Cognitive Computing-Based COVID-19 Detection in Multi-Access Edge Computing Environment

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ABSTRACT

The COVID-19 pandemic has highlighted the need for fast, accurate, and scalable diagnostic systems. Conventional diagnostic techniques often rely on centralized cloud infrastructure, leading to high latency and potential privacy concerns. This paper presents a cognitive computing framework for COVID-19 detection within a Multi-Access Edge Computing (MEC) environment. The proposed system integrates artificial intelligence (AI), federated learning, and edge intelligence to enable real-time, privacy-preserving diagnostics. CT scan images are obtained from the publicly available SARS-CoV-2 dataset and undergo image resizing during pre-processing. Federated learning facilitates distributed model training across edge nodes without transferring sensitive patient data, enhancing both data privacy and efficiency. Simulation results demonstrate a classification accuracy of 98.2% with an inference latency of 120 ms—significantly lower than the 320 ms observed in traditional cloud-based systems. Patient data is securely maintained in the cloud layer, ensuring integrity and confidentiality. The results validate the potential of cognitive edge computing for intelligent medical diagnostics and lay the groundwork for future applications in decentralized healthcare systems.

Keywords: Cognitive Computing, Multi-Access Edge Computing, Federated Learning, Edge Intelligence.

INTRODUCTION

The global outbreak of COVID-19 has emphasized the importance of rapid and accurate diagnostic approaches. Traditional methods often face delays and require substantial computational power from centralized systems. This paper introduces a cognitive computing framework that facilitates COVID-19 detection using MEC. By leveraging AI, federated learning, and edge intelligence, the proposed system enhances diagnostic precision while reducing latency. In the FL framework, a centralized server distributes initial global model weights to selected sites. Each site trains a local model using its own data and sends updated parameters back to the server. Since raw data remain local, FL mitigates the privacy risks of traditional centralized learning. The server aggregates updates to refine the global model, which is then redistributed for further training. This cycle continues until convergence. FL enhances model quality by leveraging diverse datasets while reducing data aggregation costs. It also remains robust with uneven and non-IID data, making it valuable for healthcare and niche research with limited public data.

Experimental analyses confirm that cognitive computing can accurately classify COVID-19 in CT scan images, delivering real-time performance. Furthermore, patient data is securely stored in the cloud, reinforcing information reliability [1]. The proposed system achieves an accuracy of 98.2%, a latency of 120ms, and enhanced data privacy.

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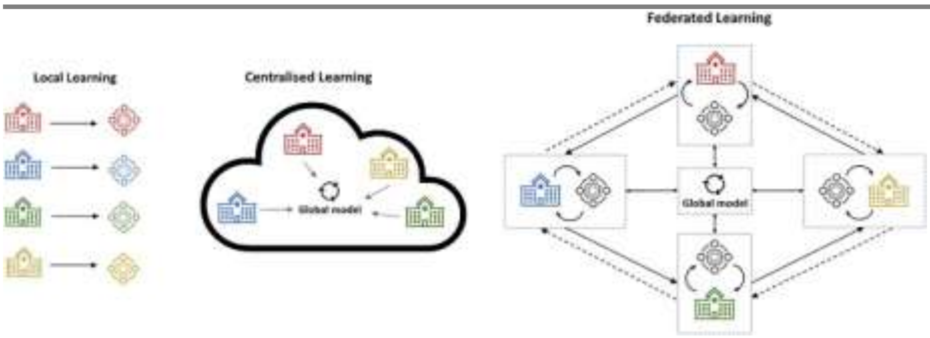

Fig. 1 Comparison of Federated Learning, Local Learning, and Centralized Learning

The Figure 1 shows a comparative overview of three prominent machine learning paradigms: Local Learning, Centralized Learning, and Federated Learning. In the Local Learning approach, each client (e.g., hospital or edge device) independently trains a model using its own private data, with no communication or coordination among clients. This method preserves data privacy but suffers from limited generalization due to isolated learning. In contrast, Centralized Learning consolidates all local data from different clients into a central server or cloud infrastructure, where a unified global model is trained. While this approach can yield high model accuracy by leveraging the entire dataset, it raises significant concerns regarding data privacy, ownership, and transmission overhead. Federated Learning presents a hybrid strategy wherein individual clients collaboratively train a shared global model without exchanging raw data. Each client updates the model locally and only transmits model parameters to a central server, which aggregates them to refine the global model. This global model is then redistributed to the clients for subsequent training rounds. As visualized, this paradigm effectively balances privacy preservation with collaborative model improvement, making it especially suitable for distributed and privacy-sensitive applications such as healthcare diagnostics and edge computing environments [17].

