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Adaptive Federated Learning with PSO-Based Optimization for Privacy-Preserving IoT-Based Real-Time Stroke Monitoring Systems

Prisilla N.[1] and N. Gomathi[2]

1) Research Scholar, Department of Computer Science and Engineering Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology Avadi, Chennai, Tamil Nadu, India. nprisimsc@gmail.com
2) Professor, Department of Computer Science and Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, Tamil Nadu, India. gomathin@veltech.edu.in

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Abstract: *Brain stroke is one of the leading causes of death and long-term disability worldwide. Recent advancements in Internet of Things (IoT) technologies enable continuous monitoring of patients using wearable sensors and medical devices. However, the centralized approach of traditional ML systems in IoT enabled healthcare applications increases the concern about data privacy, security and regulations. Federated learning enables collaborative model training without sharing raw data with a centralized server, which helps preserve the confidentiality and privacy of the patient's personal data. This paper investigates the application of Federated Learning (FL) in privacy-preserving IoT- based stroke monitoring systems. In addition, the paper identifies the major challenges of FL in real-world IoT settings, including communication overhead, data heterogeneity, security threats, and practical implementation challenges. Finally, the proposed framework achieves an overall detection accuracy of 98.20%. The paper also discusses open research directions and future opportunities for integrating Federated Learning with IoMT and edge computing. Furthermore, the paper investigates the applicability of multiple clustering methods at the federated nodes to properly organize stroke assessment data, thus improving scalability and interpretability. The experimentation that has been conducted indicates that FL is much less expensive and requires significantly less communication than traditional centralized systems while providing nearly equivalent performance. Nevertheless, current research offers little attention to IoT-based real-time stroke monitoring while protecting patient privacy. This article suggests an IoT framework for privacy-preserving stroke monitoring based on federated learning in order to overcome this constraint.*

Keywords*—Federated Learning, Internet of Things IoT, Stroke Monitoring, Privacy Preservation, Edge Computing*

I. INTRODUCTION

A major source of mortality and long-term disability is stroke. Millions of people experience stroke each year worldwide. Therefore, early detection and ongoing tracking of stroke patients to optimize clinical results and reduce mortality are major priorities [1]. Most traditional healthcare systems for monitoring patients utilize either manual observation or centralized machine-learning models that necessitate centralized collection and storage of patient sensitive information [2]. These systems provide predictive insights for healthcare applications. However, they raise

concerns related to privacy, security, and regulatory compliance when dealing with personal health information. The ongoing progress of IoT technology has enabled continuous patient monitoring through wearable devices or medical sensors. While performing IoT-based stroke monitoring, measurements like heart rate, blood pressure, oxygen saturation as well as neural signal measurements such as EEG waveforms can be captured at the same time. These systems can also send notification of the presence of a risk of stroke, as they will send hospital staff notifications if any of the monitored vital signs indicate an increased risk of a stroke; therefore, violation of patient privacy and security, as well as regulatory compliance, is an ongoing issue with these types of IoT devices/systems. The wide array of sensitive data produced by IoT devices used in real-time monitoring generates serious concerns around unauthorized access, unauthorized use, or data breaches [2] [3]. Centralized data processing increases the potential of privacy violations and increases latency. This decreases the timeliness of responding to life-threatening emergent situations e.g., a stroke in patients and able to send data in real-time As such, Federated Learning (FL) is a viable avenue for overcoming the barriers of traditional monitoring systems and is an innovative way to enable multiple organizations to collaborate and develop Machine Learning ML models utilizing their IoT devices and the associated data [3]. Stroke is one of the main contributors to mortality rates across the globe. It demands real-time and constant monitoring for efficient intervention. The current IoT-based health care systems have centralized machine learning models. This has created a number of challenges in terms of privacy and security. Even though FL has resolved the issue of centralized machine learning models to some extent by providing decentralized machine learning models, the current stroke prediction system based on FL has created a number of challenges in terms of communication costs and client participation. It does not support real-time adaptability in dynamic IoT environment.

