Intelligent Handwriting-Based System For Predicting Schizophrenia And Bipolar Disorder With Xai Interpretability

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Abstract: Historically, SZ and bipolar disease have been sought using costly imaging mechanisms such as MRI. These are the procedures that are difficult to reach and the patients do not always adhere to the instructions. The solution to these constraints based on handwriting analysis is a cost-effective method of analyzing one that uses motor aberrancies that are commonly detected in such situations. Here, DataRepository SAV dataset of Figshare is used with handwriting-derived features used in classification. Preprocessing involves the selection of statistically strong features and SMOTE to correct the presence of imbalance in classes. It has a great number of ML algorithms that include ANN-Net, LR, LDA, KNN, and (SVM with linear and RBF kernels). Another type of Voting Classifier that fuses Quantum SVM and Boosted Decision Tree is also introduced to enhance the capability of prediction. Measures of performance are evaluation measures such as accuracy, precision, recall, F1-score, MCC and the confusion matrix. The group achieved 100 percent accuracy on the test set. The techniques of XAI, such as LIME and SHAP, are employed to ensure that the findings are interpretable. Such techniques demonstrate the most significant features to make predictions. The completed model is launched into use with the help of a web application based on Flask that allows it to receive input in real-time and sort patients by type appropriately.

***"Index Terms:** Handwriting analysis, Schizophrenia detection, Bipolar disorder classification, Machine learning, Explainable AI, Synthetic Minority Oversampling Technique (SMOTE)".*

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1. INTRODUCTION

SZ and bipolar disease are chronic mental disorders, which are characterized by the distortion of perceiving reality, cognitive disorders and abnormal social behavior [1]. Diagnosis of mental diseases is usually based on a structured system of clinical interview and systems such as Diagnostic and Statistical Manual of Mental diseases (DSM-5) [2]. A clinical evaluation (e.g., PANSS) is used regularly to determine the severity of the symptoms in SZ [3]. Nevertheless, conventional diagnostic techniques are limited by subjectivity because patients can underreport the symptoms, and doctors often have to struggle to distinguish between schizophrenia and other psychiatric conditions. Manual diagnosis of bipolar disorder is also time consuming and in practitioner hands and prone to misjudgment just as seen in the case of errors and thus more effective ways of diagnosis need to be devised.

The development of AI has resulted in ML strategies that are currently viable in classifying diseases in various sectors. Parkinson disease [4], heart failure [5], breast cancer identification [6], and stroke assessment [7] are just but a few of the healthcare fields that automated techniques have been proposed [1], and these methods have demonstrated high performance and improved diagnostic specificity. Being driven by these developments, scholars have explored its use in mental health problems. Winterburn et al. applied standard ML classifiers such as the LR, linear discriminant analysis, and support vector machines to the MRI data, and achieved an accuracy of up to 73.5% in identifying the SZ patients and healthy individuals [8]. Subsequently, Messinger et al. demonstrated that RF models have the capability of classifying psychiatric patients including SZ with an accuracy rate of 92.9% [9]. These studies confirm the application of ML in psychiatric diagnosis, but there are still issues with researching data and scalability.

Imaging diagnostic procedures have a considerable potential, but they cannot be used due to their excessive cost, inaccessibility, and specialized equipment. Patients also need to remain motionless when undergoing scans, which is not easy when people have SZ or bipolar disorder. There is, therefore, a rising demand in non-invasive and cost effective alternatives, including the analysis of handwriting. According to the study conducted by Gawda, schizophrenic, bipolar, and normal people have extremely different densities of handwriting. It implies that the handwriting might be an effective diagnostic instrument [10]. The abnormalities in motor behavior in SZ and bipolar illness as illustrated by the movements of the handwriting have been periodically recorded in clinical studies and assessed as being unique characteristics to the disease spectrum. Such findings highlight handwriting as a behavioral biomarker that can be subjected to systematic analysis allowing to objectively and automatically classify schizophrenia and bipolar disorder.

This paper outlines a ML system in the form of handwriting to provide accurate, objective, and scalable diagnostic support to help people with schizophrenia and bipolar disorder given these challenges and opportunities.

2. LITERATURE REVIEW

Winterburn et al. [11] explored the application of machine learning techniques to classify the schizophrenia patients using MRI images. They employed a multi-method and multi-dataset structure in their study and used logistic regression models, SVM, and linear discriminant analysis. Apparently, they claimed that the accuracy margin was 73.5% maximum, indicating that the combination of imaging methods and ML can be utilized in psychiatry diagnosis. The results however established that generalization is not easy to achieve across the datasets. This paper demonstrated potential of MRI based diagnostics as well as pointed out limitations like cost, accessibility and patient compliance, which limit its feasibility in widespread use in clinical practice.

