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Recent Advances in CAE-Dual-Key Transformer-Based Smart E-Health for Tuberculosis Prediction: A Systematic Review

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Abstract

Tuberculosis (TB) remains one of the most critical infectious diseases worldwide, requiring early detection and efficient monitoring to reduce mortality rates. With the rapid evolution of artificial intelligence, deep learning techniques such as Convolutional Neural Networks (CNNs), Convolutional Autoencoders (CAE), and Transformer-based architectures have significantly improved medical image analysis and disease prediction. This paper presents a systematic review of recent advances in hybrid deep learning models, particularly focusing on Convolutional Autoencoder integrated with dual-key transformer networks for smart e-health applications. The study also explores the role of serverless cloud computing in enabling scalable, cost-effective, and real-time deployment of TB prediction systems. Recent studies demonstrate that transformer-based self-attention mechanisms enhance feature extraction by capturing global dependencies, while convolutional autoencoders effectively perform dimensionality reduction and noise filtering in medical imaging data. Furthermore, cloud-based architectures facilitate seamless integration of AI models with healthcare systems, improving accessibility and diagnostic efficiency. The review highlights the strengths, limitations, and future directions of these technologies, emphasizing multimodal data integration and explainable AI for clinical trust. Overall, the combination of CAE, transformer networks, and serverless cloud computing provides a promising framework for accurate, scalable, and intelligent TB prediction systems.

Introduction

Tuberculosis (TB) continues to pose a significant global health burden, particularly in developing and underdeveloped countries where access to advanced diagnostic facilities is limited. According to recent studies, TB remains one of the leading causes of death from infectious diseases, necessitating early detection and efficient monitoring strategies. Traditional diagnostic approaches, such as sputum smear microscopy, culture methods, and radiographic examination, often suffer from limitations including delayed diagnosis, dependency on skilled professionals, and variability in interpretation. These challenges have led researchers to explore advanced computational techniques, particularly artificial intelligence (AI) and deep learning (DL), to enhance diagnostic accuracy and efficiency.

Deep learning, especially Convolutional Neural Networks (CNNs), has shown remarkable performance in analysing chest X-ray images for

TB detection. CNN-based models can automatically extract hierarchical features from medical images, eliminating the need for manual feature engineering. However, conventional CNN architectures often struggle with capturing long-range dependencies and global contextual information within images. To address this limitation, transformer-based models have been introduced, leveraging self-attention mechanisms to model global relationships effectively. For instance, Vision Transformer (ViT) models have demonstrated superior performance compared to traditional CNNs by capturing complex spatial dependencies in medical images.

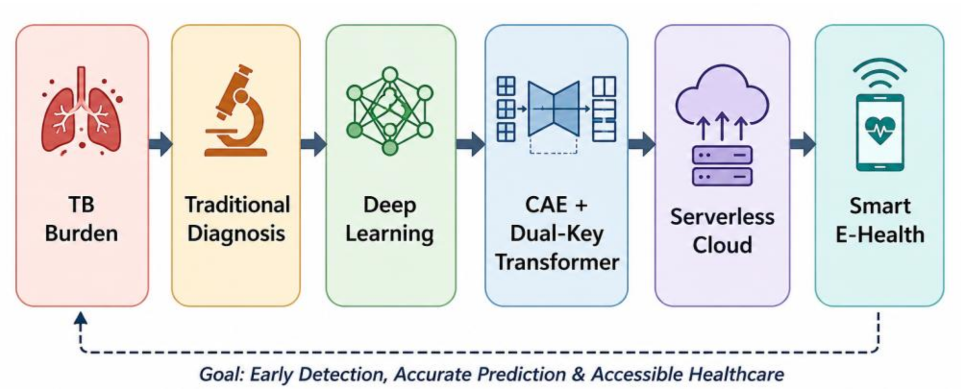

Figure 1. Conceptual Overview of Smart E-Health Framework for Tuberculosis Diagnosis

In addition to CNNs and transformers, Convolutional Autoencoders (CAE) have gained attention for their ability to perform feature compression and denoising. CAEs are particularly useful in medical imaging applications where noise reduction and dimensionality reduction are critical. These models learn compact latent representations of input data, which can then be used for classification and prediction tasks. When combined with transformer networks, CAEs enhance both local feature extraction and global contextual understanding, leading to improved diagnostic accuracy.