The major contributions of this research are:

- Proposed Adaptive Federated Learning (AFL) framework for real-time stroke prediction in IoT environments.
- Proposed dynamic client selection mechanism to improve efficiency and reduce communication costs.
- Proposed CNN-LSTM-GRU hybrid model for effective temporal and spatial feature extraction.
- Proposed Particle Swarm Optimization (PSO) for adaptive hyperparameters tuning.

II. RELATED WORK

Early detection of brain stroke is important because it can significantly reduce mortality and improve preventive healthcare. Recent research works have also attempted to employ federated learning methodologies for the purpose of medical image analysis as well as stroke segmentation to resolve the issues of domain shift encountered during the course of the research, However, the existing literature, such as [4], used federated learning for medical image segmentation. But the proposed method does not deal with IoT data in real-time. In [5], the authors proposed AI-based stroke prediction using bio-signals. But the proposed method does not deal with data privacy. The proposed method combines federated learning with hybrid deep learning and PSO to improve accuracy and data privacy in IoT environments. Traditional ML models e.g., Logistic Regression, Support Vector Machine SVM, Decision Tree, Random Forest and Neural Networks have been successful to a degree in identifying stroke risk factors based on predictors of stroke such as age, hypertension, diabetes, glucose levels and lifestyle behaviors. Deep learning techniques like CNN and LSTM are also utilized for medical risk forecasting and disease prediction in healthcare applications [6]. A number of studies have shown that using hybrid models and ensemble learning generally results in greater accuracy of prediction; however, Federated learning platforms have also been developed to assist in the training of models across multiple hospitals while ensuring the privacy and security of patient data are observed [7]. However, these methods often require centralized data collection. Which creates privacy and security issues in healthcare applications. IoT-based health monitoring systems have shown the potential for continuous monitoring of physiological parameters and providing early warning signs for stroke risk [8]. Federated learning FL has emerged as a privacy preserving alternative to centralized ML to address this issue. With FL it is possible to collaboratively train models across a variety of distributed users and to keep sensitive patient data at the point of origin. As a result of strict regulations concerning data sharing, as well as institutional data silos that can exist in the healthcare industry, FL has become a subject of much research in the context of healthcare application. Lastly, several recent publications in IEEE have used FL for prediction of diseases, analysis of medical images and forecasting of clinical outcomes; all of which indicate that the use of FL can achieve performance comparable to that of centralized ML models while maintaining patient confidentiality. In spite of recent developments in federated learning for healthcare, some limitations persist and have not been addressed: The existing methods do not consider dynamic client selection, resulting in inefficient training in heterogeneous IoT environments.

High communication overhead between devices and servers makes federated learning less suitable for real-time applications. No consideration for adaptive learning to handle non-IID data in healthcare. Most methods either focus on accuracy or privacy but not on both for real-time stroke monitoring systems.

III PROPOSED METHODOLOGIES

The proposed model integrates FL with deep learning architectures including CNN, LSTM, and GRU, combined with particle Swarm Optimization (PSO) for hyperparameter Optimization in stroke prediction. In addition to the conventional federated learning process, the proposed system also includes the dynamic selection of clients, in which only active and high-quality IoT devices are considered for the federated learning process. This helps in the reduction of communication overhead and the speed of convergence.