Similarly, Walsh-Messinger et al. [12] broadened the application of ML by considering the relevance of various variables in categorizing psychiatric diseases. Their study combined symptoms, cognitive, and multilayer clinical predictors to come up with models that enhanced interpretability and predicted accuracy. Through a multi level framework, the scientists could determine the extent of the influence of clinical and cognitive factors in influencing classification decisions. This approach assisted us in comprehending how the diagnostic processes were better as it revealed that non-biological variables (as cognitive functioning) were significant to classify people more effectively. These were a notable contribution to alleviating over reliance on medical imaging and posed an even more holistic view of psychiatric diagnosis.

A new development direction was established by Gawda [13] who investigated handwriting as a source of biomarkers of schizophrenia and affective disorders. The study used Raygraf computer software in order to assess the density parameters of handwriting samples and found statistically significant differences between healthy and patients. These findings demonstrated that psychiatric disease motor and cognitive impairments can be depicted through handwriting style, which provides a more economical and efficient alternative to MRI and other diagnosis methods. The paper primarily focused on handwriting as one of the potential ways to accomplish automated psychiatric diagnosis, which is a significant departure in traditional neuroimaging-based approaches.

Meanwhile, Pereira et al. [14] examined the dynamics of handwriting to diagnose the Parkinson disease automatically. They found that examining motor skills during handwriting can be a useful method of determining whether an individual has a motor dysfunction due to their observation that timing and speed of the movement might serve as a good indicator of handwriting dysfunction. The approach combined feature engineering with machine learning classifiers in creating a structured framework that could be specific to psychiatric disorders such as schizophrenia and bipolar disorder, which are motor anomalies. Their study confirmed the use of handwriting analysis as a diagnostic tool and formed the basis of applying similar methods to mental illnesses.

Based on the overlap of motor symptoms and mental illnesses, Crespo et al. [15] performed a research on the movement of handwriting to test motor symptoms among the schizophrenia spectrum disorders and the bipolar disorder. They demonstrated that handwriting characteristics could easily differentiate clinical groups and healthy controls demonstrating that motor impairments were identical across all patient groups. Their study fused quantitative motor measures and machine learning models in demonstrating a considerable amount of evidence that handwriting can be applied as a non-psychiatric diagnosis behavioral measure. This study was especially significant because it revealed that handwriting could be used to identify minor motor issues that arise in such diseases, thus, it was a inexpensive and scaled method of diagnosing these diseases.

Crespo et al. [16] then built on this point of view by examining the spatial features of handwritten words as evidence of cognitive control. Their study focused on such variables as spatial organization, stroke distribution, and coherence in text, which are impaired in schizophrenia and bipolar illness due to the deficit in the executive functions. They demonstrated that movement is not the only problem that is revealed in the writing of handwriting. This paper highlighted that handwriting is a complex tool that can both signify motor and cognitive impairment and, therefore, the future of handwriting as a method of psychiatric evaluation and classification using machine learning.

Ali et al. [17] suggested a machine learning network to identify the Parkinson disease automatically with sustained phonation information. They constructed a hybrid that was effective in distinguishing between victims of Parkinson and healthy individuals using a combination of linear discriminant analysis and a genetically-adjusted neural network. Although it focused primarily on speech-based features, this publication demonstrated how handwriting analysis might be applied in psychiatry similarly and emphasized the necessity to combine various domains of features with the most effective classifiers. Their study showed how hybrid approaches could be used to overcome the weakness of single-model systems and enhance diagnostic accuracy.

In another domain, Rasheed et al. [18] derived a DL-based method of automatic classification of brain cancers using MRI images. They employed convolutional neural networks as their methodology in order to extract hierarchical properties of imaging data that rendered the classification far better than traditional ML frameworks. It was dedicated to the discovery of tumors, but also demonstrated the power of DL in the analysis of medical images and suggested the opportunities to use the similar designs in psychiatric diagnosis. But it further exacerbated the issues of imaging-based solutions, including high cost, resource requirements and patient compliance issues.

