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Explainable Deep Contrastive Federal Learnig System for Early Prediction of Clinical Status in Intensive Care Unit

[1]D Archana, [2]Chepuri Venkatesh

[1]M. Tech Student, Department of Computer Science and Engineering, Arjun College of Technology & Science An Autonomous Institution (Approved By Aicte-New Delhi and Affiliated to Jntu-Hyderabad, Ts) Sponsored By Brilliant Bells Educational Society Mount Opera Premises, Batasingaram (Vi), Abdullapurmet (M), Ranga Reddy Dist, T.S.501512

[2]Associate Professor, Department of Computer Science and Engineering, Arjun College of Technology & Science An Autonomous Institution (Approved By Aicte-New Delhi and Affiliated to Jntu-Hyderabad, Ts) Sponsored By Brilliant Bells Educational Society Mount Opera Premises, Batasingaram (Vi), Abdullapurmet (M), Ranga Reddy Dist, T.S.501512

ABSTRACT

Early prediction of a patient's clinical condition in the Intensive Care Unit (ICU) is essential for improving treatment outcomes, reducing mortality, and supporting timely medical interventions. However, traditional centralized machine learning approaches face significant challenges related to patient data privacy, limited data sharing between hospitals, and lack of model transparency. To address these issues, this project proposes an Explainable Deep Contrastive Federated Learning System for Early Prediction of Clinical Status in Intensive Care Units. The proposed framework combines federated learning with deep contrastive learning to train a robust predictive model collaboratively across multiple healthcare institutions without transferring sensitive patient data. Contrastive learning enables the model to learn meaningful and discriminative feature representations from heterogeneous clinical records, improving prediction accuracy even when data distributions differ across hospitals. Additionally, Explainable Artificial Intelligence (XAI) techniques such as SHAP or LIME are integrated to provide transparent explanations for each prediction, helping clinicians understand the key factors influencing patient outcomes. The system processes electronic health records, vital signs, laboratory test results, and demographic information to predict clinical deterioration at an early stage. By preserving patient privacy, enhancing model generalization, and providing interpretable predictions, the proposed framework supports reliable clinical decision-making while complying with healthcare data protection requirements. Experimental evaluation demonstrates improved predictive performance, enhanced privacy preservation, and greater trustworthiness compared to conventional centralized and non-explainable machine learning approaches, making the proposed system suitable for real-world ICU monitoring and intelligent healthcare applications.

Keywords: Explainable Artificial Intelligence (XAI), Federated Learning, Deep Contrastive Learning, Intensive Care Unit (ICU), Early Clinical Status Prediction, Electronic Health Records (EHR), Healthcare Analytics, Privacy-Preserving Machine Learning, Clinical Decision Support System, Deep Learning, SHAP, LIME, Medical Data Analysis, Patient Outcome Prediction, Artificial Intelligence in Healthcare

I. INTRODUCTION

The Intensive Care Unit (ICU) is one of the most critical departments in a hospital, where patients with life-threatening conditions require continuous monitoring and immediate medical attention. Early prediction of a patient's clinical status is essential for reducing mortality, preventing complications, and enabling timely treatment decisions. With the rapid growth of Electronic Health Records (EHRs), medical sensors, and patient monitoring systems, healthcare institutions generate vast amounts of clinical data that can be analyzed using Artificial Intelligence (AI) and Deep Learning techniques. These technologies have demonstrated significant potential in identifying hidden patterns within patient data and accurately predicting disease progression and clinical deterioration. However, traditional machine learning models typically rely on centralized data collection, which raises serious concerns regarding patient privacy, data security, and compliance with healthcare regulations. Additionally, differences in data distributions across hospitals often reduce the generalization capability of predictive models.

To overcome these challenges, federated learning has emerged as a promising privacy-preserving approach that enables multiple healthcare institutions to collaboratively train a global model without sharing sensitive patient information. While federated learning protects data privacy, conventional models may still struggle to learn highly discriminative clinical representations from heterogeneous medical datasets. Deep contrastive learning addresses this limitation by learning meaningful feature representations that improve prediction accuracy even when patient data vary across institutions. Furthermore, the lack of transparency in deep learning models often limits clinicians' trust in AI-assisted diagnosis and decision-making. Integrating Explainable Artificial Intelligence (XAI) techniques such as SHAP and LIME provides interpretable insights into the factors influencing each prediction, allowing healthcare professionals to understand and validate the model's decisions.