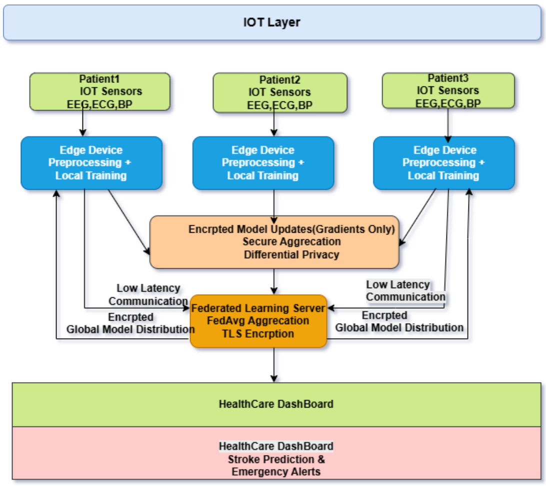


Fig. 1. Block Diagram of Proposed FL-PSO framework

Physiological data such as EEG data can be analyzed using deep learning methods to obtain relevant features for healthcare-related predictions [9]. FL models are created the models are trained; and hyper-parameters are optimized through the use of the PSO algorithm.

A. Dataset Details

In this study, a publicly available dataset on stroke prediction is utilized in simulating a distributed IoT-based environment in the field of healthcare. In this regard, the dataset is distributed across multiple client nodes. Although real-time sensor data such as EEG is not utilized in this study, the framework is designed to support such IoT-based data streams.

Stage	**Dataset**	**Data Sampling and Scale**	**Output**
Preprocessing	EEG & Stroke Motion	5110 patients 256 Hz 50Hz motion	Local feature extraction and model training raw data stays on device
Federated Learning	Aggregated device model updates	10 devices Client devices 511 records per device After local training	Encrypted transmission of model updates no raw data shared
Central Server	Global Model	Aggregation performed across FL rounds	Secure aggregation global model shared back to devices
Stroke Prediction & Monitoring	Patient Monitoring Output	Real-Time inference from trained global model	Only prediction results shared

TABLE I. DATASET DETAILS

B. OBTAINING AND PREPARING DATA

The data for federated learning was pre-processed on local machines attached to the respective client no client communicates with a central data store to ensure privacy and to meet data protection standards. First, unwanted attributes in dataset were deleted in order to prevent bias and repetition while learning. Some attributes like gender, occupation, residential address, alcoholic status were converted into numerical values using label encoding. Decentralized federated learning architectures allow distributed devices to jointly learn machine learning models with reduced communication overhead and data privacy issues [10]. This encoded numerical value allows the information to be processed correctly by machine learning and deep learning methods. Statistical imputation methods were used to fill in missing values for physiological measurements. Instrumental features such as age, glucose level and body mass index BMI were normalized so that they will not affect the training. The processed data were then separated into training 70%, validation 15% and testing 15% data at each client node in order to provide a means for evaluating the federated model with no sharing of sensitive data

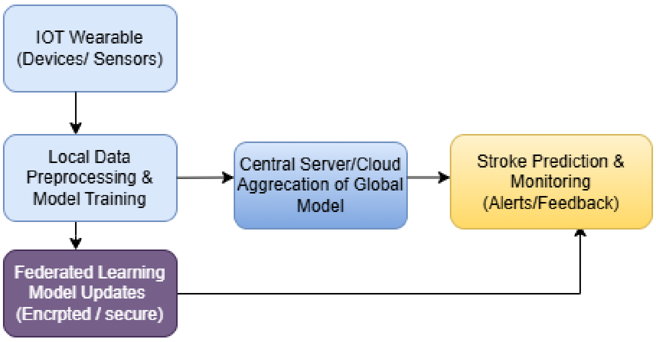


Fig. 2. Block Diagram of Federated IoT Stroke Detection

C. Managing Unbalanced Data

Class imbalance occurs with stroke prediction datasets; there are many fewer strokes than there are non-strokes. This class imbalance causes model bias towards using more of the majority class than the minority class, resulting in lower sensitivity when determining critical stroke occurrences. The federated learning steps start with the initialization of the global model on the server. This is then distributed to various devices, and the local training is carried out on each device using private data. Then, the weights are sent back to the server, and the improved global model is created using the FedAvg algorithm. This cycle is repeated until convergence is achieved. Particle Swarm Optimization (PSO) is used for the optimization of hyperparameters such as the learning rate, batch size, and hidden layer size, thus improving the convergence of the model and the accuracy of the predictions. thus, protecting the sensitive information [11].