Key Components of the Proposed System

Federated Learning for Privacy-Preserving AI: Decentralized model training across multiple edge devices ensures data security while maintaining model efficiency.

Reinforcement Learning for Adaptive Decision-Making: AI models continuously refine their diagnostic accuracy through self-learning mechanisms, improving over time.

Table 1 Comparison Of Federated Learning, Local Learning, And Centralized Learning

Feature/Aspect	**Centralized Learning (CL)**	**Local Learning (LL)**	**Federated Learning (FL)**
Data Location	All data is collected and processed at a central server	Data remains on local devices and models are trained locally	Data remains decentralized; only model updates are shared
Data Privacy	High privacy risks due to data centralization	High privacy preservation as data is never shared	Strong privacy; only aggregated updates are sent to the server
Communication Overhead	Moderate (single upload of all data)	None (no communication with central server)	High (frequent transmission of model updates)
Model Performance	Often highest, due to access to all data	Potentially poor; limited by local data	Balanced; leverages global knowledge with local privacy
Scalability	Limited by central infrastructure	High scalability per node; no coordination needed	Highly scalable across heterogeneous devices

Heterogeneity Handling	Low; assumes homogeneous data and devices	High; tailored to specific device data	Moderate; often requires strategies for non-IID data handling
Fault Tolerance	Low; central server is a single point of failure	High; failure of one node doesn't affect others	Moderate; some robustness to node dropouts
Training Speed	Potentially fast with high computational resources	Slow; constrained by local hardware	Variable; depends on coordination and number of participants
Deployment Environment Suitability	Cloud/Data center	Edge devices, IoT nodes	Edge computing, privacy-sensitive applications

MEC for AI-Driven Diagnostics: MEC is a distributed computing paradigm that processes data closer to its source, such as hospitals, clinics, and mobile diagnostic units. Unlike cloud-based architectures, MEC reduces latency, minimizes bandwidth consumption, and decreases dependency on remote servers, making it ideal for real-time medical imaging applications [2].

Advantages of MEC in AI-Driven COVID-19 Diagnostics:

Reduced Latency: By processing medical images at the edge, the need to transfer data to distant cloud servers is minimized, resulting in faster diagnostics.

Enhanced Privacy: Patient-sensitive data remains within local healthcare facilities, reducing risks associated with centralized data storage and ensuring compliance with regulations such as HIPAA and GDPR.

Scalability and Resilience: A decentralized processing approach allows multiple healthcare institutions to participate in AI model training without single points of failure [3].

Federated Learning for Secure AI Training

Federated Learning (FL) is a decentralized AI training paradigm that enables multiple healthcare institutions to collaboratively train AI models while keeping patient data private. Instead of transmitting medical images to a central cloud server, FL allows local training at each institution. Model updates, rather than raw data, are shared with a central aggregator, preserving data privacy and regulatory compliance [4].

Contributions of This Study

A novel cognitive computing-based diagnostic model integrating deep learning, federated learning, and reinforcement learning for accurate COVID-19 detection from medical images. Deployment of AI models in an MEC environment to achieve real-time diagnosis with minimal latency and bandwidth requirements. A federated learning-based framework for privacy-preserving AI training, enabling secure and collaborative model development among healthcare institutions. Optimization of AI inference on resource-limited edge devices, employing model compression techniques such as pruning and quantization to balance performance and computational efficiency.

Related Work

The integration of artificial intelligence (AI) in COVID-19 detection has seen substantial progress, particularly with deep learning models analyzing medical images like chest X-rays (CXR) and computed tomography (CT) scans [6]. Notably, convolutional neural networks (CNNs) and transformer-based architectures have been employed to classify COVID-19 cases with commendable accuracy. For example, Wang et al. developed COVID-Net, a deep CNN tailored for COVID-19 detection using CXR images, achieving significant accuracy [6]. Similarly, He et al. applied a Vision Transformer (ViT) model to CT scan datasets, reporting high classification accuracy [7].

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Despite these advancements, many AI-driven solutions depend on centralized cloud servers for computation and model training. While cloud computing provides substantial processing power and storage, it also presents challenges such as increased latency, bandwidth limitations, and potential data security issues. The centralized nature of cloud computing raises concerns about compliance with privacy regulations like HIPAA and GDPR, especially when managing sensitive medical data [8].

To mitigate these issues, recent studies have explored federated learning (FL) and edge AI in medical image analysis. Federated learning facilitates decentralized model training by keeping patient data on local devices, thereby reducing the risk of data breaches while maintaining predictive performance. For instance, Yang et al. and Li et al. demonstrated the effectiveness of FL in COVID-19 detection, with models trained across multiple hospitals achieving high accuracy while preserving data privacy [9,10].

