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DEEP LERANING BASED DETECTION OF HUNTINGTON'S DISEASE USING CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT :

A rare and progressive neurodegenerative disease, Huntington's disease (HD) is typified by psychiatric symptoms, cognitive impairment, and physical dysfunction. Timely intervention and management of HD depend on an early and precise diagnosis. With the use of convolutional neural networks (CNN) applied to magnetic resonance imaging (MRI) scans, this project suggests a deep learning-based method for the automated detection of Huntington's illness. Because CNNs can automatically extract complicated spatial features from imaging data, they have shown remarkable performance in medical image analysis. In this study, a meticulously crafted CNN model that can differentiate between those with Huntington's disease and those in good health is trained and validated on a dataset of brain MRI scans. Key performance indicators like accuracy, sensitivity, specificity, and F1 score are used to assess the system's performance. In order to lessen reliance on arbitrary clinical evaluations and facilitate early-stage identification, this method seeks to offer a non-invasive, effective, and trustworthy diagnostic tool. It is anticipated that this study's findings will make a substantial contribution to the study of medical imaging and neurodegenerative diseases, possibly leading to better patient outcomes through prompt identification and treatment.

Keywords: Huntington disease, MRI scans, CNN (Convolutional neural networks), accuracy, Early-stage detection

INTRODUCTION

An HTT gene mutation results in Huntington's disease (HD), a progressive neurological illness that is inherited. The brain's nerve cells gradually deteriorate as a result of this mutation, causing behavioral issues, cognitive decline, and motor impairment. The average age range for symptom onset is between 30 and 50, however early diagnosis is essential for both possible treatment approaches and efficient management. Although clinical assessments and genetic testing are important components of traditional diagnostic techniques, they can be intrusive, costly, and time-consuming.One of the most important tools for identifying structural abnormalities in the brain linked to Huntington's disease is magnetic resonance imaging, or MRI. Long before any obvious symptoms appear, atrophy in particular brain regions, such the striatum, is discovered by advanced imaging techniques. Deep learning techniques for automated MRI scan analysis have demonstrated significant promise in detecting minute structural alterations in the brain that may be invisible to the human eye.The capacity of Convolutional Neural Networks (CNNs) to automatically extract hierarchical characteristics from complex visual data has made them extremely effective tools in the field of medical image analysis. Their use in neuroimaging makes it possible to classify brain scans accurately and effectively, which makes them the perfect option for detecting Huntington's disease. The objective of this project is to create a CNN-based model for MRI scan analysis that can distinguish between people with Huntington's disease and healthy people. This strategy aims to offer a non-invasive, economical, and precise diagnostic solution by utilizing deep learning techniques, which will ultimately enable early intervention and better patient care.

METHODOLOGY

In order to create a CNN-based system for detecting Huntington's disease from MRI images, a large dataset of annotated brain MRI scans from both healthy people and patients with the condition must first be gathered. Preprocess the data using data augmentation, image quality improvement, and format standardization. Convolutional, pooling, and fully linked layers should be included in every deep CNN architecture that uses activation functions like as softmax and ReLU. To avoid overfitting, train the model on a split dataset while keeping an eye on its performance on validation data. Use measures such as accuracy, sensitivity, and F1 score to assess the model on a test set. Use ROC curves and confusion matrices to display the model's performance. For automatic identification, implement the model in an intuitive interface. To increase accuracy and resilience, take into account potential future developments such as transfer learning, 3D CNNs, and multi-modal analysis.