Samuel et al. [19] proposed an integrated decision support system to predict the risk of heart failure by combining the artificial neural networks with the fuzzy AHP. This mixed approach facilitated the easy integration of clinical and demographic data to come up with valid predictions. The novelty of the present study was seen in the combination of machine learning with the application of fuzzy logic in making multi-criteria decisions, which showed significant enhancement in interpretability and clinical relevance. The improved methodological features of this study stimulated psychiatry, where combination of various variables, such as the symptoms, handwriting features, and other demographical data, may elevate the classification effectiveness and clinical significance.

Finally, Lemaître et al. [20] addressed one of the largest issues related to the application of machine learning in medical diagnostics: imbalance in the classes. They created the Imbalanced-learn Python toolbox, of which one resampling technique is the SMOTE. This set of tools was actually beneficial in simplifying the work of making models better when the representation of minority classes like individuals with mental illnesses is low. Their strategy contributed to ensuring that the model training and testing were fair through the equalization of the classes distributions. It was possible since healthcare applications could make more precise diagnostic predictions.

3. MATERIALS AND METHODS

The proposed solution is machine learning to detect SZ and bipolar disorder based on handwriting. It applies DataRepository SAV dataset at Figshare that possesses handwriting-derived traits, which are correlated with motor issues. SRF selection is applied to preprocessing in order to retain important features and SMOTE follows to correct their class imbalance. Classification may be carried out by a number of methods, including ANN-Net, Logistic Regression, LDA, Naive Bayes, KNN, and SVM with linear and RBF kernels. It is also represented by a new Voting Classifier which integrates Quantum SVM with a Boosted Decision Tree. The results can be made easier to comprehend using explainable AI tools such as LIME and SHAP, and can be used more easily with a web application written in Flask.

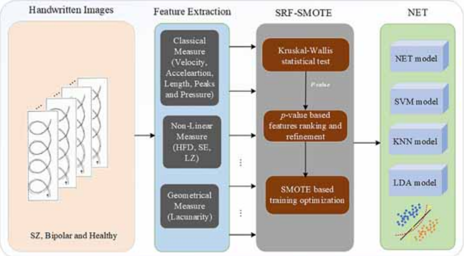


Fig.1 Proposed Architecture

Description for Arch

a) Dataset Collection:

The SAV dataset, which was acquired through Figshare, comprises of 98 records including 24 attributes that report demographic, clinical, and handwriting-based motor aspects that are relevant to the study of schizophrenia and bipolar disorder. It contains data on the age of the person, sex, diagnosis, drug dose, PANSS scores, and fine handwriting measurements such as speed, acceleration, length, pressure, peaks, fractal dimensions, entropy, and lacunarity. The combination of these properties is an indication of cognitive and motor abnormalities associated with psychiatric diseases, which provides significant basis in preprocessing, feature selection, and ML-based classification of patient groups.

b) Data Visualization:

Correlation matrices and sample outcome plots are made in order to take a first glance of the dataset. The correlation heatmap demonstrates the relationship between numerical attributes that may help to identify multicollinearity and feature relevance. Count plots of outcome variables (Grupo) also indicate the distribution of classes and non-uniform distribution of classes. This graphic exploration assists you to comprehend the data model, relationships and variability. It forms the foundation of the subsequent preprocessing, feature engineering and model selection.

c) Feature Selection:

The most important factors influencing the categorization are identified by the help of the Boruta algorithm which is applied to SRF. Boruta works with the help of a RF model to determine the most important features and retains only the ones that can produce decent predictions. This is to ensure that redundant or repetitive functionality is removed and this makes the model more efficient and easy to learn. The strategy brings 11 major handwriting-based and diagnostic characteristics that contain basic behavioral and motor patterns.

d) Resampling the Data:

We address the issue of class imbalance with the help of the SMOTE. SMOTE balances the dataset by wholly synthetic samples of the minority class by interpolating between the closest similar samples of that class. This approach prevents the model having a bias towards the dominant group and it becomes more predictive of unattended classes. Resampling is then followed by StandardScaler to ensure that all the variables play equal roles in training machine learning classifiers through the normalization of the distributions of features.

e) Training and Testing:

The cleaned and balanced dataset is further divided into a training set and a testing set, of which 80 percent of the information is divided into a training set and 20 percent to a testing set. ML models are trained using the training set and tested using the testing set. This ensures that such performance appraisals are objective and prevents overfitting. Reproducibility is achieved through the use of fixed random seed in the split. This ensures that the results of experiments are always identical and that measurements can be applied in the evaluation of results.

f) Algorithms:

SRF-SMOTE-Net: Artificial Neural Network gathers advanced non-linear interactions of features on the basis of handwriting-created data. It identifies the presence of small motor abnormalities, simplifies the observation of latent patterns, and enhances the accuracy of diagnosing patterns where the classical statistical approach might fail due to variation.

