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EARLIER DETECTION OF PARKINSON'S DISEASE FROM BRAIN MRI IMAGE USING DEEP LEARNING

Ms. S. Puvaneswari*1, R. Sindhu*2

*1Assistant Professor, Department Of Computer Science And Engineering, Kings College Of Engineering, Punalkulam, Pudukottai DT, Tamilnadu, India.

*2Student, Department Of Computer Science And Engineering, Kings College Of Engineering, Punalkulam, Pudukottai DT, Tamilnadu, India.

ABSTRACT

Parkinson's disease (PD) is a progressive neurodegenerative condition characterized by the gradual deterioration of specific nerve cells in the brain, particularly those responsible for producing dopamine. Existing systems implemented to detect PD using different types of Machine Learning (ML) models such as Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbour (KNN), to differentiate between healthy and PD patients by MRI. But these algorithms are time-consuming and accuracy is less. So this study introduces a novel approach for the early prediction of Parkinson's disease (PD) using Convolutional Neural Networks (CNN). Leveraging the power of deep learning, specifically tailored to image analysis, our proposed CNN algorithm analyses medical imaging data to detect subtle patterns indicative of Parkinson's disease. The research utilizes a diverse dataset of neuroimaging scans, incorporating magnetic resonance imaging (MRI), to train and validate the CNN model. The system aims to provide accurate and efficient predictions, enabling early diagnosis and intervention. Through rigorous evaluation and validation, our CNN algorithm demonstrates promising results, showcasing its potential as a valuable tool in disease diagnosis. This project contributes to the ongoing efforts in leveraging advanced technology for the early detection and management of neurodegenerative diseases, ultimately improving patient outcomes and enhancing the effectiveness of healthcare interventions.

Keywords: Gathering Dataset, Binarization, Feature Selection, CNN Classification, And Disease Diagnosis.

I. INTRODUCTION

Parkinson's disease is a progressive neurological disorder that affects movement. It is caused by the degeneration of nerve cells in a part of the brain called the substantia nigra, which is responsible for producing dopamine, a neurotransmitter that helps regulate movement. As dopamine levels decrease, a person with Parkinson's disease may experience tremors, stiffness, slowness of movement, and difficulty with balance and coordination. Parkinson's disease is more common in people over the age of 60, but it can also affect younger people. There is currently no cure for Parkinson's disease, but treatments such as medication, therapy, and surgery can help manage the symptoms and improve the quality of life. It is important for people with Parkinson's disease to work closely with their healthcare team to develop an individualized treatment plan. Parkinson's disease is a chronic and progressive disorder, meaning that it worsens over time. The symptoms of Parkinson's disease can vary from person to person and can be divided into two main categories: motor symptoms and non-motor symptoms. Motor symptoms include tremors, rigidity, bradykinesia (slowness of movement), and postural instability (difficulty maintaining balance). These symptoms can make it difficult for people with Parkinson's disease to perform daily tasks, such as getting dressed, eating, and writing. Non-motor symptoms of Parkinson's disease can include depression, anxiety, sleep disturbances, constipation, and loss of sense of smell. These symptoms can have a significant impact on quality of life and may appear before motor symptoms. The exact cause of Parkinson's disease is not yet fully understood, but it is thought to involve a combination of genetic and environmental factors. There is ongoing research aimed at better understanding the disease and developing new treatments. Management of Parkinson's disease typically involves a multidisciplinary approach, which may include medication, physical therapy, occupational therapy, speech therapy, and surgery. The goal of treatment is to manage symptoms, maintain function, and improve quality of life. It is also important for people with Parkinson's disease to maintain a healthy lifestyle, including regular exercise and a balanced diet. Living with Parkinson's disease can be challenging, but with proper management and support, people with Parkinson's disease can continue to lead fulfilling lives. It is important for people with

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Parkinson's disease to stay informed about their condition and to work closely with their healthcare team to develop an effective treatment plan.

