Schizophrenia Diagnosis using Optimized Federated Learning Models

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Summary

With the privacy concern of mental patients' records as it is protected with federal privacy legislation, this paper proposes an optimized federated learning model for schizophrenia detection from functional magnetic resonance imaging (fMRI) and structural magnetic resonance imaging (sMRI) outputs. As the diagnosis of schizophrenia has no biological indicator, this study investigated the human brain's functional and structural defense for the disorder. fMRI and sMRI have an effective contribution to the diagnosis of schizophrenia and differentiate it from a healthy one. The proposed models predict schizophrenic states among The 10th annual MLSP competition data. To improve the classification of traditional models on magnetic resonance data, meta-heuristic models are proposed to improve the classification accuracy and the generalization ability. The features selected by the swarm intelligence algorithms are used as the most influential factors in the creation of machine learning algorithms and the evaluation of the proposed hybrid models. The proposed federated learning models and a hybrid K-NN model reached 100% of accuracy, and area under curve metrices.

Keywords:
Federated Learning, Schizophrenia, fMRI, sMRI, Swarm Intelligence.

1. Introduction

A disorder of schizophrenia that causes sensory deficits, delusions, hallucinations, and strange behavior is called a thought disorder. Disorders are considered psychotic disorders because the symptoms reflect a loss of contact with the perceived reality. Serious mental illness can only be treated by early diagnosis and initiation of treatment protocols. So, people with these disorders can experience recovery [1]. Schizophrenia is also an important obstacle for people to interpret reality abnormally. It results in a combination of hallucinations, delusions, and severely disturbed thoughts and actions that can interfere with and interfere with everyday functions. Schizophrenia is often a disorder that always occurs in youth. Early diagnosis reduces the burden on the family and increases the potential for effective treatment to reduce social costs. There is no objective metric for schizophrenia. Diagnosis decisions for schizophrenia include tests that help rule out disorders with similar symptoms, as well as alcohol and drug screening. The doctor may additionally request imaging studies, like functional magnetic resonance imaging (fMRI) and structural magnetic resonance imaging (sMRI) [2]. Magnetic resonance imaging (MRI) can be a type of scan that uses a strong magnetic field and radio waves to provide detailed pictures of the inside of the body. Outputs vary widely due to the type of examination, and structural MRI provides information about the shape, size, and integrity of brain structures. Most studies take measurements on 3T scanners. However, functional resonance imaging (fMRI) measures inadequate changes in blood flow that occur with brain activity. it can detect abnormalities in brain function that other imaging techniques cannot find. The results of an MRI help diagnose mental disorders, plan treatment, and monitor the effectiveness of previous treatments.

1.1. Motivation and contribution

Schizophrenia may be a severe mental disorder affecting approximately 24 million people or 1 in 300 people worldwide. [3] It causes mental illness, is associated with serious disability, and should affect all areas of life, including personal, family, social, educational, and professional functions. About two out of three people with psychosis within the world don't receive specialist psychological care caused by diagnosis failure. Automatic aiming will become a superb solution to the matter of mental state.

- There is no single test for schizophrenia, and that state is usually diagnosed after evaluation by mental health experts.
- Unavailability of accessing patients' data because it is protected with federal privacy legislation.
- Schizophrenia disorder has symptoms of depression, mania, or both types of symptoms, which cause a huge confusion at diagnosis.

The proposed solution is built to classify schizophrenia from sMRI and fMRI data, which is abundant from the machine

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learning signal processing dataset. By the hybridization of ML algorithms as logistic regression, k-nearest neighbors, naive bayse, decision tree, random forest, and support vector machine. And swarm intelligence optimizers like the firefly algorithm and jaya algorithm. Also, the solution solved the federal privacy legislation for patients' data by the proposed federated learning model.

1.2. Paper Organization

The paper is organized as: Section 2 devoted for related work. Section 3 presents approaches that describe (models, and the swarm intelligence algorithms); Section 4 reflects on the implementation of models; Section 5 presents on the experiential setup; Section 6 presents the experimental results; while Section 7 points out the core conclusions of the proposed model and highlights the future work.

2. Related Work

Machine learning may be a promising technique for the patient-specific prediction of mental disorders. However, the reason behind schizophrenia remains poorly understood, Therefore, the diagnosis of schizophrenia is primarily based on the patient's behavioral performance. Finding an effective way to increase the diagnosis rate of schizophrenia is very urgent. There are many contributions within the field of diagnosis schizophrenia with a large variance of datatype.