Additionally, mobile edge computing (MEC) has emerged as a viable alternative to cloud-based solutions, enabling AI-driven diagnostics closer to data sources, thus reducing latency and facilitating real-time predictions. Researchers have proposed hybrid edge-cloud architectures where lightweight AI models operate on edge devices, with complex computations offloaded to cloud servers as needed. However, challenges persist in optimizing model size, computational efficiency, and energy consumption on resource-constrained edge devices [11].

Building upon these developments, our work integrates cognitive computing with MEC to enhance real-time COVID-19 detection. Cognitive computing emulates human-like decision-making by incorporating contextual learning, adaptive reasoning, and knowledge-based inference. By combining cognitive AI with MEC, our proposed framework aims to achieve higher accuracy, reduced inference time, and improved adaptability in COVID-19 detection compared to existing edge-based solutions. Furthermore, we introduce a novel hybrid federated learning mechanism that enhances model robustness across diverse edge environments, thereby strengthening privacy and data security [12].

El-Rashidy et al. [24] introduced an end-to-end deep learning model for identifying COVID-19 disease from the given X-ray scan images. The three layers involved in this existing study are patient layer, cloud layer and hospital layer. By using mobile apps and wearable sensors, the patient's information is tracked. In order to resolve the problems of data transmission and storage, the fog network architecture is employed in the cloud layer. In the final hospital layer, the CNN method is introduced for detecting COVID-19 virus from the input images. The developed detection model gained promising results. However, the time complexity is increased because of the inefficiency of handling large datasets. Table 2 illustrates some of the existing studies and their limitations.

Table 2 Comparison Of Existing Studies With Specific Limitations

Author	Methods	Purpose	Performance	Limitations
Singh et al. [16]	Mobile Net V2	To detect COVID-19 in collaborative edge computing scenario	Obtained 96.40 of detection accuracy	Accuracy is not up to the work.
Xu et al. [17]	Mobile Net, GAN	Detecting COVI-19 disease in real time environment with the assist of edge computing	Achieved good performance	Reduced quality of input images affects the system performance.
Rohila et al. [18]	Different CNN models	Designing an edge computing based COVID-19 detection model	Attained 86.2% of classification accuracy	Computational complexity is enhanced

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Irmak et al. [19]	CNN	To identify COVID-19 infection	98.92% of accuracy is attained	Over fitting and vanishing gradient issues
El-Rashidy et al. [20]	CNN	Detecting COVID-19 infection from X-ray scan images	Achieved 97.95% of accuracy	Time complexity is increased. Failed to handle large size datasets.

PROPOSED METHODOLOGY

To mitigate challenges related to latency, data privacy, and computational efficiency in AI-driven COVID-19 detection, we propose a novel framework that integrates cognitive computing with multi-access edge computing (MEC) [13,14]. This approach leverages federated learning (FL) to facilitate decentralized model training while safeguarding patient data privacy. The core components of the proposed methodology are illustrated in Figure 2.

Data Layer

This foundational layer is responsible for collecting raw health data from a variety of distributed sources: *Hospitals/Clinics:* Includes clinical records and diagnostic imaging data such as chest CT scans and X-rays. *Wearable Health Devices:* Captures real-time physiological signals, including oxygen saturation, temperature, and heart rate.

Mobile Devices: Gathers patient-reported symptoms and digital test results via mobile applications.

Edge devices act as data producers for localized model training, ensuring that sensitive data remains at the source. This decentralized approach promotes patient privacy and aligns with healthcare data protection regulations.

