Modified Federated Learning for Parkinson's Disease Prediction

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ABSTRACT

Parkinson's Disease (PD) is a common neurodegenerative condition characterized by tremors, stiffness, and bradykinesia. Early PD detection and prediction are critical for optimizing treatment regimens and improving patient outcomes. This research investigates the efficacy of machine learning algorithms in PD diagnosis and progression prediction. A review of relevant literature was conducted, including research that used various datasets and machine learning algorithms. These algorithms include Support Vector Machines (SVM), Naive Bayes (NB), K-Nearest Neighbors (KNN), Multilayer Perceptron (MLP), Decision Trees (DT), Random Forest (RF), Expectation-Maximization (EM), Principal Component Analysis (PCA), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Support Vector Regression (SVR), and Attention-based Deep Convolutional Neural Networks (ADCNN). The results demonstrate the potential of machine learning techniques in enhancing PD diagnosis and prediction accuracy. Feature selection, model optimization, and integration of multiple modalities, such as genetic, imaging, and clinical data, have shown promise in improving model performance. The findings suggest that machine learning can complement traditional diagnostic methods and aid in early detection and personalized treatment planning for patients with PD. Future research should focus on developing explainable Artificial Intelligence (AI) models and conducting large-scale longitudinal studies to validate the performance and generalizability of machine learning models in real-world clinical settings. By addressing these challenges, machine learning can significantly contribute to advancing PD research and improving patient care.

Keywords-federated learning; Parkinson's Disease (PD); prediction; data preprocessing; K-Nearest Neighbors (KNN); data privacy; aggregation

I. INTRODUCTION

Parkinson's Disease (PD) is a neurodegenerative disorder affecting the neurons of the center region of the midbrain, called the substantia nigra. PD causes problems with both motor and non-motor symptoms. The main indicators of PD are characterized by four symptoms: tremor, rigidity, bradykinesia, and postural instability. The initial symptoms include shaking, difficulty in walking, and slowness in movement. Late phase symptoms entail anxiety, dementia, and depression, while symptoms like emotional, sleep, and sensory problems may also occur. The detection and diagnosis of PD at an early stage can be useful and important for a patient's health [1]. Medical Support Systems (MDSS) have utilizied treatment and diagnosis methods that apply AI to clinical datasets, demonstrating the importance of effective learning. Different machine learning and data mining methods can be used for AI-assisted treatment and diagnosis of PD. Machine learning and data mining often employ similar methods; however, machine learning techniques focus on prediction, whereas data mining concentrates on detection [2].

Machine learning and deep learning techniques can be applied to various PD datasets. These datasets are often directly collected from sources, including motion sensors (movement), smartphones (audio signals), Electroencephalogram (EEG) signals, or brain signals. Online datasets collected from various patients and healthy individuals are also available. Many researchers utilize online datasets to enhance the efficiency of their techniques, based on machine learning and deep learning [3]. The advancements in data collection technology have resulted in significant amounts of data, and thus there is a need to introduce efficient methods to classify and extract new information from these data. Data mining, machine learning, and deep learning are often employed for this purpose [1, 3].

The availability of large healthcare data from different clinical institutions, pharmaceutical industries, and patients has provided an opportunity to derive data-driven insights and enhance the quality of healthcare delivery. However, the complex and sensitive nature of healthcare data, which are often fragmented and private, makes it difficult to produce robust results, creating a barrier in the development of effective and generalizable analytical approaches [4]. Federated learning is a solution to address this issue. The former is a system that trains a common global model on a centralized server while keeping the private information inside local institutions. Federated learning can thus link disparate healthcare data sources while maintaining privacy and security [4].

PD significantly affects patients' lives, healthcare systems, and societies due to its chronic progression and difficulties in early diagnosis. Traditional machine learning models for PD prediction often rely on centralized data, which requires collecting sensitive health information from different sources, such as hospitals, research institutions, and patient records. However, such centralization also introduces data privacy and security concerns, as well as compliance with standards like HIPAA and GDPR. These compliances potentially limit the quantity and diversity of data employed to train models. Moreover, the decentralized nature of healthcare data within organizations restricts the development of robust, generalizable models that can learn from intricate PD symptoms, including both motor and non-motor symptoms.

