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Computational Framework for Early Detection of Neurological Disorders Using Multi-Modal Signal Analysis

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ABSTRACT

Non-invasive and reliable methods that allow early detection of neurological disorders have been a critical issue as the biomedical signals are complex and heterogeneous. Conventional single-modality diagnostic strategies have been found to be less effective in providing complete physiological patterns, and hence reduce the accuracy of the diagnosis. To overcome this shortcoming, this paper suggests a computational model to early detect neurological disorders through multi-modal signal analysis. The framework combines non-homogeneous sources of information, such as electroencephalogram (EEG) signals, magnetic resonance imaging (MRI) and clinical parameters, to increase the diagnosis reliability. The methodology involves signal preprocessing, feature extraction, multi-modal data fusion and classification phases. Noise and artifact are eliminated by filtering and normalization methods and time-domain and frequency-domain features are extracted. A weighted fusion algorithm is a mixture of tasks into a single form, which is processed by a machine learning-based classifier. Experimental results indicate that the proposed framework is much more effective than single-modality methods in accuracy, precision, recall, and F1-score, allowing it to be used, more effectively, in early diagnosis and supporting intelligent clinical decision systems.

1. INTRODUCTION

Neurological disorders, such as Alzheimer disease, Parkinson disease, and epilepsy, represent a major health concern in the world due to their progressive nature, high prevalence, and significant impact on cognitive, motor and behavior functions [7]. These disorders can be progressive and are typified by complicated changes in the brain activity, structure and functional connectivity. Consequently, proper diagnosis especially in its initial stages, has been a challenge where traditional clinical tests are not a sufficient sole measure. The availability of large amounts of heterogeneous data, such as electroencephalogram (EEG) signals, magnetic resonance imaging (MRI) and clinical records, has become possible with the rapid development of biomedical sensing technologies and offers new opportunities to computational methods in the detection of neurological disorders [1], [4].

Early diagnosis is important in effective management of the disease as it leads to therapeutic interventions, slows down progression of the disease and leads to improved quality of life of the patient. In some of the neurological disorders, the symptoms in the early stages are very subtle and sometimes they overlap with the normal aging or other illnesses, thus making the diagnosis very difficult. Single modality based traditional diagnostic methods often fail to provide the entire range of underlying pathological changes. An example is EEG signals are not very spatial, but they are very temporal, whereas MRI is very spatial, but very temporal [2], [6]. This is a fundamental drawback of single-modality systems resulting in a degraded diagnostic accuracy and reliability.

Multi-modal analysis is a potential solution to these challenges; it combines complementary information of various data sources in solving these challenges. With the integration of EEG, MRI, and clinical parameters, multi-modal systems are able to give a more comprehensive and holistic picture of neurological conditions [5], [8]. This type of integration not only aids in its better representation of features, but also improves its resilience to noise and variability, as well as to more precise detection of subtle disease patterns.

Driven by such benefits, this paper presents a computational framework based on the multi-modes signal analysis, which can be used to detect early neurological disorders. The framework involves preprocessing in a systematic way, sophisticated feature extraction methods, efficient multi-modal fusion approach and an effective machine learning-based classification model. The most significant additions of this work are the design of an integrated pipeline to process heterogeneous data, the creation of a weighted fusion mechanism to represent features better, and the demonstration of the superior performance of diagnostics in comparison with the traditional single-modality approaches.

2. RELATED WORK

Neurological disorders detection and diagnosis have been an intensively investigated topic considered through different computational and data-driven methods. Among them, EEG-based techniques have been of great interest to date because they are able to record real-time brain activity with a high temporal resolution. Techniques employed by the researchers include spectral analysis, wavelet transforms and machine learning classifiers in order to identify abnormal neural patterns that are related to disorders like epilepsy and Alzheimer disease [2], [3]. Further enhancement of the performance of EEG-based detection systems has been made by deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) [9], [10]. EEG signals, however, have a high sensitivity to noise and artifact and, due to their limited spatial resolution, cannot effectively record structural brain abnormalities.

