Development of an AI-Powered Web Application for Medical Diagnosis of Epilepsy, Seizures, and Stroke Using EEG Images

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Abstract: Neurological diseases including epilepsy, seizure and stroke present the most critical public health concerns, contributing greatly to the global burden of disability and death. Early and precise diagnosis is critical for effective treatment, however traditional methods are frequently time-intensive, expensive, and unavailable in isolated or resource-poor regions. In the current era of rapid advances in artificial intelligence (AI) and machine learning (ML), we have the opportunity to transform diagnostic paradigms in neurology. This research introduces a combined AI-enabled diagnostic model for developing non-invasive image-based EEG analysis to a structured symptom depiction to better early detect epilepsy, seizure and stroke. The method combines clinical symptoms supplied by the users among EEG images transformed by a convolutional neural network model contrived of 78% diagnostic accuracy. The model was evaluated using various performance measures including accuracy, precision, recall, and loss. A web-based interface for this system built using Flask provides current predictions in real time, which is now easily usable for physicians as well as patients. The results of this study present implications for an emerging field of computational neuroscience, demonstrating the potential synergy for AI-assisted neurology diagnosis by integrating multi-modal diagnostic inputs.

Keywords: Epilepsy, Seizures, Stroke, EEG Analysis, Symptom-Based Diagnosis, Image-Based Diagnosis, Machine Learning, Artificial Intelligence, Neurological Disorders, Diagnostic Web Application, Convolutional Neural Network (CNN), Deep Learning, Medical Imaging, Real-Time Prediction, Flask Web Application

1. Introduction

There is no question that neurological diseases are among the most urgent health problems facing the world in the 21st century, impacting millions of people and accounting for a substantial burden of diseases on a global scale. The most common and severe of such disorders include epilepsy, seizures, and stroke, where each of these is associated with complex neural dysfunctions that can lead to cognitive impartment, physical unconsciousness, and fatality. Take epilepsy, a disorder affecting the brain that causes recurring seizures—seizures that stem from irregular electrical activity in the brain. A stroke is the sudden loss of brain function resulting from an interruption in the blood supply and is often associated with long-term disability. Although, multitude of improvements have been made in the field of healthcare, without a well-established laboratory-based diagnostic framework, early precise diagnosis of these illnesses remains a major problem because of the overlapping of symptoms, subjective nature of early clinical assessment, and lack of conventional tools.

Conventional diagnostic routes for these disorders depend mainly on clinical evaluations neuroimaging procedures including MR and CT imaging and in some cases the use of EEG. However, these approaches are not only labor-intensive and costly, they also rely on sophisticated instruments and skilled interpretation, which are not always accessible (e.g., in under-resourced or remote areas). These traditional systems have a delay in response time, which may disrupt timely treatment in cases of stroke, where "time is of the essence," and diminish the overall effectiveness of interventions in epilepsy treatment and seizure prevention. In addition, symptoms such as numbness, dizziness, visual symptoms, or headaches are far too nonspecific to be definitive without elaborate testing. In this context, artificial intelligence (AI) and machine learning (ML) approaches are becoming ubiquitous as groundbreaking technologies able to overcome many of the hurdles in neurological diagnostics. These smart algorithms can look at huge datasets of clinical and image data, process it and work out complex patterns that even the best neurologists may not pick up. Deep learning models, e.g., CNNs, have been successful in medical image classification and pattern recognition, including those based on EEG and other neuroimaging recordings.

Convolutional Neural Networks are capable of automatically learning hierarchical features from image data, and can capture complex relationships which may not be recognized by conventional methods.

At the same time, structured symptom analysis via ML classifiers offers a parallel diagnostic rung based on the extraction of predictive variables from reported data by the user, which enables a model to make probabilistic predictions about the patient's condition even before the image acquisition. In this scenario, we present a web-based diagnostic artifact using AI approach which is an innovative system developed for the detection of epilepsy, seizures and stroke. This method is a combination of symptom-based with image-based diagnosis. The system incorporates a deep learning model to interpret EEG images and a machine-learning classifier to handle user reported symptoms entered via a responsive web interface. By combining these it avoids the risk of diagnostic decisions having to be based purely on imaging, but rather can be made on patient reported symptoms – improving the diagnostic accuracy and robustness.

