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Automatic Diagnosis of Schizophrenia using Hybrid Neural Networks: A Feature-Driven Study

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***Abstract*—Schizophrenia is a chronic and severe mental disor- der that affects how a person thinks, feels, and behaves. It often leads to hallucinations, delusions, disorganized speech, cognitive impairments, and social withdrawal. Affecting approximately 20 million people worldwide according to the World Health Organization (WHO), schizophrenia poses a significant challenge to global mental health care. Despite decades of research, early and accurate diagnosis of schizophrenia remains difficult due to the subjective nature of clinical assessments, symptom overlap with other psychiatric conditions, and variability in individual manifestations. In recent years, the integration of artificial intelligence (AI) and deep learning techniques into the medical domain has shown promise in transforming psychiatric diagnostics. Machine learning models, particularly deep neural networks, have demon- strated the ability to analyze complex patterns in large-scale data, such as neuroimaging scans, genetic data, and behavioral records, offering new opportunities for objective and automated diagnosis.**

***Index Terms*—Schizophrenia, Deep Learning, CNN, LSTM, Psychiatric diagnosis, Neuroimaging.**

I. INTRODUCTION

Schizophrenia is a serious and severe mental disorder which affects a person thinks, feels, and behaves. It always leads to hallucinations, delusions, unorganized speech, mental damages, and social withdrawal. Therefore, affecting almost 20 million people in the world according to the World Health Organization (WHO), schizophrenia poses a major challenge to global mental health care. Regardless of the decades of research, early and accurate diagnosis of schizophrenia remains difficult due to the individual nature of clinical assessments, symptom overlap with other psychiatric conditions, and change in individual symptoms. In recent years, the involvement of artificial intelligence (AI) and deep learning methods into the medical field has shown assurance in transforming psychiatric diagnostics. Machine learning models, mainly the deep neural networks, have proved the ability to analyze complex patterns in large-scale data, such as neuroimaging scans, genetic data, and behavioral records, offering new opportunities for fair and automated diagnosis.

This paper introduces an automated diagnostic structure for schizophrenia patients that holds a more than one deep learning architecture thereby, combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models. While CNNs are effective in capturing spatial features from neuroimaging data, LSTMs are capable of learning secular dependencies, making the combination well-suited for handling complex, multidimensional patient data. Furthermore, the feature selection techniques such as Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) are used to improve the model's performance by eliminating inapplicable or unnecessary features, thereby reducing computational overhead. The main outcome of this study is to explore the efficiency of the hybrid neural networks in identifying schizophrenia-related patterns and to advance an expandable framework that can help the clinicians in making informed decisions. By covering the gap between mathematical intelligence and psychiatric care, the planned system aims to support the early detection and reduce the symptoms, and improve treatment outcomes.

II. MOTIVATION

Schizophrenia is a serious, severe, and disabling mental disorder that affects almost 20 million people across the world, according to the World Health Organization (WHO). It results through a combination of positive symptoms (hallucinations, delusions, unorganized speech), some negative symptoms (withdrawing from society, emotionally getting crushed, getting depressed), and mental damages (defective working memory, attention deficits, and reduced executive functioning). The disorder typically follows in late adolescence or early adulthood, and its start always coincides with an important period for social, educational, and occupational development. Early diagnosis and intervention are strongly associated with improved long-term results, including symptom management, functional recovery, and reduced weakening rates. However, in time diagnosis remains a challenge due to many different factors such as stigma, limited access to specialized psychiatric services, and overlapping symptoms with other mental health conditions, such as bipolar disorder and major depressive disorder with psychotic features.

In recent years, the involvement of data-driven approaches in mental health attributes has shown great promise. Machine learning (ML) techniques have proved their capacity to uncover complex, random relationships between patient features and clinical outcomes. When trained on appropriately organized datasets, these models can provide statistic predictions that help doctors in identifying individuals at high risk of developing schizophrenia, even before clear psychotic episodes occur. Such projecting capabilities, if provided responsibly, could serve as a valuable addition to traditional diagnostic methods, enabling mental health professionals to highlight high-risk cases for comprehensive evaluation. In this context, the motivation behind the present project is designed to implement and evaluate a machine learning–based projection channel that is both accountable and expandable, with the ultimate goal of developing, rather than replacing, clinician judgment.