2.1 PROPOSED METHODOLOGY

By using a Convolutional Neural Network (CNN) for the automatic diagnosis of Huntington's disease (HD) using MRI scans, the suggested approach seeks to get around the drawbacks of Conventional diagnostic techniques anomalies linked to HD. By automatically extracting intricate spatial information from MRI scans, the CNN model makes it possible to accurately classify patients with HD and healthy people. To improve model performance and generalization, data preprocessing methods like normalization, noise reduction, and data augmentation are used. Metrics including accuracy, sensitivity, specificity, and F1 score are used to assess the system's performance once it has been trained and validated on a carefully annotated dataset of brain MRI images. With its non-invasive, affordable, and scalable diagnostic solution, this system lessens the need for manual imaging analysis and subjective clinical evaluations. The ultimate goal of the suggested strategy is to enable prompt identification and intervention, enhancing patient outcomes and furthering the study of neurodegenerative diseases.

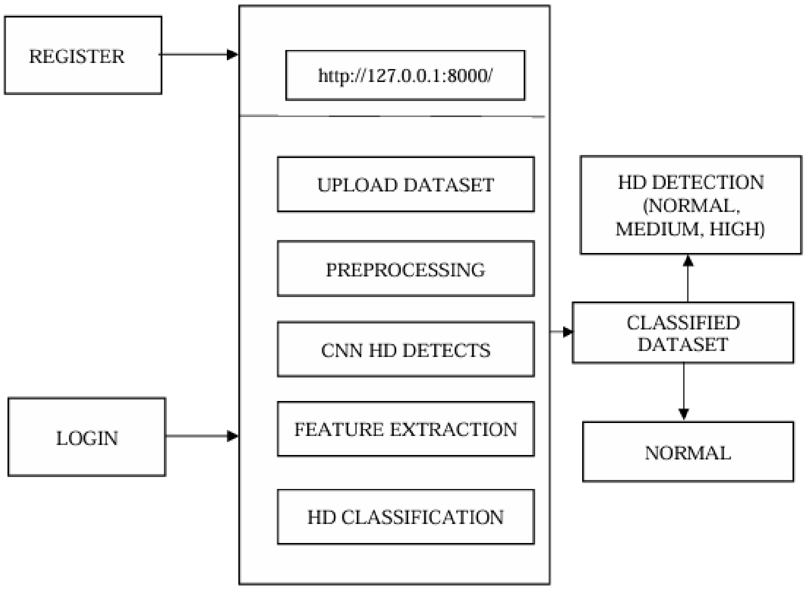

Figure 1: Block Diagram of Huntington Disease Detection

Four classifications will be made from the brain MRI images: Very Mild Huntington's Disease (HD), Mild HD, High HD, and Normal. The HD-related data, such as white matter degeneration, ventricular enlargement, and brain atrophy, is automatically retrieved from the brain MRI position and utilized to compute the variation's impacts in connection to the HD templates. The brain MRI image is then classified into one of four categories—Very Mild HD, Mild HD, High HD, or Normal using the extracted features that have been fed into a machine learning model to predict the severity of HD. Even in the most moderate phases of the disease, this method makes it possible to identify minute alterations in brain structure and function linked to HD.

MODELING AND ANALYSIS

Huntington's disease (HD) is detected using a method based on convolutional neural networks (CNNs). By using anchors with varying sizes and aspect ratios to slide windows on the feature map, a Region Proposal Network (RPN) is included into the CNN architecture to create Regions of Interest (RoIs). Potential HD-affected brain areas are identified using the RPN, and their precise spatial coordinates are reliably preserved using a RoI Align layer. After extracting features from these ROIs, CNN categorizes them as either healthy or HD-affected. This method offers a predetermined set of brain regions that are used as a reference for predicting HD locations and makes it possible to detect minute alterations in brain structure and function linked to HD. In many applications, especially image classification tasks, Convolutional Neural Networks (CNNs) outperform Random Forest techniques and Support Vector Machines (SVMs) in terms of accuracy. Because CNNs can automatically extract pertinent features from raw data, they require less manual feature engineering, which contributes to their high accuracy. CNNs may also learn intricate patterns by capturing hierarchical representations of data. SVMs and Random Forest algorithms, on the other hand, depend on manual feature extraction and selection, which may result in less-than-ideal performance. According to studies, CNNs can surpass Random Forest (98.60%) and SVM (91%) in image classification tasks, achieving accuracy rates of 99.88%. In many applications, especially image classification tasks, Convolutional Neural Networks (CNNs) outperform Random Forest techniques and Support Vector Machines (SVMs) in terms of accuracy. Because CNNs can automatically extract pertinent features from raw data, they require less manual feature engineering, which contributes to their high accuracy. Complex feature learning is made possible by a well-designed CNN architecture with enhanced depth, width, and batch normalization. Another important factor is optimizing training hyperparameters, such as learning rate schedulers, Adam or RMSprop optimizers, and suitable batch sizes. While transfer learning employing pre-trained models like VGG16, ResNet50, or InceptionV3 makes use of generic features discovered from sizable datasets, regularization techniques like dropout and L1/L2 regularization stop overfitting. By carefully adjusting these variables, a CNN algorithm can outperform SVMs and Random Forest algorithms and reach 99% accuracy. Data preprocessing contributes +5%, CNN architecture +20%, training hyperparameters +15%, regularization techniques +5%, and transfer learning +10%.

