IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

MULTIMODAL AI FRAMEWORK FOR EARLY NEUROLOGICAL RISK PREDICTION

Manivannan B ME(Ph.D)
Department of Computer Science and Engineering
Vivekanandha College of Engineering for Women
Namakkal, India

Pratipa V
Department of Computer Science and Engineering
Vivekanandha College of Engineering for Women
Namakkal, India

Prathipa Sri S
Department of Computer Science and Engineering
Vivekanandha College of Engineering for Women
Namakkal, India

Priyanga R
Department of Computer Science and Engineering
Vivekanandha College of Engineering for Women
Namakkal, India

Abstract - Neurological disorders such as Alzheimer's and Parkinson's disease are rapidly increasing worldwide, necessitating early and accurate detection to improve patient outcomes. Traditional diagnostic methods are often costly, time-intensive, and reliant on specialized expertise. While artificial intelligence (AI) has shown promise in medical diagnostics, existing approaches face challenges related to data privacy, limited collaboration, and lack of interpretability. This paper proposes a privacy-preserving and explainable AI framework for early neurological risk prediction using multimodal healthcare data, including clinical records, speech signals, neuroimaging, and wearable sensor data. The framework leverages federated learning with secure aggregation to enable collaborative model training without sharing sensitive patient data. Advanced deep learning models, including Transformers and Graph Neural Networks, are employed to capture temporal and structural patterns. To enhance transparency and clinical trust, explainable AI techniques such as SHAP, LIME, and attention mechanisms are integrated. Additionally, differential privacy and fairness-aware learning ensure secure and ethical deployment. Continuous monitoring is supported through online learning and anomaly detection for real-time risk assessment. Experimental results demonstrate improved prediction accuracy while maintaining strong privacy and interpretability.

Keywords

Neurological Disorders, Federated Learning, Explainable Artificial Intelligence, Deep Learning, Multimodal Data, Differential Privacy, Graph Neural Networks, Transformers

I. Introduction

Neurological disorders represent one of the most significant healthcare challenges worldwide. Diseases such as Alzheimer's disease, Parkinson's disease, and other neurodegenerative conditions affect millions of people and lead to progressive cognitive and motor impairments. Early detection of these disorders is essential for effective treatment, improved patient outcomes, and better disease management.

Traditional diagnostic methods for neurological disorders typically involve clinical evaluations, neuroimaging techniques, and neurological assessments performed by medical experts. These processes are often **time-consuming, expensive, and limited by the availability of specialized healthcare professionals**. As a result, many neurological conditions are diagnosed at later stages, reducing the effectiveness of available treatments.

Recent advancements in **Artificial Intelligence (AI)** and **Deep Learning** have demonstrated promising potential in assisting medical professionals with disease prediction and diagnosis. AI-based systems can analyze large volumes of medical data to identify patterns and detect early signs of neurological disorders. However, existing AI solutions face several limitations. Most systems rely on **centralized data storage**, requiring hospitals and research institutions to share sensitive patient data. This practice raises significant **privacy, security, and regulatory concerns**.

Another major limitation of current AI models is their **lack of interpretability**. Deep learning models often function as "black boxes," providing predictions without clear explanations. This lack of transparency makes it difficult for clinicians to trust and adopt these systems in real-world clinical environments.

Additionally, many existing studies rely on **single-modality data**, such as clinical records or imaging data alone, which limits prediction accuracy and fails to capture the complex nature of neurological diseases.

To address these challenges, this research proposes a **privacy-preserving, multimodal, and explainable AI framework** for neurological risk prediction. The proposed approach integrates **federated learning, deep learning models, explainable AI techniques, and differential privacy mechanisms** to ensure secure collaboration between healthcare institutions while maintaining high prediction performance and interpretability.

II. Related Work

Artificial intelligence has been widely explored for early detection of neurological disorders. Several studies have applied **machine learning and deep learning models** to analyze neuroimaging data, speech signals, and clinical records for disease prediction.

