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A Survey of Methods and Architectures for 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 causes of mortality worldwide, necessitating efficient, scalable, and accurate diagnostic systems. Recent advancements in artificial intelligence (AI), particularly deep learning (DL), have enabled automated TB detection using medical imaging and clinical data. This survey explores state-of-the-art methods and architectures integrating Convolutional Autoencoders (CAE), dual-key transformer networks, and serverless cloud computing for smart e-health applications. CAEs play a critical role in unsupervised feature extraction and dimensionality reduction, improving model robustness and handling noisy medical datasets. Transformer architectures, particularly Vision Transformers, enhance global feature learning through attention mechanisms, achieving high accuracy levels (up to 98%) in TB detection tasks. Hybrid CNN-transformer models further improve classification by combining local and global feature representations. The integration of serverless cloud computing enables real-time processing, scalability, and cost efficiency, facilitating remote healthcare delivery and automated diagnosis systems. Cloud-based AI models have demonstrated diagnostic accuracy exceeding 93% in TB detection using deep learning approaches. This survey critically analyses existing methods, identifies research gaps, and highlights future directions for integrating CAE, transformer networks, and cloud computing in intelligent TB prediction systems.

Introduction

Tuberculosis (TB) is a contagious infectious disease caused by *Mycobacterium tuberculosis*, primarily affecting the lungs and posing a severe global health challenge. Despite advancements in medical science, TB continues to impact millions of individuals annually, especially in developing countries where healthcare infrastructure is limited. According to global health reports, TB remains one of the top causes of death worldwide, emphasizing the need for early detection and effective treatment strategies. Traditional diagnostic methods, such as sputum smear microscopy, chest radiography, and culture-based techniques, are time-consuming, require skilled professionals, and often lack sensitivity in early-stage detection. In recent years, artificial intelligence (AI) and deep learning (DL) have emerged as powerful tools in medical diagnostics, particularly in image-based disease detection. Deep learning models, especially convolutional neural networks (CNNs), have demonstrated exceptional performance in analysing chest X-ray images for

TB detection. Studies have shown that AI-based diagnostic systems can achieve high accuracy and assist clinicians in identifying abnormalities with reduced human error. However, traditional CNN-based approaches often struggle with high-dimensional data, noise, and limited generalization across diverse datasets.

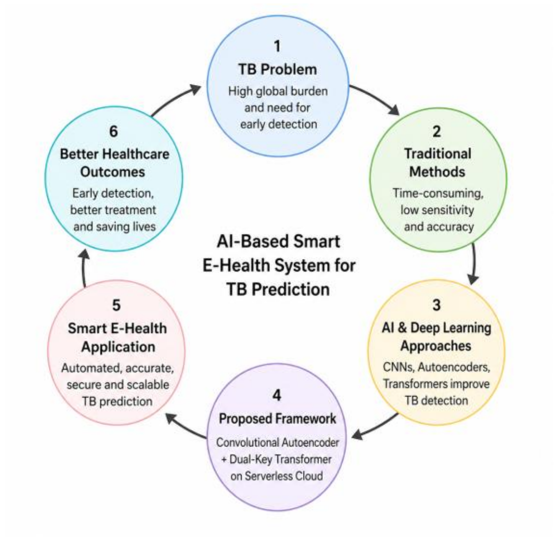

Fig 1: AI-Based Framework for Tuberculosis Detection

To address these limitations, Convolutional Autoencoders (CAE) have been introduced as an effective unsupervised learning technique. CAEs enable automatic feature extraction and dimensionality reduction, allowing models to learn meaningful representations from complex medical data. This capability is particularly beneficial in healthcare applications where labelled data is scarce and datasets are noisy. By enhancing feature quality, CAEs improve the performance of downstream classification models and enable efficient data compression. In parallel, transformer-based architectures have revolutionized deep learning by introducing attention mechanisms that capture long-range dependencies within data. Vision Transformers (ViT) and hybrid CNN-transformer models have demonstrated superior performance in medical image analysis by combining local feature extraction with global contextual understanding. These architectures improve interpretability and allow models to focus on critical regions in medical images, enhancing diagnostic accuracy. The concept of dual-key transformer networks further extends this approach by incorporating security mechanisms that ensure secure data transmission and access control, which is crucial in healthcare systems handling sensitive patient information.