Zhu Yafei, et al. [4] proposed a weighted deep forest model, which incorporates a weighted elegance vector, and a prediction elegance vector. the version is used to categorize practical magnetic resonance imaging (fMRI) data. it extracted practical connection (FC) capabilities from fMRI data. Then Principal issue analysis (PCA) is used to lessen the size of FC capabilities. If datasets have unbalanced data, the Synthetic Minority Oversampling Technique (SMOTE) is used to stability the data, as compared with the class effects acquired through conventional classifiers, this class accuracy is better.

Prabhakar, et al. [5] proposed three feature extraction techniques are employed with four optimization algorithms and Adaboost classifier and Naïve Bayesian Classifier, from analyzing the Electroglottograph (EGG) signal to diagnose schizophrenia. We have described average performance measurements between classifiers with different optimization techniques that have different characteristics for health control and schizophrenia. The average error rate was calculated by various optimization methods with different characteristics for health control and schizophrenia and displayed below the classifier.

Jeong-Youn Kim, et al. [6] studied the resting EEG network function is well classified into positive, negative, and cognitive / dismantling symptoms between schizophrenia patients and normal controls, and between hypo schizophrenia and hyper schizophrenia. I suggested that I could do it. This is because the network function of the brain is calculated from the EEG source activity. Schizophrenia patients were divided into two groups (high and low) using the Positive and Negative Syndrome Scale (PANSS), depending on the symptoms of positive, negative, and cognitive / disorder.

Brisa S. Fernandes, et al. [7] studied the diagnosis of bipolar and schizophrenia, differential diagnosis of bipolar and schizophrenia with potential clinical utility can be predicted by computer-assisted machine learning algorithms using blood and cognitive biomarkers, to multiple domains. Their integration is based on being superior to algorithms based on only one domain.

Beomjun Mina, et al. [8] proposed a model aims to use machine learning analysis of static electroencephalography (EEG) to predict individual responses to electroconvulsive therapy (ECT) in patients with schizophrenia. The results of the study suggest that higher effective connectivity in the frontal region may be associated with the preferred ECT response. In addition, individual decisions to perform ECT in clinical practice may be complemented by resting EEG biomarkers of the ECT response in schizophrenic patients.

Johannes Kirchebnerb, et al. [9] proposed a new methodological approach, the null hypothesis significance test (NHST), and a multimodal classifier were used for variable preselection. Next, we created a machine learning algorithm using the most influential variables and evaluated the two final models (with and without substitution). The results provide new insights into factors that may affect persistent discomfort in a particular subset of patients with schizophrenia spectrum disorders.

Máté Baradits, et al. [10] studied the microstate segmentation of resting EEG records and provided a useful function to successfully distinguish between healthy controls from patients with schizophrenia. Use machine learning techniques to apply multivariate pattern analysis of microstate functions to create specific feature sets that represent microstate functions. We compared a machine learning approach to classify patients with schizophrenia using these features with previous EEG-based machine learning studies.

Hussein K. Al-Hakeim, et al. [11] studied major neuro-cognitive psychosis (MNP) neuro-immuniform fingerprint (MNP). This was best predicted by the combination of CCL11, TNFα, IL1β and Sil1RA. The combination of markers described above defines MNP as a particular neuroimmune disease, and the increase in immunogenicity determines the symptoms of memory and leadership and emergence (psychosis, hostility, suggestion, manners and negative).

Caroline W. Espinola, et al. [12] proposed machine learning classifiers that use voice parameters, especially support vector machines, have high expectations for the detection of schizophrenia. There are linguistic abnormalities such as tangentiality, derailment, scholarship, coined words, lack of language, and prosody. They focused on language cues as a possible indicator of schizophrenia.

Jieun Kima et al. [13] classified schizophrenia. However, other psychiatric disorders such as depression, obsessive-compulsive disorder, and attention deficit / hyperactivity disorder (ADHD) can also be distinguished and diagnosed using the proposed method. Then, when ranking features using false positive rate (FDR) criteria and cross-correlation measurements, select the top 10 features and use a thorough search to combine them with the highest accuracy. I found.

Shih-Chieh Lee, et al. [14] Using machine learning technology, we have improved the discriminating ability of FERD screeners. The data are from previous studies. An artificial neural network was developed based on the test taker's response to the FERD screener to determine whether the patient was a schizophrenic patient or a healthy adult (168 items). The performance of the MLFERD screener was evaluated using a stratified 5-fold cross-validation method. The MLFERD screener appears to be more discriminating than the FERD screener in distinguishing between individuals with schizophrenia and healthy adults.

