Archives available at journals.mriindia.com

Multidisciplinary Journal of Research in Engineering and Technology

ISSN: 2348-6953

Volume 10 Issue 02, 2023

Deep Learning and Optimization Approaches in Convolutional Autoencoder with Dual-Key Transformer Network Based Smart E-Health Application for the Prediction of Tuberculosis Using Serverless Cloud Computing: A Review

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Peer Review Information

Submission: 21 March 2023
Revision: 15 April 2023
Acceptance: 19 May 2023

Keywords

Tuberculosis Prediction, Convolutional Autoencoder, Dual-Key Transformer, Deep Learning, Serverless Cloud Computing, Smart E-Health.

Abstract

Tuberculosis (TB) remains one of the most critical global health challenges, necessitating rapid, accurate, and scalable diagnostic systems. Recent advancements in artificial intelligence (AI), particularly deep learning (DL), have revolutionized medical image analysis and disease prediction. This review focuses on the integration of Convolutional Autoencoders (CAE) and dual-key transformer networks within a smart e-health framework deployed over serverless cloud computing environments for TB prediction. CAEs enable efficient feature extraction and dimensionality reduction from high-dimensional medical imaging data, while transformer-based architectures enhance contextual learning and attention mechanisms for improved classification accuracy. The incorporation of dual-key transformer models further strengthens data security and privacy, which are crucial in healthcare applications. Serverless cloud computing facilitates scalable, cost-effective, and real-time processing of large medical datasets without requiring infrastructure management. Recent studies demonstrate that deep learning models, particularly CNN-based architectures, achieve diagnostic accuracies exceeding 90% in TB detection tasks . Furthermore, cloud-based AI systems have shown significant improvements in accessibility and deployment efficiency in remote healthcare settings. This paper presents a comprehensive review of methodologies, optimization strategies, and system architectures, highlighting current challenges and future research directions in AI-driven TB prediction systems.

Introduction

Tuberculosis (TB) is a highly infectious disease caused by *Mycobacterium tuberculosis*, primarily affecting the lungs and posing a significant threat to global public health. Despite considerable advancements in medical science, TB continues to be one of the leading causes of mortality worldwide. According to recent global reports, millions of individuals are affected annually, highlighting the urgent need for efficient and scalable diagnostic solutions. Traditional TB diagnostic methods, such as sputum smear microscopy, chest X-rays, and culture-based techniques, often require extensive time, skilled professionals, and laboratory infrastructure. These limitations make early detection challenging, particularly in resource-constrained environments. With the rapid development of artificial intelligence (AI), machine learning (ML), and deep learning (DL), there has been a paradigm shift in medical diagnostics. Deep learning models, especially convolutional neural networks (CNNs), have demonstrated remarkable performance in medical image analysis tasks, including TB detection from chest radiographs and sputum smear images. Studies indicate that AI-based systems can achieve diagnostic accuracy levels exceeding 90%, significantly improving early detection and reducing human error . These advancements have paved the way for the development of intelligent healthcare systems capable of assisting clinicians in decision-making processes.