SRF-SMOTE-LR: It is easy to visualize the locations of handwriting patterns in a straight line using Logistic Regression. SRF eliminates the factors that do not count whereas SMOTE ensures that the data is distributed uniformly. It is such an easy and understandable strategy that makes it easy to make decisions and aids clinical systems which require explaining how they place patients in categories to achieve reliable outcomes.

SRF-SMOTE-LDA: Linear Discriminant Analysis reduces the dimension and distances between classes. It identifies the characteristics of handwriting that do matter, which leads to a more accurate classification and retains a high level of interpretability, which should be simple and effective in clinical environments, where the diagnostic decision support system should be.

SRF-SMOTE-GNB: Gaussian Naïve Bayes is a probabilistic model that examines motor problem based handwriting characteristics. It is quick and precise in classification and presumes conditional independence, and thus is a reliable method of identifying schizophrenia, bipolar illness, and control patients who are healthy.

SRF-SMOTE-KNN: The KNN classifies handwritten samples according to the similarity with the closest feature points. The qualities selected by SRF ensure that the information is relevant, and the ones selected by SMOTE ensure that the information is balanced. This example-based approach can easily be scaled to discover the motor abnormalities and assist in accurate classification without the complex assumptions and model specific structures.

SRF-SMOTE-SVM (Linear): SVM linear Operating with a linear kernel constructs the most optimal separating hyperplanes on handwriting characteristics. SRF removes the irrelevant variables, SMOTE ensures that there is an even distribution of classes, and the model ensures that accuracy is consistent at all times through the use of clear bounds. This provides good diagnostic assistance at minor overfitting.

SRF-SMOTE-SVM (RBF): The SVM RBF kernel maps features on the handwriting into higher dimensions in order to be separated in non-linear manner. Combined with SRF selection and SMOTE balance, it is an effective approach with the overlapping distributions, enhancing predictive accuracy and ensuring that the psychiatric diagnostic categories are assigned appropriately.

SRF-SMOTE-Voting Classifier (Quantum SVM + Boosted DT): This ensemble is quantum SVM + Boosted Decision Tree that maximizes their advantages. The data is improved by features selected by SRF and SMOTE balance and the errors are minimized by consensus based learning leading to an improvement in accuracy and a good diagnostic classification system.

g) Integration of XAI and Flask Framework:

The system applies XAI methods such as LIME and SHAP to simplify the understanding of classification models that utilize information that is presented by handwriting. LIME provides a local explanation of the influence of each attribute on a particular prediction. SHAP, in its turn, provides global and instance-level information through force charts, summary plots, and waterfall visualization. They collaborate to make decisions explicit by demonstrating the extent to which factors are important and influential in influencing the outcomes of the diagnostic.

The solution is made available through a Flask framework used in real-time interaction. The web interface allows the user to add input data and the model to produce predictions and display LIME and SHAP visualizations. This integration makes complex XAI methods closer to real world applications giving doctors the confidence, clarity and ease of use with automated classification systems.

4. EXPERIMENTAL RESULTS

Accuracy: Accuracy of the test is the ability of the test to distinguish between the sick and healthy patients. We require to determine the ratio of true positives to the true negatives in all the cases on which a test was applied to determine the accuracy of the test. In math, this can be said as:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \, (1)$$

Precision: Precision is the percentage of correctly identified cases or samples out of the ones that were classified to be positive. Therefore, the equation of the accuracy is:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} \, (2)$$

Recall: Keep in mind: Recall is used in machine learning to evaluate the ability of the model to locate all the pertinent examples of a given type of a class. It is a ratio of the number of the correct positive predictive to the total number of actual positives. This provides some sense of the effectiveness of a model in capturing examples of a particular class.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \, (3)$$

F1-Score: F1 score can be used to assess the accuracy of a machine learning model. It combines both precision and recall of a model. The accuracy statistic enumerates the number of times that a model was correct on the entire dataset.

$$F1\ Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100(1)$$

MCC: In ML, the Matthews coefficient (also known as the Matthews correlation coefficient or MCC) is used to estimate the effectiveness of binary classifiers. It examines all the four fields of a confusion matrix in order to determine the similarity of the anticipated and real binary outcomes.

