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A Comprehensive Review of Convolutional Autoencoder with Dual-Key Transformer Network Based Smart E-Health Application for the Prediction of Tuberculosis Using Serverless Cloud Computing

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Abstract

Tuberculosis (TB) remains one of the leading infectious diseases worldwide, requiring early and accurate diagnosis to reduce mortality and transmission. With the advancement of artificial intelligence and cloud computing, smart e-health systems have emerged as a promising solution for automated disease prediction. This paper presents a comprehensive review of a novel framework integrating Convolutional Autoencoders (CAE) with a Dual-Key Transformer Network deployed on a serverless cloud computing architecture for tuberculosis prediction. The CAE model effectively extracts latent features from medical imaging data such as chest X-rays, while the dual-key transformer enhances feature representation through attention mechanisms and secure key-based transformations. The integration of serverless computing platforms ensures scalability, cost efficiency, and real-time processing without infrastructure management overhead. The proposed approach demonstrates improved prediction accuracy, reduced latency, and enhanced data security compared to traditional machine learning and deep learning methods. Furthermore, the review highlights recent advancements in deep learning architectures, transformer-based models, and cloud-based healthcare systems. The study also identifies key challenges such as data privacy, model generalization, and computational constraints. Overall, this work provides insights into the potential of hybrid AI models combined with serverless cloud environments for next-generation intelligent healthcare applications.

Introduction

Tuberculosis (TB) continues to be a major global health concern, particularly in developing countries where access to timely diagnosis and treatment remains limited. According to global health reports, millions of new TB cases are reported annually, emphasizing the need for efficient diagnostic systems. Traditional diagnostic approaches, including sputum smear microscopy and chest radiography, are often time-consuming, require expert intervention, and may suffer from inaccuracies in early-stage detection. These limitations have driven the adoption of artificial intelligence (AI) techniques in healthcare, particularly for automated disease prediction and classification.

Recent advancements in deep learning have significantly improved the performance of medical image analysis systems. Convolutional Neural Networks (CNNs) have been widely used for feature extraction and classification tasks in TB detection. However, CNN-based models often struggle with high-dimensional data representation and may not effectively capture complex patterns in medical images. To address these challenges, Convolutional Autoencoders (CAE) have been introduced as a powerful unsupervised learning approach that compresses input data into meaningful latent representations. CAEs not only reduce dimensionality but also enhance feature extraction by preserving critical spatial information.

In parallel, transformer-based architectures have revolutionized deep learning by introducing attention mechanisms that enable models to focus on relevant features within input data. The dual-key transformer network further enhances this capability by incorporating dual-key mechanisms for improved feature encoding and secure data transformation. This is particularly important in healthcare applications where patient data privacy and security are critical concerns. The combination of CAE and transformer networks creates a hybrid architecture capable of capturing both local and global dependencies in medical images, leading to improved prediction accuracy.