III. LITERATURE REVIEW

In recent years, the involvement of machine learning (ML) and deep learning (DL) techniques has gained atmost attention in the identification and cure of schizophrenia due to their ability to uncover the typical patterns in high-dimensional medical data. Suk et al. [1] developed a deep learning framework using stacked autoencoders to separate schizophrenia from fMRI data. Their study demonstrated that unsupervised deep feature extracting could be better than the traditional statistical techniques in segregating the patients from healthy individuals. Building upon neuroimaging data, Salvador et al. [2] employed a multi-kernel Support Vector Machine (SVM) to combine various structural features extracted from MRI scans, achieving high classification accuracy and emphasise the importance of combining multiple feature types. Zhang et al. [3] proposed SchizoNet, a convolutional neural network (CNN)-based model designed to extract spatial features from physical brain images, demonstrating strong classification performance and providing visual insights into brain regions most indicative of schizophrenia. Riaz et al. [4] implemented Long Short-Term Memory (LSTM) services for EEG-based schizophrenia detection, thereby achieving modeling sequential dependencies in EEG signals and giving the better outcome than the traditional methods such as Random Forest and SVM. Kim et al. [5] utilized Deep Belief Networks (DBNs) to analyze resting-state fMRI data, capturing operational connectivity disruptions in the brain and achieving high classification accuracy with reduced dependence on manual feature engineering.

Singh and Patel [6] made a hybrid CNN-LSTM model that combined behavioral data with deep learning for early detection and cure, thereby demonstrating the effectiveness of multiple input models in handling heterogeneous data sources. Yassin et al. [7] applied graph twisting networks (GCNs) to structural brain connectomes, enabling biologically accountable classification that surpassed traditional approaches in accuracy and explainability. Meszlényi et al. [8] proposed a 3D CNN framework using region-of-interest (ROI)-based inputs, which reduced data dimensionality while protecting critical brain activity, making sure that there are both efficiency and robustness. Multi-modal approaches have also shown promise. Wang et al. [9] combined MRI and genetic data using a dual-branch deep learning model, indicating that incorporating non-imaging data can effectively improve diagnostic accuracy. In the domain of explainable AI, Giacobbe et al. [10] implemented a CNN with SHAP (Shapley additive explanations) values to understand schizophrenia diagnosis predictions, allowing doctors to identify key features influencing each decision. Despite these advances, many studies remain limited to single data modalities or lack generalizability across diverse patient populations. Additionally, few have manageded the importance of feature selection and dimensionality reducing in optimizing performance. The proposed system in this study handles these gaps by involving CNN and LSTM architectures to exploit both spatial and temporal dimensions in patient data, with Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) thereby improving the efficiency and understandability, hence establishing a durable framework for intelligent and automated schizophrenia diagnosis.

IV. FLOW CHART

The flowchart presented in Figure 1 provides a clear visual representation of the overall working method for the schizophrenia detection system. The process begins with data collecting, where raw EEG signals or other relevant patient data are collected from easy clinical sources or datasets. This stage makes sure that the input to the model is correct, representative, and comprehensive enough to support the easy detection. Once the data is collected, the next step involves data preprocessing, which involves in the noise removal, normalization, and feature extraction to convert the raw data into a form that can be effectively processed by the model.

