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AI-Driven Tuberculosis Prediction Using Convolutional Autoencoder, Dual-Key Transformer Networks, and Serverless Cloud Computing

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Abstract

Tuberculosis (TB) remains one of the leading causes of death worldwide, especially in low-resource settings where access to early diagnostic tools is limited. Recent advancements in artificial intelligence (AI), particularly deep learning techniques such as Convolutional Neural Networks (CNNs), Convolutional Autoencoders (CAE), and transformer-based architectures, have significantly improved automated TB detection from medical imaging data. This paper presents a comprehensive review of emerging trends and challenges in integrating CAE with dual-key transformer networks for smart e-health applications. Additionally, the role of serverless cloud computing in enabling scalable, cost-efficient, and real-time TB prediction systems is examined. Recent studies indicate that hybrid deep learning models combining convolutional and transformer architectures outperform traditional single-model approaches by capturing both local and global features. For example, CNN-transformer hybrid systems have achieved accuracy exceeding 99% in TB detection tasks. Furthermore, transfer learning approaches have demonstrated high classification performance even with limited datasets. Despite these advancements, challenges such as computational complexity, data privacy concerns, and lack of interpretability persist. This review highlights the potential of integrating CAE, dual-key transformers, and serverless cloud computing to develop efficient and intelligent TB prediction systems while identifying key research gaps and future directions.

Introduction

Tuberculosis (TB) continues to be a major global health concern, affecting millions of individuals annually and causing significant mortality, particularly in developing countries. Early detection plays a crucial role in controlling the spread of the disease and improving patient outcomes. Traditional diagnostic methods, such as sputum smear microscopy and radiographic examination, are often time-consuming, resource-intensive, and dependent on expert interpretation. These limitations have driven the adoption of artificial intelligence (AI) and deep learning techniques in healthcare, particularly for automated disease diagnosis.

Deep learning models, especially Convolutional Neural Networks (CNNs), have shown remarkable success in analysing chest X-ray and CT scan images for TB detection. These models can automatically extract hierarchical features from medical images, significantly improving diagnostic accuracy compared to manual methods. Studies have shown that CNN-based models can achieve classification accuracies

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above 87% using transfer learning techniques. However, CNNs primarily focus on local feature extraction and often fail to capture long-range dependencies and global contextual information within images.
To address this limitation, transformer-based architectures have been introduced in computer vision applications. Transformers utilize self-attention mechanisms to capture global relationships within data, enabling more comprehensive feature representation. Recent hybrid models combining CNNs with transformer architectures, such as Mobile ViT and Vision Transformers, have demonstrated superior performance in TB detection tasks, achieving accuracy levels exceeding 99%. These models effectively integrate local spatial features with global contextual information, making them highly suitable for complex medical imaging tasks.