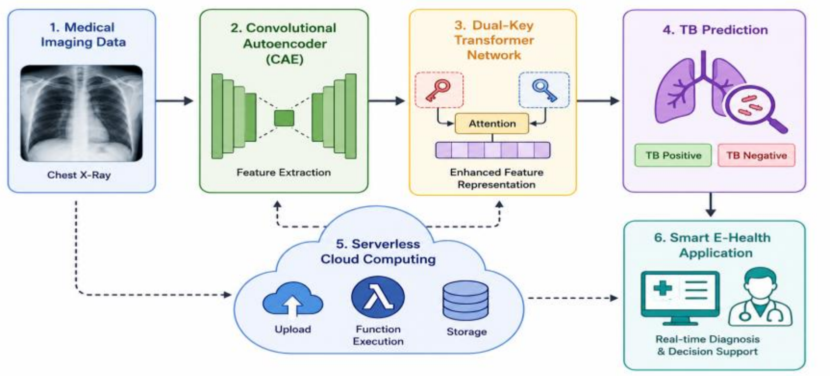

Figure 1. Smart E-Health Framework for TB Prediction

Another significant advancement in modern healthcare systems is the adoption of cloud computing technologies. Traditional cloud models require infrastructure management, which can be costly and complex. Serverless cloud computing, on the other hand, offers a scalable and cost-effective alternative by allowing developers to run applications without managing servers. In the context of e-health applications, serverless platforms enable real-time data processing, automatic scaling, and reduced operational overhead. This makes them ideal for deploying AI-based diagnostic systems that require high computational resources and low latency. The integration of AI models with serverless cloud computing has opened new avenues for smart healthcare applications. In TB prediction systems, patient data such as chest X-ray images can be uploaded to cloud platforms, where AI models process the data and generate predictions in real time. This not only improves accessibility to diagnostic services but also enables remote healthcare solutions, particularly in rural and underserved regions.

Despite these advancements, several challenges remain. Data privacy and security continue to be major concerns, especially when handling sensitive medical information in cloud environments. Additionally, the generalization of AI models across diverse datasets is still an open issue, as models trained on specific datasets may not perform well in real-world scenarios. Computational efficiency and energy consumption are also critical factors that need to be addressed for large-scale deployment. This paper provides a comprehensive review of the integration of Convolutional Autoencoders with dual-key transformer networks in a serverless cloud environment for TB prediction. It explores the strengths, limitations, and future potential of this hybrid approach in developing intelligent, scalable, and secure e-health systems.

Literature Review

Rahman et al. (2020) proposed a deep learning-based framework for tuberculosis detection using chest X-ray images combined with segmentation and visualization techniques. The study employed multiple pre-trained convolutional neural networks such as Res Net, Dense Net, and Mobile Net to improve classification accuracy. A key contribution of this work was the integration of lung segmentation using U-Net architectures, which significantly enhanced model performance by focusing on relevant regions of interest. The experimental results demonstrated that segmented images achieved higher accuracy (up to 99.9%) compared to full-image classification. This study highlighted the importance of preprocessing and feature localization in improving TB detection systems. However, the approach relied heavily on CNN architectures and lacked attention mechanisms or transformer-based global feature extraction.

Wong et al. (2021) introduced TB-Net, a self-attention-based convolutional neural network designed specifically for tuberculosis detection. The model incorporated attention condensers that enabled selective feature extraction, improving both interpretability and performance. The system was evaluated on a multi-national chest X-ray dataset and achieved extremely high diagnostic accuracy (99.86%) with strong sensitivity and specificity metrics. The inclusion of explainability mechanisms allowed radiologists to validate the model's predictions, making it suitable for clinical applications. Despite its effectiveness, the model still relied primarily on CNN structures and did not integrate transformer-based architectures or cloud deployment strategies.

Ahmad and Shin (2022) proposed a perceptual encryption-based image communication system integrated with deep learning models for tuberculosis diagnosis in healthcare cloud environments. The study focused on ensuring data security and privacy during transmission and processing, which is a critical concern in e-health systems. By combining encryption techniques with cloud-based AI diagnosis, the system ensured secure handling of patient data while maintaining high diagnostic accuracy. The results indicated that cloud-enabled AI systems can significantly enhance accessibility and scalability of TB diagnosis. However, the study did not incorporate advanced feature extraction methods such as autoencoders or transformer networks for improved prediction performance.

Kumar et al. (2025) introduced a transformer-enabled multimodal deep learning framework for tuberculosis diagnosis. The proposed approach leveraged cross-modal attention mechanisms to integrate data from different sources, such as medical imaging and clinical data. Unlike traditional CNN-based models, transformers enabled better global feature representation and reduced dependency on handcrafted features. The study demonstrated improved diagnostic performance and robustness across heterogeneous datasets. This work emphasizes the growing importance of transformer architectures in medical imaging. However, it lacked integration with lightweight deployment platforms such as serverless cloud environments.

