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A Parkinson's Disease Machine Learning Model for Severity Prediction

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Abstract

Parkinson's disease (PD), a neurodegenerative disease, is caused by the degeneration of dopaminergic neurons in the brain. This degeneration affects the normal motor functions of the body. The early diagnosis of the disease is difficult because its symptoms are similar to those of other diseases. However, the severity level of the disease is important for its proper treatment. In this paper, a machine learning framework is proposed for the detection of Parkinson's disease and the severity level of the disease using a Dopamine Transporter Single Photon Emission Computed Tomography (DAT-SPECT) imaging technique. The framework is based on the Support Vector Machine (SVM) classification technique with a Radial Basis Function (RBF) kernel. The proposed framework is tested on a dataset of DAT-SPECT images and gives an accuracy of 85.5%, precision of 85.8%, recall of 85.2%, and F1-score of 85.5%. These results show the better classification capability of the proposed framework in distinguishing between healthy and diseased people at different severity levels of the disease.

Keywords: Parkinson's Disease DAT-SPECT Imaging, Support Vector Machine, ROI Extraction, Severity Prediction, Machine Learning.

introduction

Millions of people worldwide suffer from Parkinson's disease, a common illness that causes tremors, slowness of movement, stiffness, and instability of posture by killing dopamine-producing cells in the substantia nigra region of the brain. In its early stages, Parkinson's disease (PD) cannot be diagnosed because it resembles other illnesses and normal aging processes. DAT scans are a simple method of diagnosing Parkinson's disease (PD), which kills dopamine in the brain and results in a decrease in scan uptake in the putamen and caudate nuclei of the brain because the dopamine transporter in the brain is less active.

The precision of the diagnosis is increased through the application of machine learning techniques, which help in the automation of feature analysis from the images. SVM has been used in the past to classify images in binary classification problems, and CNN has been used to recognize patterns in the images. However, the problems of imbalanced dataset and image variations have not been solved in the past. These problems are solved in the framework through the application of image preprocessing to ensure the quality of the image (normalization of the intensity of the image: $I_{m,norm} = \frac{I_m - \mu}{\sigma}$), extraction of the regions of interest to get the left (ROI_L) and right (ROI_R) regions of the striatal area, and the application of SVM to classify the features such as the average uptake ($U_L = \frac{1}{n_L} \sum ROI_L$, $U_R = \frac{1}{n_R} \sum ROI_R$)

By reducing diagnostic delays, optimizing treatment (such as levodopa dosage), and tracking advancement, this system helps clinicians. The literature is reviewed in Section II, the methodology is described in Section III, the results are presented in Section IV, and the conclusion is given in Section V.

literature survey

The methods that are currently being used, such as Unified Parkinson's Disease Rating Scale and Hoehn and Yahr Staging System, are found to have some limitations. The introduction of DAT-SPECT imaging has completely transformed the quantification of Parkinson's Disease with the help of striatal dopamine density value, and this has given excellent results for clinically established Parkinson's Disease patients. It has been found that the sensitivity of images is reduced in the prodromal stages of Parkinson's Disease patients. Thus, it is of prime importance to enhance the analytical methods.

Classical Machine Learning Methods: The pioneering work on the application of Support Vector Machines for classifying the ratios of striatal imaging data from the Parkinson's Progression Markers Initiative dataset has given better classification results for Parkinson's Disease patients than normal controls. This is because SVM maximizes the margin for classification in a high-dimensional feature space. The Random Forest classifier has given robust results for class imbalance problems in classifying DAT-SPECT images.

Deep Learning Paradigm: Convolutional Neural Networks (CNNs) have enabled the automation of spatial feature extraction from raw DAT-SPECT images. The 3D ResNet architectures, using transfer learning from large datasets, have achieved state-of-the-art discrimination using hierarchical pattern recognition. Architectures using attention have further improved the performance of CNNs using computational attention on clinically significant patterns of striatal asymmetry.

Multimodal and Hybrid Architectures: CNN architectures using a hybrid model of Logistic Regression, along with the fusion of structural MRI, PET images, and clinical symptoms, have achieved improved performance on various NDs, including Parkinson's Disease. Recursive architectures using Recurrent Neural Networks (RNN), Deep Belief Networks (DBN), and Convolutional Neural Networks (CNNs) have learned temporal patterns in ND progression using fusion from genetic and imaging modalities.