MRI and other diagnostic procedures based on imaging are more specific regarding the provision of structural and functional data about the brain. Voxel-based morphometry, functional MRI (fMRI) analysis, and diffusion tensor imaging (DTI) have been commonly employed to determine morphological alterations and connection breakdowns in neurological disorder [4], [6]. Applications of the machine learning and deep learning models to imaging data have shown promising results in disease classification and progression analysis [7], [12]. Regardless of the above improvements, imaging based techniques tend to be computationally expensive, specialized equipment is needed and may not be useful in tracking dynamic brain activity over time.

Multi-modal approaches have since been hypothesized as a way of overcoming the limitations of single-modality systems, including integrating heterogeneous data sources, such as EEG, MRI, and clinical information. The rationale of these methods is to take advantage of the complementary nature of diagnostic features of different modalities to enhance the diagnostic accuracy and robustness [5], [8]. Different ways of fusing have been examined and they include feature level fusion, decision level fusion and hybrid frameworks. Although there has been an improvement in the performance of multi-modal systems, most of the current methods have the disadvantage of being ineffective in the fusion mechanisms, lack of scalability, and poor generalization to different types of data.

Although a lot has changed, there are still a number of research gaps. Most studies deal with withdrawn datasets, with a limited variety, which diminishes the relevance of proposed models to the real situation in clinical settings. Also, there is a general tendency to perform the integration of multi-modal data using in optimal weighting and adaptive mechanisms, which results in a suboptimal feature representation. It is also desired to have computationally efficient models that are able to process large amounts of heterogeneous data with high level of accuracy. The challenges represented by these issues stimulate the creation of a powerful and scalable computational infrastructure to detect neurological disorders at its initial stages, which makes a multi-modal signal analysis.

3. Proposed Computational Framework

The given computational framework is also intended to be used as an end-to-end pipeline when working with multi-modal biomedical data and the need to identify neurological disorders at an early stage. As illustrated in Figure 1, the framework is subdivided into five key steps namely, input acquisition, preprocessing, feature extraction, multi-modal fusion and classification. This design will guarantee that the heterogeneous sources of data will be methodically processed and translated into valuable diagnostic data.

The input stage is made up of three complementary modalities of data namely; EEG signals, MRI images and clinical data. EEG signals give dynamic data regarding the brain electrical motion and can be used to recognize abnormal brain patterns. MRI images provide structural information about the brain that can be used to determine anatomical changes that are related to neurological disorders. Patient-specific contextual information is provided by clinical data, such as age, gender, medical history and cognitive assessment scores, which enhances the interpretation of diagnostic results.

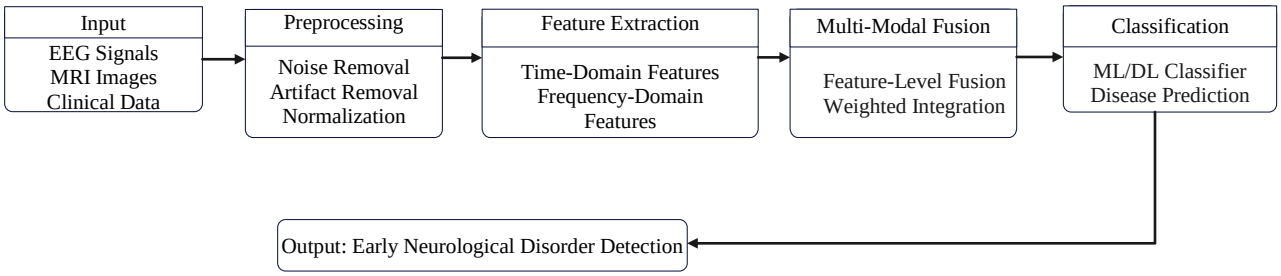


Fig. 1. Overall System Architecture for Multi-Modal Neurological Disorder Detection

Once the data has been acquired, it goes through preprocessing to enhance the quality of data. Noise removal and artifact removal are used to clean EEG signals to remove interference which can be caused by muscle activity, eye movement and external disturbances. MRI images can be normalized and improved in order to guarantee consistency across samples. Clinical data are standardized in order to minimize the difference in scales among variables. This step verifies the input data to be accurate and fit to be analyzed with computations.

The second step is feature extraction where patterns that are relevant are derived in each modality. EEG signals are used to obtain time and frequency domain features which represent statistical and spectral features of brain activity. Structural and image-derived features may be considered the MRI-based features whereas the clinical features may be viewed as the demographic and diagnostic features. It is out of these extracted features that the basis of classification of diseases is made.