The present study addresses these challenges using federated learning, a privacy-preserving framework that facilitates collaborative learning without compromising data confidentiality. Federated learning is a promising method used by healthcare institutes to locally train models on private data and only send model parameters to a central server for aggregation. The main objective of the current study is to enhance PD prediction with minimal loss in a resource-constrained environment by combining federated learning with the KNN algorithm. The proposed model is a simple, interpretable, and robust classifier that deals with high-dimensional PD features such as voice habits and movement trajectories. This approach not only avoids the limitation of centralized solutions but also provides equitable access to high-quality PD diagnostics within distributed healthcare networks, resulting in early interventions and improved patient outcomes.

To enhance PD prediction, authors in [1] proposed an approach that uses machine learning techniques in combination with filter- and wrapper-based selection methods. Various methods and algorithms have been proposed to improve the accuracy and early detection of PD. Authors in [2] introduced a hybrid intelligent system that utilizes noise reduction, clustering, and prediction algorithms. By addressing multi-collinearity issues and employing SVR and the Adaptive Neuro-Fuzzy Inference System (ANFIS), the system shows significant improvements in predicting PD progression. Authors in [3, 4] explored the use of deep learning techniques, such as deep knowledge creation networks and recurrent networks, to identify PD symptoms. Their proposed system, called DMVDA, incorporates acoustic deep neural networks and demonstrates promising results in identifying PD symptoms.

Authors in [5, 6] compare different approaches and algorithms for feature selection and classification. They utilized an evolutionary algorithm and RF classifier combination, achieving very high accuracy. Utilizing voice source information for PD detection was investigated in [7, 8], where traditional pipeline and end-to-end classifier architectures were explored. A combination of baseline and QCP-based glottal features yielded the highest accuracy for the traditional approach, while an end-to-end approach using QCP-based glottal flow signals achieved the best results.

Furthermore, the role of phonemic groups [9], handwriting analysis [10], and dimensionality reduction techniques [11] for PD detection has been explored. These methodologies include GMM-UBM classifiers with phonemic grouping, dynamically enhanced static handwriting, and a hybrid intelligent system. These systems combine Linear Discriminant Analysis (LDA) and Genetic Algorithms (GA), achieving high accuracy in identifying PD. Machine learning techniques have also been employed in PD diagnosis [12, 13]. SVM, GA, and Chaotic Map-Based Bat Algorithms (CMBA) have been deployed to enhance the intelligence and efficiency of the models. Deep learning methods, including PCA, neural networks, Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM), have shown potential in PD prediction [5, 14-17]. The combination of SVM and RF classifiers in an ensemble modeling approach [18] and the hybrid approach of utilizing multiple machine learning techniques [6] have also been proposed to improve accuracy in PD diagnosis.

Moreover, a deep learning model for early PD diagnosis [19] incorporates multiple components to enhance predictive capabilities. In the domain of chronic kidney disease, authors in [20] introduced a privacy-preserving federated learning framework integrated with homomorphic encryption, achieving a prediction accuracy of 98.6%. It was reported that federated learning with a homomorphic encryption framework introduced a layer-wise encryption strategy, securing model parameters, bias, and feature normalization, ensuring end-to-end confidentiality while maintaining performance comparable to unencrypted models. This approach aligns with the utilization of Federated Averaging (FedAvg) for PD prediction in the present study, highlighting the broader applicability of encrypted federated learning in healthcare for protecting sensitive electronic health records. Unlike prior studies that rely on centralized data aggregation, this research focuses on a privacy-preserving federated learning framework specifically for the LSVT voice rehabilitation dataset. The contribution of the proposed work lies in the application of the KNN algorithm with federated learning for training and testing the voice rehabilitation dataset for PD prediction.