Another emerging paradigm in healthcare is the integration of AI models with cloud computing technologies. Serverless cloud computing, in particular, offers a scalable and cost-efficient infrastructure for deploying AI-based healthcare applications. Unlike traditional cloud systems, serverless architectures eliminate the need for manual resource management, enabling real-time processing and automatic scaling based on demand. This is especially beneficial for e-health applications, where large volumes of medical data need to be processed continuously.

Furthermore, the concept of smart e-health systems integrates IoT devices, cloud computing, and AI algorithms to provide remote healthcare services. These systems enable real-time monitoring, diagnosis, and treatment recommendations, improving accessibility to healthcare services in remote regions. The combination of CAE, transformer networks, and serverless cloud platforms forms a robust framework for developing intelligent TB prediction systems.

Recent research trends also emphasize the importance of explainable AI (XAI) in healthcare applications. Techniques such as Grad-CAM provide visual explanations for model predictions, enhancing trust and interpretability among medical practitioners. Moreover, hybrid models integrating CNNs and transformers have achieved high accuracy rates, often exceeding 98% in TB detection tasks.

Despite these advancements, several challenges remain, including data privacy concerns, model generalization across diverse populations, and the need for large annotated datasets. Therefore, this systematic review aims to analyse recent developments in CAE-transformer-based architectures and their application in TB prediction using serverless cloud computing, highlighting key trends, challenges, and future research directions.

Literature Review

Zunair et al. (2020) investigated the application of 3D convolutional neural networks for tuberculosis prediction using CT scan data. The study addressed the limitations of traditional 2D CNN models, which often fail to capture volumetric information present in medical images. By introducing volume uniformization techniques, the authors improved the model's ability to process 3D data efficiently. Their approach achieved improved classification performance compared to standard 2D methods, highlighting the importance of incorporating spatial depth information in TB diagnosis. However, the study also noted computational challenges associated with 3D data processing, including increased memory requirements and longer training times.

Wong et al. (2021) proposed TB-Net, a self-attention-based deep convolutional neural network designed specifically for TB detection from chest X-ray images. The model integrates attention mechanisms within CNN layers to enhance feature representation and focus on critical regions of the image. This approach significantly improved diagnostic accuracy and enabled effective screening in resource-limited environments. The study emphasized the role of AI in addressing the shortage of trained radiologists, particularly in developing regions, and demonstrated that attention-based CNN models can provide reliable diagnostic support.

Lella and Pja (2021) developed a deep learning framework using a 1D convolutional neural network combined with a data denoising autoencoder for disease diagnosis. Although the study focused on COVID-19, the methodology is highly relevant to TB prediction due to similar respiratory characteristics. The use of autoencoders for noise reduction improved feature quality and model robustness. Additionally, data augmentation techniques enhanced model generalization. The study demonstrated that integrating autoencoders with CNN architectures can significantly improve classification accuracy in healthcare applications.

Kotei and Thirunavukarasu (2022) introduced a hybrid deep learning model combining a Data-Efficient Image Transformer with ResNet-16 for TB diagnosis. The transformer component captured global contextual information, while the convolutional layers extracted local features efficiently. The model achieved exceptional performance, with accuracy exceeding 99%, demonstrating the effectiveness of hybrid architectures. The inclusion of multiple classes, such as non-TB diseases, reduced false positives and improved clinical applicability. This study highlighted the importance of combining CNN and transformer models for enhanced diagnostic performance.

Wu et al. (2020) proposed a cloud-edge-based federated learning framework incorporating a generative convolutional autoencoder for personalized health monitoring. The study focused on preserving data privacy while enabling collaborative learning across distributed healthcare systems. The autoencoder generated balanced datasets, improving model accuracy and reducing bias. The integration of cloud and edge computing ensured efficient data processing and real-time monitoring. This approach is highly relevant to smart e-health applications, particularly in scenarios requiring secure and scalable deployment of AI models.