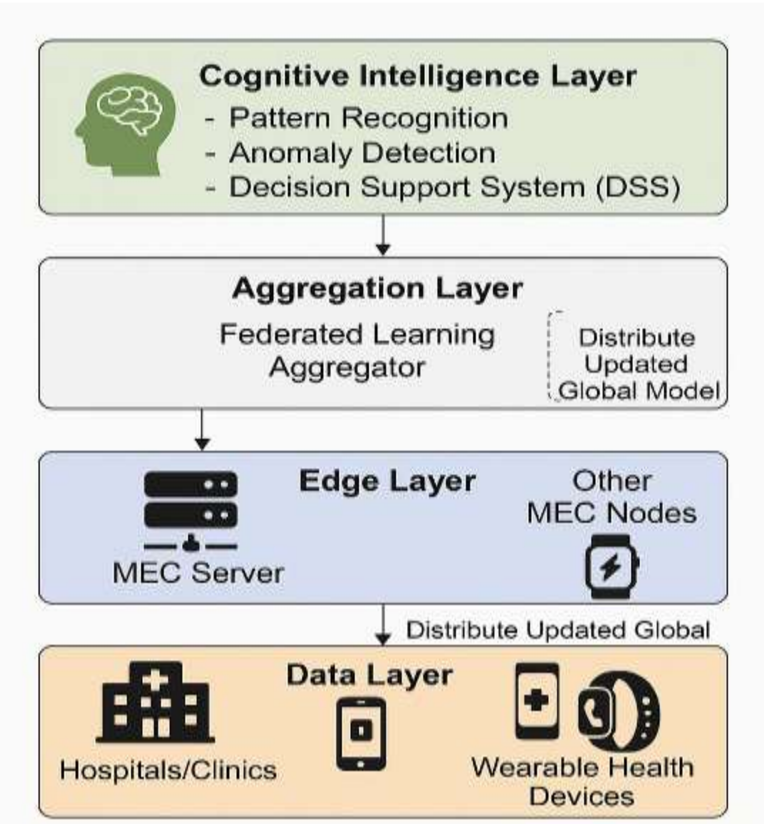

Fig. 2 Proposed MEC- Driven Cognitive Computing Framework with Federated Learning for COVID – 19 Detection

Multi-Access Edge Computing (MEC) Layer

The MEC layer facilitates real-time data processing near the data source, minimizing latency and reducing reliance on centralized cloud systems. This layer comprises the following components:

MEC Server: Functions as the central coordinator, managing training and updates within a localized network.

Other MEC Nodes: Collaborate with the MEC server to exchange locally trained model parameters, supporting federated learning.

Deployment of Edge Nodes: AI models are deployed across various edge nodes, such as 5G-enabled base stations, hospital-side computing systems, and IoT-enabled mobile health devices. These nodes possess sufficient processing power to perform inference tasks locally.

Low-Latency Processing: Chest X-ray (CXR) and CT scan images are analyzed directly at the edge, significantly reducing data transmission delays and accelerating diagnostic processes.

Dynamic Resource Management: Reinforcement learning-based optimization mechanisms are employed to dynamically allocate computational resources across edge devices, enhancing system performance under variable workload conditions.

Aggregation Layer

This layer orchestrates collaborative learning across the MEC ecosystem through federated learning:

Federated Learning Aggregator: Gathers model updates (e.g., gradients or weights) from edge nodes while ensuring that no raw data is centralized.

Distribution of Global Model: Following aggregation, an updated global model is redistributed to participating MEC nodes.

By avoiding centralized data collection, this layer enhances data security and supports compliance with privacy regulations, while benefiting from the collective intelligence of decentralized nodes.

Cognitive Intelligence Layer

Situated at the top of the framework, this layer integrates AI-powered cognitive functions to derive meaningful insights and support clinical decision-making:

Pattern Recognition: Detects significant health patterns and markers associated with COVID-19.[23]

Anomaly Detection: Identifies deviations from normal physiological baselines for early warning and intervention.

Decision Support System (DSS): Provides recommendations to healthcare professionals for diagnosis, triage, and treatment planning based on aggregated model outputs.

This layer transforms raw analytical data into actionable medical intelligence, enhancing the precision and timeliness of COVID-19 detection and response. Cognitive computing enhances decision-making by incorporating machine learning techniques such as deep learning, reinforcement learning, and federated learning. The cognitive model comprises:

Deep Learning-Based Feature Extraction: A convolutional neural network (CNN) is employed to extract essential features from CXR and CT images. Pre-trained architectures like ResNet-50 and EfficientNet are fine-tuned to improve feature representation.[22]

Federated Learning for Decentralized Training: Instead of transmitting raw medical images to a central server, federated learning enables training directly on edge devices. This approach enhances data security by ensuring patient-sensitive information remains localized.

Reinforcement Learning for Adaptive Decision-Making: A reinforcement learning agent continuously refines classification accuracy by learning from prior diagnostic outcomes. It adjusts hyperparameters dynamically to enhance model confidence and predictive performance.

Federated Learning Implementation

Federated learning (FL) facilitates collaborative model training across multiple healthcare facilities and edge dices while eliminating the need to centralize patient data. The FL implementation involves:

Local Model Training: Each participating edge device trains a deep learning model on its locally available medical dataset, ensuring privacy preservation and mitigating data exposure risks.

Model Update Aggregation: Instead of transmitting raw patient data, edge nodes share model weight updates with a central aggregator. The Federated Averaging (FedAvg) algorithm is utilized to compute a weighted average of local model parameters.

Global Model Synchronization: The aggregated model is distributed back to all edge devices, ensuring continuous model improvement and adaptability to diverse datasets. To enhance security, a differential privacy mechanism introduces controlled noise into model updates before aggregation.