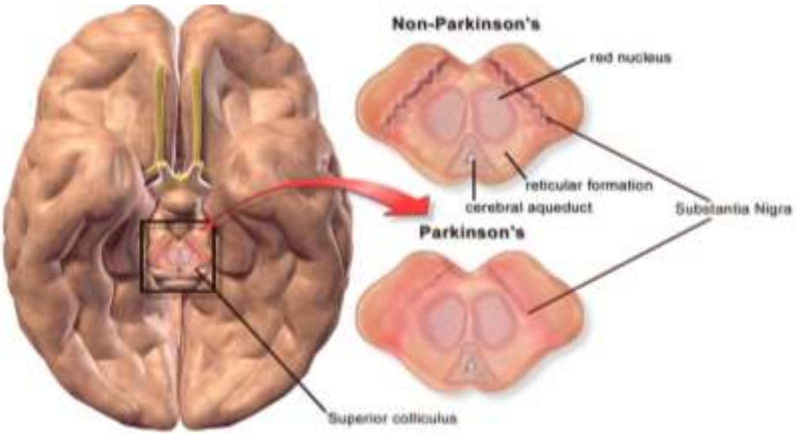

Fig: Parkinson Disease

Objectives:

One of the primary objectives of Parkinson's disease prediction is to detect the disease in its early stages, before the onset of significant motor symptoms. Early detection can help to improve treatment outcomes and quality of life for patients by enabling earlier intervention and disease management. Another objective of Parkinson's disease prediction is to monitor the progression of the disease over time. By analyzing data from various sources, machine learning algorithms can detect changes in symptoms and motor function and provide insights into disease progression. This information can help doctors to adjust treatment plans and provide personalized care.

II. METHODOLOGY

1. Data Collection:

Gather a diverse dataset of brain MRI images including scans from both healthy individuals and patients diagnosed with Parkinson's disease. Ensure the dataset covers a wide range of demographics, imaging protocols, and disease stages to improve the model's robustness.

2. Data Preprocessing:

Normalize the intensity values of MRI images to reduce inter-patient variability.

Standardize the image dimensions and voxel sizes to ensure consistency across the dataset.

Apply skull stripping to remove non-brain tissues from the images.

Optionally, perform data augmentation techniques such as rotation, translation, scaling, and flipping to increase the variability of the dataset.

3. Model Architecture Selection:

Choose a suitable deep learning architecture for the task. Convolutional Neural Networks (CNNs) are commonly used for image classification tasks due to their ability to automatically learn hierarchical features from the data. Consider state-of-the-art architectures such as ResNet, DenseNet, or Inception for improved performance.

4. Model Training:

Split the dataset into training, validation, and test sets. Typically, 70-80% for training, 10-15% for validation, and the remaining for testing.

Initialize the chosen model with random weights or pre-trained weights if available.

Train the model using the training set with appropriate loss functions (e.g., binary cross-entropy for binary classification).

Utilize techniques such as transfer learning if data availability is limited, by fine-tuning pre-trained models on the MRI dataset.

5. Hyperparameter Tuning:

Experiment with different hyperparameters such as learning rate, batch size, optimizer (e.g., Adam, SGD), and dropout rates to optimize the model's performance on the validation set.

Use techniques like grid search or random search to efficiently explore the hyperparameter space.

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6. Evaluation:

Evaluate the trained model's performance on the test set using metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC).

Additionally, analyze the confusion matrix to understand the model's performance across different classes (healthy vs. Parkinson's disease).

7. Interpretability:

Employ techniques such as class activation maps, gradient-weighted class activation mapping (Grad-CAM), or layer-wise relevance propagation (LRP) to interpret the model's predictions and identify regions of the brain contributing to the classification decision.

8. Validation and Clinical Integration:

Validate the model's performance on independent datasets to assess its generalization ability.

Collaborate with medical experts to integrate the model into clinical workflows, ensuring compliance with regulatory standards and ethical considerations.

Develop user-friendly interfaces or software for healthcare professionals to utilize the model for early detection of Parkinson's disease.

9. Continuous Improvement:

Regularly update the model with new data to adapt to emerging patterns and improve its performance over time.

Monitor the model's performance in real-world clinical settings and incorporate feedback from users to address any issues or limitations.