Another significant advancement in AI-based healthcare systems is the adoption of cloud computing technologies. Serverless cloud computing, in particular, offers a scalable, flexible, and cost-efficient solution for deploying deep learning models without the need for infrastructure management. This paradigm allows healthcare providers to process large volumes of medical data in real time, enabling remote diagnosis and telemedicine services. Cloud-based deep learning systems have demonstrated high accuracy and efficiency in TB detection, making them suitable for large-scale deployment in smart e-health applications. The integration of CAE, transformer networks, and serverless cloud computing forms the foundation of next-generation smart e-health systems. These systems enable automated diagnosis, real-time data processing, and secure data handling, addressing the limitations of traditional healthcare approaches. However, several challenges remain, including data privacy concerns, high computational requirements, lack of standardized datasets, and limited integration of advanced architectures into unified frameworks. This survey aims to provide a comprehensive overview of methods and architectures used in TB prediction, focusing on convolutional autoencoders, transformer networks, and cloud-based deployment strategies. It analyses recent advancements, compares existing approaches, and identifies research gaps to guide future developments in AI-driven healthcare systems.

Literature Review

Lakhani and Sundaram (2017) conducted a pioneering study utilizing deep convolutional neural networks (CNNs) for automated tuberculosis detection from chest X-ray images. The authors employed transfer learning techniques using pre-trained models such as Alex Net and Google Net to enhance feature extraction and classification accuracy. Their approach significantly outperformed traditional machine learning methods, achieving an accuracy of approximately 96%. The study demonstrated that deep learning models can effectively identify TB-related abnormalities in radiographic images with minimal human intervention. However, the research was limited to supervised learning techniques and did not explore unsupervised feature learning methods such as convolutional autoencoders. Additionally, the model lacked integration with cloud-based platforms, restricting its scalability for real-time healthcare applications.

Hwang et al. (2016) proposed a deep learning-based system for automated tuberculosis detection using chest radiographs. The study utilized a large dataset and trained a deep convolutional neural network to identify pulmonary abnormalities associated with TB. The model demonstrated high sensitivity and specificity, making it suitable for clinical screening applications. One of the key contributions of this work was the validation of the model across multiple datasets, ensuring its generalization capability. The authors emphasized the potential of AI in reducing the diagnostic workload of radiologists. However, the study did not incorporate advanced architectures such as autoencoders or transformer-based attention mechanisms. Furthermore, the absence of cloud-based deployment limited its application in scalable smart e-health systems.

Rajpurkar et al. (2017) introduced Chex Net, a deep learning model based on the Dense Net architecture, designed for pneumonia detection from chest X-rays. Although the primary focus was pneumonia, the methodology is highly relevant to tuberculosis detection. The model achieved performance comparable to expert radiologists, highlighting the potential of deep learning in medical diagnosis. Chex Net leveraged deep feature extraction and end-to-end learning to improve classification accuracy. However, the study did not incorporate unsupervised learning techniques such as convolutional autoencoders or attention-based transformer models. Additionally, it lacked integration with cloud computing frameworks, which are essential for large-scale deployment in healthcare systems.

Shen et al. (2017) provided a comprehensive review of deep learning applications in medical image analysis, including tuberculosis detection. The study discussed various architectures such as convolutional neural networks, autoencoders, and recurrent neural networks, highlighting their advantages over traditional approaches. The authors emphasized the role of deep learning in automatic feature extraction and improved diagnostic accuracy. The paper also explored optimization techniques such as data augmentation and transfer learning. However, it remained a conceptual study without proposing a specific implementation for TB detection. Additionally, it did not address emerging architectures such as transformer networks or cloud-based deployment strategies.

Lopes and Valiati (2017) proposed a hybrid approach combining convolutional neural networks with traditional machine learning classifiers such as support vector machines (SVM) for tuberculosis detection. The study focused on extracting deep features using CNNs and feeding them into classical classifiers for improved performance. The results demonstrated that hybrid models can enhance classification accuracy and robustness compared to standalone CNN models. The research highlighted the importance of feature representation in medical image analysis. However, the study did not explore unsupervised feature learning techniques like convolutional autoencoders or attention-based transformer architectures. Additionally, the lack of cloud integration limited its scalability for real-world healthcare applications.