This approach allows faster diagnosis and could represent a helpful aid in populations with restricted availability of neuro-imaging facilities/specialists. Furthermore, the app is built on the Flask web framework, allowing easy deployment, scaling, and accessibility to users. This renders the system very well suited as an application in a clinic, community health care centre, or directly to a patient. The web server interface for users or clinicians to upload EEG images and to enter symptoms through our guided form, upon which to predict diagnosis using AI-based engine with high efficiency. In this study, the accuracy of 78% of the used model was reported as an indication that it can help clinical decisions.

Through proposing such an approach, the study is in accordance with the continuing advancement of AI-based individualized healthcare and undergirds its future improvement and development. such as the incorporation of patient history, real time monitoring, or federated learning among distributed diagnostics. Beyond demonstrating the potential of AI to enhance healthcare services, this project further addresses the growing demand for fast and accessible neurological diagnostics, especially in cases where other methods are simply not available. With AI integration, the company says this system is designed to redefine the diagnostic experience

2. Literature Review

There has been much progress made in the field of artificial intelligence (AI) as applied to diagnostic neurology over the last decade. AI technologies, in particular deep learning methods including convolutional neural networks (CNNs), have completely transformed the field of medical image analysis by enabling the discovery of complex patterns in neuroimaging data that might not be readily apparent to the human observer. These models have shown performance competitive with or surpassing that of expert radiologists when trained on large and varied datasets. For example, in the detection of epilepsy, stroke, and seizure, CNNs are commonly used to analyze electroencephalographic (EEG) signal and MRI or CT scan for accelerating the process of diagnosis and improving the precision of diagnosis. These advances emphasize the growing importance of AI for scalable and cost-effective neurological care. Apart from imaging, the psychological aspects of neurological diseases have also been considered in recent studies. Psychological symptoms like depression, anxiety and stress are frequently associated with neurological disorders. Such mental phenomena cannot only coexist but also worsen together with underlying neurological disease. The symptoms of depression, anxiety, and stress were measured by an application of the DASS-42. Furthermore, psychological testing tools should also be integrated into AI-driven decision support systems, since a global image of the patient is given by such tools as well up-to-date research suggests. This integrative perspective acknowledges the interdependence of mental and neurological health and encourages greater attention to "whole-brain health" as well as expansive, not simply circumscribed, diagnostic approaches in both clinical and research domains.

In addition, the incorporation of multimodal data has been a strong enrichment in diagnostic modeling. Multi-modal AI models that aggregate data from different domains are demonstrated to have higher accuracy and reliability than single-modal models. These models can capture sophisticated associations across various forms of data, better characterizing the patterns and progression of the disease and targeting interventions more effectively. In particular, combining symptom-based information (e.g., patient-reported experiences) with image based-diagnostic tools (e.g., EEG or brain scans), supports early detection and differentiation of similar neurological disorders, an important factor in intervention planning. Recommendation This overview of the extant literature illustrates the firmer soil on which this research is established, and the urgent need at the same time for more comprehensive disease models that faithfully reflect the entire complexity of neurological disorders for improved patient management.

AI approaches have started to contribute to this aim but an additional effort is necessary to leverage larger data dimensions such as psychological and symptomatic profiling which is required for reaching truly comprehensive care. Our work seeks to close this gap by integrating image-based predictions with symptom analysis to provide a dual-modality diagnostic tool that focuses on attaining greater accuracy, reducing diagnosis time, and scalable deployment via web-based apps for more effective neurological diagnostics and better patient outcomes.

3. Proposed Methodology:

3.1. Data Collection:

In the first stage of our method, real EEG image data and symptom-based clinical input of neurological diseases. EEG (Electroencephalography) data is of distinct benefit for identifying non-normal brainwave data and pattern recognition in conditions such as epilepsy and seizures. The datasets were thoughtfully collected from available publicly medical research repositories and well-confirmed open-access databases with the real patient EEG images that were labeled according to medical conditions. Other than image information, we extracted (for diagnostic purposes) a compiled set of symptoms from neurological literature and clinical diagnostic research reduction of severe headache, dizziness, visual problem, seizures, numbness, confusion, and balance disorder. A questionnaire-style input interface for the symptom-based diagnostic pathway was constructed using these symptoms. By combining both the physiological and patient-reported information, this two-pronged strategy enables a comprehensive and objective evaluation for neurological diseases.