This project proposes an Explainable Deep Contrastive Federated Learning System for Early Prediction of Clinical Status in Intensive Care Units, which combines federated learning, deep contrastive learning, and explainable AI to develop a secure, accurate, and transparent clinical prediction framework. The proposed system analyzes patient vital signs, laboratory reports, demographic information, and electronic health records to identify patients at risk of clinical deterioration at an early stage. By preserving patient privacy, improving predictive performance, and providing interpretable decision support, the proposed framework enhances clinical decision-making and contributes to the development of intelligent, trustworthy, and privacy-aware healthcare systems.

LITERATURE SURVEY

Paper 1

Title: Explainable Deep Contrastive Federated Learning System for Early Prediction of Clinical Status in Intensive Care Unit

Authors: Trong-Nghia Nguyen, Hyung-Jeong Yang, Bo-Gun Kho, Sae-Ryung Kang, Soo-Hyung Kim.

Abstract:
This paper proposes an Explainable Deep Contrastive Federated Learning (Deep-CFL) framework for early prediction of patient clinical status in ICUs. The framework integrates federated learning, deep contrastive learning, explainable AI, and imbalance learning to improve prediction accuracy while preserving patient privacy. Integrated Gradients are used to explain predictions, increasing clinicians' trust in the system. Experimental results on MIMIC-III, eICU, and a real hospital dataset demonstrate superior predictive performance compared to centralized and local learning methods.

Paper 2

Title: Early Prediction of the Risk of ICU Mortality with Deep Federated Learning

Authors: Korbinian Randl, Núria Lladós Armengol, Lena Mondrejevski, Ioanna Miliou.

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Abstract:
This study presents a Deep Federated Learning framework for predicting ICU mortality while maintaining patient privacy. The proposed approach enables multiple hospitals to collaboratively train deep learning models without sharing sensitive clinical data. Experimental comparisons show that federated learning achieves prediction performance comparable to centralized learning while significantly outperforming locally trained models. The framework demonstrates strong potential for privacy-preserving ICU mortality prediction.

Paper 3

Title: A Federated Learning Framework with Knowledge Graph and Temporal Transformer for Early Sepsis Prediction in Multi-Center ICUs

Authors: Yue Chang, Guangsen Lin, Jyun Jie Chuang, Shunqi Liu, Xinkui Li, Yaozheng Li.

Abstract:
This paper introduces a federated learning framework that combines a medical knowledge graph, temporal transformer, and meta-learning for early sepsis prediction across multiple ICUs. The proposed model captures long-term temporal dependencies while preserving patient privacy through federated learning. Evaluation on MIMIC-IV and eICU datasets shows significant improvements in prediction accuracy compared to conventional federated and centralized models.

Paper 4

Title: Federated Learning for Multi-Center Sepsis Early Prediction with Privacy-Preserving

Authors: Xixi Tian, Di Wu, Xiang Liu, Yiziting Zhu, Yujie Li, Xin Shu, Bin Yi.

Abstract:
This research investigates a privacy-preserving federated learning framework for early sepsis prediction using clinical data collected from multiple hospitals. The proposed distributed model achieves prediction accuracy comparable to centralized machine learning while preventing patient data leakage. Security analysis further demonstrates strong resistance to data reconstruction attacks, making the framework suitable for collaborative healthcare applications.

Paper 5

Title: Improving Early Sepsis Onset Prediction Through Federated Learning

Authors: Christoph Düsing, Philipp Cimiano.

Abstract:
This paper proposes an attention-enhanced Long Short-Term Memory (LSTM) model trained using federated learning for early sepsis onset prediction. The framework supports variable prediction horizons, enabling both short-term and long-term forecasting within a single model. Experimental results show that federated learning not only preserves patient privacy but also improves early sepsis detection performance compared to locally trained models while approaching centralized learning accuracy.