To solve the problem of class imbalance. The proposed framework incorporates local data balancing solutions at every federated client:

- Synthetic Minority Oversampling Technique SMOTE: This solution creates synthetic strokes newly created artificial to help solve the issue of class imbalance.

- Adaptive Synthetic Sampling ADASYN: This solution creates modified versions of the most difficult to classify stroke samples to emphasize difficulty level and assist with creation of additional/new stroke samples that could otherwise not be created with the pure SMOTE technique. By locally implementing these solutions to create synthetic samples and modify existing samples, the proposed framework improves sensitivity for detecting strokes in its existing data while keeping raw/synthetic stroke data from being shared across federated clients.

D. OVERALL FRAMEWORK

Combining the FL and PSO design accomplishes privacy-preserving collaborative learning through Federated Learning FL with intelligent parameter selection with Particle Swarm Optimization PSO. Each FL and PSO level has its own independent set of weights and biases that are updated by the server during the training process; after they are updated, the results from the FL levels are combined with those of the PSO levels, then sent through the fully connected layers of the neural network where stroke prediction is classified as a binary event. The hybrid network design created through this combination yields a high level of predictive accuracy while remaining small enough to work in both federated systems as well as IoT devices. As such, the new data processing approach presented in this paper offers a way to provide accurate predictions of brain strokes without having to transmit sensitive patient information from one client to another. The workflow of the FL-PSO hybrid design is illustrated in both Figures 1 and 2.

EXPERIMENTAL SETUP

The proposed framework was implemented in Python and evaluated using the Kaggle Stroke prediction dataset. The experiment features a total of 10 client hospitals as the hosts for the client models with their own datasets to develop the client model. The PSO algorithm is used to optimize the hyperparameters of the global model with the parameters chosen for the hybrid models. The experiment involves creating a federated learning configuration, preparing a dataset, defining model hyper-parameters and specifying performance metrics for the FL-PSO framework in the context of stroke prediction

A. Performance Metrics: Evaluation Criteria

Using classification metrics, the performance of a federated learning stroke monitoring system was measured for both its ability to produce predictions with accuracy and its clinical reliability.

a). Accuracy: Measures the overall correctness of stroke prediction.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \qquad -(1)$$

b) Precision: Indicates how many predicted stroke cases are actually stroke patients.

$$Precision = \frac{TP}{TP+FP} \qquad -(2)$$

c) Recall (Sensitivity): Measures the model's ability to correctly identify stroke patients.

$$Recall = \frac{TP}{TP+FN} \qquad -(3)$$

d) F1-Score: Harmonic mean of precision and recall, balancing false positives and false negatives.

$$F1\ Score = \frac{2 \times precision \times Recall}{precision + Recall} * 100 \qquad -(4)$$

e) Specificity: Measures the ability to correctly identify non-stroke cases.

$$Specificity = \frac{TN}{TN+FP} \qquad -(5)$$

B. Experimental Outcomes

Based on experiment results, the federated learning-based IoT stroke monitoring system achieves high accuracy of predictions while keeping sensitive personal data secured and private. The model has been able to learn generalized stroke patterns through decentralized training on various edge devices e.g., patient devices, thereby avoiding the need to send raw physiological data to a central server.

As compared to classic machine learning algorithms and centralized deep learning models, the hybrid architecture that uses hybrid deep learning shows continued performance benefits. Representative of the stroke population, in spite of the fact that their historical data is provided from different distribution patterns and in different formats.