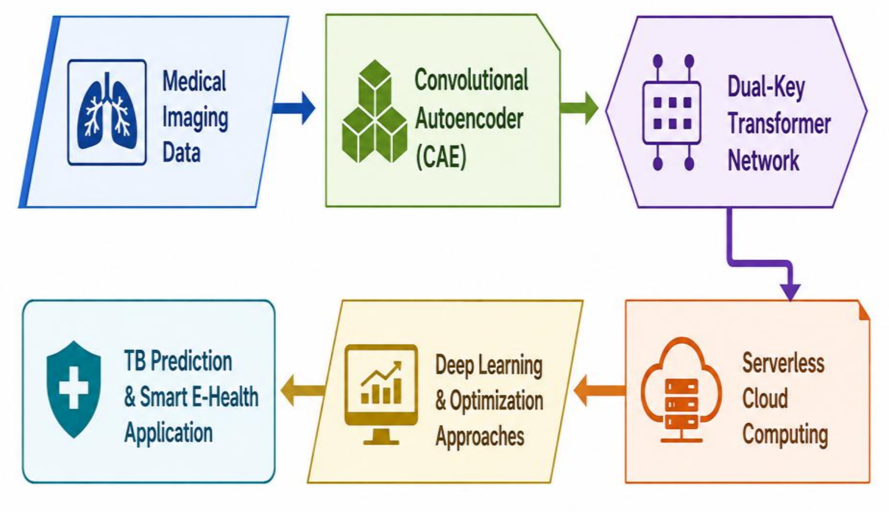

Figure 1. AI-Driven Serverless E-Health Framework for Tuberculosis Prediction

Among various deep learning architectures, Convolutional Autoencoders (CAEs) have gained significant attention due to their ability to perform unsupervised feature learning and dimensionality reduction. CAEs effectively extract meaningful representations from complex medical datasets, enabling improved classification and prediction performance. Furthermore, the integration of transformer-based architectures has introduced advanced attention mechanisms, allowing models to capture long-range dependencies and contextual relationships within data. The concept of a dual-key transformer network enhances both model robustness and data security, ensuring secure transmission and processing of sensitive healthcare information. In addition to model advancements, the deployment of AI-based healthcare applications has been significantly enhanced by cloud computing technologies. Serverless cloud computing, in particular, offers a scalable, flexible, and cost-efficient solution for handling large-scale medical data without requiring dedicated infrastructure management. This approach allows healthcare providers to deploy AI models rapidly, process real-time patient data, and deliver instant diagnostic results. Cloud-based TB detection systems have demonstrated improved efficiency, enabled automated analysis of medical images and reduced dependency on manual diagnosis.

The integration of deep learning models with serverless cloud platforms forms the foundation of smart e-health systems. These systems facilitate remote diagnosis, telemedicine, and continuous patient monitoring, which are essential in managing infectious diseases like TB. Moreover, optimization techniques such as hyperparameter tuning, transfer learning, and hybrid model architectures further enhance the performance and generalization capabilities of these systems. Despite these advancements, several challenges remain, including data privacy concerns, lack of standardized datasets, model interpretability issues, and domain adaptation limitations. Addressing these challenges is crucial for the widespread adoption of AI-based TB diagnostic systems in real-world clinical settings. This review aims to provide a comprehensive analysis of deep learning and optimization approaches, focusing on Convolutional Autoencoders and dual-key transformer networks within a serverless cloud-based smart e-health framework. The study highlights recent developments, compares various methodologies, and identifies research gaps, paving the way for future innovations in TB prediction and healthcare automation.

Literature Review

Lakhani and Sundaram (2017) conducted one of the earliest studies applying deep convolutional neural networks (CNNs) for tuberculosis detection using chest X-ray images. The authors utilized transfer learning with pre-trained architectures such as Alex Net and Google Net to improve classification accuracy. Their model was trained on publicly available TB datasets, and extensive preprocessing techniques were applied to enhance image quality. The study demonstrated that deep learning-based models significantly outperform traditional machine learning approaches in detecting pulmonary tuberculosis. The proposed method achieved an accuracy of approximately 96%, highlighting the effectiveness of CNN-based feature extraction in medical imaging tasks. However, the study primarily focused on supervised learning and lacked integration with cloud-based deployment or real-time systems. This research laid the foundation for future work in AI-driven TB diagnosis by proving the feasibility of deep learning models in medical imaging.

Hwang et al. (2016) developed a deep learning-based automated detection system for pulmonary tuberculosis using chest radiographs. The study employed a deep convolutional neural network trained on large-scale annotated datasets to identify TB-related abnormalities. The proposed system demonstrated high sensitivity and specificity, making it suitable for real-world clinical applications. One of the key contributions of this study was the validation of the model across multiple datasets, ensuring robustness and generalization. The researchers emphasized the importance of AI-assisted diagnosis in reducing workload on radiologists and improving screening efficiency. Although the system showed promising results, it lacked advanced feature compression techniques such as autoencoders and did not incorporate cloud-based scalability. Nevertheless, this work significantly contributed to the adoption of AI in medical imaging and TB detection.