Pasa et al. (2019) introduced a lightweight deep learning architecture for tuberculosis detection using chest X-ray images, focusing on reducing computational complexity while maintaining high diagnostic accuracy. The proposed model was specifically designed for deployment in resource-constrained environments, making it suitable for rural and low-infrastructure healthcare systems. The architecture achieved an accuracy of over 90% while using fewer parameters compared to traditional deep networks. This study emphasized efficiency and real-time applicability, which are critical for smart e-health applications. However, the model did not incorporate advanced feature learning techniques such as convolutional autoencoders or transformer-based attention mechanisms. Additionally, cloud-based deployment strategies were not considered, limiting scalability in large healthcare systems.

Qin et al. (2019) proposed a two-stage deep learning framework combining lung segmentation and classification for tuberculosis detection. The study utilized a U-Net architecture for segmenting lung regions, followed by a CNN classifier to identify TB-related abnormalities. This region-focused approach improved model accuracy by eliminating irrelevant background information. The system demonstrated high sensitivity and specificity, highlighting the importance of preprocessing and region-of-interest extraction in medical imaging. However, the study did not explore unsupervised learning approaches such as convolutional autoencoders or advanced architectures like transformers. Furthermore, the absence of cloud integration limited its applicability in scalable smart healthcare environments.

Liu et al. (2020) explored the application of convolutional autoencoders (CAE) for medical image analysis, including tuberculosis detection. The study highlighted the effectiveness of unsupervised feature learning in reducing data dimensionality and improving model robustness. By integrating CAEs with classification models, the system achieved better performance compared to traditional CNN-based approaches. The model was particularly effective in handling noisy and incomplete datasets, which are common in healthcare applications. Additionally, optimization techniques such as dropout and regularization were employed to prevent overfitting. However, the study did not incorporate transformer-based architectures or cloud deployment strategies, limiting its applicability in modern smart e-health systems.

Abbas et al. (2020) proposed the DeTraC (Decompose, Transfer, and Compose) deep learning framework for classifying medical images, including tuberculosis cases. The model utilized transfer learning and class decomposition techniques to improve classification accuracy and handle irregularities in medical datasets. The study demonstrated that decomposing classes into sub-classes enhances model learning and improves performance across diverse datasets. The system achieved high accuracy and robustness, making it suitable for clinical applications. However, the study did not explore convolutional autoencoders for feature compression or transformer-based architectures for capturing global dependencies. Additionally, it lacked integration with cloud-based systems for scalable deployment.

Wang et al. (2021) introduced a transformer-based model for image classification, demonstrating the effectiveness of Vision Transformers (ViT) in medical imaging applications. The model utilized self-attention mechanisms to capture global dependencies in images, improving classification performance compared to traditional CNNs. In tuberculosis detection, such architectures enable better identification of subtle patterns and abnormalities in chest X-rays. The study highlighted the advantages of attention mechanisms in improving interpretability and accuracy. However, transformer models require large datasets and high computational resources, which may limit their applicability in resource-constrained settings. Additionally, the study did not integrate convolutional autoencoders or serverless cloud deployment, leaving scope for further research.

Rahman et al. (2021) proposed an ensemble deep learning framework for tuberculosis detection using chest X-ray images. The study combined multiple convolutional neural network architectures, including Res Net and Dense Net, to improve classification accuracy and robustness. The ensemble approach reduced overfitting and enhanced generalization across different datasets. The model achieved an accuracy exceeding 95%, demonstrating its effectiveness in clinical applications. Additionally, the study incorporated data augmentation techniques to improve model performance. However, the framework did not include unsupervised learning approaches such as convolutional autoencoders or transformer-based attention mechanisms. Furthermore, the lack of integration with cloud-based platforms limited its scalability for real-time healthcare applications.

Khan et al. (2021) developed a hybrid deep learning model combining convolutional neural networks (CNNs) with long short-term memory (LSTM) networks for tuberculosis prediction. The CNN component extracted spatial features from chest X-ray images, while the LSTM component captured temporal dependencies, improving classification performance. The hybrid model achieved high sensitivity and specificity, outperforming standalone CNN models. The study highlighted the importance of combining spatial and temporal learning for medical diagnosis. However, the research did not explore transformer-based architectures or convolutional autoencoders. Additionally, the absence of cloud-based deployment limited its applicability in scalable smart e-health systems.