Lulu Zhu, et al. [15] used machine learning algorithms to analyze the expression levels of messenger RNA in the peripheral blood of 48 patients with schizophrenia and 50 healthy people, with schizophrenia patients and healthy people. The purpose was to distinguish. SVM)., Decision Trees and Random Forests. The expression of 6 mRNAs was detected using a real-time quantitative polymerase chain reaction (qRTPCR). They argued that combining genes using a machine learning approach was better than using a single gene to distinguish between schizophrenic patients and healthy people. In the SVM model, the combination of genes can be used as a diagnostic biomarker for schizophrenia.

Janek Frick, et al. [16] studied the event-related potentials to detect schizophrenia with high accuracy. Achieve a balanced accuracy of 96.4% on machine learning systems, surpassing all similar insights. To do this, they used additional sensors in the left and right hemispheres in addition to the normal central sensor. When recording the data, the design of experiments takes into account the dysfunction of the affected copy of schizophrenia. The model was successful in early detection because it was possible to screen potential patients for schizophrenia-related dysfunction as soon as the first symptoms appeared. This allows you to identify risk groups and people.

Manuel A. Vázquez, et al. [17] proposed a machine learning method that supports the diagnosis of schizophrenia using electroencephalogram (EEG) as input data. Computer algorithms not only provide diagnostic suggestions, but more importantly, provide additional information that enables clinical interpretation. It is based on an ML model called Random Forest that processes connection metrics extracted from EEG signals. In particular, generalized partially directed coherence (GPDC) and direct directed transfer function (dDTF) measurements are used to build the input capabilities of the ML model. The latter allows identification of the most performance-related functions and provides insight into the EEG signals and frequency bands associated with schizophrenia. Preliminary results of recent data suggest that signals associated with the occipital lobe appear to play an important role in diagnosing the disease. In addition, each frequency band can provide diagnostics. The Beta Band and Theta (Frequency) Band provide more relevant functionality in the implemented ML classifier.

Table 1 The related work summary

Paper	Model	Performance
Zhu Yafei , et al. [4]	gcForest model	Acc=0.72
Prabhakar, et al. [5]	Adaboost Classifier	Acc=0.99
Jeong-Youn Kim et al. [6]	Latent Dirichlet allocation (LDA)	Acc=0.81
Brisa S. Fernandes et al. [7]	LDA	Acc=0.72
Beomjun Min a et al. [8]	Random Forest	Acc=0.85
Johannes Kirchebnerb et al. [9]	Naïve bayes	Acc=0.82
Máté Baradits et al. [10]	K-mean clustering	Acc=0.83
Hussein K. Al-Hakeim et al. [11]	SVM	Acc=0.99
Caroline W. Espinola et al. [12]	SVM	Acc=0.92
Jieun Kima et al. [13]	SVM	Acc=0.96
Shih-Chieh Lee et al. [14]	Artificial Neural Network	AUC=0.97–0.99
Lulu Zhu et al. [15]	SVM	AUC=0.99
Janek Frick et al. [16]	Random Forest	Acc=0.96
Manuel A. Vázquez et al. [17]	Random Forest	AUC=0.87

All research to date has made significant contributions in a variety of methods and optimization methods. But now it offers a solution to federal privacy law on mental health data. In accordance with the Health Insurance Portability and

Accountability Act (HIPAA) privacy rules that protect health and mental health information, the privacy rules are all "protected health information" (including personally identifiable mental health information). PHI) protects. A format that includes electronic, paper, or verbal statements.

3. Approach

This section addresses the applied tools and methodology for the proposed machine learning models before and after optimization, to predict the diagnosis state of the subject. The following steps were used for building the models:

3.1. The Traditional Machine Learning Model

As shown in Algorithm 1, the proposed traditional model algorithm. In which the data loaded from CSV files, and combined to form the features vector. Then the records mapped with labels to be ready for splitting. Data split to test set 20% and train set 80%. The training model built by scikit learn API, then evaluated to return the accuracy an area under cure score.

Algorithm 1: The Traditional Learning Model

Input: MLSP challenge 24th round dataset
Output: Model Prediction Accuracy and loss
1 **Initialization:**
  Data loaded from csv ;
2 **Preprocessing:**
  Features merging;
  Data mapping;
  Data splitting;
3 **Training:**
  Build model using Sci-kit learn API ;
  Model Initializing and Training ;
4 **Evaluation:**
  Model Evaluation ;
  Return the machine learning model accuracy and auc score;

3.2. THE Swarm Optimized Machine Learning Model

As shown in Algorithm 2, the proposed swarm optimized model algorithm. In which the data loaded from CSV files, and combined to form the features vector. Then the records mapped with labels to be ready for splitting. Data split to test set 20% and train set 80%. The swarm intelligence algorithms ran to select the optimal features to optimize the scores. The features vector updates. Then the training model built by scikit learn API, then evaluated to return the accuracy an area under cure score.

