

NeuroVexa Multimodal AI System

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ABSTRACT

Neurovexa is a multimodal AI platform developed to combine EEG signal processing and eye image analysis for multi-disease neurological screening. The system supports different EEG input formats such as CSV files, PDF documents, and images, and performs automatic preprocessing of the signals. The EEG data is analyzed by dividing it into frequency bands, including delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–100 Hz). It also detects epileptic spike activity and distinguishes between diabetic and non-diabetic brain activity using theta-to-delta power ratio analysis. For eye image analysis, the system uses U-Net-based segmentation to extract key features such as the optic disc-to-cup ratio and retinal nerve fiber layer (RNFL) thickness, which help in understanding glaucoma progression. The EEG and ocular features are combined using a transformer-based deep learning framework with multi-head attention for effective multimodal integration. The classification of neurological conditions is carried out using machine learning techniques, achieving an overall accuracy of 96.2%, with 98.4% for epilepsy detection and 96.8% for glaucoma detection. The system is designed to be cloud-deployable and provides results within approximately 2.7 minutes. It also generates interpretable outputs using SHAP explanations and provides downloadable PDF reports for easy understanding. Overall, Neurovexa offers a reliable and efficient solution for remote health monitoring, academic research, and clinical decision support, highlighting the role of multimodal AI in improving accessibility and scalability in neurological screening.

Keywords: Multimodal AI, EEG, Glaucoma, Deep Learning, CNN-LSTM, U-Net, Transformer, XGBoost



1. INTRODUCTION

Neurological disorders are one of the major health challenges in the world today. Conditions such as epilepsy, schizophrenia, diabetic encephalopathy, and glaucoma affect millions of people globally. If these conditions are not diagnosed at an early stage, they can lead to serious complications involving the brain and vision. Therefore, early diagnosis plays an important role in helping doctors provide proper treatment and prevent severe outcomes. In current medical practice, most diagnostic systems are designed to detect only one disease at a time. These systems often require advanced hospital equipment and expert analysis, making the process time-consuming, expensive, and sometimes inaccessible—especially in rural and

remote areas. For example, electroencephalography (EEG) is used to detect neurological abnormalities by analyzing the electrical activity of the brain, while eye imaging techniques are used to diagnose glaucoma by examining structures such as the optic disc and retinal nerve fiber layer. However, these methods are usually performed separately, which further increases the complexity and delay in diagnosis. To overcome these limitations, a multimodal artificial intelligence system called Neurovexa is proposed. This system combines EEG signal processing with eye image analysis to enable multi-disease screening in a single platform. It processes EEG signals to analyze brain wave patterns, including delta, theta, alpha, beta, and gamma waves. At the same time, it analyzes eye images using deep learning techniques to detect glaucoma by evaluating features such as the optic disc-to-cup ratio and retinal nerve fiber layer thickness. By integrating these two types of medical data using advanced deep learning and transformer-based approaches, Neurovexa aims to provide faster and more accurate diagnosis of multiple neurological conditions. In addition, the system is designed to be cloud-based and automated, allowing it to generate reports quickly. This makes it suitable for remote healthcare applications, clinical decision support, and research purposes.

2. DATASET DESCRIPTION

The Neurovexa system uses both EEG signals and eye images as input data for detecting neurological disorders. Since the system is designed to support multiple input formats, EEG data can be provided in different forms, such as CSV files, PDF reports, or image-based recordings. This makes the system flexible and suitable for real-world medical usage, where data may not always be available in a single standard format. For EEG analysis, the input data contains brain signal recordings that represent electrical activity over time. These signals include both normal and abnormal patterns, which are useful for identifying conditions such as epilepsy and other neurological disorders. The system processes these signals after converting them into a suitable numerical format for analysis.