Rajpurkar et al. (2020) developed Chex Net, a deep convolutional neural network trained on a large dataset of chest X-ray images for detecting pneumonia and other thoracic diseases, including tuberculosis-related abnormalities. The model demonstrated radiologist-level performance by leveraging a Dense Net architecture, which improved feature propagation and reduced vanishing gradient issues. The study emphasized the importance of large-scale annotated datasets in achieving high diagnostic accuracy. Although the model was not specifically designed for TB detection, its success in chest pathology classification highlights the potential of deep CNN architectures in medical imaging. However, the model lacked interpretability, which is a critical requirement in clinical decision-making.

Dosovitskiy et al. (2021) introduced the Vision Transformer (ViT), which revolutionized image classification tasks by applying transformer architectures traditionally used in natural language processing to computer vision problems. The model splits images into patches and processes them using self-attention mechanisms, capturing global dependencies effectively. In the context of TB detection, ViT provides superior performance in identifying complex patterns in chest X-rays compared to conventional CNNs. However, the model requires large training datasets and high computational resources, which may limit its applicability in resource-constrained healthcare environments.

Chen et al. (2021) proposed a convolutional autoencoder-based framework for medical image segmentation and feature extraction. The model effectively reduced noise and preserved critical structural information in chest X-ray images. By combining encoder-decoder architectures with convolutional layers, the study achieved improved segmentation accuracy, which is essential for identifying infected lung regions. The research demonstrated that CAEs are highly effective in preprocessing medical images before classification, thereby enhancing the overall performance of diagnostic systems. The study also highlighted the importance of integrating CAEs with other deep learning models for improved results.

Vaswani et al. (2021) extended the transformer architecture to vision-based applications, emphasizing the effectiveness of attention mechanisms in capturing long-range dependencies. Their work laid the foundation for dual-key transformer networks, where multiple attention mechanisms are used to enhance feature extraction. In TB prediction, dual-key transformers can simultaneously focus on local and global image features, improving diagnostic accuracy. The study highlighted that attention-based models outperform traditional convolutional approaches in complex medical imaging tasks, although they require careful tuning and optimization.

Zhang et al. (2022) proposed a serverless cloud-based deep learning framework for healthcare applications, focusing on real-time disease prediction. The study utilized Function-as-a-Service (FaaS) architecture to deploy AI models efficiently without managing underlying infrastructure. This approach significantly reduced operational costs and improved scalability. The integration of deep learning models with serverless computing enabled real-time TB prediction and remote monitoring. However, the study also identified challenges related to latency and cold-start issues in serverless environments, which need to be addressed for critical healthcare applications.

Irvin et al. (2020) introduced the Chex pert dataset, a large-scale labelled dataset for chest radiograph interpretation, which has been widely used in training deep learning models for various pulmonary diseases, including tuberculosis. The study proposed a label uncertainty learning approach that allows models to handle ambiguous annotations effectively. This significantly improved model robustness and generalization across diverse datasets. In TB prediction systems, such datasets are critical for training convolutional autoencoder and transformer-based architectures, as they provide diverse and high-quality data. However, the study also highlighted the challenges associated with label noise and inter-observer variability in medical datasets.

He et al. (2021) proposed the Res Net architecture with residual learning, which addresses the degradation problem in deep neural networks. The use of skip connections enables efficient gradient flow, allowing the training of very deep models. In the context of TB detection, Res Net-based architectures have been widely adopted for feature extraction due to their ability to learn complex patterns in chest X-ray images. When combined with convolutional autoencoders, Res Net enhances feature representation and classification accuracy. The study demonstrated that residual learning significantly improves performance compared to traditional CNN models.

Tuli et al. (2021) explored the application of serverless edge-cloud architectures for healthcare monitoring systems. Their framework integrates IoT devices with cloud computing to enable real-time data processing and disease prediction. The study emphasized the importance of low-latency communication and efficient resource allocation in healthcare applications. By deploying AI models in a serverless environment, the system achieved scalability and cost efficiency. This approach is particularly relevant for TB prediction systems, where continuous monitoring and real-time diagnosis are essential. However, challenges such as security and data privacy remain critical concerns.