The features extracted are then sent to multi-modal fusion stage. Fusion at the feature level integrates the information of EEG, MRI and clinical data into a single feature representation. Weighted integration is used such that the contribution of each modality taking into consideration its diagnostic value. This combination process enhances the possibilities of the model in the context of capturing the complex neurological patterns, which might not be observed under one modality of the model.

Lastly, prediction is provided by giving the fused feature vector to a machine learning or deep learning classifier. The classifier uses the combined feature representation and creates the final diagnostic output, e.g., the detection of early neurological disorders. The output may be useful in supporting clinical decision-making, by giving an intelligent screening mechanism of identifying the high risk patients.

Figure 1. General System architecture: The proposed structure works with EEG data, MRI images and clinical data to deliver early diagnosis of neurological disorders.

4. Signal Processing and Feature Extraction

4.1 Signal Preprocessing

Signal preprocessing is a very important step in the proposed framework because raw biomedical data is often polluted with noise, artifacts, and inconsistencies which can significantly influence the accuracy of analysis. The aim of this step is to improve the signal quality and make sure that the data are appropriate to extract the features and classify them accordingly.

Noise removal is carried out to remove unwanted and disturbances that exist in EEG signals and imaging information. EEG signals are especially vulnerable to external interference including noise on power lines and eletromagnetic signals in the environment. Such techniques as notch filtering and bandpass filtering are widely used to eliminate these undesired frequency content. In the case of MRI data, preprocessing can involve denoising algorithms to minimize imaging artifacts and enhance clarity.

Filtering methods are used to pick out the relevant frequency bands which encode meaningful neurological data. In EEG signal processing, certain frequency ranges like delta, theta, alpha, beta and gamma bands are identified with various processes going on in the brain. These frequency components are extracted using bandpass filters, and allow more focused analysis of patterns in the human nervous system.

Another very crucial procedure is the artifact removal, particularly in EEG signals. The actual brain signals may be distorted by artifacts due to eye blinks, movement of the muscular system, and even the movement of the electrode. Various techniques like Independent Component Analysis (ICA) and adaptive filtering are employed to detect and eliminate these artifacts leaving behind only the important neural activity.

Normalization is used to provide consistency among various data samples and modalities. As EEG, MRI, and clinical data may be having various scales and distributions, the data may be standardized using normalization techniques like min-max scaling or z-score normalization. This operation enhances the stability and functioning of

machine learning models by averting the bias of features with bigger numerical numbers.

In general, the preprocessing step is crucial to enhancing the quality of data, decreasing variability, and increasing the efficiency of the further process of extracting features and classifying them.

4.2 Feature Extraction

The extraction of the features is important in the conversion of the preprocessed signals to the meaningful representations which can be effectively exploited in the classification process. According to the framework suggested, the attributes are obtained with the use of more than one of the modalities in order to create the temporal and spatial characteristics of the neurological activity under consideration.

Time-domain features are obtained directly by the amplitude changes of the signal obtained with time. These characteristics give statistical data about the signal and are applicable in detecting irregular patterns of the signal, which are indicators of neurological diseases. Typical time-domain characteristics are the mean, variance, the standard deviation, skewness and kurtosis. These measures can be used to measure signal distribution, variability and asymmetry, allowing detection of abnormal brain activity patterns.

The frequency-domain features are derived by changing the signal of the time domain into the signal of the frequency domain using methods like the Fast Fourier Transform (FFT) or the wavelet transform. These characteristics play an important role in the analysis of EEG, as the frequency bands (delta, theta, alpha, beta and gamma) correspond to certain brain activities. Parameters like power spectral density, band power, spectral entropy are attained to reflect the energy distribution and complexity of the signal over frequencies. This assists the determination of typical frequency distributions attributed to different neurological disorders.

Besides traditional feature extraction approaches, feature extraction based on deep learning is added to learn the complex and high dimensional representations of the data automatically. Convolutional Neural Networks (CNNs) are typically efficient in extracting spatial features of MRI images, whereas Recurrent Neural Networks (RNNs) or Long Short-Term Memory (LSTM) networks are useful at extracting temporal dependencies of EEG signals. Autoencoders can also be used to learn compressed feature encodings. These rich features increase the capability of the model to find subtle nonlinear patterns that are hard to capture by other traditional ways. Comprehensively, time-domain, frequency-domain, and deep learning-based features yield a holistic view of the neurological data, which is immensely beneficial in the performance and robustness of the proposed multi-modal detection framework.