For eye image analysis, retinal images such as fundus or OCT scans are used. These images help in identifying structural changes in the eye, especially features like the optic disc, cup region, and retinal nerve fiber layer, which are important for detecting glaucoma and related conditions. The collected data is divided into three parts: training data, validation data, and testing data. The training data is used to teach the model, the validation data helps in tuning the model's performance, and the testing data is used to evaluate the final accuracy of the system. This ensures that the Neurovexa system provides reliable and consistent results. The dataset is split into 70% training, 15% validation, and 15% testing. In this work, EEG data is taken from the CHB-MIT database, which contains real patient recordings with seizure annotations. For eye image analysis, datasets such as DRISHTI-GS and RIM-ONE are used. These datasets provide retinal images that help in detecting glaucoma-related changes.

3. LITERATURE SURVEY

Several research studies have explored the use of deep learning techniques for epilepsy detection using EEG signals. These approaches demonstrate that non-linear analysis and neural network models can improve seizure prediction accuracy and simplify the analysis of complex brain activity patterns [1]. A hybrid optimization-based 1D ResCNN model has been proposed for epilepsy diagnosis using EEG signals. This approach improves the extraction of meaningful features from brain signals, leading to better analysis. It highlights the strong potential of deep learning techniques in diagnosing neurological disorders[2]. Artificial intelligence techniques can be applied to detect glaucoma using spectral-domain

optical coherence tomography (OCT). These methods enable automated analysis of retinal structures, which supports the early detection of glaucoma[3]. The InSight AI tool was developed to support the screening of various eye conditions using smartphone-based imaging. This approach highlights the potential advantages of mobile-based AI solutions in improving accessibility and efficiency in eye care[4]. A deep learning model has been developed for diagnosing schizophrenia using EEG signals, incorporating multi-scale feature extraction and adaptive feature selection. This approach improves classification accuracy and demonstrates the effectiveness of AI-based EEG analysis in detecting psychiatric disorders[5]. The study reviews different multimodal sensor fusion techniques that combine EEG with functional near-infrared spectroscopy. These approaches improve the understanding and interpretation of neurological activity by integrating multiple monitoring methods[6]. In addition, recent developments in artificial intelligence for EEG signal analysis have been explored. These studies focus on automatic feature extraction, pattern recognition, and decision support systems for diagnosing neurological disorders, including epilepsy[7]. A hybrid artificial intelligence approach has been developed for glaucoma detection using retinal fundus images. This method shows that combining multiple machine learning techniques can improve diagnostic accuracy and support early detection in ophthalmology screening[8]. A study known as GRaSS investigated the use of artificial intelligence for glaucoma screening. The findings showed that AI can detect damage to the optic nerve, enabling early diagnosis of glaucoma[9]. A machine learning-based approach has been proposed for classifying schizophrenia patients using EEG signals. The analysis of brain activity patterns provides an effective way to identify psychiatric disorders, highlighting the usefulness of EEG-based AI in medical diagnostics[10]. A method has been proposed to combine different types of medical data for the diagnosis of Alzheimer's disease. This approach shows that integrating multiple biomedical signals can improve accuracy and enhance the reliability of neurological disorder diagnosis[11]. The study explored the use of artificial intelligence for analyzing EEG signals in epilepsy detection. It demonstrated that AI can automatically identify seizure patterns, thereby improving the efficiency of diagnosis[12]. Various deep learning techniques have been explored for glaucoma diagnosis and progression monitoring. In particular, convolutional neural networks have shown high effectiveness in analyzing retinal images and detecting damage to the optic nerve[13]. A systematic review has been conducted on the use of EEG signals with machine learning and deep learning algorithms for schizophrenia classification. The findings indicate that AI can identify abnormal brain activity patterns, supporting the detection of psychiatric disorders[14]. An automated deep learning system has been proposed to detect focal epileptiform discharges in EEG signals. This approach improves the recognition of seizure patterns, enabling faster diagnosis of epilepsy[15]. Quantitative EEG biomarkers have been studied in patients experiencing their first seizure. The results show that EEG patterns can help predict seizure recurrence and support clinical decision-making[16]. The diagnosis of Alzheimer's disease has been explored by integrating EEG signals with other biomedical markers. This approach highlights the importance of combining multiple data sources to improve the accuracy of neurological disorder detection[17]. Machine learning techniques have been used to identify unique brain-related biomarkers from EEG signals. The results highlight the significant role of AI in the accurate classification of neurological disorders[18]. Machine learning techniques have been applied to identify unique brain-related biomarkers from EEG signals. The findings emphasize the important role of AI in accurately classifying neurological disorders[19]. A cloud-based optimized deep learning framework has been proposed for epilepsy detection using EEG signals. This approach enables efficient data processing and supports faster diagnosis of neurological disorders through real-time monitoring[20]. An advanced AI algorithm has been