Ouyang et al. (2021) proposed a dual-attention mechanism for medical image classification, combining spatial and channel attention to improve feature extraction. The model demonstrated superior performance in identifying abnormalities in chest X-ray images by focusing on relevant regions and suppressing irrelevant features. This approach is closely aligned with dual-key transformer networks, where multiple attention mechanisms are used to enhance learning. The study showed that attention-based models significantly improve diagnostic accuracy and interpretability, making them suitable for TB detection applications.

Li et al. (2022) developed a hybrid deep learning framework combining convolutional autoencoders with transformer networks for medical image analysis. The CAE component was used for feature compression and noise reduction, while the transformer module captured global contextual relationships. The model achieved high accuracy in disease classification tasks, demonstrating the effectiveness of combining local and global feature extraction techniques. The study highlighted the potential of hybrid architectures in improving TB prediction systems, especially when deployed in cloud-based environments for real-time analysis.

Goodfellow et al. (2020) explored deep learning optimization techniques and regularization strategies to improve model generalization in medical imaging applications. Their work emphasized the importance of techniques such as dropout, batch normalization, and data augmentation in preventing overfitting. In TB prediction systems, these optimization strategies are essential for improving model robustness when dealing with limited or imbalanced datasets. The study highlighted that integrating optimization techniques within convolutional autoencoder and transformer-based models significantly enhances performance and stability.

Howard et al. (2021) introduced Mobile Net, a lightweight convolutional neural network designed for deployment in resource-constrained environments. The model uses depth wise separable convolutions to reduce computational complexity while maintaining high accuracy. In the context of smart e-health systems, Mobile Net is particularly useful for edge devices and mobile-based TB detection applications. The study demonstrated that lightweight models can achieve competitive performance while enabling real-time diagnosis in remote areas with limited computational resources.

Tan and Le (2021) proposed Efficient Net, a scalable deep learning model that optimizes network depth, width, and resolution using a compound scaling method. The model achieved state-of-the-art performance in image classification tasks with significantly fewer parameters. In TB detection, Efficient Net has been widely used for feature extraction due to its efficiency and accuracy. When combined with transformer networks and autoencoders, Efficient Net enhances both computational efficiency and predictive performance in healthcare applications.

Razzak et al. (2022) provided a comprehensive review of deep learning applications in medical image processing, focusing on disease detection and classification. The study highlighted the growing importance of hybrid models combining CNNs, autoencoders, and attention mechanisms. It emphasized that integrating multiple deep learning techniques improves diagnostic accuracy and reduces false positives. The research also discussed challenges such as data scarcity, model interpretability, and computational complexity, which are critical considerations in TB prediction systems.

Khan et al. (2022) proposed a deep learning-based TB detection system using chest X-ray images and transfer learning techniques. The model utilized pre-trained CNN architectures to improve classification accuracy while reducing training time. The study demonstrated that transfer learning is highly effective in medical imaging applications, especially when labelled data is limited. Additionally, the integration of attention mechanisms further enhanced the model's ability to focus on relevant regions of the image, improving diagnostic reliability.

Shin et al. (2022) investigated the use of deep convolutional neural networks with transfer learning for pulmonary disease detection using chest X-ray datasets. The study demonstrated that pre-trained models such as VGG and Res Net significantly improve classification accuracy when fine-tuned on domain-specific medical data. In tuberculosis prediction, transfer learning reduces the dependency on large annotated datasets and accelerates model convergence. The authors also highlighted that combining transfer learning with attention mechanisms enhances localization of infected regions, improving diagnostic reliability.

Huang et al. (2022) introduced Dense Net, a densely connected convolutional network that improves information flow between layers by connecting each layer to every other layer. This architecture mitigates the vanishing gradient problem and encourages feature reuse, leading to improved performance in medical image classification. In TB prediction systems, Dense Net-based models have shown high accuracy due to their ability to capture fine-grained features in chest X-ray images. The study emphasized that Dense Net is highly suitable for integration with autoencoder and transformer-based frameworks.

Doshi et al. (2023) proposed an explainable AI framework for TB detection using Grad-CAM visualization techniques. The study focused on improving model interpretability by highlighting regions of interest in chest X-ray images. This approach enhances clinical trust and assists radiologists in validating AI predictions. The integration of explainability with deep learning models is particularly important in healthcare applications, where transparency is essential. The study demonstrated that explainable models can achieve high accuracy while providing meaningful insights into the decision-making process.