Existing system

Parkinson's disease is a neurodegenerative disorder that affects the central nervous system, and diagnosis typically involves a combination of clinical assessments and medical imaging, such as magnetic resonance imaging (MRI). There are several existing systems for Parkinson's disease prediction from brain MRI, including:

- Voxel-based Morphometry (VBM): VBM is a technique that involves comparing the gray matter volume between different groups of subjects to identify changes in brain structure that may be indicative of Parkinson's disease.

Disadvantages: VBM results can be highly sensitive to the quality of the input images. Increases the risk of false positives

- Support vector machine (SVM): SVM is a type of machine learning algorithm that can be used to classify different brain images based on patterns in the data. SVM has been used successfully to predict Parkinson's disease from brain MRI data.

Disadvantages: Difficulty handling noisy data, computationally intensive for large datasets

- Random forest (RF): RF is a machine learning algorithm that is particularly effective in handling high-dimensional data. It has been used successfully in Parkinson's disease prediction from brain MRI data.

Disadvantages: Computational complexity, handling imbalanced datasets

Disadvantages:

- Only support the small set of images
- Supervised approach
- High level false positive rate
- Computational complexity is high

Proposed system

- The project deals with the deep learning based method for extraction of features from the segmented region to detect and classify the normal and abnormal brain cells of medical brain MRI images for a large database.
- The proposed approach extracts texture and shape features of the brain region from the MRI scans and a neural network is used as a multi-class classifier for the detection of various stages of Parkinson's disease.
- The proposed approach is under implementation and is expected to give better accuracy as compared to conventional approaches.

Advantages:

- Accuracy

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- Efficiency
- Non-invasive
- Cost-effective

System Requirement:

Hardware requirements

Processor	: Intel core processor 2.6.0 GHZ
RAM	: 1GB
Hard disk	: 160 GB
Compact Disk	: 650 Mb
Keyboard	: Standard keyboard
Monitor	: 15-inch color monitor

Software requirements

Operating system	: Windows OS
Front End	: PYTHON
IDE	: PYCHARM
Libraries	: Tensorflow, KERAS

III. MODELING AND ANALYSIS

Deep Learning is a subset of machine learning that involves training artificial neural networks with multiple layers to recognize patterns in data. Deep learning algorithms can be used for a wide range of tasks such as image and speech recognition, natural language processing, and even playing games like Go and Chess. The main advantage of deep learning over traditional machine learning approaches is its ability to automatically learn features from raw data without the need for manual feature engineering. This is accomplished by stacking multiple layers of neurons, each of which performs a nonlinear transformation of the input data. The output of one layer serves as the input for the next layer, allowing the network to gradually learn increasingly complex representations of the input data. Popular deep learning algorithms include Convolutional Neural Networks (CNNs) for image and video processing, Recurrent Neural Networks (RNNs) for sequential data processing such as natural language processing, and Generative Adversarial Networks (GANs) for generating realistic images and videos. Training deep learning models requires large amounts of labeled data and significant 3 computational resources. However, recent advancements in hardware and software have made it easier to train deep learning models on a wide range of applications. Deep learning algorithms are based on artificial neural networks, which are inspired by the structure and function of the human brain. The networks consist of layers of interconnected nodes, or neurons, that process information in a hierarchical manner. The input data is fed into the first layer of the network, which extracts basic features. The output of this layer is then passed to the next layer, which extracts more complex features based on the previous layer's output, and so on. The process of training a deep learning model involves adjusting the weights and biases of the network's neurons to minimize the difference between the predicted output and the actual output. This is done by using a loss function that quantifies the difference between the predicted and actual output, and an optimization algorithm that updates the network's weights and biases to minimize this loss function. The most commonly used optimization algorithm is called stochastic gradient descent. One of the key advantages of deep learning is its ability to handle unstructured data such as images, video, and text. Convolutional Neural Networks (CNNs) are particularly effective at processing images and video, while Recurrent Neural Networks (RNNs) are better suited for sequential data processing such as natural language processing. Deep learning has had a significant impact on a wide range of industries, including healthcare, finance, and transportation. For example, deep learning algorithms are used in medical imaging to help diagnose diseases such as cancer, in finance to detect fraudulent transactions, and in transportation to improve self-driving cars' performance. However, deep learning is not without its challenges. One of the biggest challenges is the need for large amounts of labeled data to train the models effectively. This can be particularly challenging for applications where the data is scarce or expensive to collect. Additionally, deep learning models are often black boxes, meaning it can be challenging to

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interpret how the model arrives at its predictions. This can be problematic for applications where interpretability is important, such as in healthcare or finance.