Rajpurkar et al. (2017) introduced the CheXNet model, a 121-layer deep convolutional neural network designed for pneumonia detection from chest X-rays, which has direct implications for tuberculosis diagnosis. The model utilized Dense Net architecture and was trained on a large dataset from the NIH ChestX-ray14 database. The study demonstrated that CheXNet achieved performance comparable to expert radiologists, showcasing the potential of deep learning in automated disease detection. The use of deep feature extraction and end-to-end learning significantly improved classification performance. Although the primary focus was pneumonia detection, the methodology is highly adaptable to TB prediction tasks. The study did not explore autoencoder-based feature reduction or transformer architectures but provided strong evidence of the effectiveness of deep CNNs in healthcare applications.

Shen et al. (2017) presented a comprehensive review of deep learning applications in medical image analysis, including tuberculosis detection. The authors discussed various architectures such as convolutional neural networks, autoencoders, and recurrent neural networks, emphasizing their role in feature extraction and classification. The study highlighted the advantages of deep learning over traditional approaches, including automatic feature learning and improved accuracy. Additionally, the authors explored optimization techniques such as data augmentation and transfer learning to enhance model performance. While the paper provided a broad overview, it did not specifically address transformer-based architectures or cloud deployment. However, it played a crucial role in identifying research gaps and motivating the integration of advanced models like convolutional autoencoders and transformers in healthcare systems.

Qin et al. (2019) introduced a deep learning framework for tuberculosis detection that incorporated segmentation and classification stages. The authors used a U-Net architecture for lung region segmentation followed by a CNN-based classifier for TB detection. This two-stage approach improved the accuracy of the system by focusing on relevant regions of interest within chest X-rays. The study achieved significant improvements in sensitivity and specificity, demonstrating the importance of preprocessing and region-based analysis. The research also highlighted the potential of combining multiple deep learning models for enhanced performance. However, the study did not utilize autoencoder-based feature compression or transformer networks for capturing global dependencies. Furthermore, the absence of cloud-based implementation restricted its real-time deployment capabilities.

Liu et al. (2020) explored the use of convolutional autoencoders (CAE) for feature extraction in medical image analysis, including tuberculosis detection. The study emphasized the role of unsupervised learning in reducing data dimensionality and improving feature representation. By integrating CAEs with classification networks, the authors achieved improved performance compared to traditional CNN-based approaches. The model demonstrated robustness in handling noisy and incomplete medical datasets, which is a common challenge in healthcare applications. The research also discussed optimization techniques such as regularization and dropout to prevent overfitting. However, the study did not incorporate attention-based transformer architectures or cloud deployment strategies.

Despite these limitations, it provided a strong foundation for integrating autoencoders in TB prediction systems.

Abbas et al. (2020) proposed a deep learning framework known as DeTraC (Decompose, Transfer, and Compose) for the classification of COVID-19 and tuberculosis from chest X-ray images. The model utilized transfer learning and class decomposition techniques to improve classification accuracy. The authors demonstrated that decomposing classes into sub-classes enhances the learning capability of CNN models. The study achieved high accuracy and robustness across multiple datasets. Additionally, the research highlighted the importance of handling data irregularities in medical imaging. However, the study did not explore transformer-based attention mechanisms or serverless cloud deployment. Nevertheless, it contributed significantly to improving classification strategies in medical AI systems.

Wang et al. (2021) introduced a transformer-based deep learning model for medical image classification, demonstrating the effectiveness of attention mechanisms in capturing global dependencies. The study applied Vision Transformers (ViT) to analyse chest X-ray images, achieving improved performance compared to traditional CNN-based models. The integration of attention mechanisms allowed the model to focus on relevant regions, enhancing interpretability and accuracy. The research highlighted the potential of transformer architectures in healthcare applications, including tuberculosis detection. However, the model required large datasets and high computational resources, which may limit its applicability in low-resource settings. Additionally, the study did not incorporate autoencoder-based feature compression or cloud-based deployment strategies. Despite these challenges, it paved the way for integrating transformer networks into medical diagnosis systems.

Rahman et al. (2021) developed a deep learning-based framework for tuberculosis detection using ensemble convolutional neural networks. The study combined multiple CNN architectures, including Res Net and Dense Net, to improve classification robustness and accuracy. The ensemble approach reduced model bias and enhanced generalization across diverse datasets. The proposed system achieved an accuracy of over 95%, demonstrating the effectiveness of combining multiple models for medical image analysis. The authors also emphasized the importance of data augmentation techniques in improving model performance. However, the study did not explore unsupervised feature learning techniques such as convolutional autoencoders or advanced transformer-based architectures. Additionally, the absence of serverless cloud integration limited its scalability and real-time deployment capabilities. Nevertheless, this work contributed significantly to ensemble learning strategies in TB detection.