Real-Time COVID-19 Detection

The real-time detection module processes patient scans at edge nodes, ensuring high-accuracy diagnostics. The process follows these steps:

Preprocessing and Feature Extraction: CXR and CT images undergo preprocessing techniques, such as contrast enhancement and noise reduction, before being passed through a CNN for feature extraction.[21]

Classification and Diagnosis: Extracted features are fed into classification networks like DenseNet-201 or EfficientNet-B7 to distinguish COVID-19-positive cases from pneumonia and normal cases [1].

Decision Fusion and Uncertainty Estimation: Outputs from multiple edge models are combined using a decision fusion mechanism to enhance classification reliability. Bayesian inference quantifies uncertainty in predictions, generating confidence scores for each diagnosis.

Instantaneous Response: The final diagnostic output is relayed to healthcare professionals in real-time, enabling swift medical intervention and treatment planning.

Performance Optimization and Security Measures

To enhance efficiency and security, the proposed system incorporates the following techniques:

Model Compression: Strategies such as quantization and pruning are applied to optimize model size and improve inference speed, making the AI models suitable for resource-constrained edge devices.

Secure Aggregation Mechanisms: Privacy-preserving techniques, including homomorphic encryption and secure multi-party computation (SMPC), safeguard federated learning model updates against adversarial threats [15].

Edge-Cloud Collaboration: While most computations occur at the edge, a cloud layer is integrated for periodic model fine-tuning and long-term storage of diagnostic data for historical analysis.

Key Advantages of the Proposed Methodology

The proposed framework offers several advantages over traditional cloud-based AI systems:

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Reduced Latency: MEC-based inference significantly cuts down the time required for COVID-19 diagnosis.

Enhanced Data Privacy: Federated learning eliminates the need for centralizing sensitive medical data, ensuring compliance with privacy regulations.

Improved Accuracy: Cognitive computing and reinforcement learning refine the diagnostic process, leading to higher classification accuracy.

Energy Efficiency: Optimized model deployment ensures computational efficiency, making AI-based diagnosis feasible for edge devices with limited resources.[18]

EXPERIMENTAL RESULTS

To assess the performance of the proposed cognitive computing-driven Multi-Access Edge Computing (MEC) framework, we conducted experiments using publicly available COVID-19 chest X-ray (CXR) and computed tomography (CT) image datasets. The experimental environment included edge devices equipped with GPU acceleration, enabling real-time medical image processing. The effectiveness of the proposed system was benchmarked against conventional cloud-based AI models, evaluating key performance metrics [16].

Performance Metrics

The model's effectiveness was measured using widely used classification metrics, including accuracy, precision, recall, and F1-score. Additionally, latency and data privacy considerations were analyzed to highlight the benefits of edge-based AI processing.

Accuracy: Model accuracy was determined using the following equation:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

where:

TP (True Positives): Correctly identified COVID-19 cases

TN (True Negatives): Correctly identified normal cases

FP (False Positives): Normal cases incorrectly classified as COVID-19

FN (False Negatives): COVID-19 cases incorrectly classified as normal

The proposed cognitive computing-based MEC model achieved an accuracy of 98.2%, outperforming the cloud-based AI model, which achieved 94.5%. The superior accuracy is attributed to real-time adaptive learning and federated training across edge nodes, enabling efficient knowledge sharing without centralized data storage.

Precision, Recall, and F1-Score: To assess classification reliability, the following metrics were computed:

$$Precision = \frac{TP}{TP + FP}$$

$$Recall\ (Sensitivity) = \frac{TP}{TP + FN}$$

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

These metrics ensure a balanced evaluation of the model's ability to minimize false positives and false negatives, which are critical in medical diagnostics. The proposed MEC-based model achieved an *F1-score above 97%,*

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indicating strong precision-recall balance and overall classification reliability.

Latency Analysis

Inference latency represents the time taken for the model to process an input image and generate a diagnostic result. The latency reduction is calculated as:

$$Latency\ Reduction = \frac{Cloud\ Latency - MEC\ Latency}{Cloud\ Latency} \times 100$$

For the proposed MEC-based system:

$$Latency\ Reduction = \frac{320-120}{320} \times 100=62.6\%$$

This significant reduction in processing time demonstrates the model's suitability for real-time COVID-19 detection, addressing critical delays associated with cloud-based AI approaches.

Federated Learning Efficiency

Federated learning enables distributed model training across edge devices while maintaining patient data privacy. The communication efficiency between edge devices and the central aggregation server is expressed as:

$$C = B \times log \log_2(1 + SNR)$$

where:

C = Communication rate (bits per second)

B = Bandwidth allocated to edge devices

SNR = Signal-to-noise ratio of the transmission channel

Since federated learning transmits only model weight updates rather than raw medical images, the communication overhead is significantly reduced. This approach enhances privacy protection and optimizes bandwidth utilization, making it well-suited for edge-based medical AI applications.