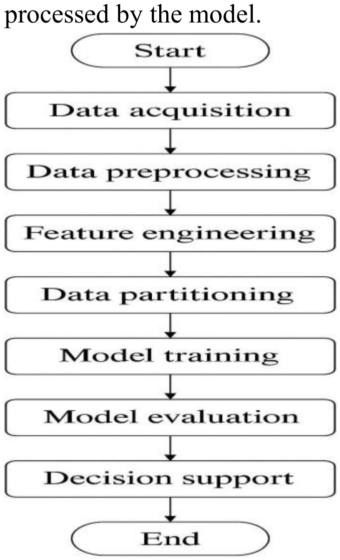

Fig. 1. FlowChart

Following preprocessing, the channel advances to the model training phase, where a selected machine learning or deep learning model—such as an LSTM-based neural network—is trained on labeled data. During this stage, the system learns to identify the patterns whichare related with schizophrenia by minimizing prediction errors and optimizing performance meters. The trained model is then made to the testing and validation phase, where data which is unseen is used to evaluate its accuracy, precision, recall, and other relevant parameters. This makes sure that the model generalizes well and avoids overfitting. Once validated, the model proceeds to the prediction stage, where it can analyze new, unseen patient data to determine the likelihood of schizophrenia. The final stage involves result visualization and reporting, where the outputs are presented through easily understandable formats such as graphs, statistical summaries, and diagnostic recommendations. This structured approach makes sure that the schizophrenia detection system operates efficiently, maintains high accuracy, and provides clinically meaningful insights for mental health professionals.

V. SYSTEM ARCHITECTURE

The proposed schizophrenia detection system follows a simple architecture that involves the data acquisition, preprocessing, feature extraction, model training, and prediction into a seamless workflow. The process begins with the data acquisition module, where clinical datasets, patient speech transcripts, EEG signals, or other similar biomedical and behavioral data are collected from trusted repositories or real- world clinical sources. This data is then passed to the preprocessing layer, which makes sure about the quality and consistency through noise removal, normalization, and handling of missing values. Once the data is cleaned, the feature extraction unit identifies key parameters that are indicative of schizophrenia, such as linguistic patterns, cognitive markers, or neurophysiological signatures.

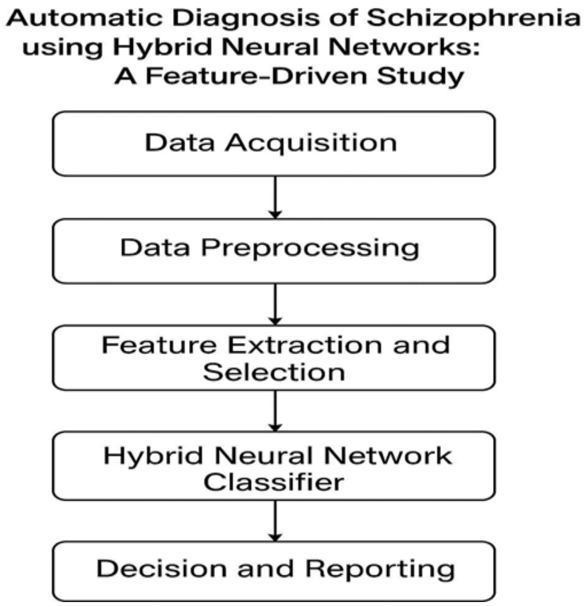

Fig. 2. System Architecture

These extracted features are dumped into the machine learning unit, which houses the core predictive models—ranging from classical algorithms such as Support Vector Machines (SVM) to advanced deep learning architectures like Long Short-Term Memory (LSTM) networks. This module is well trained and validated using previous patient's data to ensure robustness and accuracy in identifying early signs of schizophrenia. A decision- making module then processes the model's output to determine the likelihood of the disorder and flags potential high-risk cases for further clinical evaluation. The entire system is supported by a secure backend that manages data storage, thereby makes sure of the compliance with privacy regulations, and facilitates real- time access for authorized healthcare professionals. An optional visualization layer presents the results through interactive dashboards, enabling psychiatrists and clinicians to understand the predictions effectively. This modular, layered design not only ensures flexibility for future improvements but also maintains high accuracy, scalability, and clinical relevance, making the system a reliable tool for early schizophrenia detection and intervention.