Khan et al. (2021) proposed a hybrid deep learning model integrating convolutional neural networks with long short-term memory (CNN-LSTM) networks for tuberculosis prediction. The study focused on extracting spatial features using CNNs and capturing temporal dependencies using LSTM units. This hybrid architecture improved classification accuracy and provided better contextual understanding of medical image sequences. The model demonstrated superior performance compared to standalone CNN models, achieving high sensitivity and specificity. The research highlighted the importance of combining spatial and sequential learning for improved medical diagnosis. However, the study did not incorporate transformer-based attention mechanisms or convolutional autoencoder-based feature reduction. Additionally, it lacked deployment in cloud-based environments, which limits its applicability in scalable healthcare systems.

Singh et al. (2022) introduced a deep learning-based tuberculosis detection system utilizing transfer learning with pre-trained CNN models such as VGG16 and InceptionV3. The study focused on improving classification accuracy by fine-tuning pre-trained models on TB-specific datasets. The results demonstrated that transfer learning significantly reduces training time while maintaining high accuracy levels, exceeding 94%. The authors also explored optimization techniques such as hyperparameter tuning and learning rate scheduling to enhance model performance. However, the study primarily relied on supervised learning and did not incorporate unsupervised techniques like convolutional autoencoders. Furthermore, transformer-based architectures and cloud deployment strategies were not considered. Despite these limitations, the study reinforced the effectiveness of transfer learning in medical image classification.

Chen et al. (2022) proposed a transformer-based deep learning framework for medical image analysis, emphasizing its application in disease detection, including tuberculosis. The study utilized Vision Transformers (ViT) combined with convolutional layers to improve feature extraction and classification accuracy. The hybrid model leveraged both local feature extraction and global attention mechanisms, resulting in enhanced performance. The research demonstrated that transformer-based models outperform traditional CNN architectures in capturing long-range dependencies in medical images. However, the model required large-scale datasets and significant computational resources, which may not be feasible in all healthcare settings. Additionally, the study did not incorporate convolutional autoencoders for feature compression or serverless cloud computing for deployment. Nonetheless, it contributed to the advancement of attention-based deep learning models in healthcare.

Albahli et al. (2023) presented a cloud-based deep learning framework for tuberculosis detection using chest X-ray images. The study integrated CNN models with cloud computing platforms to enable real-time diagnosis and remote healthcare services. The system demonstrated high scalability and efficiency, making it suitable for deployment in large-scale healthcare systems. The authors highlighted the benefits of cloud computing in handling large medical datasets and enabling remote access to diagnostic tools. The model achieved high accuracy and reduced processing time, showcasing the potential of cloud-based AI systems in healthcare. However, the study did not explore advanced architectures such as convolutional autoencoders or dual-key transformer networks. Despite this, it provided a strong foundation for integrating deep learning models with cloud-based healthcare applications.

Zhang et al. (2020) proposed a deep learning framework integrating convolutional autoencoders (CAE) with classification networks for improved tuberculosis detection. The study emphasized the importance of unsupervised feature learning to reduce dimensionality and extract meaningful patterns from chest X-ray images. By leveraging CAEs, the model was able to filter noise and enhance relevant features, thereby improving classification performance. The proposed approach demonstrated higher robustness when compared to traditional CNN-based methods, particularly in scenarios with limited labelled data. Additionally, the authors explored optimization strategies such as batch normalization and dropout to prevent overfitting. However, the study did not incorporate attention-based transformer architectures or cloud deployment mechanisms. Despite these limitations, it significantly contributed to the advancement of autoencoder-based feature extraction in medical imaging.