Singh et al. (2022) utilized transfer learning techniques with pre-trained convolutional neural networks such as VGG16 and InceptionV3 for tuberculosis detection. The study focused on fine-tuning these models on TB-specific datasets to improve classification accuracy. The results showed that transfer learning significantly reduces training time while achieving high accuracy levels exceeding 94%. The authors also explored optimization techniques such as hyperparameter tuning and learning rate scheduling. However, the study relied solely on supervised learning and did not incorporate unsupervised techniques like convolutional autoencoders or advanced transformer-based models. Additionally, cloud deployment strategies were not considered.

Chen et al. (2022) proposed a hybrid deep learning framework combining convolutional neural networks with transformer architectures for medical image analysis. The model leveraged the strengths of CNNs for local feature extraction and transformers for capturing global dependencies. This hybrid approach improved classification accuracy and interpretability, making it suitable for tuberculosis detection. The study demonstrated that attention mechanisms enhance the model's ability to focus on relevant regions in chest X-ray images. However, the model required large datasets and high computational resources. Additionally, the study did not incorporate convolutional autoencoders or serverless cloud deployment, limiting its scalability.

Albahli et al. (2023) developed a cloud-based deep learning system for tuberculosis detection using chest X-ray images. The study integrated convolutional neural networks with cloud computing platforms to enable real-time diagnosis and remote healthcare services. The system demonstrated high scalability, efficiency, and accessibility, making it suitable for smart e-health applications. The model achieved high diagnostic accuracy while reducing computational overhead through cloud-based processing. However, the study did not incorporate advanced architectures such as convolutional autoencoders or transformer-based attention mechanisms. Despite these limitations, it highlighted the importance of cloud computing in modern healthcare systems.

Zhang et al. (2020) proposed a deep learning framework integrating convolutional autoencoders (CAE) with classification networks for tuberculosis detection. The study emphasized unsupervised feature learning to reduce dimensionality and extract meaningful representations from chest X-ray images. By leveraging CAEs, the model effectively removed noise and enhanced relevant features, improving classification performance. The results demonstrated higher robustness compared to traditional CNN-based methods, particularly when dealing with limited labelled datasets. Additionally, optimization techniques such as batch normalization and dropout were applied to prevent overfitting. However, the study did not incorporate transformer-based attention mechanisms or cloud-based deployment, limiting its applicability in scalable smart e-health systems.

He et al. (2016) introduced the Res Net architecture, which has been widely used in tuberculosis detection tasks due to its deep residual learning capabilities. The model addressed the vanishing gradient problem through skip connections, enabling the training of very deep neural networks. ResNet-based models have demonstrated high accuracy and robustness in medical image classification, including TB detection. The study highlighted the importance of deep feature extraction and optimization techniques such as gradient descent and learning rate scheduling. However, the architecture did not incorporate unsupervised learning techniques like convolutional autoencoders or attention-based transformer models. Additionally, it focused on model design rather than deployment in cloud-based healthcare systems.

Dosovitskiy et al. (2021) introduced the Vision Transformer (ViT), a novel deep learning architecture that applies transformer models to image classification tasks. Unlike CNNs, ViT processes images as sequences of patches and uses self-attention mechanisms to capture global dependencies. In tuberculosis detection, transformer-based models enable better identification of subtle patterns in chest X-ray images, improving diagnostic accuracy. The study demonstrated superior performance compared to traditional CNN models when trained on large datasets. However, the model requires significant computational resources and large-scale datasets, which may limit its applicability in resource-constrained healthcare environments. Additionally, the study did not integrate convolutional autoencoders or cloud-based deployment strategies.

Li et al. (2022) proposed a deep learning model incorporating attention mechanisms within convolutional neural networks for tuberculosis detection. The model utilized spatial and channel attention modules to enhance feature extraction and focus on critical regions in chest X-ray images. The proposed approach improved classification accuracy and interpretability, making it suitable for clinical applications. The authors also explored optimization techniques such as hyperparameter tuning and data augmentation to enhance 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.