Algorithm 2: The Swarm Optimized Machine Learning Model

Input: MLSP challenge 24th round dataset
Output: Model Prediction Accuracy and loss
1 **Initialization:**
  Data loaded from csv;
  Set number of agents 100;
  set maximum iterations 50;
2 **Preprocessing:**
  Features merging;
  Data mapping;
  Data splitting;
3 **Features selection:**
  Run Swarm feature selection Optimizer;
  Swarm Optimizer selected features applied ;
4 **Training:**
  Build machine learning model using Sci-kit learn API;
  Model Initializing and Training ;
5 **Evaluation:**
  Model Evaluation ;
  Return the machine learning model accuracy and auc score;

3.3. The Federated Learning Model

As shown in Algorithm 3, the proposed federated learning model [18] algorithm. In which the data loaded from CSV files, and combined to form the features vector. Then the records mapped with labels to be ready for splitting. Data split to test set 20% and train set 80%. The training data preprocessed for federated learning. The model built by keras API, it trained on local clients the updated the global one to evaluate, and return the accuracy an area under cure score.

Algorithm 3: The Federated Learning Model

Input: MLSP challenge 24th round dataset
Output: Model Prediction Accuracy and loss
1 **Initialization:**
  Data loaded from csv ;
2 **Preprocessing:**
  Features merging;
  Data mapping;
  Data splitting;
  Data were repeated to simulate the number of clients;
  Data shuffled to avoid getting the same results;
  Data grouped into batches to enhance performance;
  Data cached in memory for better performance;
3 **Training:**
  Build sequential deep learning model using Keras API;
  Build Federated Learning Model ;
  Collecting local models gradients and updates to be sent to the global model;
  Model Initializing and Training ;
4 **Evaluation:**
  Model Evaluation ;
  Return the machine learning model accuracy and loss for each round;

3.4. Firefly Algorithm

The Firefly Algorithm [19] is a bio-stimulated metaheuristic set of rules for optimization problems. Introduced through Yang on the University of Cambridge in 2010. This set of rules is stimulated through the night time flashing conduct of fireflies. One of the 3 policies used to create the set of rules is that everyone fireflies are unisex. That is, every firefly may be interested in different mild fireflies. The 2d rule is that the brightness of the firefly is decided through the encoded goal characteristic. The very last rule is that allure is at once proportional to brightness, however decreases with distance, fireflies circulate in a brighter direction, and if there may be not anything bright, they circulate randomly. Note that the set of rules shows n × n, however the quantity of goal characteristic rankings consistent with loop is 1 rating consistent with firefly. Therefore, the entire quantity of critiques of the goal characteristic is (quantity of generations) x (quantity of fireflies). The main update formula for any pair of two fireflies xi and xij.

$$x_i^{t+1} = x_i^t + \beta \exp[-\gamma r^2_{ij}] + \alpha_t \varepsilon_t \quad (1)$$

where αt is a parameter controlling the step size, while ε_t is a vector drawn from a Gaussian or other distribution.

3.5. Jaya Algorithm

The JAYA algorithm [20] combines the principle of survival of the fittest of evolutionary algorithms with the attractiveness of the global optimal solution of swarm intelligence methods. First, carefully analyze the optimization model and convergence characteristics of the JAYA algorithm. Then the proposed version of the JAYA algorithm was considered. Examples: fix, binary, hybrid, parallel, chaos, multipurpose, etc. Various applications that work with related versions of the JAYA algorithm are also described and summarized based on some problem areas. In addition, the open-source code for the JAYA algorithm will be identified, providing a wealth of resources to the JAYA research community. A critical analysis of the JAYA algorithm shows the advantages and limitations of dealing with optimization problems. Finally, this paper concludes with the conclusions proposed and possible future improvements to improve the performance of the JAYA algorithm. Readers of this overview can identify the best domains and applications used in the JAYA algorithm and justify their JAYA-related contributions. The value of the best candidate is obtained during the ith iteration as per the following.

$$X'_{j,k,i} = X_{j,k,i} + r_{1,j,i} (X_{j,best,i} - |X_{j,k,i}|) - r_{2,j,i} (X_{j,worst,i} - |X_{j,k,i}|) \quad (2)$$

$X'_{j,k,i}$ is accepted if it gives better function value. All the accepted function values at the end of the iteration are maintained and these values become the input to the next iteration.

