research and development to refine these tools, ensuring their practicality, affordability, and applicability across diverse healthcare settings.

5.1 | Implications for Nursing Practice and Implementation

Nurses play a critical role in implementing AI tools and algorithms into clinical practice for the diagnosis and management of TB. Their role extends from understanding and integrating AI technologies into patient care to ensuring the proper application of these tools for accurate and timely diagnoses. The use of AI in clinical settings can significantly enhance diagnostic accuracy, reduce human error, and provide data-driven insights that support evidence-based decision-making.

To effectively implement AI-based diagnostic tools, nurses must be equipped with appropriate training that covers both the technical and practical aspects of using these technologies. This includes understanding the underlying algorithms, such as CNN and SVM, as well as the interpretation of results generated by AI models. Nurses should also be familiar with patient privacy and data security protocols when handling AI-generated health data to maintain trust and comply with ethical standards.

Collaboration with multidisciplinary teams, including radiologists, data scientists, and healthcare IT specialists, is essential for the successful integration of AI into patient care. Nurses can act as liaisons between technology developers and patient care units, ensuring that the technology is user-friendly and patient-centered. Additionally, nurses must stay updated with current research and

TABLE 3 | The optimal results of included studies by the algorithm.

Algorithm/ references	CNN	Deep learning	Decision tree	Random forest	Logistic regression	Support vector machines	Multilayer perceptrons	Naive Bayes	CAD4TB	qXR	Lunit INSIGHT (Lunit)	GFNN	PLS-DA
Han et al. (2022)	X[a]												
Yan et al. (2022)		X[a]											
Orjuela-Cañón et al. (2022)			X	X	X[a]	X[a]	X[a]						
Nijiati et al. (2021)	X[a]												
Sharma et al. (2021)			X[a]			X[a]		X[a]					
Zhang et al. (2024)	X[a]												
Qin et al. (2019)									X[a]	X[a]	X[a]		
Huang et al. (2023)	X[a]												
Mithra and Sam Emmanuel (2021)												X[a]	
Ejiyi et al. (2024)	X[a]												
Hrizi et al. (2022)						X[a]							
Beccaria et al. (2018)				X[a]		X[a]							X[a]
Total included studies by algorithm (n, %)	5 41.5%	1 8.3%	2 16.7%	2 16.7%	1 8.3%	4 33.3%	1 8.3%	1 8.3%	1 8.3%	1 8.3%	1 8.3%	1 8.3%	1 8.3%
Total optimal result by algorithm (n, %)	5 100%	1 100%	1 50%	1 50%	1 100%	4 100%	1 100%	1 100%	1 100%	1 100%	1 100%	1 100%	1 100%

Abbreviations: CAD4TB, computer-aided detection for TB; CNN, convolutional neural network; GFNN, Gaussian-fuzzy-neural network; PLS-DA, partial least squares discriminant analysis; qXR, qure artificial intelligence for chest x-ray.
[a]Optimal result.

guidelines to advocate for the adoption of effective and evidence-based AI diagnostic solutions in their healthcare facilities.

Furthermore, nurses can play a significant role in ensuring that AI technologies are implemented in a way that enhances patient-centered care. They should be trained not only in the technical aspects but also in the human factors that affect the use of AI, such as communication with patients about the role of AI in their diagnosis and treatment. This will help to foster trust and acceptance of AI among patients. Nurses should advocate for the continuous evaluation of AI tools to assess their impact on patient outcomes and ensure that they are being used appropriately, ethically, and equitably. By incorporating these strategies, nurses will be crucial in ensuring that AI is integrated in ways that truly benefit both patients and healthcare providers.

5.2 | Study Limitation

This systematic review has certain limitations that warrant consideration. First, the inclusion of studies published only between 2019 and 2024 may have excluded earlier relevant research, thereby limiting the historical scope of the analysis. Potential biases in data collection processes or algorithm design were not comprehensively analyzed, which could influence the reliability, fairness, and applicability of ML models across different settings. Additionally, the absence of standardized evaluation metrics across studies posed challenges for directly comparing the performance of various ML algorithms. Moreover, the selection of English-only studies may limit the scope of the articles identified.

The review also did not explore practical implementation challenges, such as resource constraints, infrastructure requirements, and workforce readiness, which are critical factors for successfully integrating ML tools into clinical practice. Furthermore, variations in patient populations and healthcare contexts across studies limit the generalizability of the findings to diverse global environments. These limitations highlight the need for future research to address these gaps and advance the development of robust, equitable, and widely applicable ML models for diagnosing pulmonary TB.

6 | Conclusion

This systematic review underscores the significant potential of various AI algorithms in enhancing the diagnosis of TB, demonstrating that ML-based methods can improve diagnostic accuracy and clinical outcomes. The findings suggest that algorithms such as CNN and SVM are most commonly utilized and effective, particularly when applied to CRs and CT scans. The review highlights the importance of integrating these tools into clinical practice to support healthcare professionals in making timely and accurate diagnoses, ultimately leading to better patient management and outcomes.

The inclusion of AI diagnostic tools in routine clinical practice will require comprehensive training for healthcare providers, particularly nurses, who are pivotal in bridging the gap between technology and patient care. While the implementation of AI in healthcare holds immense promise, further research and development are needed to optimize these tools for broader and more varied clinical settings. As the field of AI in healthcare continues to evolve, healthcare systems must foster an environment that supports continuous education, collaboration, and adaptation to technological advancements.

6.1 | Relevance for Clinical Practice

The findings of this study highlight the potential of ML models to enhance the accuracy and efficiency of pulmonary TB diagnosis, particularly in resource-limited settings. By integrating ML-based diagnostic tools into clinical practice, nurses can support early detection, reduce diagnostic delays, and improve patient outcomes. Nursing professionals can play a crucial role in implementing these technologies by collaborating with multidisciplinary teams, ensuring the reliability of AI-assisted diagnostics, and educating patients on the benefits of ML-driven screening methods. Additionally, the adoption of ML models in nursing practice can streamline workflow efficiency, optimize resource utilization, and contribute to evidence-based decision-making in TB management.

Author Contributions

Kewalin Pongsuwun: conceptualization, investigation, writing – original draft, visualization, validation, methodology, software, formal analysis, data curation, supervision, resources. **Wimolrat Puwarawuttipanit:** conceptualization, supervision, investigation, writing – original draft, visualization, validation, methodology, formal analysis, resources, data curation. **Sunisa Nguantad:** investigation, writing – original draft, methodology, software, formal analysis. **Benjakarn Samart:** investigation, writing – original draft, methodology, software, formal analysis. **Udsaneyaporn Pollayut:** investigation, writing – original draft, methodology, software, formal analysis. **Pham Thi Thanh Phuong:** investigation, writing – original draft, methodology, software, formal analysis. **Suebsarn Ruksakulpiwat:** writing – original draft, funding acquisition, investigation, conceptualization, methodology, validation, visualization, writing – review and editing, software, formal analysis, project administration, supervision, data curation, resources.

Ethics Statement

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Supporting Information related to this article can be found in the online version.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.