Deep learning algorithms:

There are several types of deep learning algorithms, each of which is designed to solve different types of problems. Some of the most popular deep learning algorithms include:

Convolutional Neural Networks (CNNs): These are commonly used for image and video processing. They use a technique called convolution to extract features from the input image or video.

Recurrent Neural Networks (RNNs): These are used for sequential data processing, such as natural language processing. They can capture the context and relationship between different elements in a sequence.

Generative Adversarial Networks (GANs): These are used for generating new data that is similar to the input data. They consist of two networks: a generator network that generates new data and a discriminator network that evaluates whether the generated data is similar to the real data.

Autoencoders: These are used for unsupervised learning and feature extraction. They consist of an encoder network that compresses the input data into a lower-dimensional representation and a decoder network that reconstructs the original input from the compressed representation.

Deep Belief Networks (DBNs): These are used for unsupervised learning and feature extraction. They consist of multiple layers of restricted Boltzmann machines (RBMs) that can learn hierarchical representations of the input data.

Long Short-Term Memory (LSTM) Networks: These are a type of RNN that is designed to handle long-term dependencies in sequential data. They use memory cells and gates to selectively remember or forget information from previous time steps.

Each of these deep learning algorithms has its own strengths and weaknesses, and the choice of algorithm depends on the specific problem being solved.

IV. RESULTS AND DISCUSSION

The sign facts that are obtained from key characteristics datasets in experimental outcomes are used to gauge how beneficial the recommended approach is. F-measure, Recall, and Precision are used to assess the system's
performance.

Precision =TP/(TP+FP)

Recall =TP/(TP+FN)

F measure = 2* (Precision*Recall)/(Precision+Recall)

The ratio of the overall number of flawless predictions to the entire quantity of test data is known as accuracy (ACC). Another way to show it is as 1 - ERR. The accuracy ranges from 0.0 to 1.0, with 1.0 being the best attainable accuracy.

ACC= (TP+TN)/(TP+TN+FN+FP) x 100

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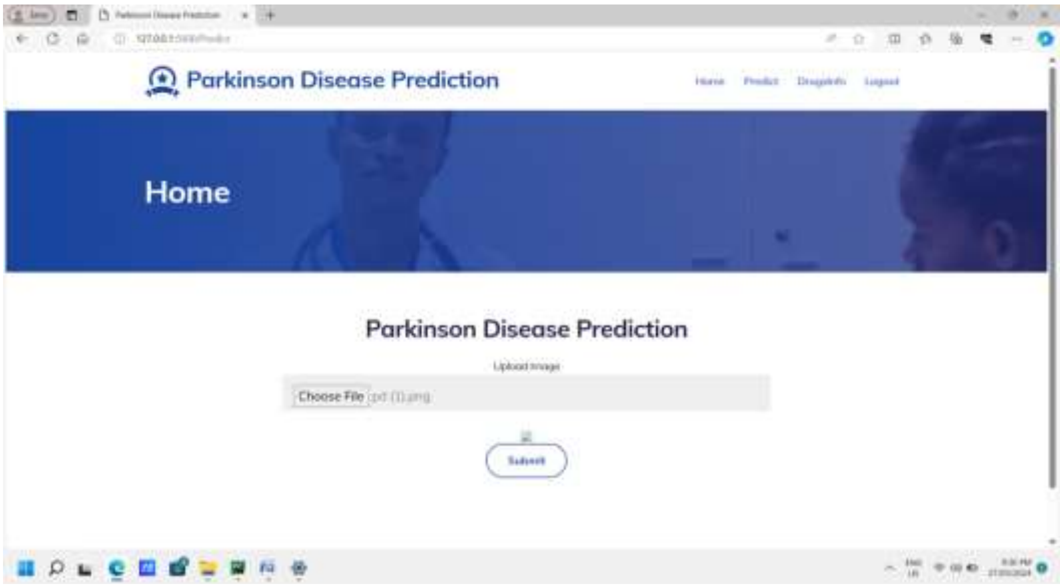