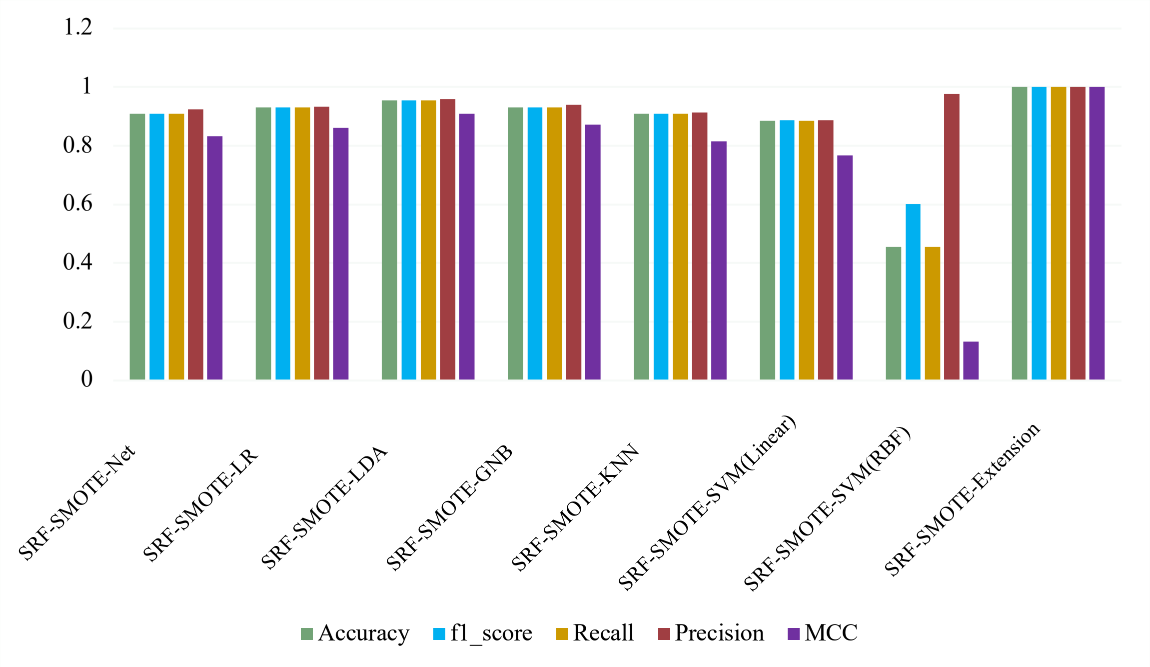
$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN}} \qquad (5)$$

Table.1 Performance Evaluation Table

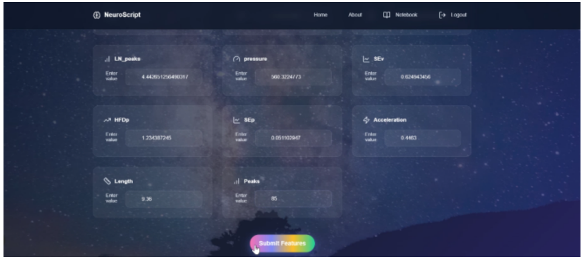
ML Model	Accuracy	f1_score	Recall	Precision	MCC
SRF-SMOTE-Net	0.909	0.909	0.909	0.924	0.833
SRF-SMOTE-LR	0.932	0.932	0.932	0.933	0.861
SRF-SMOTE-LDA	0.955	0.955	0.955	0.959	0.910
SRF-SMOTE-GNB	0.932	0.931	0.932	0.940	0.872
SRF-SMOTE-KNN	0.909	0.910	0.909	0.914	0.816
SRF-SMOTE-SVM(Linear)	0.886	0.887	0.886	0.888	0.768
SRF-SMOTE-SVM(RBF)	0.455	0.601	0.455	0.978	0.133
SRF-SMOTE-Extension	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

Table (1) compares the models of handwriting based classification in terms of accuracy, F1-score, recall, precision, and MCC. The SRF-SMOTE-Extension technique is definitely more superior to all other models as it gives improved results on all measures.