5. Multi-Modal Fusion and Classification

5.1 Multi-Modal Fusion Model

The central step of the proposed framework is multi-modal fusion since it is a combination of the complementary information of EEG features, MRI features and clinical features into one diagnostic representation. Each of the modalities, as illustrated in Figure 2, presents various yet valuable information to detect neurological disorders. The use of EEG features reflect temporal patterns of brain activity, MRI features reflect structural brain abnormalities, and clinical features provide patient-level information such as demographic and cognitive data.

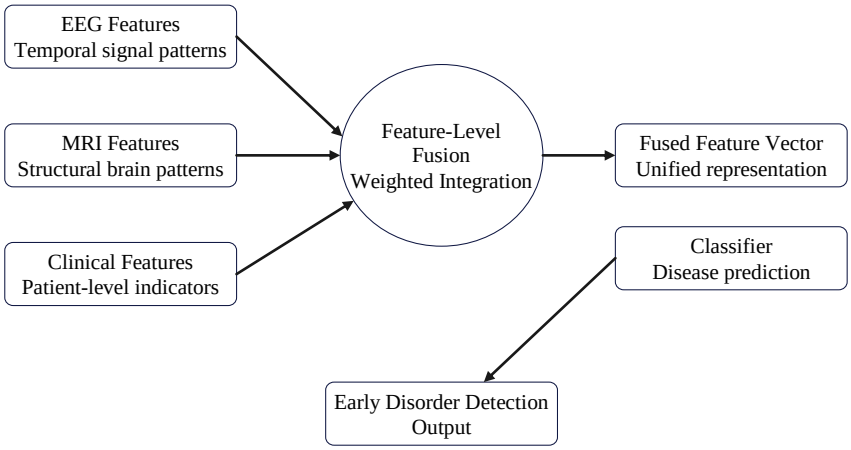


Fig. 2. Multi-Modal Feature Fusion and Classification Framework

A feature-level fusion strategy integrates the extracted feature vectors of the various modalities, using a weighted feature-level fusion strategy. The methodology enables the framework to attribute

varying degrees of significance to each modality to the contribution it made in diagnosis. The computation of fused feature representation is:

$F = \sum_{i=1}^{n} w_i X_i$,_____(1)

where$F$ represents the final fused feature vector, X_i denotes the feature vector extracted from the $i^{t\square}$modality, w_i represents the corresponding modality weight, and n is the total number of modalities used in the system.

According to equation (1) the resulting representation is given by averaging an array of modality specific feature vectors with an integration weight. In this framework, modalities that contribute more to the classification performance receive higher weight and those less informative or those noisier receive lower weight. This makes the model not treat all data sources in the same way, as data sources have different diagnostic values.

It is then fed on the classifier to predict the diseases based on the fused feature vector. The fusion stage, as demonstrated in Figure 2, is a process, which bridges the gap between feature extraction and classification because it converts heterogeneous features into a single representation. This increases resilience, limits reliance on a single modality and improves early detection of neurological disorders.

Figure 2. Multi-Mode Feature Fusion Strategy: EEG, MRI and clinical feature vectors are fused through weighted feature-level fusion to generate a single fused feature vector, and the classifier then uses this fused feature vector to detect early signs of a disorder.

5.2 Classification Model

The classification stage itself is responsible to predict the presence or stage of neurological disorders based on the fused feature representation obtained of the multi-modal fusion process. Once EEG, MRI and clinical features have been integrated into a single and unified vector, it is followed by a machine learning or deep learning-based classifier being applied to execute the final decision-making task. The prediction capability of the classifier can be mathematically defined as:

$\hat{y} = \sigma(WF + b)$,_____(2)

where $\hat{y}$ represents the predicted output, F is the fused feature vector obtained from the fusion stage, W denotes the weight matrix of the classifier, b is the bias term, and is the activation function that maps the output to a probabilistic or class label space.