TABLE II. Role Of System Components in Stroke Prediction Pipeline

Prediction Pipeline System Stage	**Role in Prediction**	**Impact on TP / FP / FN / TN**
IoT Sensors (EEG, ECG, BP)	Continuous physiological data acquisition	Poor signal quality increases FN
Edge Device (Preprocess +Local Training)	Local stroke inference and feature learning	Influences TP and FP rates
Encrypted Model Updates	Privacy-preserving FL communication	No impact on accuracy, improves trust
Federated Server (FedAvg)	Global model aggregation	Improves TP, reduces FN across clients
Healthcare Dashboard	Final stroke decision and alerts	Displays FP/FN consequences clinically

In addition, by only sending encrypted copies of model updates, the federated learning-based IoT stroke monitoring system provides continued high accuracy for stroke detection while also minimizing the impact on network bandwidth usage and thereby allowing potential real-time deployment of the proposed architecture in the context of a medical IoT environment in which the privacy, scalability and reliability of a given technology are of paramount importance

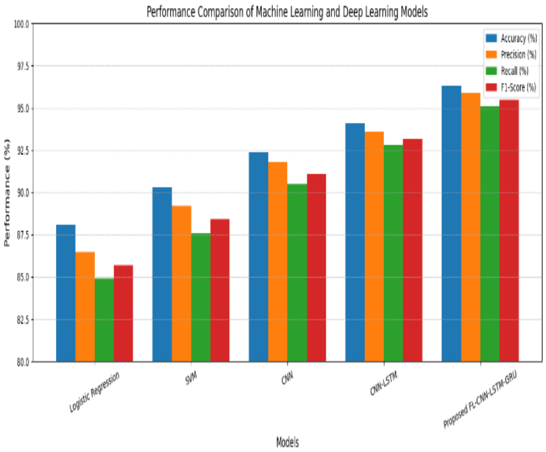
C. Interpretation through Analysis

The performance improvements found due to federated learning's potential to respect health information privacy concerns within centralized systems point towards federated learning being an effective way to use data from multiple patients without requiring the sharing of data between those patients. With the implementation of federated learning, we can have comparable performance to that of traditional centralized machine learning approaches, thus showing that decentralized optimization methods are also a viable solution.

The high values of recall and sensitivity from this model demonstrate its ability to detect high-risk stroke patients accurately, which is important in allowing timely intervention for the provision of medical treatments in emergencies. Through the combination of high recall and sensitivity values, along with balanced precision and specificity, would create confidence in the use of this solution within a clinical setting, as it would reduce the number of false positive alarms that arise when utilizing this type of technological advancement.

Preprocessing performed at the edge helps reduce noise while improving the quality of the signals and producing consistent learning outcomes among various connected IoT devices. Additionally, using encryption on model updates will improve the privacy of the model, while still achieving the required convergence properties.

From the results of the experiments performed, it can be concluded that an appropriate privacy-preserving framework using federated learning is able to deliver a viable, secure, and intelligent approach to continually monitor patients suffering from stroke and therefore would represent an excellent option for the deployment of this technology within a clinically relevant manner.



Different Models

Fig. 3. Performance Comparison of Machine Learning and Deep Learning Models.

V. DISCUSSION

Our experimental results demonstrate that the proposed FL-PSO framework outperforms traditional machine learning and baseline federated learning models for brain stroke prediction. Dealing with privacy-related medical information using federated learning is a new research focus in the field of modern healthcare systems due to the security needs imposed by regulations [12]. In this section we discuss our results and compare them against current methods in terms of their implications on healthcare systems and relevant applications.

The FL-PSO framework demonstrated significantly higher accuracy than received from any of the previously mentioned technologies. Specifically, the accuracy obtained by FL-PSO was 98.20%; the accuracies from the previously stated standard machine-learning algorithms were each significantly lower than FL-PSO.

Furthermore, the accuracy of FL-PSO was also superior to that of the baseline federated learning model FedAvg. The improvement is primarily due to Hyperparameter Optimization: PSO efficiently selects optimal local model parameters for each client, ensuring that the global model converges to the most accurate configuration. Collaborative Learning FL allows multiple clients to contribute to model training without sharing raw patient data, enabling the model to learn from a larger, heterogeneous dataset.