II. METHODOLOGY

Figure 1 illustrates the workflow of the proposed method for PD prediction. Each client receives a data subset of the LSVT dataset, followed by local normalization of this subset using z-score normalization. Each client then splits its local dataset into an 80% training set and a 20% testing set. This is followed by local training of the KNN classifier ($k = 5$) on the training subset. Clients then compute class probability predictions on their test data, with prediction summaries sent to the central server. Finally, the server aggregates predictions using FedAvg to produce a global decision. The global performance is reported using metrics such as accuracy, precision, and recall.

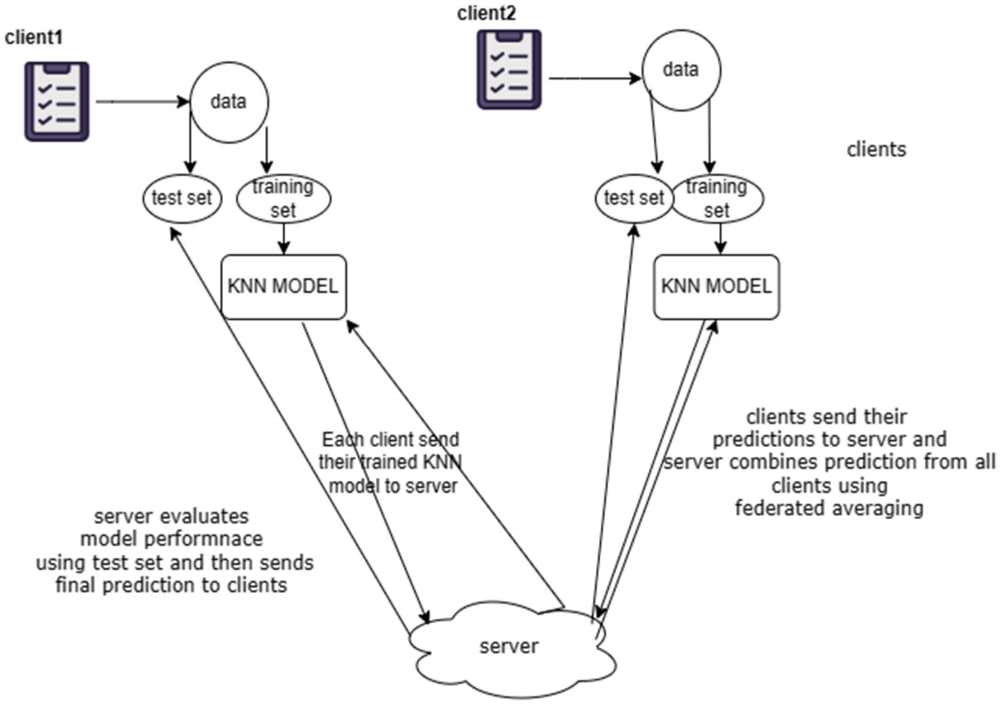

Fig. 1. Workflow of the proposed method.

A. Proposed Method

KNN is one of the most popular and simplest classification methods for supervised machine learning. It uses nearby data points to identify the group associated with data points. A data instance is assigned to the most common class among its nearest neighbors, as determined by a distance function based on the majority vote of its neighbors. This distance function uses the Euclidean distance formula [21]:

$$D_{xy} = \sqrt{\sum_{k=1}^{n}(x_k - y_k)^2}$$

where D_{xy} denotes the distance between data points x and y, k represents each data point, and n denotes the total number of attributes (features).

The study proposes a federated learning–based PD prediction framework using the KNN classifier. KNN was selected due to its simplicity, interpretability, and efficiency in handling high-dimensional biomedical features such as voice-derived attributes. Moreover, KNN avoids iterative gradient updates, making it suitable for privacy-preserving federated environments with limited computational resources. Each client locally trained a KNN classifier using its local data. After empirical validation, the number of neighbors was set to $k = 5$, which provided the best trade-off between bias and variance on the validation sets across clients. The Euclidean distance metric was employed, as all features were normalized to zero mean and unit variance during preprocessing. Instead of sharing data samples, each client computed local class probability for its test instances based on its KNN model, and transmitted only prediction summaries to the central server. FedAvg is a communication strategy for remote training with a significantly large number of clients. To protect their privacy, FedAvg clients save their data locally, and client-client communication is facilitated via a central parameter server. The server aggregates client-side predictions using the FedAvg strategy, producing a global decision that reflects knowledge learned from all participating clients while preserving data privacy. This central server, which also receives the clients' updated parameters, sends the parameters to each client [22]. Algorithm 1 presents the proposed framework for PD prediction:

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Algorithm 1. Proposed federated learning
inspired method for PD prediction.
For Client Side:
1. Collect data from sources relevant to
PD.
2. Preprocess the collected data.
3. Split the preprocessed data into
training and testing sets.
4. Train a KNN classifier using the
training set.
5. Test the KNN classifier using the
testing set and calculate the parameters.
For Server Side:
1. Collect the trained KNN classifiers
from all clients.
2. Use FedAvg to combine the KNN
classifiers into a single aggregated
classifier.
3. Use the aggregated classifier for
prediction.
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B. Dataset Description

The study utilized the LSVT voice rehabilitation dataset [23] to validate the proposed methodology. The dataset contains 14 subjects (6 women and 8 men) with PD, with 9 speech samples of each patient. Each sample contains 309 features from various pronunciation tasks (5 samples were taken before treatment, 4 samples were taken after treatment). The ages of the individuals ranged from 51 to 69 years, with a mean and an SD of 61.9 and 6.5, respectively. Samples were collected while subjects made continuous vowel sounds with a resolution of 16 bits and a sampling frequency of 44.2 kHz. Each subject contributed nine speech samples derived from sustained vowel phonation tasks, resulting in a total of 126 instances. Each instance contained 309 voice-related features, including jitter, shimmer, and harmonicity measures. The dataset was partitioned across federated clients to simulate decentralized clinical environments. Each client retained its local subset and performed training and evaluation independently.

III. EXPERIMENTAL RESULTS

Table I presents the performance of different classifiers using various feature selection algorithms. The proposed FedAvg-KNN classifier achieved an accuracy of 82.8%, a precision of 86.0%, a recall of 88.4%, and an AUC of 86.7%. The results indicate that the proposed method performs well in accurately detecting PD. It outperforms FedAvg-SVM, FedAvg-RF, and FedAvg-DT in terms of accuracy, precision, recall, and AUC. This suggests that the combination of feature selection and the KNN classifier provides better performance for PD detection.

TABLE I. COMPARISON OF DIFFERENT CLASSIFIERS USING FEATURE SELECTION METHODS

Method	Accuracy (%)	Precision (%)	Recall (%)
FedAvg-SVM	0.825	0.859	0.869
FedAvg-RF	0.827	0.802	0.883
FedAvg-DT	0.820	0.815	0.822
FedAvg-KNN (proposed)	0.828	0.860	0.884

Table II presents the comparative performance metrics of several models. The proposed model, FedKNN, achieved an accuracy of 86.2%, a precision of 88.3%, and a recall of 88.9%. These findings demonstrate that the introduced approach is very effective at detecting PD. Furthermore, the performance of the proposed FedKNN method was compared with other machine learning techniques, including FedCNN and FedRNN. The results suggested that the proposed model achieved superior accuracy, precision, and recall, outperforming existing baseline models for PD detection and feature selection using the federated learning algorithm.

TABLE II. COMPARISON OF PERFORMANCE METRICS FOR SEVERAL MODELS

Model	Accuracy	Recall	Precision
FedCNN	85.3	87.1	88.5
FedRNN	84.6	85.8	86.7
FedKNN (proposed)	82.8	88.4	86.0

Figures 2-4 compare the precision, accuracy, and recall of the proposed model with other machine learning techniques. The proposed method yields promising results for PD detection. Its high accuracy, precision, and recall suggest its usefulness in effectively diagnosing PD cases. These findings have significant implications for early diagnosis and intervention in PD, leading to improved patient outcomes and more efficient healthcare management.