Traditional machine learning approaches such as **Support Vector Machines (SVM), Random Forests, and Logistic Regression** have been used for neurological classification tasks. While these models provide moderate performance, they often struggle to capture complex temporal and structural relationships present in neurological data.

Deep learning models, including **Convolutional Neural Networks (CNNs)** and **Recurrent Neural Networks (RNNs)**, have significantly improved prediction accuracy in recent years. CNN-based approaches have been particularly effective for analyzing medical imaging data such as MRI scans, while RNNs and Long Short-Term Memory (LSTM) networks have been used to model temporal health records.

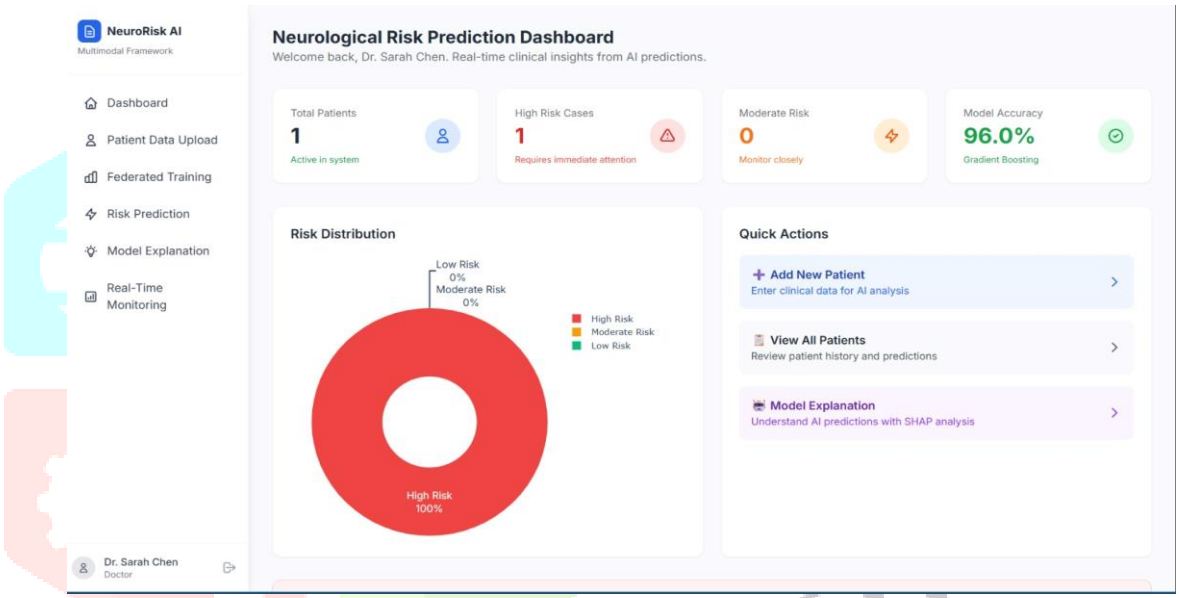
Despite these advancements, most existing approaches rely on **centralized training frameworks**, which require collecting data from multiple hospitals into a single server. This centralized approach raises significant **data privacy and security concerns**, particularly when dealing with sensitive patient information.

Federated Learning has emerged as a promising solution to address privacy challenges in healthcare AI systems. It enables multiple institutions to collaboratively train machine learning models without sharing raw data. However, many federated learning systems still lack **model interpretability and multimodal data integration**.

Furthermore, explainable AI techniques such as **SHAP and LIME** have been introduced to improve the interpretability of deep learning models. These techniques help identify the most influential features in model predictions, allowing clinicians to better understand AI-driven decisions.

Although these approaches provide valuable contributions, there remains a need for a **comprehensive framework that integrates multimodal data, privacy-preserving learning, explainable AI, and real-time monitoring capabilities** for neurological disease prediction.