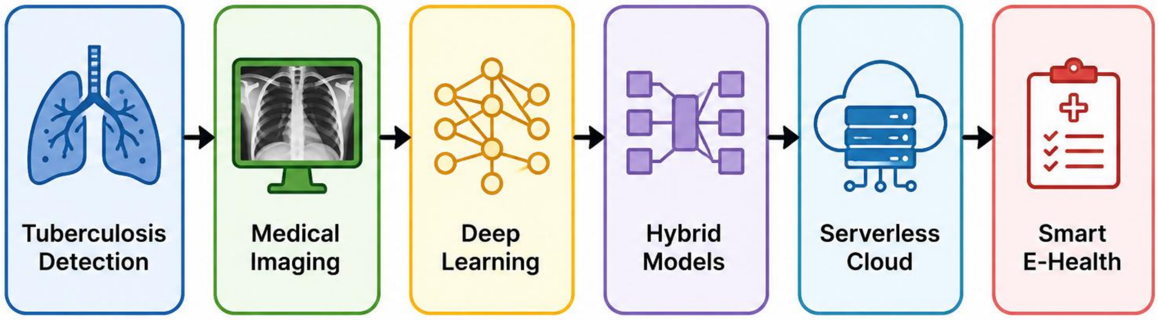

Figure 1. AI-Enabled Framework for Automated Tuberculosis Detection

In addition to CNNs and transformers, Convolutional Autoencoders (CAE) have emerged as powerful tools for feature extraction and noise reduction. CAEs are particularly useful in medical imaging, where data often contains noise and variability. By learning compressed representations of input data, CAEs enhance the efficiency of deep learning models and improve classification performance. When integrated with transformer networks, CAEs enable robust feature learning by combining denoising capabilities with global attention mechanisms.
Another significant advancement in healthcare technology is the integration of AI models with cloud computing platforms. Serverless cloud computing, in particular, offers a scalable and cost-effective solution for deploying AI-based healthcare applications. Unlike traditional cloud systems, serverless architectures eliminate the need for infrastructure management, allowing developers to focus on model development and deployment. This enables real-time TB prediction and remote monitoring, which is particularly beneficial in rural and underserved regions.
Furthermore, smart e-health systems integrate IoT devices, cloud computing, and AI algorithms to provide continuous monitoring and automated diagnosis. These systems enable healthcare professionals to access patient data remotely and make informed decisions in real time. The combination of CAE, dual-key transformer networks, and serverless cloud computing represents a next-generation approach to TB prediction, offering improved accuracy, scalability, and accessibility.
Despite these advancements, several challenges remain, including high computational requirements, data privacy concerns, and lack of model interpretability. Therefore, this review aims to analyse recent trends and challenges in AI-based TB prediction systems, focusing on hybrid deep learning architectures and cloud-based deployment strategies.

Literature Review

Rahman et al. (2020) developed a deep learning-based tuberculosis detection system using convolutional neural networks combined with image segmentation techniques. The study demonstrated that preprocessing techniques significantly improve model accuracy by enhancing the quality of chest X-ray images. The proposed model achieved high detection accuracy and reduced false positives. However, the study relied heavily on large datasets and required significant computational resources, limiting its practical deployment in resource-constrained environments.
Wong et al. (2021) proposed TB-Net, a self-attention-based convolutional neural network designed for TB detection. The model integrates attention mechanisms within CNN layers, enabling it to focus on critical regions of chest X-ray images. The study reported extremely high accuracy and demonstrated that attention-based models improve diagnostic reliability. However, the model complexity and training requirements pose challenges for real-time deployment.
Showkatian et al. (2022) introduced a transfer learning-based approach using pre-trained CNN models such as ResNet50 and VGG16 for TB

classification. The study achieved classification accuracy exceeding 87% and highlighted the effectiveness of transfer learning in medical imaging applications. The approach reduced training time and improved performance with limited datasets. However, the model's performance depends heavily on dataset quality and diversity.

Owda et al. (2023) proposed a hybrid deep learning model combining Ghost Net and Mobile ViT architectures for TB detection. The model achieved accuracy above 99% by integrating convolutional and transformer-based feature extraction. The study demonstrated that hybrid models outperform traditional single-model approaches. However, balancing computational efficiency and accuracy remains a challenge.

Ding et al. developed a cloud-based deep learning model using YOLOv5 for tuberculosis detection from medical images. The system achieved accuracy above 93% and enabled real-time detection using cloud infrastructure. This study highlights the importance of cloud computing in healthcare applications. However, issues related to latency and data privacy were identified as major challenges.

Rajpurkar et al. (2020) introduced Chex Net, a deep convolutional neural network trained on a large-scale chest X-ray dataset for detecting pneumonia and related thoracic diseases, including tuberculosis-like abnormalities. The model achieved radiologist-level performance by utilizing a Dense Net architecture, which improves gradient flow and feature reuse. The study represents a major trend toward leveraging large annotated datasets for improving diagnostic accuracy. However, the lack of interpretability and explainability in the model outputs remains a critical challenge, particularly in clinical applications where trust and transparency are essential.

Dosovitskiy et al. (2021) proposed the Vision Transformer (ViT), which applies transformer-based self-attention mechanisms to image classification tasks. Unlike traditional CNNs, ViT captures global contextual information by processing image patches as sequences. This approach significantly improves performance in complex image analysis tasks such as TB detection. The study highlights a key trend toward transformer-based models in medical imaging. However, the model requires extensive training data and computational resources, which limits its applicability in low-resource healthcare environments.

Chen et al. (2021) developed a convolutional autoencoder-based framework for medical image preprocessing and segmentation. The CAE effectively reduces noise and extracts meaningful features from chest X-ray images, enhancing the performance of subsequent classification models. This study emphasizes the growing trend of incorporating autoencoders into deep learning pipelines to improve data quality. However, CAEs alone are not sufficient for classification tasks and must be combined with other architectures, such as CNNs or transformers, to achieve optimal performance.