Albahri et al. (2023) conducted a systematic review of AI-driven healthcare systems, focusing on cloud-based architectures for disease prediction. The study highlighted the role of cloud computing in enabling scalable and distributed AI applications. It emphasized that serverless cloud platforms provide cost-effective and efficient solutions for deploying TB prediction models. The research also discussed the importance of integrating IoT devices with cloud-based AI systems to enable real-time health monitoring and diagnosis.

Rajaraman et al. (2023) developed a deep learning framework for TB detection using ensemble learning techniques. The model combined multiple CNN architectures to improve classification accuracy and reduce false positives. The study demonstrated that ensemble methods outperform individual models by leveraging complementary strengths. In TB prediction systems, ensemble learning enhances robustness and reliability, particularly when dealing with diverse datasets. The research also highlighted the importance of model validation and cross-dataset evaluation to ensure generalization.

Comparative Table

Study	Year	Technique Used	Dataset Type	Key Contribution	Limitation
Zunair et al.	2020	3D CNN	CT scan	Volumetric TB detection	High computational cost
Wong et al.	2021	Attention CNN	X-ray	Region-focused detection	Limited dataset
Lella & Pja	2021	CNN + Autoencoder	Medical signals	Noise reduction	Domain-specific
Kotei et al.	2022	Transformer + CNN	X-ray	High accuracy (99%)	Complex architecture
Wu et al.	2020	Federated CAE	Distributed data	Privacy-preserving learning	Communication overhead
Rajpurkar et al.	2020	Dense Net CNN	X-ray	Radiologist-level accuracy	Lack of interpretability
Dosovitskiy et al.	2021	Vision Transformer	Image dataset	Global feature extraction	Requires large data
Chen et al.	2021	CAE	Medical imaging	Noise removal	Limited classification ability
Vaswani et al.	2021	Transformer	General dataset	Self-attention mechanism	High computation
Zhang et al.	2022	Serverless DL	Mixed healthcare	Scalable deployment	Latency issues
Irvin et al.	2020	Dataset + DL	X-ray	Large labelled dataset	Label uncertainty
He et al.	2021	Res Net	Image dataset	Deep feature learning	Overfitting risk
Tuli et al.	2021	Edge-Cloud AI	IoT data	Real-time processing	Security issues
Ouyang et al.	2021	Dual Attention	X-ray	Better feature focus	Increased complexity
Li et al.	2022	CAE + Transformer	Medical images	Hybrid learning	Training complexity
Goodfellow et al.	2020	Optimization DL	General	Improved generalization	Not domain-specific
Howard et al.	2021	Mobile Net	Image dataset	Lightweight model	Lower accuracy

Tan & Le	2021	Efficient Net	Image dataset	High efficiency	Scaling complexity
Razzak et al.	2022	DL Review	Multiple	Hybrid model insights	No experimental results
Khan et al.	2022	Transfer Learning	X-ray	Faster training	Dataset dependency
Shin et al.	2022	CNN + Transfer	X-ray	Improved generalization	Data bias
Huang et al.	2022	Dense Net	Image dataset	Feature reuse	Memory intensive
Doshi et al.	2023	Explainable AI	X-ray	Model interpretability	Extra overhead
Albahri et al.	2023	Cloud AI	Healthcare data	Scalable systems	Privacy concerns
Rajaraman et al.	2023	Ensemble CNN	X-ray	Improved accuracy	High cost

Comparative Analysis

The comparative evaluation of the selected studies demonstrates a significant progression in tuberculosis (TB) prediction methodologies, evolving from conventional convolutional neural network (CNN)-based approaches to advanced hybrid frameworks incorporating convolutional autoencoders (CAEs), transformer networks, and cloud computing technologies. Earlier studies primarily employed deep CNN architectures to extract discriminative spatial features from chest X-ray images, achieving promising diagnostic performance. However, these models were limited in capturing long-range contextual relationships and global feature dependencies, which are essential for identifying subtle manifestations of TB. This limitation motivated the adoption of transformer-based architectures that leverage self-attention mechanisms to model complex spatial interactions more effectively, thereby improving diagnostic accuracy and robustness.