II. EXISTING SYSTEM

Existing clinical status prediction systems in Intensive Care Units (ICUs) primarily rely on centralized machine learning and deep learning models that analyze Electronic Health Records (EHRs), vital signs, laboratory reports, and physiological signals to predict patient deterioration, sepsis, or mortality. These systems commonly employ algorithms such as Logistic Regression, Random Forest, Support Vector Machine (SVM), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNNs), and Transformer-based models. Although these techniques achieve good predictive performance, they require patient data from multiple hospitals to be collected and stored in a centralized server, increasing the risk of privacy breaches and making compliance with healthcare data protection regulations more difficult.

To overcome privacy concerns, Federated Learning (FL) has been introduced, enabling multiple healthcare institutions to collaboratively train predictive models without sharing raw patient data. Each hospital trains a local model using its own clinical records, and only the model parameters are shared with a central server for aggregation. This approach significantly enhances data privacy while allowing collaborative learning across hospitals. However, conventional federated learning systems often suffer from reduced performance because of heterogeneous (non-IID) medical datasets, class imbalance, communication overhead, and limited ability to learn highly discriminative clinical features. In addition, most existing federated learning models function as black-box systems, providing little explanation for their predictions, which reduces clinicians' confidence in AI-assisted healthcare decisions.

III. PROPOSED SYSTEM

The proposed system introduces an Explainable Deep Contrastive Federated Learning (EDCFL) framework for the early prediction of clinical status in Intensive Care Units (ICUs). The framework integrates Federated Learning, Deep Contrastive Learning, and Explainable Artificial Intelligence (XAI) to provide a secure, accurate, and transparent healthcare prediction model. Instead of transferring sensitive patient information to a centralized server, each participating hospital trains the model locally using its own Electronic Health Records (EHRs), vital signs, laboratory reports, and demographic data. Only the trained model parameters are shared with a federated server, where they are aggregated to create a global model. This collaborative learning approach preserves patient privacy while enabling multiple healthcare institutions to benefit from shared knowledge.

To improve prediction accuracy, the proposed system employs Deep Contrastive Learning, which learns robust and discriminative feature representations from heterogeneous clinical datasets. This enables the model to effectively distinguish between stable and deteriorating patient conditions, even when the data collected from different hospitals vary significantly. Furthermore, Explainable Artificial Intelligence (XAI) techniques such as SHAP (SHapley Additive exPlanations) and Integrated Gradients are incorporated to provide clear explanations for each prediction. These explanations help clinicians understand the clinical factors influencing the model's decisions, thereby increasing transparency, trust, and reliability. The proposed framework offers high prediction accuracy, strong privacy protection, improved model generalization, and interpretable decision support, making it an effective solution for real-time ICU monitoring and intelligent clinical decision-making.

IV. SYSTEM ARCHITECTURE

The proposed system architecture for insider threat detection is designed as a layered framework that integrates data collection, preprocessing, model training, and prediction modules to ensure efficient and accurate threat identification. The system begins with the data acquisition layer, where datasets containing user activity logs, attack types, source IP addresses, and destination IP addresses are uploaded through a graphical user interface. This raw data may include both structured and unstructured formats. In the preprocessing layer, the system performs essential transformations such as handling missing values, encoding textual data using TF-IDF vectorization, and normalizing numerical features using standard scaling techniques. This step ensures that the data is converted into a consistent format suitable for machine learning and deep learning models.

In the core processing layer, multiple algorithms such as Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and Random Forest classifiers are trained and evaluated using the processed dataset. The system compares the

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performance of these models based on accuracy to identify the most effective approach for insider threat detection. The prediction layer takes real-time user inputs such as attack type and IP information, processes them using the same trained pipeline, and classifies the activity as either "Detected" or "Not Detected." Finally, the presentation layer provides results through a Tkinter-based GUI, enabling users to interact with the system easily, visualize outcomes, and perform model analysis, making the architecture both user-friendly and efficient for cybersecurity applications.