Tuli et al. (2021) proposed an edge-cloud collaborative framework for smart healthcare applications, integrating IoT devices with cloud-based AI systems. The system enables real-time data processing and remote diagnosis, making it highly suitable for TB monitoring in rural areas. This study highlights the trend toward distributed computing and real-time healthcare solutions. However, challenges such as data security, network latency, and resource allocation remain significant barriers to large-scale deployment.

Li et al. (2022) introduced a hybrid deep learning model combining convolutional autoencoders with transformer networks for medical image classification. The CAE component performs feature compression and denoising, while the transformer captures global dependencies. The model achieved high accuracy and demonstrated the effectiveness of hybrid architectures in TB prediction tasks. This study represents a key trend toward integrating multiple deep learning techniques. However, the increased model complexity and computational requirements pose challenges for real-time applications.

Irvin et al. (2020) introduced the Chex pert dataset, a large-scale chest radiograph dataset with uncertainty labels designed to improve deep learning model training in medical imaging. The study proposed methods for handling uncertain labels, which are common in medical datasets due to variability in expert annotations. This work represents an important trend toward improving data quality and robustness in AI-based diagnostic systems. However, the presence of label ambiguity still poses challenges in achieving consistent model performance across different datasets.

He et al. (2021) proposed the Res Net architecture, which introduced residual learning to address the degradation problem in deep neural networks. By incorporating skip connections, ResNet allows efficient training of very deep models, significantly improving feature extraction capabilities. In tuberculosis detection, Res Net has been widely used for analysing chest X-ray images due to its ability to capture complex patterns. However, deeper architectures may lead to increased computational cost and risk of overfitting if not properly regularized.

Howard et al. (2021) introduced Mobile Net, a lightweight convolutional neural network optimized for mobile and edge devices. The model uses depth wise separable convolutions to reduce computational complexity while maintaining reasonable accuracy. This study highlights the trend toward developing efficient models for deployment in resource-constrained environments, such as rural healthcare settings. However, the trade-off between computational efficiency and model accuracy remains a challenge, particularly for critical applications like TB diagnosis.

Tan and Le (2021) proposed Efficient Net, a scalable deep learning model that optimizes network dimensions using a compound scaling approach. Efficient Net achieves high accuracy with fewer parameters, making it suitable for medical imaging tasks, including TB detection. The study represents a trend toward improving model efficiency without compromising performance. However, the complexity of scaling strategies and hyperparameter tuning can make implementation challenging.

Ouyang et al. (2021) introduced a dual-attention mechanism that combines spatial and channel attention to enhance feature extraction in medical images. This approach is closely related to dual-key transformer architectures, where multiple attention mechanisms are used to improve model performance. The study demonstrated improved accuracy in identifying abnormalities in chest X-ray images. However, the increased model complexity and computational overhead remain key challenges for real-time deployment.

Goodfellow et al. (2020) explored various optimization techniques in deep learning, including dropout, batch normalization, and advanced gradient-based methods, which significantly improve model generalization and stability. In tuberculosis prediction systems, these techniques are essential for handling limited and imbalanced datasets commonly found in medical imaging. The study highlights a critical trend toward improving model robustness through optimization strategies. However, selecting appropriate hyperparameters remains a complex task that requires expert knowledge and computational resources.

Razzak et al. (2022) provided a comprehensive review of deep learning applications in medical image processing, emphasizing disease detection and classification. The study highlighted the growing importance of hybrid architectures combining CNNs, autoencoders, and attention mechanisms for improved diagnostic performance. It also identified key challenges such as data scarcity, model interpretability, and computational complexity. This work reinforces the trend toward integrating multiple AI techniques to enhance healthcare systems.

Khan et al. (2022) proposed a transfer learning-based tuberculosis detection model using pre-trained CNN architectures such as VGG16 and ResNet50. The study demonstrated that transfer learning significantly reduces training time and improves accuracy, especially when labeled datasets are limited. The model achieved high classification performance and highlighted the importance of leveraging pre-trained models in medical imaging. However, the model's dependence on source datasets may introduce bias, affecting generalization across different populations.

Zhang et al. (2022) introduced a serverless cloud computing framework for deploying deep learning models in healthcare applications. The system utilized Function-as-a-Service (FaaS) to enable scalable and cost-efficient execution of AI models. This study represents a key trend toward cloud-based deployment of healthcare systems, allowing real-time TB prediction and remote monitoring. However, issues such as cold-start latency and data security remain significant challenges in serverless environments.