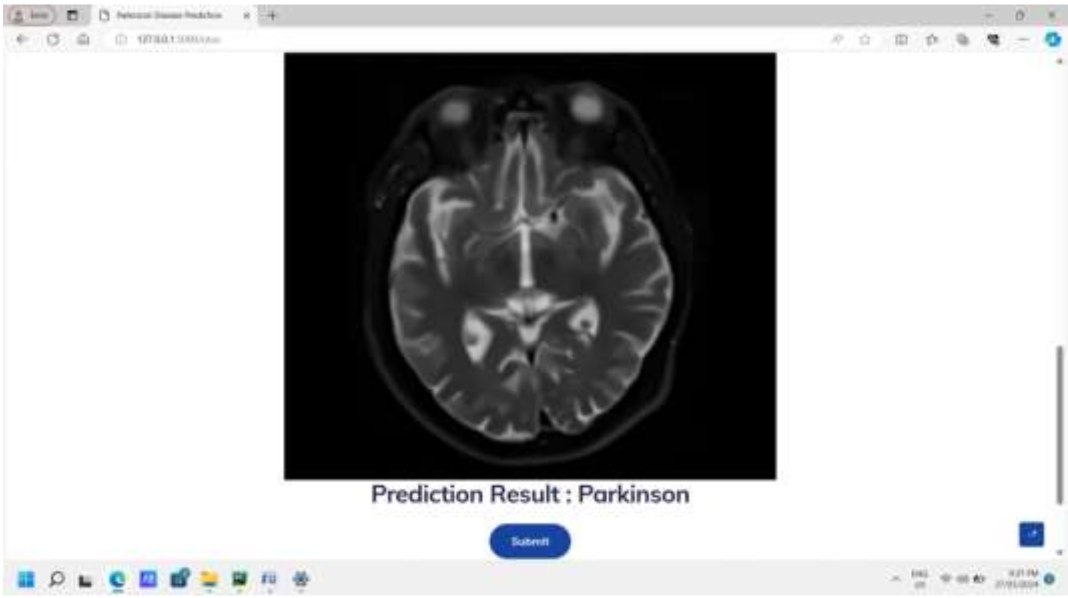

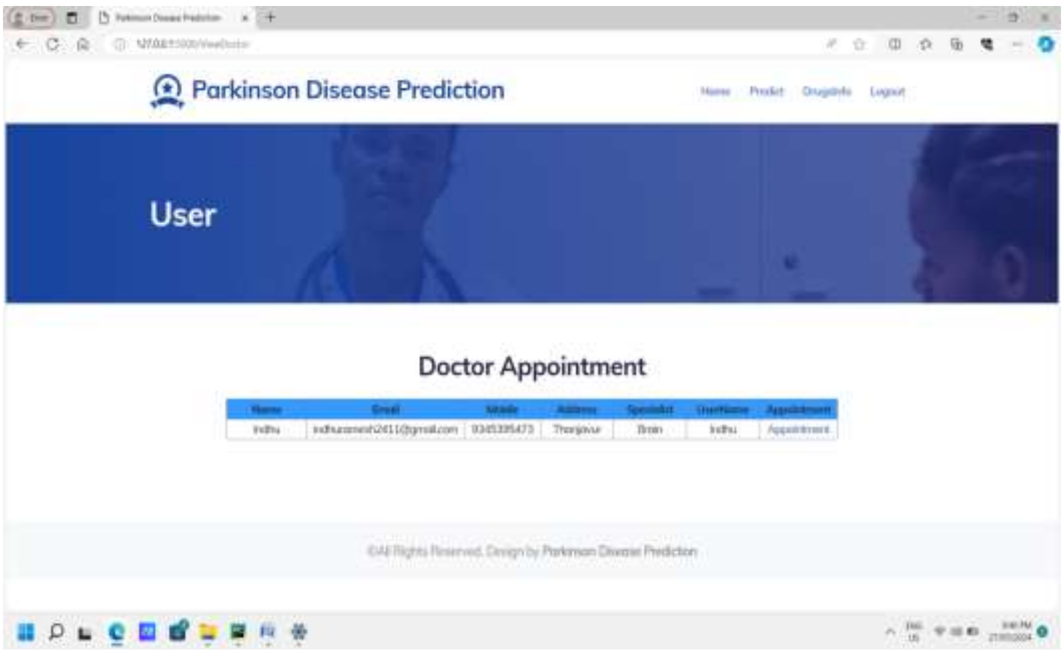