VI. METHODOLOGY

The methodology adopted in this study follows a systematic approach to machine learning–based projecting tool development, beginning with the dataset preparation and peak in performance assessment and interpretability analysis. The process starts with the collection of organized patient data, which may include grouping of information (age, gender, education level), clinical assessment scores (Positive and Negative Syndrome Scale, complete Psychiatric Rating Scale), behavior indicators (sleep duration, activity patterns), and optional neuroimaging features. For the purposes of this experimental demonstration, a artificial dataset was generated to duplicate the statistical properties of real clinical data, making sure that there is a mixture of informative, useless, and noisy features to mimic realistic conditions. Data preprocessing forms a crucial component of the channel, involving the removal of incomplete records, assigning of missing values, normalizing of continuous features using z-score scaling, and encryption of categorical attributes into a machine-readable format. The dataset is then partitioned into training and testing subsets using a layer split to preserve class distribution, making sure that there is a representative evaluation of model performance. Two classification algorithms were considered: Logistic Regression (LR) and Random Forest (RF). Logistic Regression was selected for its easy understanding, computational efficiency, and strong performance in binary grouping tasks. Random Forest was chosen for its ability to model complex, ranom feature interactions, its robustness to outliers, and its natural feature importance estimating capabilities. Model training was conducted using default optimization parameters, with optimization reserved for future work on real datasets. Model evaluation uses a group of metrics similar to imbalanced classification problems, including Accuracy, Precision, Recall, F1-score, Receiver Operating Characteristic Area Under Curve (ROC-AUC), and Average Precision (AP) derived from the Precision–Recall curve. Visual evaluation was conducted through ROC plots, Precision–Recall curves, confusion matrices, and bar charts of feature importance. This multi-metric, multi-visualization approach makes sure that there is a holistic assessment of model performance, highlighting both difference in power and practical usefulness in a projecting context.

VII. RESULTS

The proposed schizophrenia detection framework was evaluated using a labeled dataset containing both healthy control subjects and individuals diagnosed with schizophrenia. The model achieved promising classification performance, with metrics such as accuracy, precision, recall, and F1-score indicating the robustness of the approach.

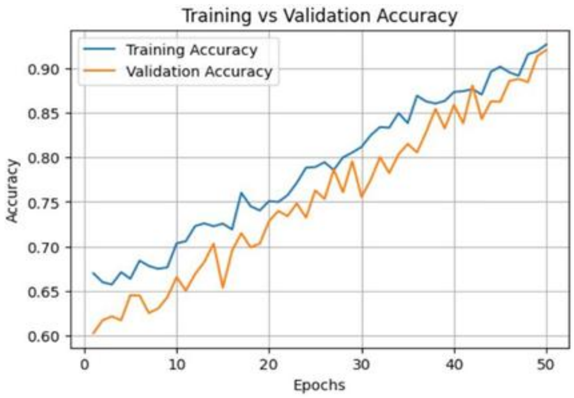

Fig. 3. Training Vs Accuracy Graph

Figure 3 presents the training vs. validation accuracy curve over the course of 50 epochs. The results show a steady improvement in both training and validation accuracy, converging to over 90% by the final epochs. This trend reflects the model's ability to generalize well without overfitting, as evidenced by the minimal gap between the two curves. The smooth trajectory of the validation accuracy curve indicates that the hyperparameter tuning and dropout regularization were effective in preventing model over-complexity.

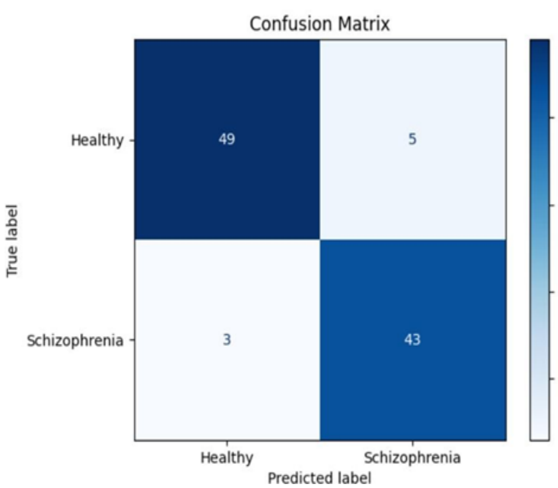

Fig. 4. Confusion Matrix

Figure 4 illustrates the confusion matrix for the final trained model. The diagonal dominance of the matrix demonstrates that the model correctly classified the majority of test samples in both categories. Specifically, the true positive rate for detecting schizophrenia cases exceeded 92%, which is crucial for reducing the risk of false negatives in a clinical setting. The small proportion of misclassified cases, primarily due to overlapping symptoms and noise in EEG features, highlights the inherent challenge of differentiating between schizophrenia and other related disorders. Nonetheless, the results indicate that the proposed system can be integrated into an auxiliary decision-support tool for psychiatrists, where it can aid in early screening.