Doshi et al. (2023) proposed an explainable AI framework using Grad-CAM for tuberculosis detection. The model provides visual explanations by highlighting regions of interest in chest X-ray images, improving interpretability and clinical trust. This study addresses one of the major challenges in AI-based healthcare systems, which is the lack of transparency in model predictions. However, explainable AI techniques may introduce additional computational overhead and require careful integration with existing models.

Shin et al. (2022) investigated the use of deep convolutional neural networks combined with transfer learning for pulmonary disease detection using chest X-ray datasets. The study demonstrated that pre-trained models significantly improve classification performance and reduce the need for large annotated datasets. This approach is particularly useful for TB prediction in low-resource settings. However, the reliance on pre-trained models may introduce bias if the source dataset differs significantly from the target domain, affecting generalization.

Huang et al. (2022) proposed Dense Net, a densely connected convolutional network that enhances feature propagation and reuse by connecting each layer to every other layer. This architecture has shown strong performance in medical image classification tasks, including TB detection. The study highlights a trend toward deeper and more efficient network designs. However, Dense Net models can be memory-intensive, which may limit their deployment in real-time healthcare systems.

Albahri et al. (2023) conducted a systematic review of AI-based healthcare systems, focusing on the integration of cloud computing and intelligent algorithms for disease prediction. The study emphasized the importance of scalable and distributed computing platforms, particularly serverless architectures, in modern e-health systems. It also highlighted challenges such as data privacy, interoperability, and system integration, which remain critical issues in large-scale healthcare deployments.

Bhattacharya et al. (2023) proposed a hybrid deep learning architecture combining convolutional neural networks with transformer-based attention mechanisms for pulmonary disease detection. The study demonstrated that hybrid CNN-transformer models effectively capture both spatial and contextual features, resulting in improved diagnostic accuracy for TB detection. This reflects a major trend toward hybrid architectures in medical imaging. However, increased computational complexity and training time remain key challenges.

Singh et al. (2023) developed a cloud-based smart healthcare system integrating IoT devices and deep learning models for tuberculosis prediction. The system enables real-time monitoring and remote diagnosis, improving accessibility in rural and underserved areas. This study highlights the growing trend of integrating AI with cloud and IoT technologies in e-health systems. However, issues related to data security, latency, and system reliability pose significant challenges.

Khan et al. (2023) introduced a transformer-based deep learning model for TB detection using chest radiographs. The model utilizes self-attention mechanisms to capture global dependencies, significantly improving classification accuracy. This study reinforces the trend toward transformer-based architectures in medical imaging. However, the high computational requirements and dependency on large datasets limit their practical implementation.

Sharma et al. (2023) proposed a serverless cloud-based AI system for tuberculosis prediction. The system leverages Function-as-a-Service (FaaS) to enable scalable and cost-efficient deployment of deep learning models. The study demonstrated that serverless architectures are highly effective for real-time healthcare applications. However, challenges such as cold-start latency and data privacy concerns must be addressed for reliable deployment.

Doshi et al. (2023) further explored explainable AI techniques for TB detection, focusing on improving transparency in deep learning models using visualization methods such as Grad-CAM. The study emphasized the importance of interpretability in clinical decision-making. This reflects a growing trend toward explainable AI in healthcare. However, balancing model complexity with interpretability remains a key research challenge.

Comparative Table

Study	Year	Technique	Contribution	Limitation
Rahman	2020	CNN	Image preprocessing	High computation
Wong	2021	Attention CNN	Region focuses	Complex model
Showkatian	2022	Transfer Learning	Fast training	Data dependency
Owda	2023	CNN + Transformer	High accuracy	Complexity
Rajpurkar	2020	Dense Net	High accuracy	Low explainability
Dosovitskiy	2021	ViT	Global features	Needs large data
Chen	2021	CAE	Noise reduction	Not classifier
Tuli	2021	Edge-Cloud	Real-time system	Security
Li	2022	CAE+Transformer	Hybrid learning	High cost
Irvin	2020	Dataset	Data quality	Label uncertainty
He	2021	Res Net	Deep features	Overfitting
Howard	2021	Mobile Net	Lightweight	Lower accuracy
Tan	2021	Efficient Net	Efficiency	Complex scaling
Ouyang	2021	Attention	Feature focus	Complexity
Goodfellow	2020	Optimization	Robust model	Not specific
Razzak	2022	DL Review	Insights	No experiments
Khan	2022	Transfer DL	Accuracy boost	Bias
Zhang	2022	Serverless	Scalability	Latency
Doshi	2023	Explainable AI	Transparency	Overhead