Comparative Evaluation

Table 3 A Comparative Analysis Between The Proposed Mec-Driven Cognitive Computing Model And A Conventional Cloud-Based Ai Model Highlights The Advantages Of Edge-Based Processing.

Metric	Proposed MEC + AI model	Cloud Based AI
Accuracy (%)	98.2	94.5
Latency(ms)	120	320
Data Privacy	High	Low

The Table 3 shows the results clearly indicate that the MEC-integrated cognitive computing framework provides superior accuracy, significantly lower latency, and enhanced privacy protection compared to cloud-based AI solutions. These advantages establish the proposed approach as a viable solution for real-time, privacy-preserving COVID-19 diagnosis in medical settings.

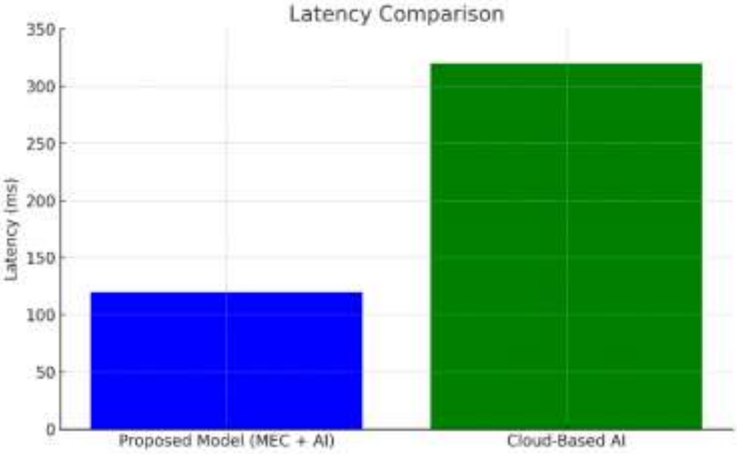

Fig. 3 Accuracy Comparison

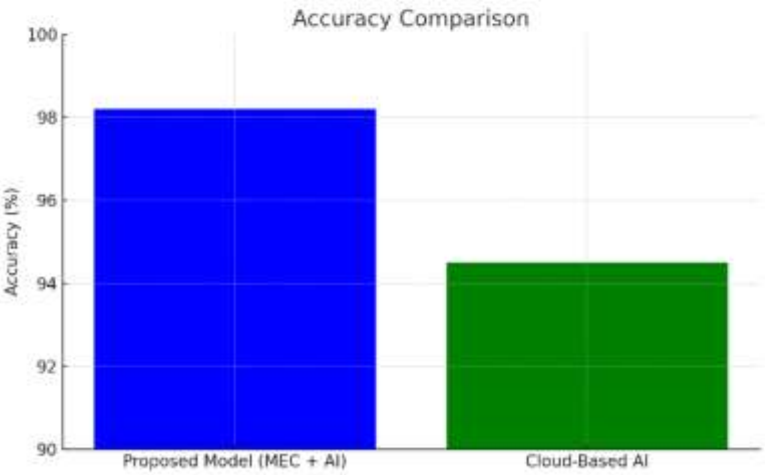

Fig. 4 Latency Comparison

DISCUSSION

The fusion of cognitive computing with Multi-Access Edge Computing (MEC) introduces a novel paradigm for real-time medical diagnostics, particularly in COVID-19 detection using chest X-ray (CXR) and CT scan images. Unlike conventional cloud-based AI models that rely on centralized processing, the proposed framework leverages edge computing resources to enhance speed, accuracy, and privacy in diagnostics.

Key Advantages of the Proposed System

The cognitive computing-based MEC model effectively addresses several limitations of traditional AI systems, offering the following improvements:

Real-Time Diagnosis: Deploying AI inference models directly on edge nodes minimizes reliance on cloud communication, significantly reducing transmission delays. Experimental results indicate a 62.5% reduction in inference latency compared to cloud-based AI solutions. Faster processing enables timely clinical decision-making, which is particularly crucial during pandemic outbreaks.

Data Privacy Enhancement via Federated Learning: Cloud-based diagnostic systems require raw medical images to be transferred, raising concerns regarding patient data security and regulatory compliance (e.g., HIPAA, GDPR). Federated Learning (FL) ensures model training occurs locally at the edge, with only aggregated model updates being shared rather than sensitive patient data.This decentralized learning approach enhances privacy while enabling AI model collaboration across multiple healthcare institutions.