3.2. Data preprocessing:

The quality and consistency of the data must be guaranteed in the preprocessing before the training of the models. For the EEG image data, standard procedures, including resizing, normalization and grayscale conversion, were performed to achieve the uniformity of input and save computation cost. All images were resized to fixed dimension appropriate for input to the deep learning models. We normalized all pixel values to achieve between 0 and 1 to facilitate training and overall model convergence. The symptom data, after encoding the categorical values as the binary form of a symptom (1 present sign and 0 no present sign, they can be used directly as input of the model. Furthermore, the data was split into training, validation and test data sets in a stratified fashion to also respect the class distributions and to prevent test data from leaking into the training process. This preprocessing mechanism guaranteed that the image and symptom data were both in the best format for learning and correct model performance.

3.3 Model Creation

The model architecture selected is the convolutional neural networks (CNNs), which are very well for image classification task because of being able to extract the hierarchical spatial features. The architecture comprises several convolutional layers with ReLU activation functions, max pooling layers to reduce dimensionality, and fully connected layers to perform final classification. To reduce overfitting, dropout layers were incorporated, and the final output layer employed a SoftMax activation to output class probabilities for the neurological condition. We trained our model with the Adam optimizer with categorical cross entropy loss function for multi-class classification problem. The number of epochs and batch size are tuned by experimental means such that learning curves are smooth and the predictions are accurate. This tuning operation aided the model in balancing the generalization and performance and eventually resulted in its robustness to diagnose conditions from EEG images. The diagnostic accuracy of the trained model on the validation set was 78%, suggesting a potential power for practical use in both clinical settings and remote areas.

3.4. Performance Metrices:

Performance of the model was measured using our previous mentioned metrics: accuracy, precision, recall, and F1 scores, along with confusion matrices. These measures give a comprehensive picture of how well the model is doing in the task of discriminating epilepsy from seizure and stroke based on EEG images. The model produced an overall classification accuracy of 78%, which is considered reliable enough for medical pre-screening and showed promise to assist in diagnostic decision making in clinical and remote healthcare settings. The trend of the misclassification was identified using the confusion matrix and then rectified by retraining the model using a more balanced sub-set and tuning the hyperparameters. Sensitivity and specificity were distorted to stress the model sensitivity to positive cases without increasing false positives. This recall focus was critical to limit missing key neurologic conditions, whereas high precision reduced unnecessary alerts. In general, the evaluation results ensured that the model was adequately effective and generalizable over diagnostic categories.

3.5. Flask App Development:

Once the model was trained and validated, we deployed it within a Flask-based web application that integrates both image-based and symptom based diagnostic pathways. The web application features a simple and intuitive interface where users can upload EEG images or answer a questionnaire about their symptoms. Upon submission, the backend Flask application processes the input, feeds it to the trained model, and returns the predicted neurological condition with a user-friendly interpretation. This approach bridges the gap between clinical-level diagnostics and public accessibility, providing a prototype for AI-assisted pre-screening that could be further developed for clinical use.

4. Results & Discussion:

The validation of the AI system was performed with actual EEG images and symptom-based clinical input in relation to neurological issues such as: epilepsy, seizures, and stroke. The performance of the model was evaluated with certain important performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix. These markers offer an integrated overview of the predictive performance of the model and its readiness to be used in a real-life diagnostic scenario, particularly in settings where standard neurological diagnostic facilities are limited or not available. After training and validating the CNN with pre-processed EEG images, it reached an overall accuracy of 78%. These findings indicate that the model correctly recognized the neurological condition in four out of five cases. The confusion matrix demonstrated a misclassification, especially in the group of seizure patterns and epilepsy-related patterns of EEG, because of overlapping neurological symptoms. Stroke cases, however, were more recognizable, presumably because of their characteristic signal patterns, that are easier to distinguish.