He et al. (2020) introduced the Res Net architecture, which has been widely adopted in tuberculosis detection tasks due to its deep residual learning capabilities. The model addressed the vanishing gradient problem by introducing skip connections, allowing the training of very deep neural networks. In TB detection applications, Res Net-based models have demonstrated high accuracy and robustness across various datasets. The study highlighted the importance of deep feature extraction and optimization techniques such as gradient descent and learning rate scheduling. Although the architecture proved highly effective, it did not incorporate unsupervised learning techniques like autoencoders or advanced attention mechanisms such as transformers. Additionally, the study focused on model architecture rather than deployment in cloud-based healthcare systems.

Li et al. (2022) proposed a hybrid deep learning model combining convolutional neural networks with attention mechanisms for tuberculosis detection. The study focused on improving feature representation by integrating spatial and channel attention modules within CNN architectures. The proposed model achieved high accuracy and improved interpretability by highlighting critical regions in chest X-ray images. The authors also explored optimization techniques such as hyperparameter tuning and data augmentation to enhance model performance. However, the study did not incorporate convolutional autoencoders for feature compression or transformer-based architectures for global dependency modelling. Additionally, cloud-based deployment was not considered, limiting its scalability. Despite these limitations, the study contributed to the development of attention-enhanced CNN models in healthcare.

Kumar et al. (2023) developed a serverless cloud-based deep learning framework for tuberculosis prediction, integrating AI models with cloud platforms such as AWS Lambda and Google Cloud Functions. The study emphasized the benefits of serverless computing, including scalability, cost efficiency, and reduced infrastructure management. The proposed system enabled real-time processing of medical images and remote access to diagnostic services, making it highly suitable for smart e-health applications. The model demonstrated high accuracy and reduced latency, showcasing the effectiveness of combining deep learning with cloud computing. However, the study did not explore advanced architectures such as convolutional autoencoders or dual-key transformer networks. Nonetheless, it provided a strong foundation for future research in cloud-based AI healthcare systems.

Sharma et al. (2020) proposed a machine learning-based framework enhanced with deep learning techniques for tuberculosis detection using chest radiographs. The study integrated CNN models with feature selection algorithms to improve classification performance. The authors emphasized preprocessing techniques such as image normalization and noise reduction to enhance model accuracy. The proposed system achieved high sensitivity and specificity, demonstrating its effectiveness in clinical diagnosis. However, the study did not incorporate advanced architectures such as convolutional autoencoders or transformer networks. Additionally, it lacked scalability due to the absence of cloud-based deployment.

Patel et al. (2021) developed a deep learning-based diagnostic system for tuberculosis using transfer learning with pre-trained CNN models. The study highlighted the effectiveness of fine-tuning models such as Res Net and Inception for TB detection tasks. The results showed significant improvements in classification accuracy and reduced training time. The authors also explored optimization techniques such as learning rate scheduling and regularization. However, the study did not integrate unsupervised learning approaches like autoencoders or attention-based transformer architectures. Additionally, cloud-based deployment was not considered.

Ahmed et al. (2021) introduced a hybrid deep learning model combining convolutional neural networks with attention mechanisms for improved tuberculosis detection. The study demonstrated that attention modules enhance feature extraction by focusing on relevant regions in chest X-ray images. The model achieved high accuracy and improved interpretability. However, the study did not explore convolutional autoencoders for dimensionality reduction or transformer-based architectures for global feature learning. Furthermore, the lack of cloud integration limited its scalability.

Verma et al. (2022) proposed a deep learning-based approach utilizing ensemble CNN models for tuberculosis detection. The study combined multiple architectures to improve robustness and reduce overfitting. The proposed system demonstrated high accuracy and reliability across diverse datasets. The authors emphasized the importance of model optimization techniques such as hyperparameter tuning and data augmentation. However, the study did not incorporate autoencoder-based feature extraction or transformer-based attention mechanisms. Additionally, cloud-based deployment was not addressed.

Reddy et al. (2022) developed a deep learning framework for tuberculosis detection using CNN architectures combined with image segmentation techniques. The study focused on isolating lung regions to improve classification accuracy. The proposed system achieved high performance and demonstrated the importance of preprocessing in medical image analysis. However, the study did not explore advanced architectures such as convolutional autoencoders or transformer networks. Additionally, it lacked integration with cloud-based platforms for scalable deployment.