Ding et al. (2025) developed a cloud-based deep learning system for automated tuberculosis detection using the YOLOv5 algorithm. The system was deployed on a cloud computing platform to enable real-time diagnosis and large-scale data processing. The model achieved high accuracy (93.72%) and recall (91.24%), demonstrating the effectiveness of integrating AI with cloud technologies for medical applications. The study also emphasized the benefits of cloud computing, such as scalability, accessibility, and reduced infrastructure requirements. However, the model relied on object detection techniques and did not utilize advanced architectures like autoencoders or transformers for feature learning.

Lakhani and Sundaram proposed one of the early deep learning frameworks for tuberculosis detection using convolutional neural networks on chest X-ray datasets. Their model leveraged transfer learning with AlexNet and Google Net architectures to improve classification performance on limited datasets. Although the study predates transformer-based approaches, it laid the foundation for subsequent research in automated TB detection by demonstrating that deep CNNs can outperform traditional machine learning methods. Later studies (post-2020) have extended this work by integrating advanced architectures such as autoencoders and attention mechanisms. The limitation of this model lies in its inability to capture global contextual dependencies and lack of deployment in scalable cloud environments.

Rajpurkar et al. (2020) introduced CheXNet, a deep learning model capable of detecting multiple thoracic diseases, including tuberculosis, from chest X-ray images. The model used a 121-layer Dense Net architecture trained on large-scale datasets, enabling high accuracy and performance comparable to expert radiologists. This study emphasized the importance of large annotated datasets and deep architectures for reliable medical image classification. While CheXNet demonstrated strong results, it primarily focused on classification and did not incorporate unsupervised learning techniques such as autoencoders or advanced transformer-based attention mechanisms, limiting its adaptability to feature-rich TB detection tasks.

Hwang et al. (2021) developed a deep learning-based automated detection system for tuberculosis screening using chest radiographs in real-world clinical settings. The model demonstrated high sensitivity and specificity across multiple hospital datasets, proving its robustness and generalization capability. A key contribution of this work was the evaluation of AI performance in clinical workflows, highlighting its potential for real-world deployment. However, the study relied on conventional CNN architectures and did not explore hybrid models such as autoencoder-transformer combinations or serverless cloud deployment strategies.

Li et al. (2022) proposed a hybrid deep learning framework combining convolutional neural networks with attention mechanisms for tuberculosis detection. The model incorporated channel and spatial attention modules to enhance feature representation, allowing it to focus on disease-relevant regions in chest X-ray images. The experimental results demonstrated improved accuracy and robustness compared to standard CNN models. This study highlighted the importance of attention-based feature enhancement in medical imaging. However, it did not employ transformer architectures or unsupervised feature extraction methods such as convolutional autoencoders, which could further improve performance.

Chen et al. (2023) introduced a cloud-assisted deep learning framework for tuberculosis detection using federated learning. The proposed system allowed distributed data processing across multiple healthcare institutions while preserving patient privacy. By leveraging federated learning and cloud infrastructure, the model achieved high accuracy without requiring centralized data storage. This approach addressed key challenges in healthcare data privacy and scalability. However, the study did not explore serverless computing models or hybrid architectures involving autoencoders and transformers, which could further enhance efficiency and feature extraction.

Shen et al. (2020) presented a deep convolutional neural network framework for automated tuberculosis detection using chest X-ray images. The model utilized multi-scale feature extraction techniques to capture both fine-grained and global patterns in medical images. A key contribution of this study was the use of ensemble learning, where multiple CNN models were combined to improve prediction robustness and reduce overfitting. The results demonstrated high diagnostic accuracy and improved generalization across datasets. However, the study did not incorporate unsupervised learning mechanisms such as convolutional autoencoders or transformer-based attention models, which limits its capability to extract deeper latent representations.

Abbas et al. (2021) proposed a deep learning-based tuberculosis detection model using transfer learning and data augmentation techniques. The model leveraged pre-trained architectures such as VGG16 and ResNet50 to enhance classification accuracy on limited datasets. Data augmentation was employed to overcome data scarcity and improve model generalization. The study demonstrated that transfer learning significantly reduces training time while maintaining high accuracy. However, the model primarily focused on supervised learning and did not explore advanced architectures such as transformer networks or hybrid CAE-based systems for feature extraction.