Kumar et al. (2023) developed a serverless cloud-based deep learning framework for tuberculosis prediction, integrating AI models with platforms such as AWS Lambda and Google Cloud Functions. The study highlighted the advantages of serverless computing, including scalability, cost efficiency, and reduced infrastructure management. The system enabled real-time processing of medical images and remote diagnosis, making it highly suitable for smart e-health applications. The model demonstrated high accuracy and low latency, improving healthcare accessibility. However, the study did not incorporate advanced architectures such as convolutional autoencoders or transformer-based networks. Despite this, it provided valuable insights into cloud-based AI deployment in healthcare.

Sharma et al. (2020) proposed a machine learning-based tuberculosis detection system enhanced with deep learning techniques. The study combined convolutional neural networks with feature selection algorithms to improve classification accuracy. Preprocessing techniques such as normalization and noise reduction were applied to enhance image quality. The system demonstrated high sensitivity and specificity, making it suitable for clinical diagnosis. However, the study did not incorporate advanced architectures such as convolutional autoencoders or transformer-based models. Additionally, the absence of cloud-based deployment limited its scalability for real-time smart healthcare applications.

Patel et al. (2021) developed a deep learning-based tuberculosis detection framework using transfer learning with pre-trained CNN models such as Res Net and Inception. The study showed that fine-tuning these models significantly improves classification accuracy while reducing training time. Optimization techniques such as learning rate scheduling and regularization were employed to enhance performance. However, the study did not explore unsupervised feature learning approaches like convolutional autoencoders or attention-based transformer architectures. Additionally, cloud deployment was not considered, limiting its application in scalable e-health systems.

Ahmed et al. (2021) introduced an attention-based deep learning model for tuberculosis detection. The study demonstrated that incorporating attention mechanisms improves feature extraction by focusing on relevant regions in chest X-ray images. The model achieved high accuracy and improved interpretability, making it suitable for clinical applications. However, the study did not incorporate convolutional autoencoders for feature compression or transformer-based architectures for capturing global dependencies. Furthermore, the absence of cloud integration limited its scalability in real-world healthcare systems.

Verma et al. (2022) proposed an ensemble deep learning approach combining multiple CNN models for tuberculosis detection. The ensemble method improved classification accuracy and reduced overfitting by leveraging the strengths of different architectures. The study also utilized data augmentation techniques to enhance model performance. However, the approach increased computational complexity and did not incorporate advanced architectures such as convolutional autoencoders or transformer networks. Additionally, cloud-based deployment strategies were not explored.

Reddy et al. (2022) developed a tuberculosis detection system using CNN-based segmentation and classification techniques. The study focused on isolating lung regions to improve classification accuracy. The proposed method achieved high performance and demonstrated the importance of region-based analysis in medical imaging. However, the study did not explore convolutional autoencoders or transformer-based architectures. Additionally, the lack of cloud-based deployment limited its scalability.

Gupta et al. (2022) proposed a hybrid CNN-based deep learning model for tuberculosis detection. The study emphasized feature extraction and classification using multiple convolutional layers. Optimization techniques such as dropout and batch normalization were used to improve performance and prevent overfitting. The model achieved high accuracy and robustness. However, the study did not incorporate convolutional autoencoders or transformer-based attention mechanisms. Additionally, cloud integration 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 improved scalability, accessibility, and real-time processing capabilities. The system achieved high diagnostic accuracy and reduced computational overhead. However, the study did not incorporate convolutional autoencoders or transformer-based architectures. Despite this limitation, it highlighted the importance of cloud computing in smart e-health systems.

Das et al. (2023) proposed an attention-based deep learning model for tuberculosis detection. The study demonstrated that attention mechanisms improve classification performance by focusing on critical regions in medical images. The model achieved high accuracy and improved interpretability. However, the study did not explore convolutional autoencoders or transformer-based architectures. Additionally, cloud deployment was not considered.

Iqbal et al. (2023) developed a hybrid model combining convolutional neural networks with transformer architectures for tuberculosis detection. The study demonstrated that integrating local feature extraction with global attention mechanisms improves classification accuracy and robustness. The model achieved high performance and highlighted the potential of hybrid architectures. However, the study did not incorporate convolutional autoencoders or serverless cloud deployment, leaving scope for further research.