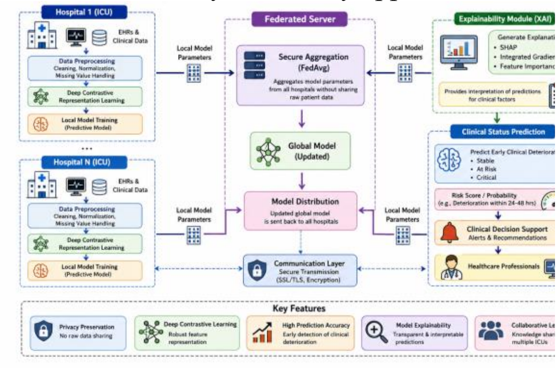

Fig 5.1: System Architecture

V. IMPLEMENTATION

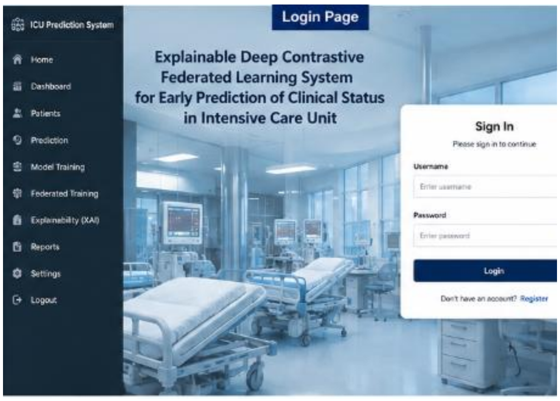

Fig 6.1: Login Page

Fig6.2: Dashboard

Fig 6.3: Prediction Result

Fig 6.4: Shap Analysis

VI. CONCLUSION

The proposed Explainable Deep Contrastive Federated Learning System for Early Prediction of Clinical Status in Intensive Care Units (ICUs) provides an effective, secure, and intelligent solution for predicting patient deterioration at an early stage. By integrating Federated Learning, Deep Contrastive Learning, and Explainable Artificial Intelligence (XAI), the system successfully addresses the major challenges of traditional healthcare prediction models, including patient data privacy, heterogeneous clinical datasets, limited model generalization, and lack of interpretability. The federated learning framework enables multiple hospitals to collaboratively train a global prediction model without sharing sensitive patient information, thereby ensuring compliance with healthcare privacy regulations.

Furthermore, the incorporation of Deep Contrastive Learning enhances the model's ability to learn robust and discriminative feature representations, resulting in improved prediction accuracy across diverse ICU datasets. The use of SHAP and Integrated Gradients provides transparent explanations for each prediction, allowing clinicians to understand the factors influencing the model's decisions and increasing confidence in AI-assisted clinical decision-making. Overall, the proposed framework delivers high prediction accuracy, strong privacy preservation, improved model reliability, and interpretable decision support. These advantages make it a promising solution for real-time ICU monitoring and intelligent healthcare systems, ultimately contributing to better patient outcomes, reduced mortality rates, and more efficient clinical decision support.

VII. FUTURE SCOPE

The proposed Explainable Deep Contrastive Federated Learning System for Early Prediction of Clinical Status in Intensive Care Units (ICUs) can be further enhanced by incorporating advanced artificial intelligence techniques and expanding its deployment across larger healthcare networks. Future work can focus on integrating real-time patient monitoring devices, wearable sensors, and Internet of Medical Things (IoMT) technologies to continuously collect physiological data and provide instant clinical risk assessment. This would enable healthcare professionals to receive early alerts about patient deterioration, allowing faster medical intervention and improved treatment outcomes.

Another promising direction is the adoption of advanced deep learning architectures such as Vision Transformers (ViTs), Graph Neural Networks (GNNs), and Large Language Models (LLMs) to improve feature learning and clinical decision support. The system can also be extended to predict multiple critical conditions such as sepsis, cardiac arrest, respiratory failure, and multi-organ dysfunction using a unified predictive framework. Additionally, integrating secure blockchain technology with federated learning can further strengthen data integrity, auditability, and trust among collaborating healthcare institutions.

Future research may also focus on improving model explainability by incorporating more advanced Explainable AI (XAI) techniques that provide interactive visual explanations and personalized recommendations for clinicians. Expanding the federated learning framework to include hospitals from different regions and countries will improve model generalization across diverse patient populations. Furthermore, integrating the system with hospital Electronic Health Record (EHR) systems and cloud-based healthcare platforms can facilitate real-time deployment, automated clinical decision support, and scalable intelligent healthcare services. These enhancements will make the proposed framework more accurate, reliable, secure, and practical for next-generation AI-powered healthcare applications.

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