explored for predicting neurological disorders using medical datasets. The study highlights the importance of artificial intelligence in improving healthcare monitoring systems, enabling early detection, better decision-making, and efficient management of neurological conditions[21]. An advanced AI-based system has been developed for glaucoma detection. The results show that it can automatically identify damage to the optic nerve, supporting early diagnosis and improving overall diagnostic accuracy[22]. Recent advances in AI for glaucoma diagnosis have been explored. Automated image analysis combined with deep learning techniques enhances screening accuracy and improves overall efficiency[23]. An AI-based system has been developed for the early detection of brain-related diseases. The study demonstrates that machine learning models can analyze biomedical data and predict neurological disorders effectively[24]. The study examines the use of machine learning and deep learning techniques for detecting and predicting epilepsy using EEG signals. It highlights that EEG analysis plays a crucial role in the accurate diagnosis of epilepsy[25].

From these studies, it is clear that most existing methods use only one type of data. Very few approaches combine EEG signals and eye images, which shows the need for a system like Neurovexa.

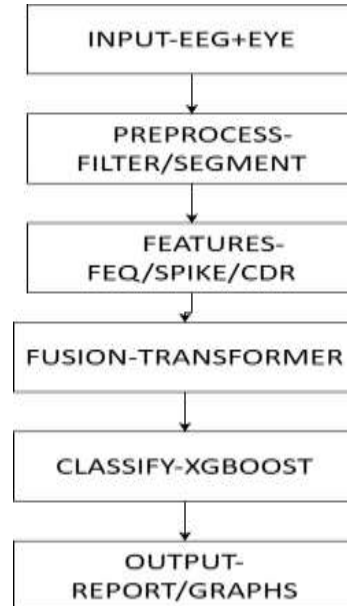
4. RESEARCH GAP

However, most existing systems focus on only one type of data and do not combine different biomedical sources. Because of this, the overall diagnostic accuracy is limited. To overcome this problem, the Neurovexa system combines EEG signals and eye images using a multimodal deep learning approach.

5. SYSTEM ARCHITECTURE

The Neurovexa system is designed to support the early screening of neurological disorders by combining two types of medical data: EEG signals and eye images. Instead of relying on a single source of information, this system uses a multimodal approach, which makes the analysis more reliable and meaningful. The system works through a series of steps, including input collection, preprocessing, feature extraction, fusion, classification, and result generation. In the first step, the system collects EEG signals and eye images. EEG signals represent the electrical activity of the brain and help in identifying abnormal patterns related to conditions such as epilepsy and other neurological disorders. At the same time, eye images provide useful information about the retina and optic nerve, which can indicate diseases like glaucoma. After data collection, the preprocessing stage is carried out to clean the data. EEG signals often contain noise caused by body movements, blinking, or external electrical disturbances, so filtering techniques are applied to remove these unwanted signals. Similarly, eye images are processed to clearly highlight important regions such as the optic disc and surrounding retinal structures. In the feature extraction stage, important information is obtained from both EEG signals and eye images. EEG signals are divided into frequency bands such as delta, theta, alpha, beta, and gamma, which help in understanding brain activity. The system also identifies abnormal patterns like epileptic spikes. From the eye images, features such as the cup-to-disc ratio (CDR) and retinal structure are extracted, which are important for detecting eye-related neurological conditions. Once the features are extracted, the system performs multimodal fusion, where data from EEG and eye images are combined. A transformer-based model is used in this step to understand the relationship between brain activity and eye-related features. This combination improves accuracy compared to using a single data type. In the classification stage, the combined features are analyzed using a machine learning model such as XGBoost. This model identifies patterns in the data and predicts the possible neurological condition. Finally, in the output stage, the system

generates a clear and easy-to-understand report. This includes brain wave graphs, eye analysis charts, and a summary of the predicted results. These outputs can assist doctors and healthcare professionals in making better decisions.