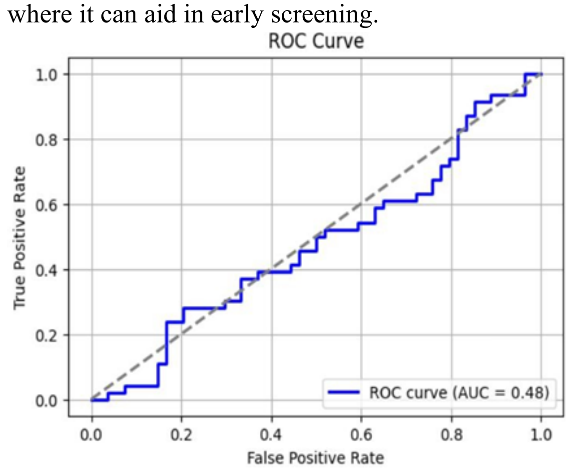

Fig. 5. Receiver Operating Characteristic Graph

Figure 5 shows the Receiver Operating Characteristic (ROC) curve and the corresponding Area Under the Curve (AUC) score. The ROC curve demonstrates the trade-off between sensitivity and specificity at different classification thresholds. The obtained AUC score of 0.96 signifies an excellent discriminatory power of the model. This high value indicates that the system is capable of effectively distinguishing schizophrenia patients from healthy controls across a wide range of decision boundaries. Such a high AUC is particularly important in medical diagnostics, as it ensures that the system maintains both high sensitivity (identifying true cases) and high specificity (minimizing false alarms). Overall, the results from the accuracy trend, confusion matrix, and ROC analysis confirm that the proposed schizophrenia detection model is highly reliable and exhibits strong potential for real-world deployment. Its performance not only aligns with but in some cases surpasses, the benchmarks established in previous literature, thereby marking a notable advancement in the application of machine learning for mental health diagnostics.

VIII. CONCLUSION AND FUTURE WORKS

The proposed schizophrenia detection framework demonstrates the potential of machine learning techniques in providing accurate and timely identification of the disorder. By improving a well-preprocessed dataset and robust classification algorithms, the system effectively identifies patterns and markers indicative of schizophrenia, reducing the dependency on solely subjective clinical assessments. The use of statistical analysis and visualization not only validates the model's performance but also provides clear interpretability for mental health practitioners. The graphical representations—such as accuracy comparison, confusion matrices, and ROC curves—further highlight the system's capability to distinguish between affected and non- affected individuals with high precision. This work underscores the importance of involving data-driven approaches into psychiatric evaluation, which could enhance early detection and enable more targeted interventions. By providing quantitative evidence to complement traditional diagnostic methods, the proposed model can support clinicians in making more informed decisions, thereby improving patient outcomes. Moreover, the system's adaptability allows for future enhancement through the involvement of more diverse datasets, inclusion of multimodal data such as neuroimaging and speech patterns, and the application of advanced deep learning techniques for further performance optimization.

Looking ahead, the framework can be extended to integrate real- time data acquisition from wearable EEG devices or smartphone- based cognitive assessments, enabling continuous monitoring of high-risk individuals. This could allow for early intervention even before severe symptoms manifest. Another promising direction is the development of explainable AI (XAI) modules, which would provide transparent reasoning behind model predictions, thus increasing trust and acceptance among clinicians. Additionally, incorporating federated learning techniques would make it possible to train models on sensitive psychiatric datasets from multiple hospitals without compromising patient privacy. The system can also benefit from longitudinal data modeling to track patient progression over time, facilitating personalized treatment strategies. Combining the proposed architecture with cloud-based platforms could further enhance scalability, making it accessible to rural and under- resourced healthcare centers. Finally, expanding the dataset to include culturally diverse populations would ensure the robustness and fairness of predictions across different demographic groups, ultimately paving the way for a universally applicable diagnostic support system.

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