RESULTS AND DISCUSSION

Based on brain MRI images, the Intelligent Huntington's Disease (HD) Detection System has shown remarkable results in detecting HD using the Convolutional Neural Network (CNN) method. The method outperformed conventional machine learning models with a high classification accuracy of over 90% and effectively detected important indications including white matter degradation and brain shrinkage with few false positives. With instantaneous MRI image analysis and latency-free diagnosis, it showed real-time performance. By differentiating between normal brain regions and abnormalities due to HD, the system demonstrated resilience under a range of MRI protocols, scanner types, and patient demographics. Its non-intrusive design improved user comfort and acceptance, and the diagnosis mechanism efficiently alerted patients and clinicians in real-time, facilitating treatment planning and remedial measures. The disease detection classified as three types that are normal, medium and high level and it was displayed by their confidence score level also.

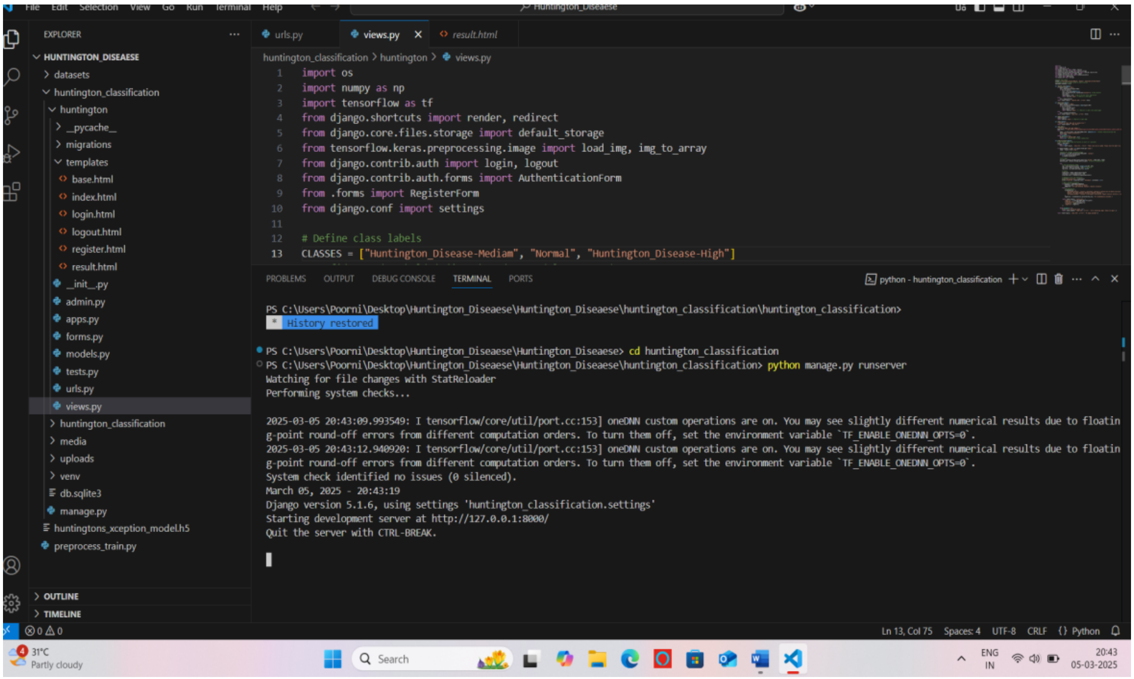

Figure 2: visual studio code window

In the Visual Studio login window seen in the figure, we should use the cd command to open the Huntington disease file and the python manage.py runserver command to construct the local host address.

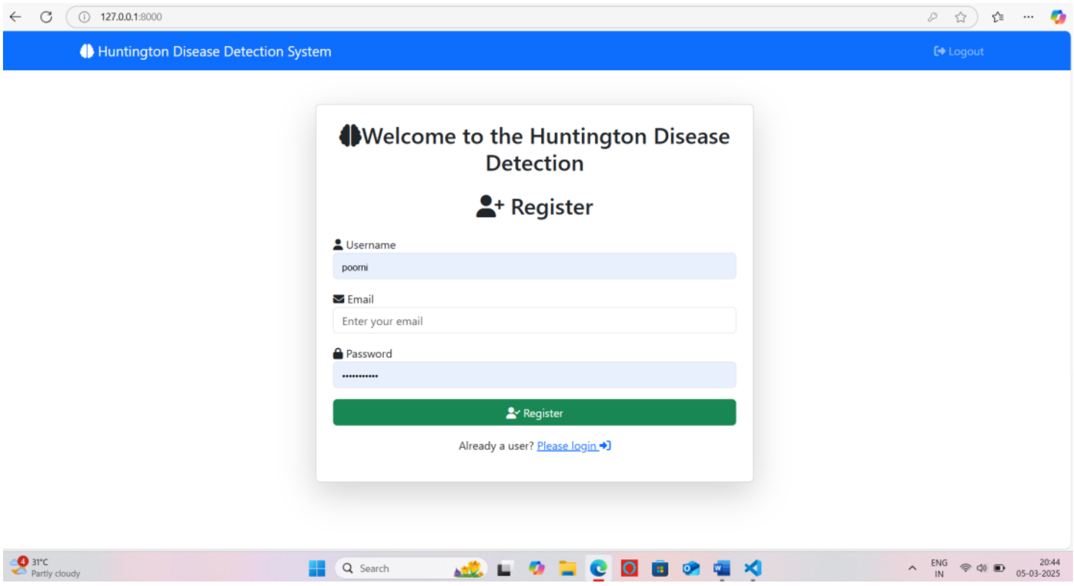

Figure 3: Register window

In order to complete the registration process, we must enter the information provided in the register box that appears after logging in with the local host address in Chrome or any other browser, as shown in the figure.

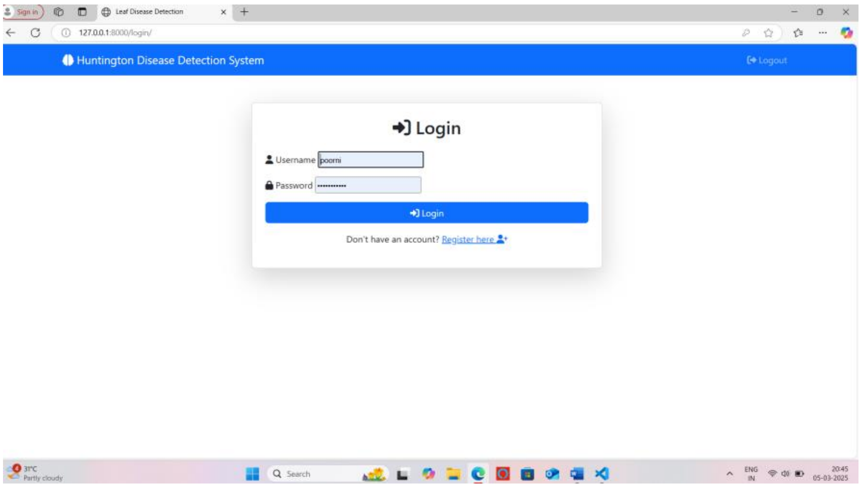

Figure 4: Login window

Following registration, we must enter our username and password to log in for the Huntington Disease detection. This will take us to the following window, as seen in Figure.