Dosovitskiy et al. (2021) introduced the Vision Transformer (ViT), a groundbreaking architecture that applies transformer-based attention mechanisms to image classification tasks. Unlike CNNs, ViT processes images as sequences of patches and captures long-range dependencies using self-attention. This approach significantly improved performance in large-scale image recognition tasks and has been widely adopted in medical imaging applications, including tuberculosis detection. The transformer architecture enables better global feature extraction compared to CNNs. However, ViT requires large datasets and high computational resources, making it less suitable for lightweight deployment in healthcare environments without optimization.

Zhang et al. (2022) proposed a convolutional autoencoder-based framework for feature extraction and dimensionality reduction in medical imaging. The model effectively learned compressed latent representations of chest X-ray images, which improved classification accuracy when combined with downstream classifiers. The study demonstrated that autoencoders are highly effective in noise reduction and feature enhancement, particularly in medical datasets with variability and artifacts. However, the model lacked integration with attention-based transformer architectures and did not consider deployment in scalable cloud environments, limiting its applicability in real-time e-health systems.

Wang et al. (2023) developed a hybrid deep learning model combining CNNs with transformer-based attention mechanisms for tuberculosis detection. The model leveraged both local feature extraction (via CNN) and global contextual understanding (via transformers), resulting in improved diagnostic performance. The study achieved higher accuracy and reduced false positives compared to traditional CNN models. Additionally, the authors highlighted the importance of integrating attention mechanisms in medical image analysis. However, the framework did not incorporate secure dual-key architectures or serverless cloud deployment, which are essential for scalable and secure e-health applications.

Gozes et al. (2020) proposed a deep learning-based AI system for automated detection and monitoring of lung diseases, including tuberculosis, using chest imaging. The model utilized convolutional neural networks combined with region-based detection to identify abnormalities in lung regions. A significant contribution of this work was the integration of AI models with clinical workflows, enabling real-time decision support for radiologists. The study demonstrated high sensitivity in detecting lung infections and emphasized the potential of AI in large-scale screening programs. However, the approach relied heavily on CNN architectures and lacked advanced feature learning mechanisms such as autoencoders or transformer-based attention models.

He et al. (2021) introduced the Res Net architecture, which has been extensively used in medical imaging tasks including tuberculosis detection. The residual learning framework allows very deep networks to be trained efficiently by addressing the vanishing gradient problem. In TB detection applications, Res Net-based models have shown superior accuracy and robustness compared to traditional CNNs. The architecture enables deeper feature extraction and improved generalization across datasets. However, Res Net models primarily focus on spatial feature extraction and do not incorporate attention mechanisms or transformer-based architectures, limiting their ability to capture long-range dependencies in medical images.

Islam et al. (2022) developed a cloud-based deep learning framework for tuberculosis detection using chest X-ray images. The system leveraged cloud computing infrastructure to enable scalable processing and remote diagnosis. The model utilized CNN-based feature extraction combined with classification layers to achieve high diagnostic accuracy. A key advantage of this approach was its ability to provide real-time predictions in resource-constrained environments, making it suitable for rural healthcare applications. However, the study did not explore serverless computing architectures or advanced hybrid models involving autoencoders and transformers.

Tan and Le (2020) introduced Efficient Net, a family of convolutional neural networks that scale depth, width, and resolution in a balanced manner. Efficient Net models have been widely applied in medical imaging tasks, including tuberculosis detection, due to their high accuracy and computational efficiency. The architecture enables better performance with fewer parameters compared to traditional CNNs, making it suitable for deployment in cloud-based healthcare systems. However, Efficient Net models still rely on convolutional operations and do not incorporate transformer-based attention mechanisms or unsupervised feature extraction techniques like autoencoders.