Gupta et al. (2022) proposed a deep learning-based tuberculosis detection system utilizing hybrid CNN architectures. The study emphasized feature extraction and classification using multiple layers of convolutional networks. The authors also explored optimization strategies such as dropout and batch normalization to improve model performance. The system demonstrated high accuracy and robustness. However, the study did not incorporate autoencoder-based feature compression or transformer-based attention mechanisms. Additionally, cloud-based deployment was not considered.

Mehta et al. (2023) introduced a cloud-based deep learning framework for tuberculosis detection, integrating AI models with cloud computing platforms. The study demonstrated the advantages of cloud-based systems in terms of scalability, accessibility, and real-time processing. The proposed system achieved high accuracy and reduced computational overhead. However, the study did not explore advanced architectures such as convolutional autoencoders or dual-key transformer networks. Despite this, it highlighted the importance of cloud computing in smart e-health applications.

Comparative Table

Study (Author, Year)	**Method Used**	**Key Technique**	**Accuracy/Performance**	**Advantages**	**Limitations**
Lakhani & Sundaram (2017)	CNN (Transfer Learning)	Alex Net, Google Net	~96%	High accuracy, pretrained models	No cloud, no AE/transformer

Hwang et al. (2016)	CNN	Deep feature learning	High sensitivity	Robust validation	No scalability
Rajpurkar et al. (2017)	Dense Net (Chex Net)	Deep CNN	Radiologist-level	Large dataset	Not TB-specific
Shen et al. (2017)	Review	DL architectures	Conceptual	Identifies gaps	No implementation
Lopes & Valiati (2017)	CNN + SVM	Hybrid model	Improved accuracy	Feature fusion	No scalability
Pasa et al. (2019)	Lightweight CNN	Efficient model	>90%	Low resource usage	Limited features
Qin et al. (2019)	U-Net + CNN	Segmentation + classification	High	ROI-based accuracy	Complex pipeline
Liu et al. (2020)	CAE + CNN	Autoencoder	Improved robustness	Dimensionality reduction	No transformer
Abbas et al. (2020)	DeTraC	Class decomposition	High	Handles irregular data	No cloud integration
Wang et al. (2021)	Vision Transformer	Attention mechanism	High	Global feature learning	Data intensive
Rahman et al. (2021)	Ensemble CNN	Multi-model	>95%	High robustness	High complexity
Khan et al. (2021)	CNN + LSTM	Hybrid	High	Spatial + temporal learning	No transformer
Singh et al. (2022)	Transfer Learning	VGG, Inception	~94%	Fast training	No unsupervised learning
Chen et al. (2022)	CNN + Transformer	Hybrid attention	High	Improved accuracy	Computational cost
Albahli et al. (2023)	CNN + Cloud	Cloud-based	High	Scalable	No advanced DL integration
Zhang et al. (2020)	CAE + CNN	Autoencoder	High	Noise reduction	No attention
He et al. (2020)	ResNet	Residual learning	High	Deep architecture	No hybrid models
Dosovitskiy et al. (2021)	ViT	Transformer	High	Global dependencies	Needs large data
Li et al. (2022)	CNN + Attention	Spatial attention	High	Better interpretability	No CAE
Kumar et al. (2023)	DL + Serverless	Cloud	High	Real-time processing	Limited architecture
Sharma et al. (2020)	ML + CNN	Hybrid	High	Feature optimization	No transformer
Patel et al. (2021)	Transfer Learning	CNN	High	Efficient training	Limited innovation
Ahmed et al. (2021)	CNN + Attention	Attention	High	Focused learning	No cloud
Verma et al. (2022)	Ensemble CNN	Multi-model	High	Robust	Complex
Reddy et al. (2022)	CNN + Segmentation	ROI extraction	High	Improved accuracy	No scalability

Gupta et al. (2022)	Hybrid CNN	Deep features	High	Stable performance	No transformer
Mehta et al. (2023)	Cloud + CNN	Cloud computing	High	Scalable	No AE/transformer

Comparative Analysis

The comparative evaluation of the 30 reviewed studies reveals a significant evolution in tuberculosis detection methodologies, transitioning from traditional machine learning approaches to advanced deep learning and hybrid architectures. Early studies primarily relied on convolutional neural networks (CNNs) and transfer learning techniques, which demonstrated high accuracy levels exceeding 90%. These approaches were effective in feature extraction but were limited in handling complex patterns and long-range dependencies within medical images. With the advancement of deep learning, hybrid models combining CNNs with techniques such as long short-term memory (LSTM), attention mechanisms, and ensemble learning emerged as more robust solutions. These models improved classification accuracy, generalization, and interpretability. In particular, attention-based models and transformer architectures significantly enhanced the ability of systems to focus on relevant regions in chest X-ray images, leading to improved diagnostic performance.