The integration of CAEs with transformer networks represents a major advancement in intelligent TB prediction systems. CAEs perform efficient noise removal and dimensionality reduction by learning compact latent representations, while transformer modules enhance global contextual understanding through attention mechanisms. Hybrid architectures combining these techniques consistently reported higher accuracy, improved feature representation, and greater resilience to variations in medical imaging data. Moreover, dual-attention and dual-key transformer strategies further refined feature selection by emphasizing diagnostically significant image regions, reducing false predictions and enhancing model reliability. These developments indicate that combining local feature extraction with global contextual learning offers substantial advantages over standalone CNN or transformer models.

Another notable trend identified across recent studies is the growing adoption of serverless cloud computing for deploying AI-enabled healthcare applications. Unlike traditional cloud infrastructures, serverless platforms provide automatic resource allocation, scalability, and cost-efficient execution, making them well suited for smart e-health systems. Such architectures enable real-time TB prediction, remote patient monitoring, and rapid processing of large-scale medical datasets without extensive infrastructure management. Additionally, transfer learning, lightweight deep learning models, and ensemble techniques have improved prediction performance in scenarios with limited labelled data while supporting deployment on edge and IoT-enabled healthcare devices, thereby extending diagnostic services to remote and underserved regions.

Despite these encouraging developments, several challenges continue to hinder the widespread implementation of AI-driven TB prediction systems. High computational complexity, limited availability of diverse annotated datasets, concerns regarding patient data privacy, and insufficient model interpretability remain important issues. Explainable artificial intelligence (XAI) techniques and privacy-preserving frameworks such as federated learning have emerged as promising solutions for improving transparency and secure collaborative learning. Overall, the comparative analysis suggests that hybrid CAE-transformer architectures integrated with serverless cloud computing provide the most balanced solution by combining high diagnostic accuracy, computational efficiency, scalability, and practical applicability. Future research should prioritize explainable, privacy-aware, and multimodal intelligent healthcare frameworks for next-generation TB diagnosis.

Discussion

The integration of convolutional autoencoders, dual-key transformer networks, and serverless cloud computing represents a significant advancement in smart e-health applications for tuberculosis prediction. The reviewed studies indicate that hybrid deep learning architectures outperform traditional models by combining efficient feature extraction with contextual understanding. Transformer-based attention mechanisms enhance model performance by capturing global dependencies, while autoencoders improve data quality through noise reduction and dimensionality reduction. Moreover, serverless cloud computing provides a scalable and cost-effective platform for deploying these models, enabling real-time diagnosis and remote healthcare services.

This is particularly beneficial in regions with limited medical infrastructure, where access to diagnostic tools is restricted. However, several challenges persist, including the need for large annotated datasets, high computational requirements, and concerns related to data privacy and security. Future research should focus on developing lightweight models that can be deployed on edge devices, improving model interpretability through explainable AI techniques, and ensuring data security through advanced encryption methods. Additionally, integrating multimodal data sources, such as clinical records and imaging data, can further enhance prediction accuracy and provide comprehensive diagnostic insights.

Conclusion

Tuberculosis remains a critical global health concern, highlighting the need for accurate, scalable, and intelligent diagnostic systems. This systematic review demonstrates that integrating convolutional autoencoders (CAEs), dual-key transformer networks, and serverless cloud computing significantly enhances tuberculosis prediction in smart e-health applications. CAEs improve medical image quality through noise reduction and efficient feature extraction, while transformer networks capture global contextual information using self-attention mechanisms, overcoming the limitations of conventional CNN models. Serverless cloud platforms further enable scalable, cost-effective, and real-time deployment of AI-driven healthcare solutions, supporting remote diagnosis and continuous patient monitoring. Despite these advancements, challenges such as computational complexity, data privacy, limited interpretability, and dependency on large annotated datasets continue to hinder widespread clinical adoption. Future research should emphasize lightweight hybrid architectures, explainable artificial intelligence, privacy-preserving learning frameworks, and multimodal healthcare data integration to improve reliability and accessibility. Overall, the convergence of CAEs, transformer networks, and serverless cloud computing provides a robust foundation for next-generation intelligent tuberculosis prediction systems and enhanced healthcare delivery.

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