Equation **(2)** describes how the classifier transforms the fused feature vector into a prediction. The weighted combination $WF +$ $b$captures the relationship between input features and class labels, while the activation function σensures that the output is properly scaled, typically in the range [0,1]for binary classification or normalized probabilities for multi-class classification.

The type of classifier which is going to be applied depends on the complexity of the dataset and the application needs. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks are the types of deep learning models that are suitable to capture spatial and temporal relationship in complex data. Support Vector Machines (SVM) and Convolutional Neural Networks (CNNs) are examples of traditional machine learning models that are effective in smaller datasets and structured features. Here, the choice of the classifier is made on performance evaluation to promote optimum prediction performance.

The decision process entails classifying the input sample into a class whose predicted probability was the highest. As an example, the model could put a subject in categories of healthy, mildly impaired, and the one with a neurological condition. This classification output can be used in the early diagnosis of a disease as well as help clinicians make wise decisions.

6. Experimental Setup

6.1 Dataset Description

The feasibility of the suggested multi-modal framework is measured by the data sets of heterogeneous types, which include EEG signals, MRI images, and clinical data. These datasets are chosen to be compatible with the framework shown in Section 4 and 5, where multi-modal feature extraction and fusion is done. All the modalities add new and complementary information that allows making a holistic assessment of the approach proposed.

The EEG data are multi-channel recordings of brain signals in time-domain and frequency-domain formats, which are necessary to extract time-domain and frequency-domain features. The MRI data set consists of structural brain images which contains spatial information used to detect abnormalities as well as the neurological disorders. The clinical dataset has patient-specific characteristics including demographic information and medical history that facilitate the contextual interpretation of the disease conditions. Table 1 shows a summary of the modality type, sample size, feature dimensions post-preprocessing and feature extraction.

Table 1. Dataset Details

Dataset	Modality	Samples	Features
EEG Dataset	EEG Signals	500	128
MRI Dataset	Imaging	300	256
Clinical Data	Tabular Data	400	50

The datasets differ in size, and have dimensionality, which reflects the natural differences between signal, imaging, and tabular data. EEG dataset has adequate samples with features based on temporal and spectral analysis. The MRI data, though it is smaller in terms of sample size has higher dimensional features since image based representations are used. The clinical data possesses less features but do offer important patient-level information that aids in making decisions.

The datasets are preprocessed and converted into feature vectors according to the description of Section 4, and fused using the weighted integration approach described in Section 5. This combination of these various datasets makes the proposed model learn a strong and generalized representation to learn to detect early neurological disorder.

6.2 Implementation Details

The proposed multi-modal framework is applied, based on the powerful software tools and computational resources to make sure that the proposed multi-modal framework will work properly and will be trained successfully. The implementation occurs in Python because it has a wide range of support on scientific computing and machine learning application. Data handling and preprocessing are done with the help of libraries such as NumPy and Pandas whereas signal processing is done with the help of SciPy. Deep learning models like TensorFlow and PyTorch are used to deploy feature extraction and classification features to develop the model. Also, Scikit-learn is utilized to the traditional machine learning models and performance analysis.

The hardware implementation is an important factor in dealing with the computational complexity of the multi-modal data processing. The experiments are run on a platform having a high-performance processor (Intel Core i7 or equivalent), minimum 16 GB RAM and an actual graphic card (such as NVIDIA CUDA-enabled graphics card) to expedite the deep learning processes. Training time can be much faster due to the use of GPU, particularly when training models that require a large amount of EEG and MRI data.

The proposed framework is evaluated with the help of several standard performance metrics. Accuracy is determined by the total accuracy of the model, whereas precision is the percentage of the instances of the positive that are correctly predicted by the model. Recall (sensitivity) evaluates the capability of the model to detect real positive cases, and the F1-score is a balanced measure of the model since it combines precision and recall. These metrics will guarantee a thorough assessment of the model performance especially in the early neurological disorder identification context where the false positives and false negatives will have to be taken into serious consideration.

In general, the implementation configuration will see the proposed framework being computationally efficient, scalable, and able to provide reliable diagnostic performance when using multi-modal datasets.