4. THE PROPOSED MODEL

4.1. Traditional Model on MLSP dataset

As shown in Fig [1], the proposed traditional model building steps are:

- Data Loading: Loading csv files of FNC features, SBM features and labels
- Merge Feature: Merge each participant features in one data frame
- Map Features with label: Creating Sample Data Dictionary as map each record of features with its label
- Split data: Creating Sample Data Dictionary for a part of data (train –test)
- Create Machine Learning Model: machine learning model created using Sci kit learn API.
- Model Initializing and Training: The iterative process initialized and begin training.
- Model Evaluation: Model performance was evaluated by print evaluation metrics.

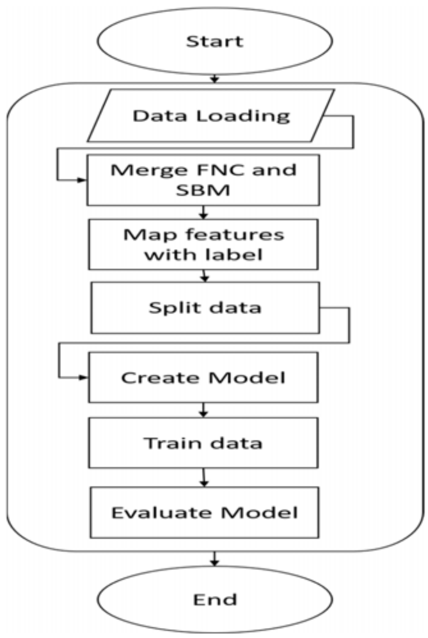

Figure 1. Machine Learning model steps

4.2. Swarm Optimization for feature selection on MLSP dataset.

As shown in Figure [2], the proposed Swarm optimized model building steps were:

- Data Loading: Loading CSV files of FNC features, SBM features, and labels.

- Merge Feature: Merge each participant's feature in one data frame.
- Map Features with label: Creating Sample Data Dictionary as a map of each record of features with its label.
- Split data: Creating Sample Data Dictionary for each a component of knowledge (train –test)
- Define swarm optimizer: Set the number of agents and number of iterations for the swarm algorithm.
- Iterations: Calculate the fitness value of iterations.
- Feature selection: Select the best-fitted set of features.
- Create Machine Learning Model: machine learning model created using Sci kit learn API.
- Model Initializing and Training: The iterative process initialized and begins training.
- Model Evaluation: An evaluation of the performance by optimal metrics.

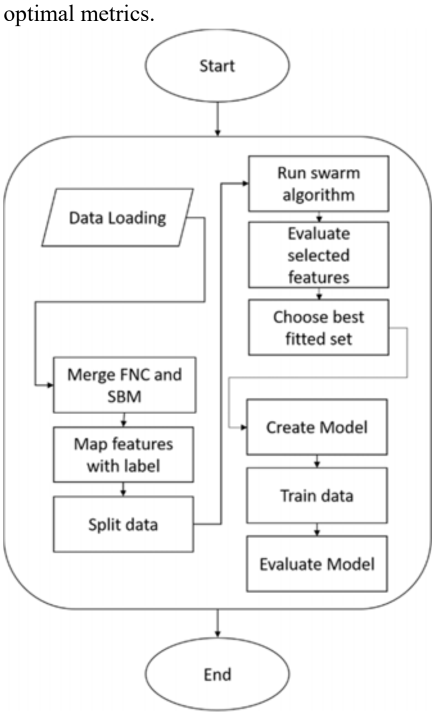

Figure 2. Hybrid model steps

4.3. Federated Model on MLSP

As shown in Figure [3], the proposed federated learning model building steps were:

- Data Loading: Loading CSV files of FNC features, SBM features, and labels.
- Merge Feature: Merge each participant feature in one data frame.
- Map Features with label: Creating Sample Data Dictionary as a map of each record of features with its label.
- Split data: Creating Sample Data Dictionary for each part of data (train –test).
- Create Keras Tensor Dataset: Build Keras dataset by tensor slices API.
- Data Repetition: Data is repeated to simulate the number of clients.
- Data Shuffling: Data shuffled to avoid obtaining identical results.
- Data Batching: Data is grouped into batches to spice up their performance.
- Create Keras Model: Build a sequential deep learning model by Keras API.
- Create Federated Learning Model: Build a federated deep learning model by Keras API.
- Model Initializing and Training: The iterative process initialized and begins training.
- Model Evaluation: An evaluation of the performance by optimal metrics.