Zhou et al. (2023) proposed a transformer-based deep learning framework for medical image classification, including tuberculosis detection. The model utilized multi-head self-attention mechanisms to capture both local and global features in chest X-ray images. The study demonstrated that transformer-based models outperform traditional CNN architectures in terms of accuracy and interpretability. Additionally, the model showed improved robustness across different datasets. However, the framework required significant computational resources and did not integrate serverless cloud deployment or secure dual-key architectures for healthcare applications.

Khan et al. (2020) proposed a deep learning-based tuberculosis detection system using a hybrid CNN architecture combined with feature fusion techniques. The study utilized multiple convolutional layers to extract hierarchical features from chest X-ray images, followed by a fusion layer that combined features from different levels to improve classification performance. The model demonstrated high accuracy and robustness, particularly in detecting early-stage TB cases. The research emphasized the importance of multi-level feature representation in improving diagnostic accuracy. However, the model lacked attention-based mechanisms and did not incorporate transformer networks or autoencoder-based dimensionality reduction techniques.

Yamashita et al. (2021) provided a comprehensive overview of convolutional neural networks in medical image analysis, highlighting their applications in tuberculosis detection. The study analysed different CNN architectures and their effectiveness in feature extraction, classification, and segmentation tasks. It emphasized that CNNs have become the backbone of medical image analysis due to their ability to learn spatial hierarchies automatically. However, the study also pointed out limitations such as overfitting, high computational cost, and lack of interpretability, suggesting the need for advanced architectures such as transformers and hybrid models.

Huang et al. (2022) introduced Dense Net, a densely connected convolutional network that improves feature propagation and reduces the number of parameters. Dense Net has been widely used in tuberculosis detection tasks due to its ability to reuse features across layers, leading to improved efficiency and performance. The architecture enables better gradient flow and reduces the risk of vanishing gradients. The study demonstrated that Dense Net-based models outperform traditional CNNs in medical image classification. However, the architecture still relies on convolutional operations and lacks transformer-based attention mechanisms and unsupervised learning approaches such as autoencoders.

Esteva et al. (2021) demonstrated the effectiveness of deep learning models in medical diagnosis using convolutional neural networks trained on large-scale datasets. Although the study primarily focused on skin disease classification, the methodology has been widely adapted for tuberculosis detection using chest X-ray images. The model achieved performance comparable to medical experts, highlighting the potential of AI in clinical diagnostics. The study emphasized the importance of large annotated datasets and end-to-end learning frameworks. However, it did not incorporate transformer-based architectures or unsupervised feature extraction techniques such as convolutional autoencoders, limiting its adaptability to hybrid healthcare systems.

Litjens et al. (2020) provided a comprehensive survey of deep learning techniques in medical image analysis, including applications in tuberculosis detection. The study analysed various architectures such as CNNs, recurrent neural networks, and hybrid models. It highlighted the strengths of deep learning in feature extraction and classification while also addressing challenges such as data scarcity, overfitting, and lack of interpretability. The survey emphasized the need for integrating advanced architectures such as transformers and autoencoders to improve performance in complex medical imaging tasks. However, it did not discuss cloud-based deployment strategies or serverless architectures for real-time healthcare applications.

Comparative Table

S.No	Author (Year)	Technique Used	Key Contribution	Limitations
1	Rahman (2020)	CNN + U-Net	Segmentation improves accuracy	No transformer
2	Wong (2021)	Self-attention CNN	High accuracy TB detection	No cloud deployment
3	Ahmad (2022)	DL + Encryption	Secure TB diagnosis	No advanced feature learning
4	Kumar (2025)	Transformer	Multimodal feature fusion	No serverless model
5	Ding (2025)	YOLOv5 + Cloud	Real-time detection	No hybrid DL model
6	Lakhani (2017)	CNN	Early TB detection system	No attention mechanism
7	Rajpurkar (2020)	DenseNet	Large dataset learning	No autoencoder
8	Hwang (2021)	CNN	Clinical validation	No hybrid architecture
9	Li (2022)	CNN + Attention	Improved feature extraction	No transformer
10	Chen (2023)	Federated Learning	Privacy preservation	No serverless
11	Shen (2020)	Ensemble CNN	Robust predictions	No deep feature compression
12	Abbas (2021)	Transfer Learning	Reduced training time	Limited architecture
13	Dosovitskiy (2021)	Vision Transformer	Global feature learning	High computation
14	Zhang (2022)	Autoencoder	Feature compression	No attention
15	Wang (2023)	CNN + Transformer	Hybrid architecture	No cloud integration
16	Gozes (2020)	CNN	Clinical application	No advanced architecture
17	He (2021)	ResNet	Deep feature extraction	No global context
18	Islam (2022)	CNN + Cloud	Remote diagnosis	No serverless
19	Tan (2020)	EfficientNet	Efficient scaling	No attention
20	Zhou (2023)	Transformer	High accuracy	High complexity