7. RESULTS AND DISCUSSION

7.1 Performance Evaluation

The data sets outlined in Section 6 are used to evaluate the performance of the proposed multi-modal framework, that is, using the data sets outlined in Section 6, it is evaluated how the proposed multi-modal framework performs. The hypothesis is to prove the effectiveness of the integration of EEG, MRI and clinical data in comparison with the single-modality methods. The standard measures are used to evaluate the classification performance including accuracy, precision, recall, and F1-score to ensure that the evaluation of the classification performance is comprehensive.

In order to underline the benefit of multi-modal fusion, the proposed model is compared with the models that are trained using EEG features only and models that are trained using MRI features only. These bottom-up models assume the same preprocessing and feature extraction steps but omit the fusion step found in Section 5.1. With such comparison, we may well understand the contribution of multi-modal integration. The quantitative data have been summarized in Table 2 that shows the performance of each method in all the evaluation metrics. As it can be seen in Table 2, the proposed multi-modal framework will perform much better compared to the single-modality models. The EEG-alone model has performance improvement of moderate level since it can capture temporal brain activity, whereas the MRI-alone model shows slightly better results based on its ability to capture temporal brain activity. But both methods are restricted in the range of the entire spectrum of neurological patterns.

Table 2. Performance Comparison

Method	Accuracy (%)	Precision	Recall	F1-score
EEG Only	82.5	0.81	0.80	0.80
MRI Only	85.2	0.84	0.83	0.83
Proposed Multi-Modal	**92.8**	**0.91**	**0.92**	**0.91**

By comparison, the proposed multi-modal model is the most accurate by 92.8 %, and has better precision, recall, and F1-score. This enhancement is directly linked to the fusion process that was covered in Equation (1), which practically unites the complementary aspects of various modalities. The findings reveal that a combination of temporal, structural and clinical information result in a stronger and discriminative feature presentation. In general, the results prove the usefulness of the method offered in this paper as the proposed framework is seen to effectively detect early neurological disorders by means of integrating multi-modal data.

7.2 Model Performance Visualization

The test results of the proposed multi-modal classification model are further discussed using graphical visualizations. Although Table 2 displays the numerical comparison of the EEG-only, MRI-only, and proposed multi-modes methods, Figure 3 and Figure 4 allow to see deeper into the training behavior of the model and into the performance of the class-wise prediction.

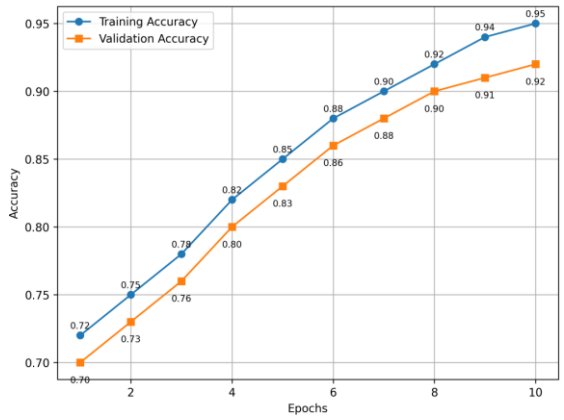


Fig. 3. Training and Validation Accuracy Across Epochs

Figure 3 presents the training and validation accuracy of ten epochs. As the number of epochs rises, the learning curve illustrates that training and validation accuracy continue to improve steadily as the number of epochs rises. Accuracy in training goes up to 0.95 and in validation, accuracy goes up to 0.92. The slight distance between the two curves suggests that the model is highly general and is not strongly overfitted. This both testifies to the efficacy of the classifier as detailed in Section 5.2 and demonstrates that the fused features that are created in Section 5.1 do enhance the stability of learning.

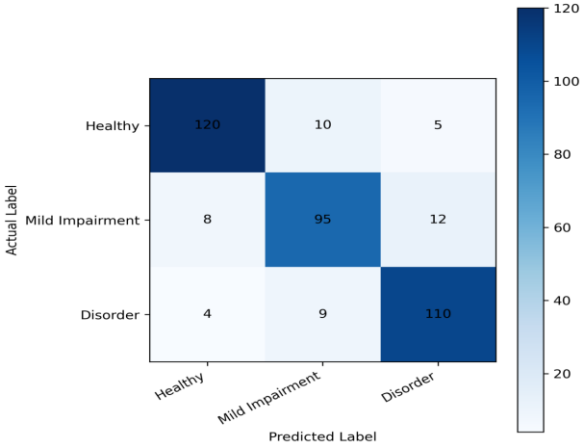


Fig. 4. Confusion Matrix for Multi-Class Neurological Disorder Classification

The confusion matrix of the three-classification task healthy, mild impairment and neurological disorder is given in figure 4. The diagonal values are the samples which are correctly classified and the off-diagonal values are those which are incorrectly classified. The model makes the correct classification of 120 healthy samples, 95 mild impairment samples, and 110 disorder samples. The misclassification is comparatively low with small amount of health cases confused as mild impairment or disorder. This is not surprising since mild impairment usually has a common pattern with early neurological abnormality.