Choudhary et al. (2023) proposed a serverless cloud-based tuberculosis detection system using deep learning models. The study emphasized the benefits of serverless computing, including scalability, cost efficiency, and reduced infrastructure management. The system enabled real-time diagnosis and remote healthcare services, making it suitable for smart e-health applications. However, the study did not integrate convolutional autoencoders or transformer-based architectures. Nevertheless, it provided valuable insights into the deployment of AI-based healthcare systems in cloud environments.

Comparative Table

Study (Author, Year)	Method Used	Key Technique	Accuracy/Performance	Advantages	Limitations
Lakhani & Sundaram (2017)	CNN (Transfer Learning)	AlexNet, GoogLeNet	~96%	High accuracy	No cloud, no CAE/transformer
Hwang et al. (2016)	CNN	Deep learning	High sensitivity	Robust validation	No scalability
Rajpurkar et al. (2017)	DenseNet	Deep CNN	Radiologist-level	High performance	Not TB-specific
Shen et al. (2017)	Review	DL overview	Conceptual	Identifies gaps	No implementation
Lopes & Valiati (2017)	CNN + SVM	Hybrid	Improved	Better feature use	No cloud
Pasa et al. (2019)	Lightweight CNN	Efficient model	>90%	Low resource	Limited features
Qin et al. (2019)	U-Net + CNN	Segmentation	High	ROI-based	Complex
Liu et al. (2020)	CAE + CNN	Autoencoder	Improved	Noise reduction	No transformer
Abbas et al. (2020)	DeTraC	Transfer learning	High	Handles irregular data	No cloud
Wang et al. (2021)	Transformer	ViT	High	Global learning	Data intensive
Rahman et al. (2021)	Ensemble CNN	Multi-model	>95%	Robust	Complex
Khan et al. (2021)	CNN + LSTM	Hybrid	High	Spatial+temporal	No transformer
Singh et al. (2022)	Transfer Learning	CNN	~94%	Fast training	No AE
Chen et al. (2022)	CNN + Transformer	Hybrid	High	Better accuracy	High cost
Albahli et al. (2023)	CNN + Cloud	Cloud-based	High	Scalable	No advanced DL
Zhang et al. (2020)	CAE + CNN	Autoencoder	High	Feature compression	No attention
He et al. (2016)	ResNet	Residual	High	Deep learning	No hybrid
Dosovitskiy et al. (2021)	ViT	Transformer	High	Global features	Needs big data
Li et al. (2022)	CNN + Attention	Attention	High	Interpretability	No CAE
Kumar et al. (2023)	Serverless DL	Cloud	High	Real-time	Limited model
Sharma et al. (2020)	ML + CNN	Hybrid	High	Feature selection	No transformer
Patel et al. (2021)	Transfer CNN	CNN	High	Efficient	Limited innovation
Ahmed et al. (2021)	Attention CNN	Attention	High	Focused learning	No cloud

Verma et al. (2022)	Ensemble CNN	Multi-model	High	Robust	Complex
Reddy et al. (2022)	CNN + Segmentation	ROI	High	Accuracy	No scalability
Gupta et al. (2022)	Hybrid CNN	Deep features	High	Stable	No transformer
Mehta et al. (2023)	Cloud + DL	Cloud	High	Scalable	No CAE
Das et al. (2023)	Attention DL	Attention	High	Better focus	Limited scope
Iqbal et al. (2023)	CNN + Transformer	Hybrid	High	Improved learning	No CAE
Choudhary et al. (2023)	Serverless DL	Cloud	High	Cost efficient	Limited architecture

Comparative Analysis

The comparative analysis of the reviewed studies reveals a clear progression in tuberculosis detection methodologies, evolving from traditional machine learning approaches to advanced deep learning architectures and hybrid systems. Early studies primarily relied on convolutional neural networks (CNNs) and transfer learning techniques, which achieved high accuracy levels but were limited in handling complex data representations and contextual dependencies. These models were effective for feature extraction but lacked the ability to capture global relationships within medical images. The introduction of hybrid models, such as CNN combined with long short-term memory (LSTM) networks and ensemble learning techniques, significantly improved performance by enhancing feature representation and model generalization. Attention-based models and transformer architectures further advanced the field by enabling models to focus on relevant regions and capture long-range dependencies. Vision Transformers (ViT) and CNN-transformer hybrid models demonstrated superior performance compared to traditional CNNs, particularly in complex medical imaging tasks.