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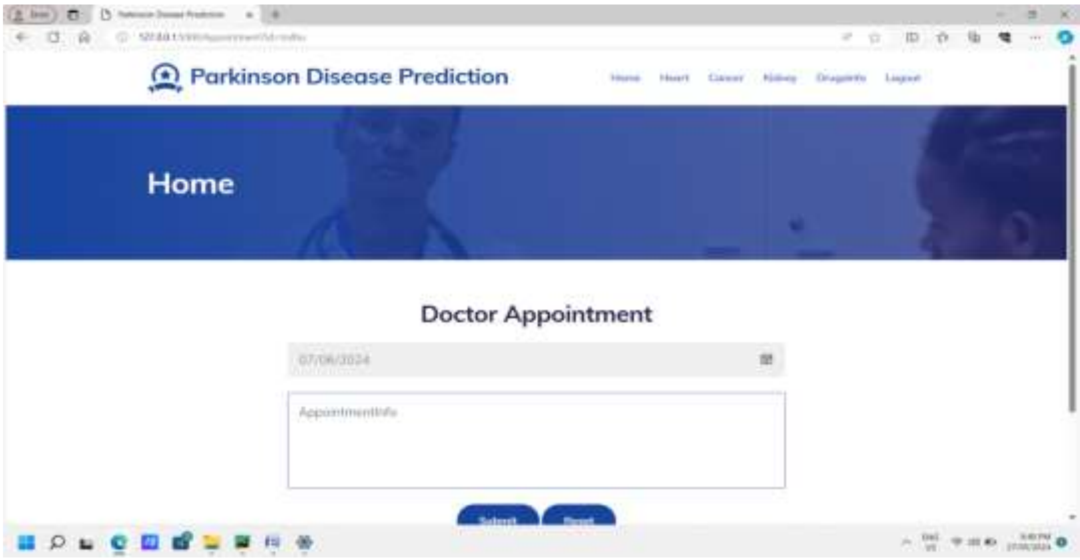