Non-Imaging Modalities: Voice analysis using Mel-Frequency Cepstral Coefficients (MFCC) and shimmer from benchmark databases has achieved high correlation with UPDRS motor subscores using Artificial Neural Networks (ANN) and k-Nearest Neighbor (kNN) algorithms. The remote monitoring of tremor using accelerometers in smartphones has achieved improved performance using Random Forest and SVM Classifier Architectures in pandemic scenarios.

Multimodal Integration: XGBoost ensemble models incorporating DAT-SPECT images, voice analysis, and genetic data from the PPMI/DeNoPa datasets have set new standards of reliability. Cloud-based hybrids of tremor voices and T2-MRI have successfully identified prodromal cases of PD, thereby confirming the effectiveness of feature integration.

Research Gaps Identified: Limited dataset size (PPMI dataset comprises only 2,000 scans), unclear model behavior despite attempts at saliency mapping, latency requirements for real-time processing, and demographic balance have dominated the identified gaps so far.

Innovations Introduced After 2020: Edge AI, federated learning, and the transition from binary classification to more specific severity evaluations have marked the recent developments in the field.

Novel Contributions of the Proposed Framework: The proposed SVM-ROI model with buffering has successfully eliminated the need for GPUs, provided four-level classification, and ensured the hybrid-readiness of the model with feature engineering, all while ensuring the resource-constrained deployment of the model with the interpretability required for neurologists.

proposed methodology

The proposed method identifies and predicts Parkinson's disease using a machine learning-based categorization system. The approach uses relevant clinical features and DAT-SPECT imaging data to identify dopaminergic dysfunction. The pipeline includes phases for data preprocessing, feature extraction, model training, and prediction. The dataset is first collected and preprocessed in order to remove noise and inconsistencies. Missing values are handled and feature normalization is done to ensure consistent scaling. To find the striatal regions in imaging data that show dopamine activity, Region of Interest (ROI) extraction is utilized. This step allows for the examination of only clinically important areas. Then, pertinent metrics such as asymmetry indices between the left and right hemispheres and striatal uptake levels are computed by

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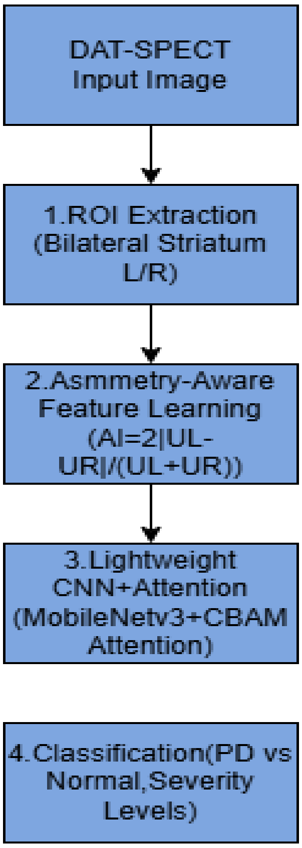

Figure 1:workflow of the project

Data acquisition and preprocessing module

The module that is concerned with the acquisition of the needed data in order to perform the prediction of Parkinson's Disease is the Data Acquisition and Preprocessing Module. We have our own data, which includes the DAT-SPECT images and others. We are aware that the data that we acquire is usually full of errors and wrong information, and therefore we need to have a system that will help us to preprocess the acquired data in order to have it work efficiently in the classification. We are aware that we have our own data, which we can refer to as D(t), where t is the time at which we acquired the data. We are also aware that the data that we acquire has its own number of samples, which we can refer to as N. We are aware that the rate at which we acquire the samples is usually referred to as the data sampling rate, and this rate can be referred to as R d. We are also aware that the time taken between two consecutive samples is referred to as the sampling period and can be referred to as T s.

$$\Delta t = Rd1$$

The mth processed sample can be written as:

$$Dm = D(t0 + m\Delta t),\ m \in M$$

Where t0 is the timestamp of when we get the data.