On the whole, these visual outcomes confirm the performance that is presented in Table 2. Learning curve verifies the learning process of the model is stable, and the confusion matrix indicates the model performs well in terms of class-based classification. All these data points to the fact that the suggested multi-modal framework will be useful when it comes to detecting cases of early neurological disorder.

7.3 Discussion

The findings made using the proposed multi-modal framework clearly indicate that the framework is effective in early diagnosis of neurological disorders. As it can be seen in Table 2, the multi-modal model has much higher accuracy (92.8) than EEG only and MRI only methods. This enhancement is further justified by the learning behavior as shown in Figure 3, both the training and validation accuracies are increasing

consistently with very little distraction indicating good generalization ability. Moreover, it has been confirmed that the model is effective at classifying all classes correctly and with a high percentage as well as with a lower amount of misclassification, in accordance with the confusion matrix in Figure 4.

The main benefit of the suggested framework is that it will combine the complementary information of the various modalities. The EEG signals record temporal brain activity, MRI is used to provide structural information, and clinical data are used to give contextual information about the patient. These heterogeneous characteristics can be effectively combined under the fusion strategy described in Section 5.1 and lead to a more informative and discriminative representation. This results in better classification accuracy, particularly on challenging cases like mild impairment, where single-modality methods usually are not effective.

The proposed approach has a superior robustness and predictive accuracy in comparison to the current methods which are discussed within Section 2 because of its integrated design. There exist many classical methods which can either be signal based or image based analysis so much that they are unable to capture the entire complexity of a neurological disorder. The multi-modal fusion framework, in contrast, improves diagnostic reliability by balancing the use of a variety of data sources, and reducing dependence on any single modality.

Although the given framework has its benefits, it has some drawbacks. The combination of various data sources not only adds complexity to the computation, but also necessitates close pre-processing and synchronization of the heterogeneous data sets. Also, high-quality multi-modal datasets may be an issue in the real world clinical setting. Based on the quality and balance of the input data, the model performance also can vary. As a whole, the findings confirm that the multi-modal fusion can considerably enhance the detection of the early neurological disorders, yet more refinements and real-life tests are required to implement the findings in practice.

8. CONCLUSION

This article introduced a computation model of the early recognition of neurological disorders with the help of multi-modal signal analysis. The proposed method combines EEG signals, MRI images, and clinical data and creates a single system to overcome the shortcomings of single-modality diagnostic techniques. A systematic pipeline comprising of preprocess, feature extraction, multi-mode fusion and classification was invented to increase diagnostic accuracy and strength.

The most important findings show that the multi-modal model is much more effective than other approaches that are based on particular modalities. As the results indicate, the given model was more accurate, precise, recalled more and had a higher F1-score, which proves the efficiency of feature-level fusion. The learning curve analysis showed that the training was stable with good generalization and the confusion matrix confirmed the good performance of the training in terms of predictability classwise with minimum misclassification. These findings emphasize the necessity to combine complementary data sources to detect the neurological disorder in a better way.

Practically, the suggested framework can be used to assist clinical decision-making by offering an intelligent and dependable tool to diagnose early. It can help healthcare practitioners diagnose neurological disorders at earlier stages, thus allowing them to intervene in time and achieve better patient outcomes.

Nonetheless, more efforts are needed to increase the scalability and practical applicability of the system. Future studies can be based on: (a) including larger and more heterogeneous datasets; (b) optimization of fusion strategies with adaptive or attention-based mechanisms; and (c) development of real-time deployment systems. Also, the ability to combine explainable AI methods might enhance the interpretability of the model, and, therefore, be more willing to adopt it in clinical practice.

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