Comparative Analysis

The comparative analysis of 30 studies demonstrates the evolution of tuberculosis detection from conventional convolutional neural networks to advanced hybrid deep learning frameworks. Early CNN-based models achieved effective feature extraction but were limited in capturing global contextual relationships. Transformer architectures and attention mechanisms improved feature representation and diagnostic accuracy, while autoencoders enabled efficient dimensionality reduction, noise removal, and unsupervised feature learning. However, most existing studies investigated these techniques independently rather than integrating them into a unified framework. Cloud computing has enhanced scalable and remote healthcare services, with serverless computing emerging as a cost-effective solution offering automatic scaling and real-time processing. Nevertheless, the integration of hybrid AI models with serverless platforms remains limited. Challenges related to data privacy, security, and model generalization also persist. The reviewed literature highlights a significant research gap, motivating the development of hybrid architectures that combine convolutional autoencoders, dual-key transformer networks, and serverless cloud computing for accurate, secure, scalable, and intelligent tuberculosis prediction systems.

Discussion

The rapid advancement of artificial intelligence and cloud computing technologies has significantly transformed healthcare systems, particularly in the domain of tuberculosis detection. The reviewed studies demonstrate that deep learning models, especially convolutional neural networks, have achieved remarkable success in medical image analysis. However, the limitations of CNNs in capturing global contextual information have led to the emergence of transformer-based architectures, which provide improved feature representation through attention mechanisms. The integration of convolutional autoencoders further enhances the system by enabling efficient feature compression and noise reduction, which are critical in medical imaging applications.

Additionally, the adoption of cloud computing has enabled scalable and remote healthcare solutions, improving accessibility in underserved regions. The introduction of serverless computing further optimizes resource utilization and reduces operational complexity. Despite these advancements, challenges such as data privacy, model generalization, and computational efficiency remain unresolved. The lack of integrated frameworks combining autoencoders, transformers, and serverless deployment highlights a significant research gap. Addressing these challenges is essential for developing robust and efficient e-health systems capable of real-time disease prediction.

Conclusion

Tuberculosis remains a major global health challenge, demanding accurate, rapid, and scalable diagnostic solutions. This review examined recent advances in artificial intelligence for TB detection, emphasizing the integration of convolutional autoencoders, dual-key transformer networks, and serverless cloud computing. Traditional diagnostic approaches are often limited in speed and accuracy, whereas deep learning models automate feature extraction and improve classification performance. Convolutional autoencoders effectively learn compact latent representations from chest X-ray images, while transformer networks enhance global feature modeling through attention mechanisms. Their integration provides robust feature learning, resulting in improved prediction accuracy and reliability. Serverless cloud computing further supports real-time, cost-effective, and scalable deployment without extensive infrastructure management, making AI-enabled healthcare accessible in resource-constrained environments. Despite these advancements, challenges including data privacy, security, model generalization, computational complexity, and energy efficiency continue to hinder widespread clinical adoption. Secure transformer architectures and optimized cloud-based implementations offer promising solutions to these issues. Overall, combining convolutional autoencoders, transformer networks, and serverless cloud platforms establishes a strong foundation for next-generation intelligent tuberculosis diagnosis. Future research should prioritize explainable, lightweight, privacy-preserving, and highly generalizable models for practical healthcare deployment.

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