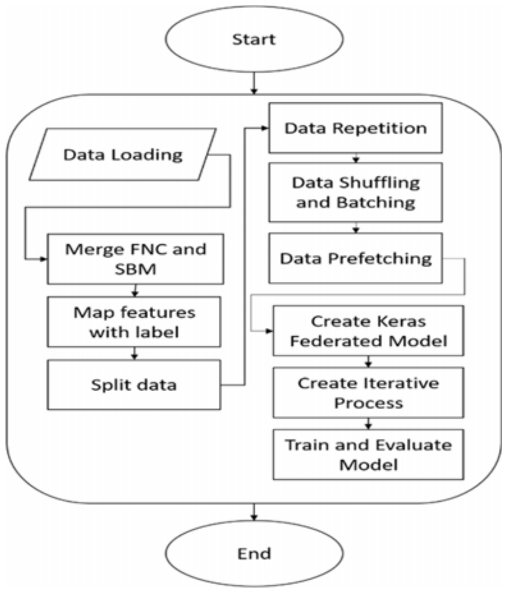

Figure 3. Federated Learning Model

5. Experimental Setup

5.1. MLSP Dataset

The purpose of the 24th Machine Learning Contest for Signal Processing [21] was to automate the diagnosis of schizophrenia using multimodal skills obtained from MRI scans. The goal of the classification task was to grasp the sole possible prediction of schizophrenia diagnosis supported the multimodal skills obtained from brain MRI scans. Each participant developed a classifier with optional feature selection that combined functional and structural resonance imaging capabilities. Data from 144 subjects were obtained employing a 3T Siemens Trio MRI scanner with a 12-channel head coil. The dataset includes 75 healthy controls (52 men, mean age = 36.27 years, SD = 11.78 years, range: 1865) and 69 schizophrenia patients (58 men, mean age = 37.32)) contained. Year) is included. SD = 13.80 years old, range: 1864). Data collection was administrated by the Mind Research Network (MRN, www.mrn.org) under the approval and supervision of the Human Experiment Research Committee of the University of latest Mexico (UNM).

5.2. Evaluation criteria

The area under the curve (AUC) may be a measure of the classifier's ability to differentiate classes and is employed as a summary of the ROC curve. the upper the AUC, the higher the performance of the model at distinguishing between the positive and negative classes. When AUC = 1, then the classifier is ready to perfectly distinguish between all the Positive and therefore the Negative class points correctly. Otherwise, If the AUC had been 0.

6. Results

6.1. Accuracy

As shown in table [2], it presented the accuracy comparison between native models and corresponding ones optimized on test set.

Table 2. Accuracy comparison on test set

Model	Natives	FA	JA
K-nearest neighbours	0.67	**1.0**	**1.0**
Logistic Regression	0.61	0.94	0.89
Naïve Bayes	**0.72**	0.83	0.89
Decision Tree	0.61	0.50	0.72
Random Forest	0.61	0.55	0.89
SVM	0.61	0.94	0.94
No of features	410	186	143

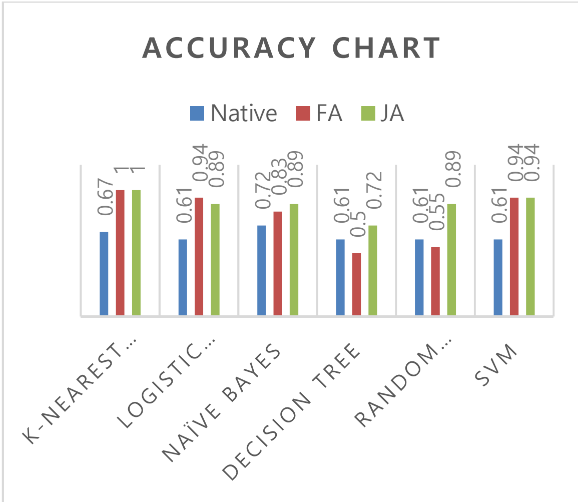

Figure 4. Accuracy Chart for native and hybrid models

6.2. Area Under Curve

As shown in table [3], it presented the AUC comparison between native models and corresponding ones optimized on test set.