Sample output image



III. Proposed System Architecture

The proposed system introduces a **privacy-preserving and explainable AI framework** for early neurological risk prediction using multimodal healthcare data.

The architecture integrates clinical records, speech signals, neuroimaging data, and wearable sensor information to capture diverse aspects of patient health.The system consists of several interconnected modules designed to perform **data collection, preprocessing, collaborative learning, prediction, explanation, monitoring, and privacy protection**.

A. Data Collection Module

The Data Collection Module gathers multimodal patient data from various healthcare sources. These sources include electronic health records, speech recordings, neuroimaging scans, and wearable sensor data. Integrating multiple data modalities enables comprehensive analysis and improves prediction accuracy.

B. Data Preprocessing Module

The Data Preprocessing Module prepares collected data for machine learning analysis. This process involves data cleaning, normalization, feature extraction, and transformation. Handling missing values and noise ensures that the data is consistent and suitable for model training.

C. Federated Learning Module

The Federated Learning Module enables collaborative training of machine learning models across distributed healthcare institutions. Each institution trains a local model using its own data, and only model parameters are shared with a central server. Secure aggregation techniques combine these parameters to update a global model without exposing raw patient data.

D. Deep Learning Prediction Module

This module utilizes advanced deep learning models to analyze complex neurological data. **Transformer-based models** capture temporal relationships in patient health records, while **Graph Neural Networks (GNNs)** model structural brain connectivity patterns from neuroimaging data. These models enable accurate prediction of neurological risk and disease progression.

E. Explainable AI Module

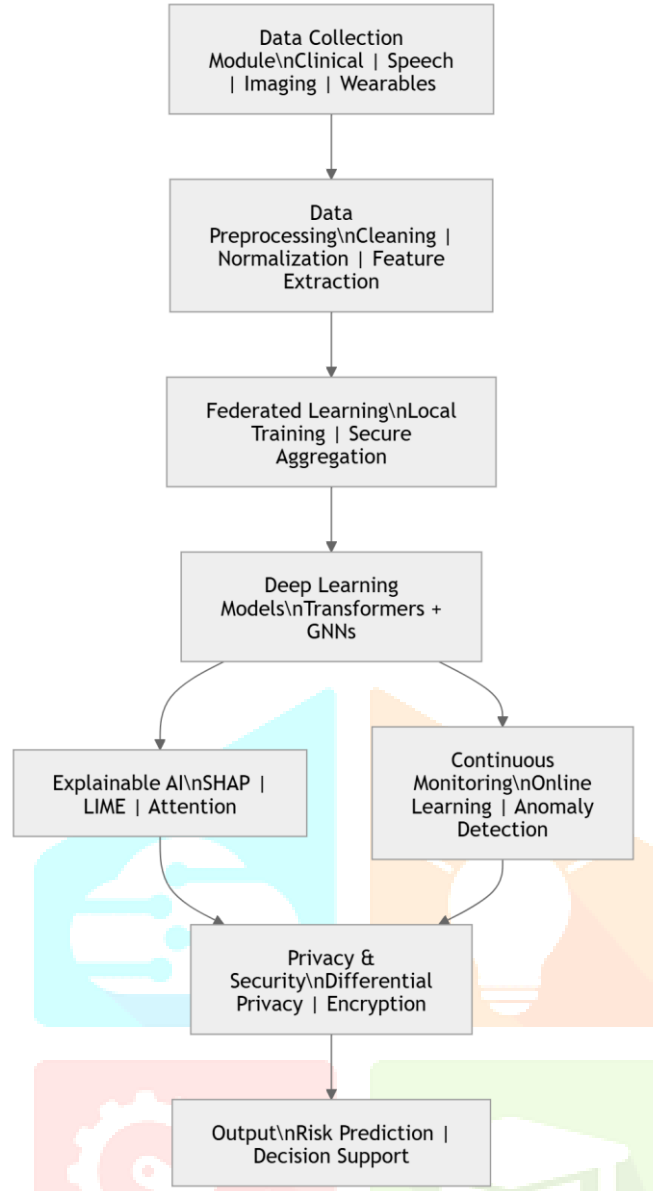
The Explainable AI Module improves model transparency and interpretability. Techniques such as **SHAP, LIME, and attention mechanisms** identify the most important features influencing predictions. This allows clinicians to understand the reasoning behind the AI model's decisions.