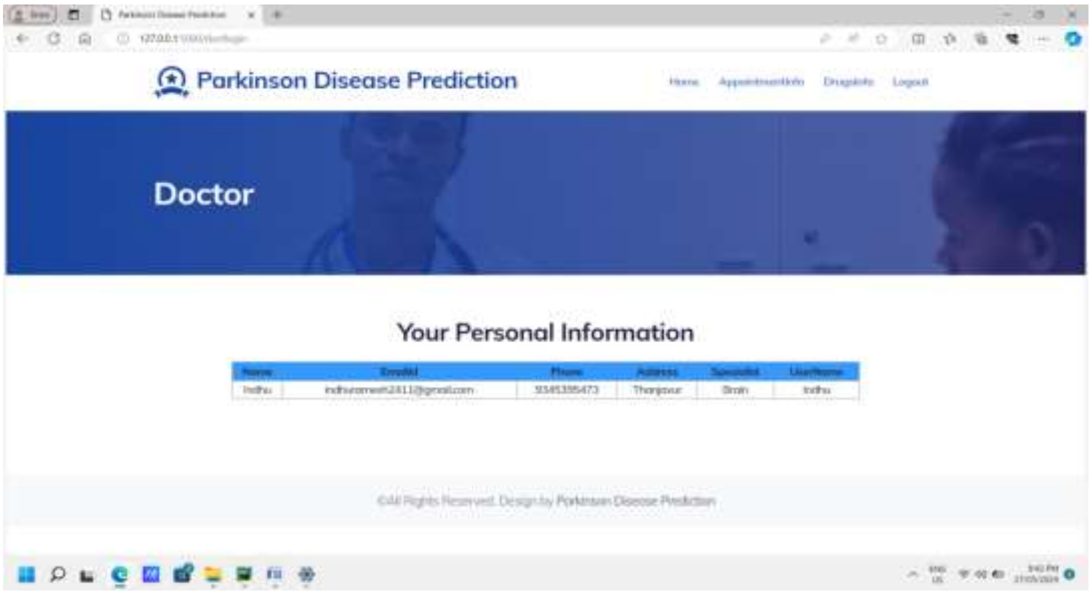

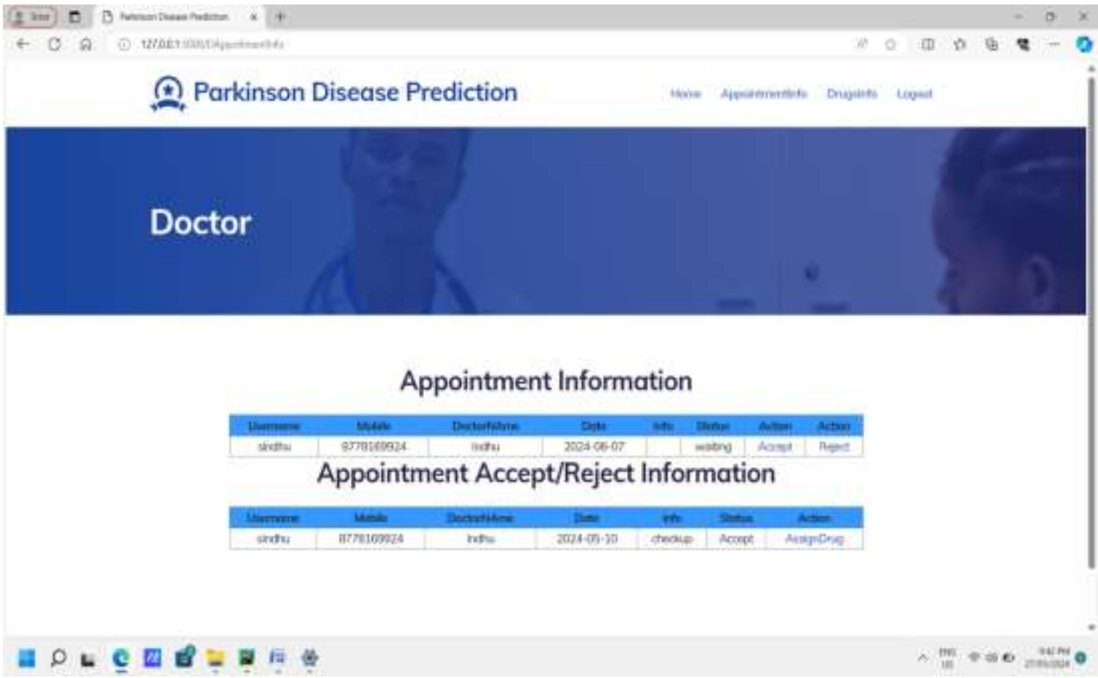

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V. CONCLUSION

In conclusion, using deep learning algorithms, specifically CNNs, for Parkinson's disease prediction from brain MRI images is a promising area of research. With the increasing availability of large, high-quality datasets and the advances in deep learning techniques, CNN models have shown excellent performance in accurately predicting Parkinson's disease from brain MRI images. The proposed system using CNNs offers several advantages over traditional machine learning algorithms, including the ability to automatically extract relevant features from the images, handle complex and non-linear relationships, and minimize overfitting. The system architecture includes various stages, such as data acquisition and pre-processing, model architecture design, training and validation, hyperparameter tuning, and evaluation. These stages require expertise in both medical imaging and deep learning and should be performed by trained professionals. Overall, the development of a CNN-based system for Parkinson's disease prediction from brain MRI images has the potential to improve diagnosis accuracy and enable earlier intervention, leading to better patient outcomes.

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