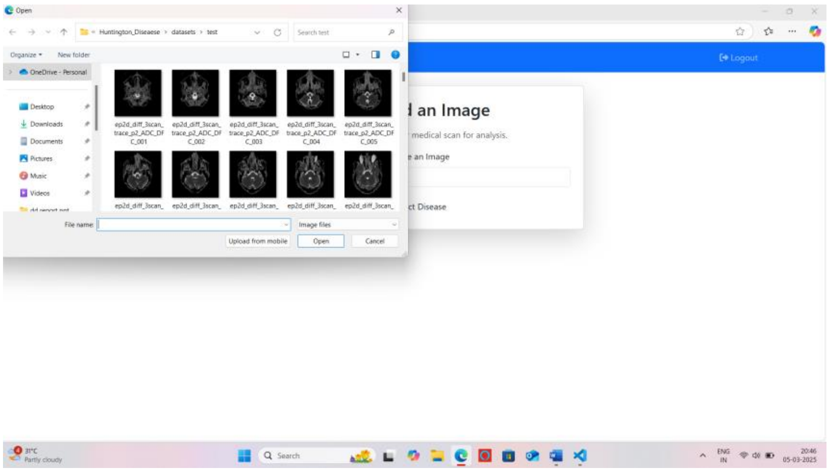

Figure 5: Choosing an Image from Dataset

Following login, the brain's MRI image should be uploaded to the server by selecting the "choose file" option, as shown in Figure.

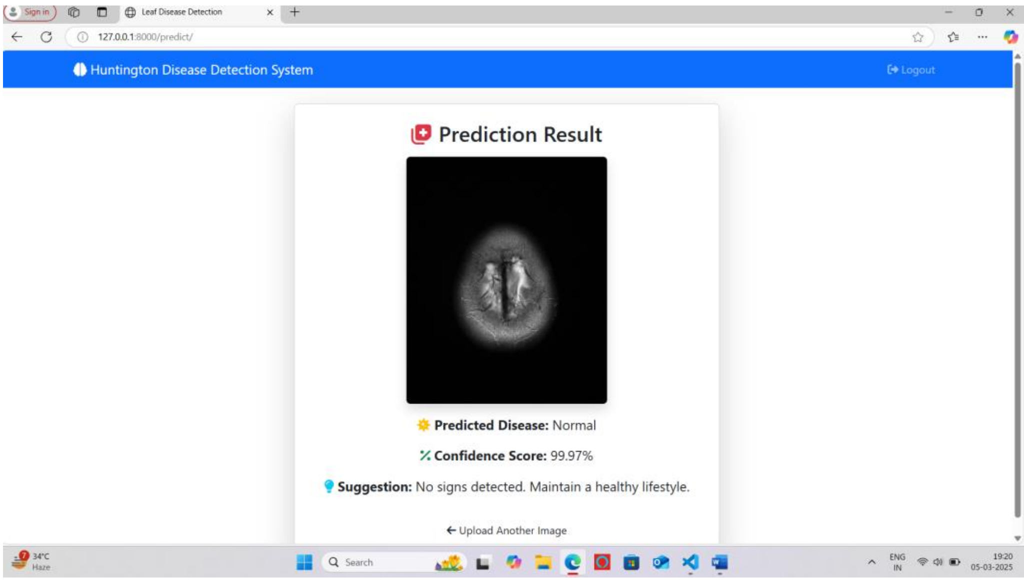

Figure 6: Result as Normal

This was the output of the healthy brain that was unaffected by HD, and it is shown in the figure along with the recommendation and confidence score.