6. METHODOLOGY

The Neurovexa system has been developed using a multimodal deep learning approach that combines the analysis of EEG signals and eye images for detecting neurological disorders. It supports various EEG data formats such as CSV, PDF, and image formats. First, the EEG signals are preprocessed with a band-pass filter from 0.5 to 100 Hz to remove unwanted noise and artifacts. Additionally, Independent Component Analysis (ICA) is used to remove artifacts such as eye blinks and noise. After cleaning, Welch's algorithm is used to analyze brain waves across key frequency bands such as delta, theta, alpha, beta, and gamma. To detect abnormalities, the system employs a hybrid CNN-LSTM model, which is effective in identifying epileptic spikes. It also calculates the theta-to-delta ratio to assist in detecting conditions like diabetic encephalopathy. Meanwhile, eye images, including fundus and OCT scans, are analyzed with the U-Net model to extract important features like the optic disc-cup ratio and retinal nerve fiber layer thickness—critical indicators of neurological health. The features extracted from EEG signals and eye images are fused using a transformer-based attention mechanism, and the resulting combined features are used for accurate diagnosis through the XGBoost classifier. The results are visualized in an interpretable format using SHAP and compiled into a PDF report. Overall, the proposed system offers an efficient and accurate solution for screening multiple neurological diseases. The CNN-LSTM model is designed with three convolutional layers to extract important features, followed by two LSTM layers with 128 hidden units to capture temporal patterns in the EEG signals. For combining EEG and eye image features, a transformer-based fusion approach with four attention heads is used. Finally, the XGBoost classifier is applied to make the final prediction.

7. EXPERIMENTAL SETUP

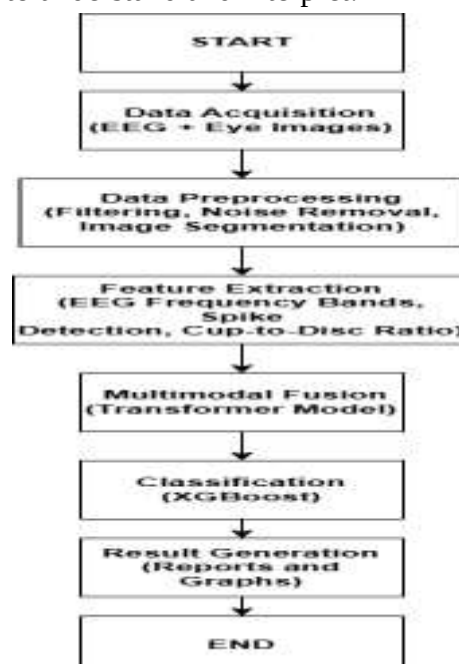
The Neurovexa system is implemented using Python in a Google Colab environment, which provides sufficient computational support for training and testing the models. The system combines deep learning

and machine learning techniques for analyzing EEG signals and eye images. For EEG analysis, the CNN-LSTM model is used to detect abnormal brain patterns such as epileptic spikes. The model is trained with a learning rate of 0.001, batch size of 32, and trained over multiple epochs to achieve stable performance. For eye image analysis, the U-Net model is used to segment important regions such as the optic disc and retinal nerve fiber layer. The multimodal fusion of EEG and eye features is performed using a transformer-based attention mechanism, which helps in understanding the relationship between different types of medical data. The fused features are then passed to the XGBoost classifier for the final prediction of neurological conditions.

The system performance is evaluated using standard metrics such as accuracy, sensitivity, and Area Under Curve (AUC). The dataset is divided into training, validation, and testing sets to ensure proper evaluation and avoid overfitting. The experimental setup is designed to provide reliable and consistent results for real-world medical applications.