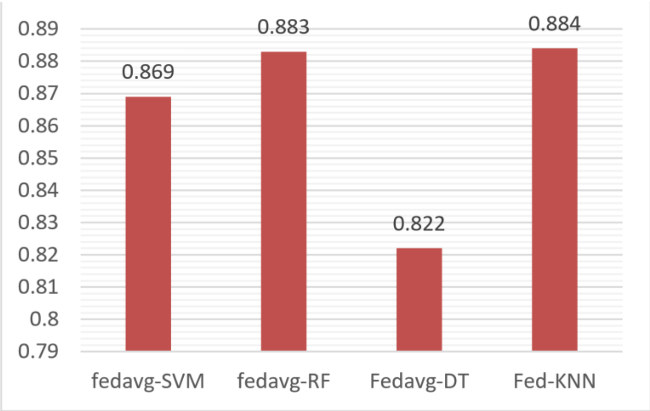

Fig. 2. Precision comparison of different machine learning models.

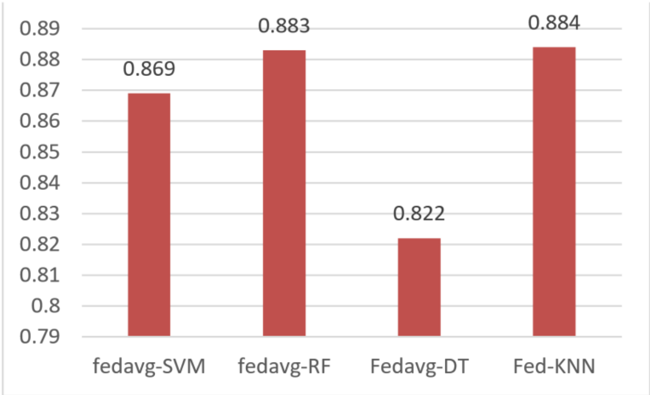

Fig. 3. Accuracy comparison of different machine learning models.

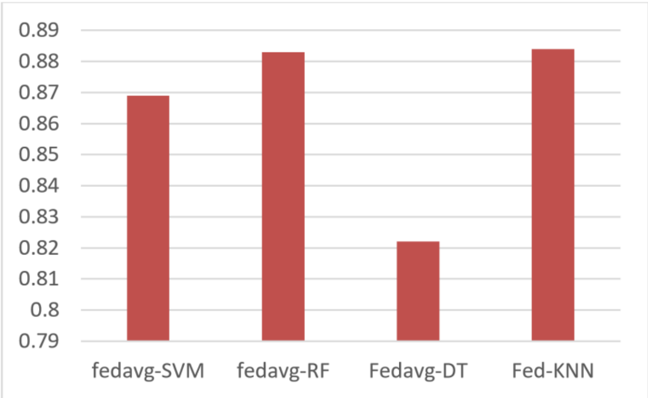

Fig. 4. Recall comparison of different machine learning models.

IV. CONCLUSION

This study provides valuable insights into the detection and prediction of Parkinson's disease (PD) using machine learning techniques. By analyzing different datasets and employing various machine learning algorithms, the study demonstrates the potential of machine learning in improving the accuracy of PD diagnosis and prediction. The discussed approaches, such as Support Vector Machines (SVM), Naive Bayes (NB), K-Nearest Neighbors (KNN), Multilayer Perceptron (MLP), Decision Trees (DT), Random Forest (RF), Expectation-Maximization (EM), Principal Component Analysis (PCA), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Support Vector Regression (SVR), Attention-based Deep Convolutional Neural Networks (ADCNN), and Convolutional Neural Networks (CNN), highlight the versatility and effectiveness of different methodologies for tackling PD detection and progression prediction. Moreover, these findings have broader implications for early detection, patient care, and personalized treatment strategies for PD. Future studies should explore the integration of multiple modalities, such as genetic, imaging, and clinical data, to enhance the performance of machine learning models. Efforts can be directed towards the development of explainable Artificial Intelligence (AI) models that provide insights into the PD detection features and patterns contributing to the disease, as well as its underlying mechanisms.

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