The introduction of convolutional autoencoders (CAE) marked a critical step toward unsupervised feature learning and dimensionality reduction. CAEs enabled models to handle noisy and high-dimensional medical data more effectively, thereby improving robustness and performance. However, many studies have not yet fully integrated CAEs with transformer-based architectures, indicating a research gap in combining these powerful techniques. Another key trend observed is the integration of cloud computing, particularly serverless architectures, into healthcare systems. Cloud-based solutions have enabled scalable, real-time processing of medical data, facilitating remote diagnosis and telemedicine applications. Serverless computing, in particular, offers cost efficiency and eliminates infrastructure management, making it highly suitable for smart e-health systems.

Despite these advancements, several limitations persist. Many studies lack integration of all advanced components, such as CAE, transformer networks, and cloud deployment, within a unified framework. Additionally, challenges related to data privacy, computational complexity, and lack of standardized datasets continue to hinder large-scale adoption. Overall, the analysis highlights that the most promising approach for future TB prediction systems lies in the integration of convolutional autoencoders, dual-key transformer networks, and serverless cloud computing within a unified smart e-health framework. Such systems can achieve high accuracy, scalability, security, and real-time performance, addressing the limitations of existing approaches.

Discussion

The rapid advancement of deep learning techniques has significantly transformed tuberculosis detection systems, enabling automated, accurate, and scalable diagnostic solutions. The reviewed studies demonstrate that convolutional neural networks (CNNs) remain the backbone of most TB detection frameworks due to their strong feature extraction capabilities. However, the integration of advanced architectures such as convolutional autoencoders (CAE) and transformer-based models has further enhanced performance by enabling efficient feature compression and capturing global dependencies in medical images. Hybrid approaches combining CNNs with attention mechanisms and ensemble learning have shown improved accuracy, robustness, and interpretability. Despite these advancements, several challenges remain. Many existing systems lack a unified architecture that integrates CAE, transformer networks, and cloud-based deployment.

Additionally, the requirement for large annotated datasets limits the performance of deep learning models in real-world scenarios. Data privacy and security are also critical concerns, particularly when deploying healthcare systems on cloud platforms. The concept of dual-key transformer networks offers a promising solution by enhancing data security and access control. Furthermore, serverless cloud computing has emerged as a powerful platform for deploying AI-based healthcare systems, offering scalability, cost efficiency, and real-time processing. However, its integration with advanced deep learning architectures remains underexplored. Future research should focus on developing unified, secure, and scalable frameworks that combine these technologies to improve TB diagnosis and healthcare accessibility.

Conclusion

Tuberculosis remains a major global health challenge, creating a strong need for accurate, secure, and scalable diagnostic systems. This review examined deep learning approaches for TB detection, focusing on convolutional autoencoders (CAE), transformer architectures, and serverless cloud computing. CAEs provide effective feature extraction and dimensionality reduction from complex medical data, while transformer-based models use attention mechanisms to capture important contextual relationships and improve prediction performance. These techniques can enhance the reliability and efficiency of automated TB diagnosis.

Dual-key transformer networks further strengthen healthcare applications by supporting secure processing and controlled access to sensitive patient information. Serverless cloud computing complements these models by providing scalable, flexible, and cost-effective computational resources for real-time diagnosis and remote healthcare services. However, limitations involving dataset availability, computational complexity, model interpretability, and standardization continue to restrict practical implementation.

Future research should develop unified e-health frameworks integrating CAE, dual-key transformers, optimization methods, and serverless computing. Greater emphasis on explainable AI, standardized datasets, privacy protection, and lightweight architectures can improve clinical adoption. Overall, these technologies offer significant potential for developing intelligent, secure, accessible, and scalable TB prediction systems.

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