Fig.2 Comparison Graph



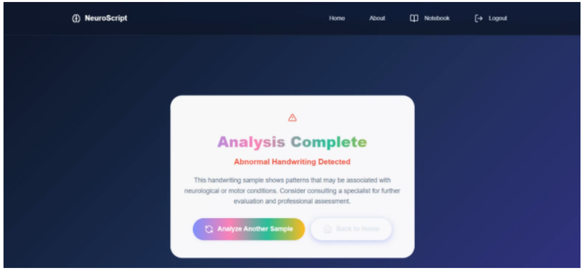
According to Fig. 2, a number of classifiers performed well in five criteria. Accuracy, f1-score, recall, precision and MCC colors are green, sky blue, orange, brown and purple respectively. All the criteria always score the highest in the SRF-SMOTE-Extension, and this fact implies that it has the highest predictive power.



Acceleration: 0.4463
Length: 9.36
Peaks: 85

Fig.3 Upload Input Data

Fig. 3 input snapshot depicts a user interface in which handwriting-generated features are typed in to identify schizophrenia and bipolar disorder.



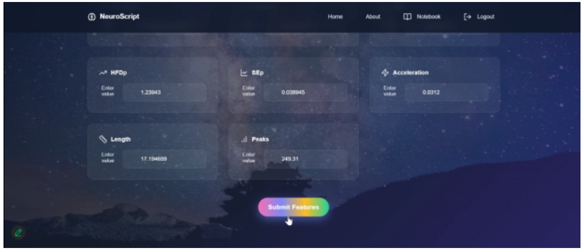
Analysis Complete

Abnormal Handwriting Detected

This handwriting sample shows patterns that may be associated with neurological or motor conditions. Consider consulting a specialist for further evaluation and professional assessment.

Fig.4 Predicted Results – Abnormal Handwriting

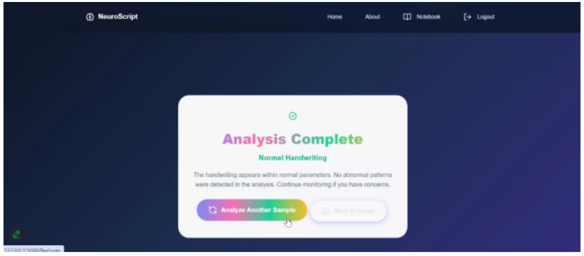
The prediction of the system provided is indicated in the output screenshot in Fig. 4 and it reads abnormal handwriting detected.



HFDp: 1.23943
SEp: 0.038945
Acceleration: 0.0312
Length: 17.194659
Peaks: 249.31

Fig.5 Upload Input Data

Fig. 5 shows the UI where users are able to input the handwriting-based features in the input screenshot.



Analysis Complete

Normal Handwriting

The handwriting appears within normal parameters. No abnormal patterns were detected in the analysis. Continue monitoring if you have concerns.

Fig.6 Predicted Results – Normal Handwriting

The output screenshot of Fig. 6 indicates how the system guessed the handwriting, and the message that is displayed is that normal handwriting has been recognized.

5. CONCLUSION

Summing it up, the method demonstrates that handwriting-based diagnosis is an effective and cost-effective method of detecting SZ and bipolar disease, to avoid issues of costly and less feasible imaging systems, such as MRI. The DataRepository SAV data set on Figshare is used as the input of the system and statistically sound feature selection is carried out to discover useful features. It also corrects the imbalance of classes using the SMOTE. Some of the machine learning methods that were trained and tested included ANN-Net, LR, LDA, Naive Bayes, KNN, and SVM (linear and RBF kernels). A Voting Classifier ensemble comprising of Quantum SVM and Boosted Decision Tree was included to further enhance performance of the Voting Classifier. It achieved 100 percent accuracy on the test set. We evaluated the model using accuracy, precision, recall, F1-score, MCC and confusion matrix. This ensured a complete picture of the extent to which it worked. Features were also easier to understand through XAI models such as LIME and SHAP, which made the model more transparent and allowed doctors to make decisions. And, at the end, the most successful model was implemented with the help of a web application that is created with Flask and allowed to make predictions and interact with users in real time in a concise and practical style.

The future of identifying schizophrenia and bipolar disorder through handwriting-based methods is in the enhancing of the dataset with diverse populations so that it will increase the generalization and resistance. It can be more accurate to combine different types of data, including voice and facial expressions, to make the diagnosis more accurate. State-of-the-art deep learning networks, federated learning and cloud systems can support large-scale implementation and protect privacy. Real-time integration of mobile and wearable devices can simplify the process of screening whether done in a clinical or non-clinical situation. Furthermore, the implementation of Explainable AI will become easier, and this will create trust among the healthcare staff. Such developments can allow physicians to initiate treatment earlier, offer a closer observation of the patients, and develop more personalized approaches to the treatment of mental disorders.

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