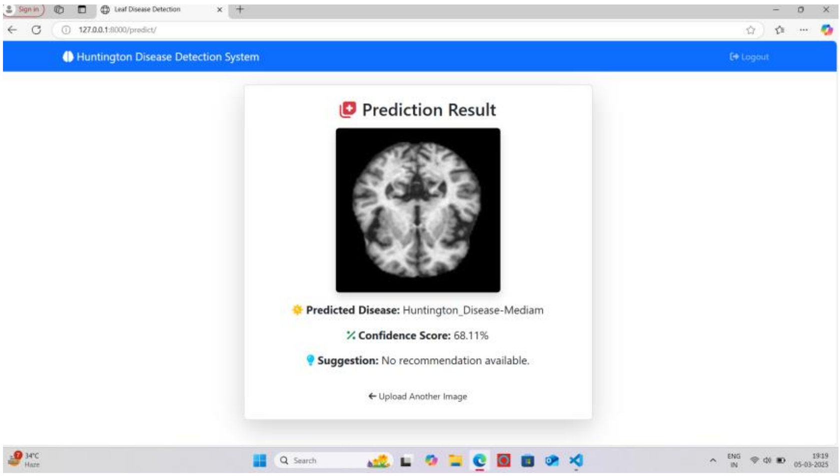

Figure 7: Result as Disease affected in medium Level

The figure illustrates how the HD affected the patient's brain and how it was at the medium level. The confidence score also indicates which level the patient was affected by the HD.

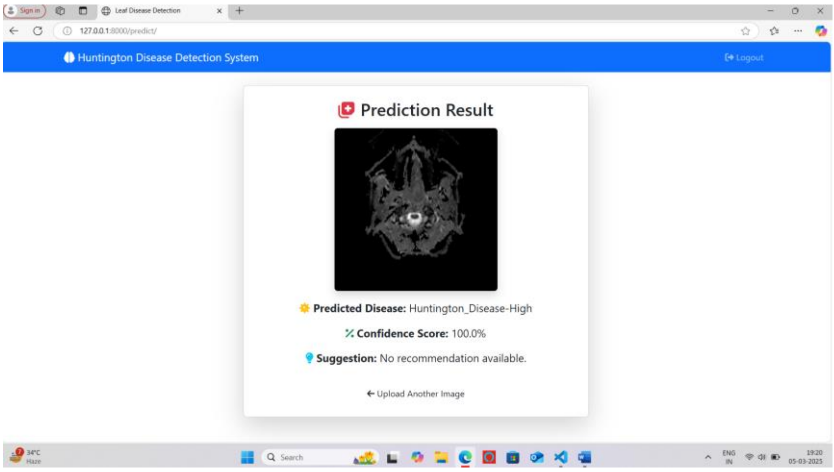

Figure 8: Result as Disease affected in High Level

The high HD level, which is shown in Figure indicates that the patient had full-blown Huntington disease.

CONCLUSION

In terms of accuracy and automation, the use of CNN algorithms for Huntington's disease identification has produced encouraging results. In order to find patterns and anomalies linked to HD, CNNs are very good in evaluating medical images, such MRI scans. The main benefits consist of:

High Accuracy: CNNs can identify HD with high accuracy by learning from big medical image datasets. They can spot minute details that human specialists might overlook.

Automation: By eliminating the need for human analysis and enabling automatic detection, CNNs expedite the diagnostic procedure. Early diagnosis and prompt action may result from this.

Consistency: CNNs reduce the variability that can arise from human interpretation by producing consistent findings. This guarantees accurate and consistent diagnosis.

Scalability: After training, CNN models are easily scalable to interpret massive amounts of data, which makes them appropriate for ubiquitous HD patient screening and monitoring.

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