Table 3. AUC comparison on test set

Model	Native	FA	JA
K-nearest neighbours	0.67	**1.0**	**1.0**
Logistic Regression	0.67	0.96	0.92
Naïve Bayes	**0.75**	0.83	0.87
Decision Tree	0.71	0.42	0.71
Random Forest	0.63	0.63	0.92
SVM	0.63	0.96	0.96
No of features	410	186	143

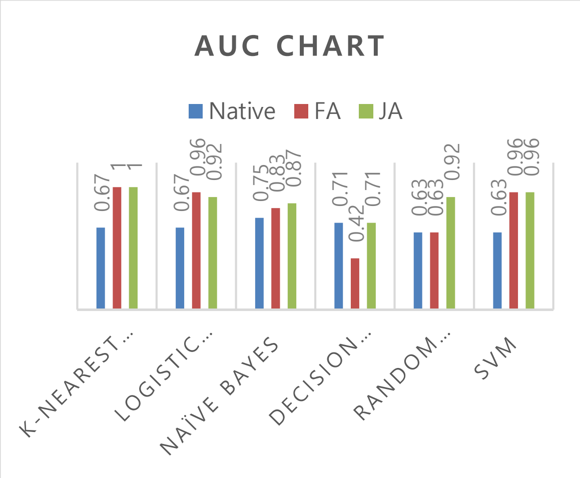

Figure 5. AUC Chart for native and hybrid models

6.3. Federated Learning Evaluation

In this study, federated learning model proposed to solve the issue of data privacy for schizophrenia prediction. The suggested model parameters have been modified many times to achieve the maximum accuracy and AUC compared with the bassline of mslp dataset. As shown in table [4] a comparison between proposed federated learning model and other best proposed models.

Table 4. Best proposed performance comparison on test set

Model	Accuracy	AUC
Federated model	**1.0**	**1.0**
KNN-FA	**1.0**	**1.0**
KNN-JA	**1.0**	**1.0**

7. Conclusion and future work

The use of machine learning classifiers with swarm intelligence-optimized MRI capabilities has suggested a promising automated diagnostic tool for detecting schizophrenia. We described average performance measurements between classifiers of various optimization algorithms with different characteristics of health care and schizophrenia cases. AUC scores were calculated and presented among the classifiers of different optimization algorithms with different selected features for normal and schizophrenia cases. Federated learning and hybrid ANN optimized the AUC score to achieve an accuracy of 1 and 100 in the test set. Outstanding performance optimization. The contribution of the integrated learning approach has solved the problem of access to patient data protected by federal privacy law. The proposed model achieved significant improvements in forecasts compared to previous related work on the same dataset and data type. However, further experimentation with larger samples is required to validate the results.

References

[1] Miseon Shim, Han-Jeong Hwang, Do-Won Kim, Seung-Hwan Lee, Chang-Hwan Im,Machine-learning-based diagnosis of schizophrenia using combined sensor-level and source-level EEG features,Schizophrenia Research,Volume 176, Issues 2–3,2016,Pages 314-319,ISSN 0920-9964,https://doi.org/10.1016/j.schres.2016.05.007.

[2] de Filippis R, Carbone EA, Gaetano R, et al. Machine learning techniques in a structural and functional MRI diagnostic approach in schizophrenia: a systematic review. Neuropsychiatr Dis Treat. 2019;15:1605-1627. Published 2019 Jun 19. doi:10.2147/NDT.S202418.

[3] Institute of health Metrics and Evaluation (IHME). Global Health Data Exchange (GHDx). http://ghdx.healthdata.org/gbd-results-tool?params=gbd-api-2019-permalink/27a7644e8ad28e739382d31e77589dd7 (Accessed 25 September 2021)

[4] Zhu, Yafei & Fu, Shuyue & Yang, Shihu & Liang, Ping & Tan, Ying. (2020). Weighted Deep Forest for Schizophrenia Data Classification. IEEE Access. PP. 1-1. 10.1109/ACCESS.2020.2983317.

[5] Prabhakar, Sunil & Rajaguru, Harikumar & Lee, Seong-Whan. (2020). A Framework for Schizophrenia EEG Signal Classification with Nature Inspired Optimization Algorithms. IEEE Access. PP. 1-1. 10.1109/ACCESS.2020.2975848.

[6] Kim, Jeong-Youn & Lee, Hyun Seo & Lee, Seung-Hwan. (2020). EEG Source Network for the Diagnosis of Schizophrenia and the Identification of Subtypes Based on Symptom Severity-A Machine Learning Approach. Journal of Clinical Medicine. 9. 3934. 10.3390/jcm9123934.