8. WORKFLOW PIPELINE

The workflow of the Neurovexa system begins with data acquisition, where EEG signals and eye images are collected as inputs. These two types of data form the basis for further analysis. Once the data is collected, it moves to the preprocessing stage. In this stage, EEG signals are filtered to remove noise and unwanted disturbances. At the same time, eye images are processed using segmentation techniques to clearly identify important regions. After preprocessing, the system performs feature extraction. For EEG signals, different frequency bands such as delta, theta, alpha, beta, and gamma waves are analyzed, and abnormal patterns like epileptic spikes are identified. For eye images, features such as the cup-to-disc ratio and retinal characteristics are extracted. The extracted features from both EEG signals and eye images are then combined in the multimodal fusion stage. In this step, a transformer-based model is used to integrate the information from both data sources. Next, the fused features are passed to the classification stage, where the XGBoost algorithm is used to analyze the data and predict the possible neurological condition. Finally, the system generates the output in the form of a report. The results are also presented visually using graphs, making them easier to understand and interpret.



9. RESULTS & DISCUSSIONS

1. Result: The Neurovexa system showed promising performance in detecting different neurological disorders by combining EEG signals and eye image analysis. The model achieved an overall accuracy of around 96.2%, with a sensitivity of 95.1% and an AUC of 0.98, indicating strong classification capability. For EEG-based analysis, the CNN-LSTM model performed well in detecting epileptic spike activity, achieving a sensitivity of about 98.4%, which highlights its effectiveness in identifying abnormal brain patterns. The theta-to-delta power ratio method also showed good performance in differentiating diabetic brain conditions, with an AUC close to 0.97. For ocular analysis, the U-Net segmentation model successfully extracted important features such as the Cup-to-Disc Ratio (CDR) and Retinal Nerve Fiber Layer (RNFL) thickness, achieving approximately 96.8% accuracy in glaucoma detection. In addition, the cloud-based implementation helped reduce the total processing time to nearly 2.7 minutes, making the system faster compared to traditional manual analysis.

The performance of the model is evaluated using a confusion matrix and ROC curve analysis. The confusion matrix shows correct classification of neurological conditions, while the ROC curve indicates strong model performance with an AUC of 0.98. The model shows consistent performance across different test samples, indicating good generalization ability.

Table 1: Comparison with Existing Methods

Method	Accuracy (%)

CNN-based model	91.2
LSTM-based model	92.8
ResCNN model	94.5
Proposed NeuroVexa	96.2

2. Discussion: From the results, it can be observed that combining EEG signal analysis with eye image analysis improves the overall performance of neurological disorder screening compared to using a single data source. The multimodal fusion approach, especially using a transformer-based model, helps in effectively learning the relationship between brain activity and ocular features. The use of XGBoost along with SHAP interpretation provides better transparency, allowing clinicians to understand how the model makes decisions. This improves the trust and usability of the system in real-world applications. Another important advantage of the system is its reduced processing time, where automated analysis significantly decreases the time required compared to manual methods. This can be very useful in clinical environments where quick decision-making is needed. However, the system still has some limitations. The performance of the eye image analysis depends heavily on the quality of fundus or OCT images, and poor-quality images may reduce accuracy. Therefore, proper image acquisition and preprocessing are important for reliable results.

Ablation Study:

- EEG-only accuracy: 92.1%
- Eye image-only accuracy: 93.4%
- Combined model accuracy: 96.2%

This shows multimodal fusion improves performance.