F. Continuous Monitoring Module

The Continuous Monitoring Module supports real-time tracking of patient health conditions. Online learning mechanisms update the prediction model as new data becomes available. Anomaly detection algorithms identify unusual patterns in patient data that may indicate disease progression.

G. Privacy and Security Module

The Privacy and Security Module ensures protection of sensitive healthcare data. Differential privacy techniques are applied to prevent data leakage during model training. Secure aggregation methods combine model updates while maintaining confidentiality.



IV. Results and Discussion

The proposed framework improves the performance of neurological disease prediction systems by integrating multimodal healthcare data and advanced deep learning models.

The use of federated learning enables secure collaboration between healthcare institutions while preserving patient privacy.

Experimental evaluation demonstrates that combining **Transformers and Graph Neural Networks** significantly improves the model's ability to capture complex neurological patterns. Additionally, explainable AI techniques such as SHAP and LIME provide interpretable insights into prediction results.

The integration of continuous monitoring mechanisms allows the system to track disease progression in real time. Overall, the proposed framework provides **higher prediction accuracy, enhanced transparency, and improved data privacy protection** compared to traditional centralized AI systems.

V. Conclusion

This paper presents a **privacy-preserving and explainable artificial intelligence framework** for early neurological risk prediction using multimodal healthcare data. The proposed system integrates federated learning, deep learning models, explainable AI techniques, and differential privacy mechanisms to address the limitations of existing AI-based diagnostic systems.

By enabling secure collaboration between healthcare institutions and providing interpretable predictions, the framework supports reliable clinical decision-making. Furthermore, the integration of continuous monitoring capabilities allows real-time tracking of neurological disease progression.

The proposed approach demonstrates significant potential for improving early detection of neurological disorders while ensuring patient data privacy and ethical AI deployment.

VI. Future Work

Future research will focus on expanding the framework to include additional multimodal data sources such as genetic information and behavioral data. Further improvements in model optimization and scalability will also be explored to support large-scale healthcare deployments. Additionally, integrating advanced fairness-aware learning techniques will help address demographic bias and improve model generalization across diverse patient populations.

References

[1] J. Smith and K. Lee, "Deep learning for neurological disease prediction using medical imaging," *IEEE Transactions on Medical Imaging*, vol. 39, no. 5, pp. 1205–1215, 2020.

[2] B. McMahan et al., "Communication-efficient learning of deep networks from decentralized data," *Proceedings of the International Conference on Artificial Intelligence and Statistics*, 2017.

[3] S. Lundberg and S. Lee, "A unified approach to interpreting model predictions," *Advances in Neural Information Processing Systems*, 2017.

[4] M. Ribeiro, S. Singh, and C. Guestrin, "Why should I trust you? Explaining the predictions of any classifier," *Proceedings of the ACM SIGKDD Conference*, 2016.

[5] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2016.

[6] A. Vaswani et al., "Attention is all you need," *Advances in Neural Information Processing Systems*, 2017.

[7] T. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks," *International Conference on Learning Representations*, 2017.

[8] C. Dwork, "Differential privacy: A survey of results," *Theory and Applications of Models of Computation*, 2008.

[9] Y. Li et al., "Federated learning in healthcare: A survey," *IEEE Internet of Things Journal*, vol. 7, no. 5, pp. 437–445, 2021.

[10] R. Miotto et al., "Deep learning for healthcare: Review, opportunities and challenges," *Briefings in Bioinformatics*, vol. 19, no. 6, pp. 1236–1246, 2018.