[7] Fernandes, Brisa & Karmakar, Chandan & Tamouza, Ryad & Tran, Truyen & Yearwood, John & Hamdani, Nora & Laouamri, Hakim & Richard, Jean-Romain & Yolken, Robert & Berk, Michael & Venkatesh, Svetha & Leboyer, Marion. (2020). Precision psychiatry with immunological and cognitive biomarkers: a multi-domain prediction for the diagnosis of bipolar disorder or schizophrenia using machine learning. Translational Psychiatry. 10. 10.1038/s41398-020-0836-4.

[8] Min, Beomjun & Kim, Minah & Lee, Junhee & Byun, Jung-Ick & Chu, Kon & Jung, Ki-Young & Lee, Sang & Kwon, Jun Soo. (2019). Prediction of individual responses to electroconvulsive therapy in patients with schizophrenia: Machine learning analysis of resting-state electroencephalography. Schizophrenia Research. 216. 10.1016/j.schres.2019.12.012.

[9] Kirchebner, Johannes & Günther, Moritz & Lau, Steffen. (2020). Identifying influential factors distinguishing recidivists among offender patients with a diagnosis of

schizophrenia via machine learning algorithms. Forensic Science International. 315. 110435. 10.1016/j.forsciint.2020.110435.

[10] Baradits, Máté & Bitter, Istvan & Czobor, Pál. (2020). Multivariate patterns of EEG microstate parameters and their role in the discrimination of patients with schizophrenia from healthy controls. Psychiatry Research. 288. 112938. 10.1016/j.psychres.2020.112938.

[11] A-Hakeim, Hussein & Almulla, Abbas & Maes, Michael. (2020). The Neuroimmune and Neurotoxic Fingerprint of Major Neurocognitive Psychosis or Deficit Schizophrenia: a Supervised Machine Learning Study. Neurotoxicity Research. 37. 1-19. 10.1007/s12640-019-00112-z.

[12] Espinola, Caroline & Gomes, Juliana & Pereira, Jessiane & Dos Santos, Wellington. (2020). Vocal acoustic analysis and machine learning for the identification of schizophrenia. Research on Biomedical Engineering. 37. 1-14. 10.1007/s42600-020-00097-1.

[13] Kim, Jieun & Kim, Min-Young & Kwon, Hyukchan & Kim, Ji-Woong & Im, Woo-Young & Lee, Sang & Kim, Kiwoong & Kim, Seung. (2020). Feature optimization method for machine learning-based diagnosis of schizophrenia using magnetoencephalography. Journal of Neuroscience Methods. 338. 108688. 10.1016/j.jneumeth.2020.108688.

[14] Lee, Shih-Chieh & Chen, Kuan-Wei & Liu, Chen-Chung & Kuo, Chian-Jue & Hsueh, I-Ping & Hsieh, Ching-Lin. (2021). Using machine learning to improve the discriminative power of the FERD screener in classifying patients with schizophrenia and healthy adults. Journal of Affective Disorders. 292. 10.1016/j.jad.2021.05.032.

[15] Zhu, Lulu & Wu, Xulong & Xu, Bingyi & Zhao, Zhi & Yang, Jialei & Jianxiong, Long & Li, Su. (2020). The Machine Learning Algorithm for the Diagnosis of Schizophrenia on the basis of Gene Expression in Peripheral Blood. Neuroscience Letters. 745. 135596. 10.1016/j.neulet.2020.135596.

[16] Frick, Janek & Rieg, Thilo & Buettner, Ricardo. (2021). Detection of schizophrenia: A machine learning algorithm for potential early detection and prevention based on event-related potentials. 10.24251/HICSS.2021.460.

[17] Vázquez, Manuel & Maghsoudi, Arash & Mariño, Inés. (2021). An Interpretable Machine Learning Method for the Detection of Schizophrenia Using EEG Signals. Frontiers in Systems Neuroscience. 15. 10.3389/fnsys.2021.652662.

[18] Lian, Xiangru, et al. "Can decentralized algorithms outperform centralized algorithms? a case study for decentralized parallel stochastic gradient descent." arXiv preprint arXiv:1705.09056 (2017).

[19] Yang, X. S. (2008). Nature-Inspired Metaheuristic Algorithms. Luniver Press. ISBN 978-1-905986-10-1.

[20] Venkata Rao, Ravipudi. (2016). Jaya: A simple and new optimization algorithm for solving constrained and unconstrained optimization problems. International Journal of Industrial Engineering Computations. 7. 19-34. 10.5267/j.ijiec.2015.8.004.

[21] K. Koncevičius, "The 10th annual MLSP competition: Third place," 2014 IEEE International Workshop on Machine Learning for Signal Processing (MLSP), 2014, pp. 1-2, doi: 10.1109/MLSP.2014.6958888.

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