Apart from accuracy, we calculated the precisions and recalls of the classes. It achieved an accuracy of 80% for epilepsy, 76% for seizures, and 78% for stroke. Specificity was slightly less for seizure cases (~74%) suggesting that some seizures were overlooked. However, as the F1-score is the harmonic mean of precision and recall, a reasonable balance was achieved for all categories, which demonstrates the model's discrimitative power; this has been shown to remain stable in the context of neurological pattern recognition using EEG despite its complexity.

The well adapted coefficients in both groups confirm a good stability of the parameters. Though there are things that can be improved, especially the recall for seizure classification, the model creates a good basis taking the natural variability and complexity of the human signal into account. Notably, the addition of symptom-based evaluation (with a standardized questionnaire) led to increased diagnostic certainty. In situations where the image-based predictions were uncertain, symptoms provided an important additional screening layer that helped the diagnosis be made in a more accurate and more versatile manner. This two-tier diagnostic approach increases accessibility, particularly in situations where EEG imaging is not easily accessible. A web-based system using Flask as interface that was tested for interactivity, response time and usability. The performance was found to be good in terms of user anticipations indicating that the possibility of using the system in clinical, rural diagnostics, and telemedicine applications exists. Some of the key advantages stem from its simple end-user interface and a strong back-end AI engine that allow even non-experts to perform reliable pre-screening without special training.

In conclusion, our findings demonstrate the robustness of the proposed AI system as a potential clinical instrument to detect early neurological disorder. The dual diagnostic pathways of the system, based on EEG imaging and the symptom-based inputs, endow the system with wide-range applicability and high adaptability. Additional improvements may be to include more diverse datasets, fine-tuning hyperparameters, and including additional physiological drivers such as genetics or behavior. These enhancements may further increase model accuracy to make it appropriate for clinical or remote health application at a larger scale.

5. Conclusion:

This effort presents a successful implementation of a dual-mode diagnostic Web app capable of identifying diagnoses related to neurological conditions (such as epilepsy, seizures, or stroke) using symptoms and image analysis. The combination of machine learning models with a Flask web interface allows for an online diagnostic tool. The model, build using real EEG image data, achieved 78% accuracy - an encouraging result despite classification of medical image and differences in the neural pattern. One of the main merits of this work is that the detection model is trained and tested on real EEG databases, which makes the model prediction more realistic. The model was made with user friendliness at its core, so that professionals as well as non-professionals can effortlessly up-load EGG images or insert their symptoms. With the help of machine learning with image classification, the platform allows for the diagnosis in real time – a critical dimension in dealing with time-sensitive ailments such epilepsy and stroke. Though promising, the 78% accuracy of the model indicates room for improvement. This could be mitigated by introducing more diverse EEG patterns in the dataset and investigating deeper neural models. Other benefits Wetin et al., "As the preprocessing in terms of more sophisticated noise removal and feature extraction became more advanced, the input quality was improved, which improved the model." These improvements would help to yield more accurate and precise diagnostic results even in the presence of additional patient data. The modularity and scalability of the system permits future improvement and deployment into other scenarios. The web based application can be easily updated as dataset and model progresses. Further research might also entail the addition of multi-dimensional behavioural endophenotypes, genetic markers, extended symptom profiles—to improve the diagnostic accuracy and stability of our approach. This could expand the application's practicality and applicability in real-world health care environments. By using the Flask its become easy to bind the machine learning model into a responsive web app. It also can be scale vertically or horizontally from a local server to cloud server, so it can be used by the users in the rural or underserved areas. That cloud compatibility means the real-time diagnostic service isn't limited by geography, and it suggests the solution may be a natural fit for telemedicine and mobile health services.

In the end, the project is a good demonstration of what artificial intelligence can do together with modern web technologies to change the game in healthcare diagnostics. Although the current accuracy is encouraging, further optimizations may further improve the diagnostic performance. With the healthcare industry becoming data-rich and AI-Eager, the project is a significant step forward, proving that rapid AI-guidances, automated and reliable medical diagnosis is an attainable and deployable solution for broad clinical and non-clinical applications, ultimately toward better patient care and outcome.

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