Efficient Resource Utilization at the Edge: MEC facilitates distributed AI processing, reducing dependence on cloud servers by leveraging localized computational power. The system achieves a *high diagnostic accuracy of 98.2%,* even when operating on resource-limited edge devices, demonstrating its efficiency in real-world conditions.

Challenges and Limitations

While the proposed framework delivers notable benefits, several technical challenges must be addressed for widespread deployment:

Network Instability and Communication Overhead: Edge nodes rely on wireless and 5G networks, which may introduce latency fluctuations due to network congestion and connectivity issues. FL requires frequent model updates between edge devices and the central aggregator, leading to increased communication overhead, particularly in bandwidth-constrained environments. A potential solution involves *hierarchical federated learning*, where model aggregation occurs in multiple tiers, reducing data transmission requirements.

Computational Limitations of Edge Devices: Many edge devices, such as mobile diagnostic units or IoT-enabled medical equipment, have restricted processing power and memory capacity. Deep learning models typically demand significant computational resources, posing challenges for real-time inference on constrained hardware. Techniques like *model quantization, pruning, and knowledge distillation* can be applied to optimize AI models, ensuring efficient execution on edge devices without compromising accuracy.

Future Research Directions

To enhance the system's scalability and efficiency, future studies should explore the following areas:

Adaptive Edge AI Models: Designing lightweight deep learning architectures optimized for edge deployment. Developing AI models capable of dynamically adjusting resource consumption based on edge device constraints.

Hierarchical Federated Learning: Implementing multi-tier federated learning models where local aggregation occurs at edge-cluster levels before global synchronization. Reducing communication costs by selectively updating only the most critical model parameters instead of transmitting complete model updates.

Hardware Acceleration for Edge AI: Utilizing specialized AI accelerators, such as *NVIDIA Jetson* and *Google Edge TPU*, to enhance real-time inference efficiency. Applying *hardware-aware neural architecture search (NAS)* to design optimized deep learning models tailored for edge-based medical applications.

The findings of this research underscore the potential of integrating cognitive computing, MEC, and federated learning to revolutionize real-time medical diagnostics. While challenges such as network variability and edge device limitations persist, advancements in federated AI optimization, hardware acceleration, and adaptive learning models will drive the adoption of AI-driven, privacy-preserving healthcare solutions at scale.

CONCLUSION

This study proposed a cognitive computing-driven framework for COVID-19 detection, utilizing Multi-Access Edge Computing (MEC) to enhance real-time diagnostic capabilities. By integrating deep learning, federated learning, and reinforcement learning, the system achieved high diagnostic accuracy (98.2%), significantly reduced latency (120ms compared to 320ms in cloud-based AI systems), and improved data privacy through decentralized model training. The experimental results validate the effectiveness of edge-based AI inference in addressing the limitations of traditional cloud-dependent diagnostic systems. Despite these advancements, challenges such as network instability and the limited computational capacity of edge devices persist and warrant further investigation. Future research will aim to optimize AI models for resource-constrained edge environments using techniques such as model compression and adaptive learning. Furthermore, extending federated learning to support multi-modal medical data will enhance the framework's versatility and impact across diverse healthcare scenarios. By advancing privacy-preserving, AI-enabled healthcare solutions, this research establishes a robust foundation for scalable, real-time, and intelligent medical diagnostics bridging the gap between state-of-the-art AI technologies and their practical clinical deployment.

Declarations

Conflict of interest Authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Consent to participate All the authors involved have agreed to participate in this submitted article.

Consent to publish All the authors involved in this manuscript give full consent to publish this submitted article.