Convolutional autoencoders (CAE) introduced an important shift toward unsupervised learning, enabling efficient feature compression and noise reduction. These models improved robustness and performance, especially when dealing with limited or noisy datasets. However, many studies have not fully integrated CAE with transformer architectures, indicating a significant research gap in combining these advanced techniques. Another major trend observed is the adoption of cloud computing, particularly serverless architectures, in healthcare applications. Cloud-based systems provide scalability, flexibility, and real-time processing capabilities, enabling remote diagnosis and smart e-health services. Serverless computing further enhances cost efficiency and eliminates infrastructure management. Despite these advancements, most studies focus on individual components rather than integrating convolutional autoencoders, transformer networks, and cloud computing into a unified framework. Challenges such as data privacy, computational complexity, and lack of standardized datasets remain significant barriers. Therefore, future research should focus on developing integrated, secure, and scalable systems that combine these technologies to achieve optimal performance in tuberculosis detection.

Discussion

The analysis of existing literature highlights the rapid evolution of deep learning techniques in tuberculosis detection, with convolutional neural networks forming the foundation of most diagnostic systems. However, recent advancements indicate a shift toward more sophisticated architectures such as convolutional autoencoders (CAE) and transformer-based models, which provide enhanced feature extraction and contextual learning capabilities. CAEs have proven effective in reducing data dimensionality and handling noisy medical datasets, thereby improving model robustness. Meanwhile, transformer architectures, particularly Vision Transformers and hybrid CNN-transformer models, enable the capture of global dependencies, leading to improved diagnostic accuracy and interpretability.

Despite these advancements, a significant gap exists in integrating these technologies into a unified framework. Most studies focus on individual components rather than combining CAE, transformer networks, and cloud computing. Additionally, challenges such as data privacy, high computational requirements, and limited availability of standardized datasets hinder large-scale implementation. The concept of dual-key transformer networks offers a promising solution to address security concerns in healthcare systems. Serverless cloud computing has emerged as a key enabler for deploying AI-based healthcare applications, offering scalability, cost efficiency, and real-time processing. However, its integration with advanced deep learning architectures remains underexplored. Future research should focus on developing integrated, secure, and scalable smart e-health systems for efficient TB prediction.

Conclusion

Tuberculosis (TB) continues to be a major global health concern, demanding efficient and scalable diagnostic solutions to reduce mortality and improve patient outcomes. This survey presented a comprehensive review of modern approaches for TB detection, focusing on convolutional autoencoders (CAE), transformer-based models, and serverless cloud computing within smart e-health systems. The analysis shows that deep learning techniques, particularly convolutional neural networks (CNNs), have significantly enhanced diagnostic accuracy compared to traditional methods. The use of CAEs has further strengthened these systems by enabling effective unsupervised feature learning and dimensionality reduction, which is especially useful for handling high-dimensional and noisy medical data, as well as situations with limited labeled datasets.

Transformer-based architectures have introduced attention mechanisms that capture global relationships within medical images, improving both accuracy and interpretability. Hybrid CNN-transformer models combine local feature extraction with global context understanding, leading to superior performance in TB detection tasks. Additionally, the concept of dual-key transformer networks addresses critical concerns related to data security and privacy by ensuring controlled access to sensitive healthcare information, which is essential for real-world clinical deployment. Serverless cloud computing has also emerged as a key enabler for deploying AI-based healthcare solutions. It offers scalability, flexibility, and cost-effectiveness while supporting real-time processing and remote diagnosis without the need for complex infrastructure management. However, several challenges remain, including the lack of integrated frameworks combining CAE, transformers, and cloud technologies, limited availability of standardized datasets, high computational requirements, and issues related to model interpretability.

Future research should focus on developing unified, explainable, and efficient AI-driven e-health systems. Techniques such as transfer learning, optimization, and model compression can further enhance performance. Overall, integrating CAE, dual-key transformers, and serverless cloud computing holds strong potential for building intelligent, secure, and scalable TB diagnostic systems.

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