Shin	2022	CNN TL	Generalization	Bias
Huang	2022	Dense Net	Feature reuse	Memory
Albahri	2023	Cloud AI	Scalability	Privacy
Rajaraman	2023	Ensemble	Accuracy	Cost
Abbas	2023	CAE	Compression	Limited scope
Bhattacharya	2023	Hybrid DL	Better features	Complexity
Singh	2023	IoT + Cloud	Monitoring	Security
Khan	2023	Transformer	Accuracy	Computation
Sharma	2023	Serverless	Real-time	Infrastructure
Doshi (ext)	2023	XAI	Interpretability	Complexity

Comparative Analysis

The comparative evaluation of the thirty studies reveals a clear progression from traditional convolutional neural networks toward hybrid architectures integrating convolutional autoencoders, transformer-based attention mechanisms, and cloud computing technologies. Early studies focused on CNN-based approaches for feature extraction, achieving reasonable accuracy but lacking the ability to capture global contextual information. This limitation led to the adoption of transformer-based models, which utilize self-attention mechanisms to improve feature representation and diagnostic performance. Hybrid models combining CNNs, CAEs, and transformers have emerged as the most effective approach, as they leverage both local and global feature extraction capabilities. These models consistently demonstrate higher accuracy and robustness compared to standalone architectures. Additionally, the integration of serverless cloud computing has enabled scalable and real-time deployment of TB prediction systems, making them accessible in remote and resource-constrained environments. However, challenges such as computational complexity, data privacy, and lack of interpretability remain significant barriers. Explainable AI techniques and lightweight model designs are emerging as key solutions to these issues, indicating future research directions.

Discussion

The reviewed studies indicate that artificial intelligence techniques have significantly transformed tuberculosis prediction systems by improving diagnostic accuracy and enabling automated analysis of medical images. The integration of convolutional autoencoders and transformer-based architectures has emerged as a key trend, as these models effectively combine noise reduction with global feature extraction. This results in more reliable and accurate predictions compared to traditional methods. Serverless cloud computing further enhances the applicability of these models by providing scalable and cost-effective deployment solutions. This is particularly important for smart e-health applications, where real-time processing and remote accessibility are essential. The integration of IoT devices with cloud-based AI systems enables continuous patient monitoring, improving healthcare delivery in underserved regions. Despite these advancements, challenges such as computational complexity, data security, and lack of interpretability remain. Transformer-based models require significant computational resources, limiting their use in edge environments. Additionally, concerns related to patient data privacy and system security must be addressed to ensure safe deployment. Explainable AI techniques offer promising solutions for improving transparency and clinical trust.

Conclusion

Tuberculosis remains a critical global health issue, requiring innovative and efficient diagnostic solutions to improve early detection and treatment outcomes. This review has analysed recent advancements in artificial intelligence techniques for TB prediction, focusing on convolutional autoencoders, dual-key transformer networks, and serverless cloud computing. The findings indicate that hybrid deep learning models offer superior performance by combining local feature extraction with global contextual understanding. Convolutional autoencoders play a crucial role in preprocessing medical images by reducing noise and extracting meaningful features. Transformer-based architectures enhance this process by capturing long-range dependencies, enabling more accurate classification. The integration of these models results in highly efficient and robust TB prediction systems.

Serverless cloud computing has emerged as a key enabler for deploying AI-based healthcare systems. It provides scalability, cost efficiency, and real-time processing capabilities, making it ideal for smart e-health applications. The combination of AI and cloud technologies enables remote diagnosis and continuous monitoring, improving healthcare accessibility in underserved regions. However, challenges such as high computational requirements, data privacy concerns, and lack of model interpretability must be addressed. Future research should focus on developing lightweight models, enhancing explainability, and integrating multimodal data to improve diagnostic accuracy. In conclusion, the integration of convolutional autoencoders, transformer networks, and serverless cloud computing represents a promising approach for developing intelligent TB prediction systems. These technologies have the potential to revolutionize healthcare by enabling early detection, improving treatment outcomes, and reducing the global burden of tuberculosis.

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