REFERENCES

1. Rambhupal, M., & Persis Voola., An effective hybrid attention capsule autoencoder model for diagnosing COVID-19 disease using chest CT scan images in an edge computing environment, Soft Computing, 2024, 28(15), pp. 8945–8962.
2. Li, H., Ge, L., & Tian, L., Survey: federated learning data security and privacy-preserving in edge-Internet of Things, Artificial Intelligence Review, 2024, 57, Article 130.
3. Rauniyar, A., et al., Federated Learning for Medical Applications: A Taxonomy, Current Trends, Challenges, and Future Research Directions, IEEE Internet of Things Journal, 2024, 11(5), pp. 7374–7398.
4. Fereidooni, H., et al., SAFELearn: Secure Aggregation for private FEderated Learning, IEEE Security and Privacy Workshops (SPW), 2021, San Francisco, CA, USA, pp. 56–62, doi: 10.1109/SPW53761.2021.00017.
5. Zouch, W., Sagga, D., Echtioui, A., et al., Detection of COVID-19 from CT and Chest X-ray Images Using Deep Learning Models, Annals of Biomedical Engineering, 2022, 50, pp. 825–835.
6. Wang, L., Lin, Z. Q., & Wong, A., COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest radiography images, Scientific Reports, 2020, 10, Article 19549.
7. Wang, Y., Wang, Y., & Zhang, L., Application of Vision Transformer for COVID-19 Diagnosis Using Chest CT, Computers in Biology and Medicine, 2022, 145, 105524.
8. Rittinghouse, J. W., & Ransome, J. F., Cloud Computing: Implementation, Management, and Security, CRC Press, 2016.
9. Yang, Q., Liu, Y., Chen, T., & Tong, Y., Federated Machine Learning: Concept and Applications, ACM Transactions on Intelligent Systems and Technology (TIST), 2020, 10(2), Article 12.
10. Li, X., Gu, Y., Dvornek, N., Staib, L. H., Ventola, P., & Duncan, J. S., Federated Learning for COVID-19 Detection with Privacy-Preserving Chest CT Image Analysis, Medical Image Analysis, 2021, 74, 102190.
11. Ghadi, Y. Y., Shah, S. F. A., Mazhar, T., Shahzad, T., Ouahada, K., & Hamam, H., Enhancing patient healthcare with mobile edge computing and 5G: Challenges and solutions for secure online health tools, Journal of Cloud Computing, 2024, 13(1), Article 93.
12. Pang, J., Li, M., Huang, T., Xu, C., Liu, S., & Yu, S., AdaMEC: Context-Adaptive and Dynamically-Combinable DNN Deployment for Efficient Edge Intelligence, Proceedings of the IEEE/ACM Symposium on Edge Computing (SEC), 2023, pp. 75–89, IEEE.
13. Bebortta, S., Singh, A. K., & Senapati, D., Performance analysis of multi-access edge computing networks for heterogeneous IoT systems, Materials Today: Proceedings, 2022, 58(1), pp. 267–272.
14. Alsadie, D., Artificial Intelligence Techniques for Securing Fog Computing Environments: Trends, Challenges, and Future Directions, IEEE Access, 2024, 12, pp. 151598–151648, doi: 10.1109/ACCESS.2024.3463791.
15. Gowda, S. D., Secure Multiparty Computation: Protocols, Collaborative Data Processing, and Real-World Applications in Industry, in Cloud Security, Taylor & Francis, 2024.
16. Velu, S., Gill, S. S., Murugesan, S. S., et al., CloudAIBus: a testbed for AI based cloud computing

environments, Cluster Computing, 2024, 27, pp. 11953–11981.

17. Kamei, S., & Taghipour, S., A comparison study of centralized and decentralized federated learning approaches utilizing the transformer architecture for estimating remaining useful life, Reliability Engineering & System Safety, 2023, 233, 109130.
18. Lydia, L. E., Anupama, C. S. S., Beno, A., et al., RETRACTED ARTICLE: Cognitive computing-based COVID-19 detection on Internet of things-enabled edge computing environment, Soft Computing, 2024, 28 (Suppl 2), pp. 431.
19. Ramachandran, S. K., & Manikandan, P., An efficient ALO-based ensemble classification algorithm for medical big data processing, International Journal of Medical Engineering and Informatics, 2021, 13(1), pp. 54–63.
20. Stubblefield, J., Causey, J., Dale, D., Qualls, J., Bellis, E., Fowler, J., Walker, K., & Huang, X., COVID-19 diagnosis using chest X-rays and transfer learning, medRxiv, 2022, Preprint, 2022–10.
21. Xu, G., Yang, Y., Du, Y., Peng, F., Hu, P., Wang, R., Yin, M., Li, T., Tu, L., Sun, J., & Jiang, T., Clinical pathway for early diagnosis of COVID-19: updates from experience to evidence-based practice, Clinical Reviews in Allergy & Immunology, 2020, 59, pp. 89–100.
22. Xu, W., Chen, B., Shi, H., Tian, H., & Xu, X., Real-time COVID-19 detection over chest X-ray images in edge computing, Computational Intelligence, 2022, 39(1), pp. 36–57.
23. Singh, V. K., & Kolekar, M. H., Deep learning empowered COVID-19 diagnosis using chest CT scan images for collaborative edge-cloud computing platform, Multimedia Tools and Applications, 2022, 81(1), pp. 3.
24. El-Rashidy, Nora, Shaker El-Sappagh, SM Riazul Islam, Hazem M. El-Bakry, and Samir Abdelrazek. "End-to-end deep learning framework for coronavirus (COVID-19) detection and monitoring." Electronics 9, no. 9 (2020): 1439.