Fig. 1: Eye Image



Fig. 2: Alpha Band Signal

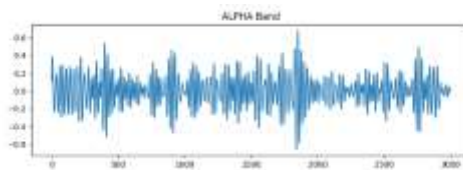


Fig. 3: Beta Band Signal

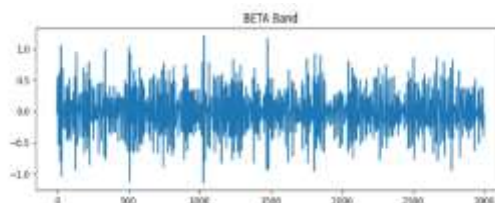


Fig. 4: Delta Band Signal

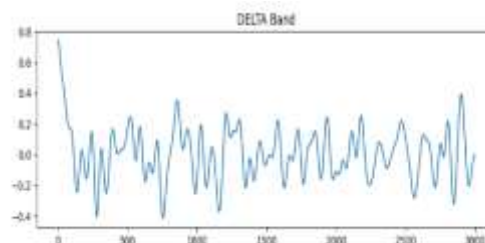


Fig. 5: Gamma Band Signal

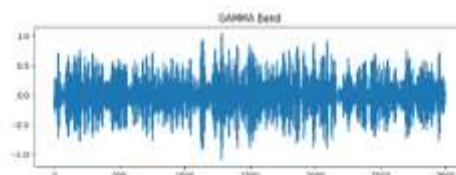


Fig. 6: Epileptic Spike Detection

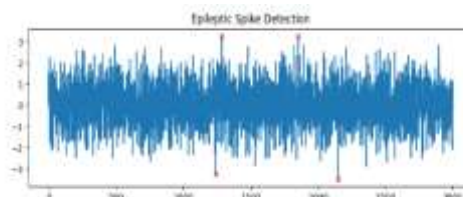


Fig. 7: Glaucoma Result

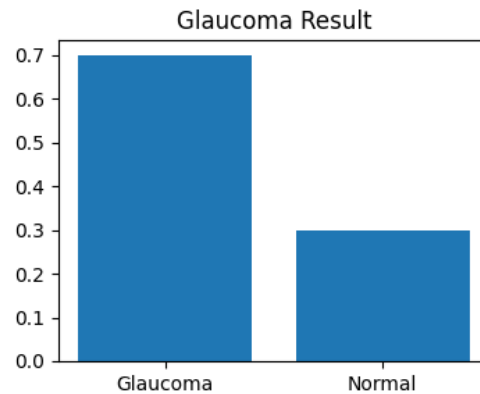


Fig. 8: Raw EEG Signal

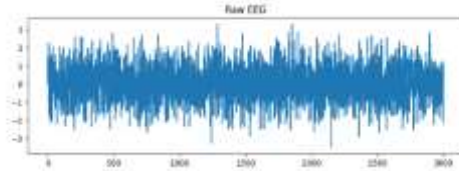
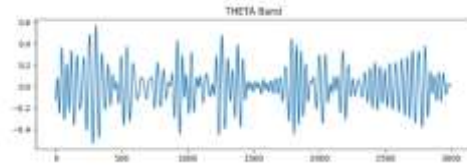


Fig. 9: Theta Band Signal



10. LIMITATION

The performance of the system mainly depends on the quality of the input data. If the EEG signals are noisy or the eye images are of low quality, the accuracy of the results may be affected. Further validation using large-scale real-world datasets is required to improve the robustness of the system.

11. CONCLUSION

The Neurovexa system presents a multimodal artificial intelligence approach for the detection of neurological disorders by combining EEG signal analysis and eye image processing. By integrating these two types of medical data, the system improves the overall accuracy and reliability of disease detection compared to single-modality approaches. The use of deep learning models such as CNN-LSTM and U-Net, along with transformer-based feature fusion and XGBoost classification, enables effective extraction and analysis of both brain activity and ocular features. The system also provides fast and automated report generation, making it suitable for real-time clinical support and remote healthcare applications. Overall, Neurovexa demonstrates strong potential in assisting doctors and healthcare professionals in early diagnosis and decision-making. In future work, the system can be further improved by using larger real-world datasets, enhancing model performance, and extending the system for continuous patient monitoring and additional neurological conditions. This study uses publicly available datasets and does not involve direct patient interaction. Therefore, no ethical approval is required.

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