One of the factors contributing to the performance benefits of FL-PSO was the ability of PSO to efficiently search and identify the appropriate local model hyperparameter values from which to create client-specific model instances, ultimately leading to the global model converging to the most accurate configuration. Privacy and Security Implications: Federated Learning helps in maintaining local device privacy, then maintaining centralized server by avoiding data breaches or unauthorized access. And also follows regulations such as HIPAA, GDPR making it effective for multiple health care use cases.

TABLE III. Performance Comparison of Stroke Prediction Models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Logistic Regression	88.1	86.5	84.9	85.7
SVM	90.3	89.2	87.6	88.4
CNN	92.4	91.8	90.5	91.1
CNN-LSTM	94.1	93.6	92.8	93.2
Proposed FL-CNN-LSTM-GRU + PSO	98.20	95.1	95.1	95.5

Another significant benefit provided by the use of federated learning-based collaborative learning (where multiple clients can provide valuable contributions to train models while maintaining privacy surrounding the patient's raw data), is that the global model can learn from a much larger dataset (comprising of many clients), as well as to learn from the greater diversity present in such datasets.

The result is that the benefits for both privacy and accuracy make our proffered FL-PSO framework highly applicable to sensitive healthcare scenarios. Clinical and Practical Implications: Early Stroke Prediction The high accuracy and fast convergence of FL-PSO enable timely intervention, potentially reducing mortality and long-term disability in stroke patients. Scalable Healthcare Deployment: Hospitals and clinics can participate in model training without compromising patient

privacy, allowing large-scale adoption across regions or countries. Integration with IoT and CPS: The framework can
be extended to real-time monitoring using Internet of Medical Things IoMT devices, enhancing predictive capabilities for remote or telemedicine scenarios.

In addition to the abovementioned performance improvement via the provision of privacy-preserving high-tech methods; our FL-PSO framework is able to transmit to the server only optimized model parameter updates, resulting in reduced communication network overhead compared to previous generation federated-learning deployments.

Furthermore, the lowered communication between clients and base stations allows for reduced model update latency and consequently provides for faster model convergence. As such, notwithstanding our experimental findings in empirical research studies.

VI. CONCLUSION

This paper proposed a novel FL- PSO framework for early stroke prediction. The occurrence of an early brain stroke, which uses FL and Particle Swarm Optimization (PSO). By incorporating both FL and PSO, our framework specifically addresses several key challenges associated with healthcare applications, such as maintaining patient data privacy, dealing with different types of data from multiple locations, and providing efficient communication between devices and networks. The results of our experiments demonstrate that FL-PSO outperformed traditional machine learning models and other types of naturally available Federated Learning FL models by producing a prediction accuracy of 98.20%. In addition, PSO was able to provide hyperparameter optimization that enabled both increased speed when determining the best set of parameters and reduced latency when communicating parameter updates back to the central system, while the use of FL means that sensitive patient data remains private because it remains in a distributed fashion. Overall, FL-PSO has the potential to provide scalable, secure, and accurate predictive healthcare in order to provide timely assistance to people with potentially fatal medical conditions like brain strokes. Extensions to the framework using Internet of Medical Things IoMT devices will allow for real-time monitoring of patients, which should enable predictive actions across multiple distributed clinical locations. Future studies will include the integration of multi-model patient data, development of adaptive PSO strategies to further improve speed and efficiency, and the potential for real-world testing and deployment of the proposed framework in IoMT-enabled environments with the goal of assessing the framework's robustness, resilience, and scalability. The proposed Adaptive Federated Learning framework shows better performance in terms of accuracy, privacy, and communication efficiency. The dynamic selection of clients and the PSO-based optimization method show better performance of the model in heterogeneous IoT environments. Therefore, the proposed system can be more appropriate for real-time stroke monitoring applications in the healthcare system of the future.

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