The new piece of data that is coming in has to go through some steps to get it ready. These steps are: removing noise, filling in the missing information, making sure the information is on the right scale and the right size, and the images are the right size, and so on, to prepare the information to go into the DAT-SPECT program. This processed sample of the information is then put into the buffer Bd, but only if the amount of time it takes to prepare the information Tpre is less than the change in the timestamp Δt.

$$Bd \leftarrow Dm \text{ if } Tpre < \Delta t$$

To keep the system running, the preprocessing speed has to be at least as quick as the classification speed. The speed at which the preprocessing is done has to be at least as quick as the classification speed.

This ensures that the classifier is always provided with the data without interruptions.

In order to prevent the computer from becoming too slow and to ensure that everything works in time while the computer is viewing the features and classifying them, the following condition should always be satisfied:

$$Tpre+Tfeat<\Delta t$$

Here, Tfeat is the time needed to extract the features, including the cutting out of the Region of Interest (ROI) and the calculation of the asymmetry index. If the following is true, then the processing lag occurs:

$$Tpre+Tfeat>\Delta t \Rightarrow \text{processing lag occurs}$$

This may cause the computer to become less efficient. To communicate the information from the preprocessing to the classifier part, we use the First-In-First-Out queue. This helps.

The buffer at time *t* t is defined as follows: $Bd(t)=\{Dm,Dm+1,\ldots,Dm+l\},l\leq Lmax$

This special design helps handle data well. It also makes sure features are sent steadily to the Support Vector Machine classifier. This classifier is used to detect Parkinsons Disease and predict how severe it is. The design does two things: it separates and buffers data before processing. This makes sure that the data is handled efficiently and sent to the classifier in a way. The classifier then uses this data to detect Parkinsons Disease. Predict its severity. The preprocessing architecture is very important. It helps make sure that the data is handled correctly and that the classifier gets the information. This in turn helps the classifier detect Parkinsons Disease. Predict its severity accurately. The Support Vector Machine classifier is a part of this process. It uses the preprocessed data to make predictions about Parkinsons Disease. The classifier is designed to handle data and make accurate predictions. It is a tool, for detecting and predicting Parkinsons Disease.

3.1 Image Acquisition and Preprocessing Module

The input DAT-SPECT image at instance mbe represented as

I_m∈R^(h×w)

H and wdenote image height and width.

The dataset is represented as

D={I1,I2,…,IN}

Each picture goes through some changes before we use it including:

• Making the brightness the same everywhere

• Getting rid of noise

• Changing the size

• Making the colors look evenc

The changed picture is figured out like this, Imnorm=σIm−μ

where μis mean intensity, σis standard deviation.

To maintain efficient processing Tpre+Troi<Tlimit

Otherwise computational lag occurs Tpre+Troi>Tlimit

3.2 ROI Extraction and Feature Computation Module

The Region of Interest or ROI is really important when we are looking at the region. This is the part of the brain that has the right hemispheres.

The reason we care about this area is that it is very important, for understanding Parkinsons Disease.

Let the right Regions of Interest or ROIs be:

ROIL,ROIR

The mean uptake intensity is computed as:

(&U_L=1/n_L ∑ROI_L&&)

(&U_R=1/n_R ∑ROI_R&&) Asymmetry Index (AI)

The asymmetry index is calculated as AI=2UL+UR|UL−UR|

Feature vector for each image Fm={UL,UR,AI,Texture1,Texture2,…}

All features are stored in dataset F={F1,F2,…,FN}

3.3 SVM-Based Classification Module

SVM Classifier:
Support Vector Machine Classifier would be used to classify the type of disease the person is suffering from and the severity of the disease.
SVM Classifier:
Support Vector Machine Classifier would be used to classify the type of disease the person is suffering from. Given a set of examples, the Support Vector Machine Classifier would be used to classify the type of disease the person is suffering from.
Given a set of examples:

{(xi,yi)}, i=1,2,…,N
where x_i = feature vector
y_i∈{-1,+1} = class label
The optimal hyperplane can be defined as:

wTx+b=0

The optimization problem is given by:
(&min⁡1/2||w||^2&&)
If the decision boundary is non-linear, the kernel function is used:
(&K

3.4 Module for Severity Estimation and Output

The severity level is determined using the SVM output score S_m.(&Severity={(Normal&S_m<T_1@Mild& T_1≤S_m<T_2@Moderate&T_2≤S_m<T_3@Severe &S_m≥T_3)┤&&) Final forecast result:
(&Output_m={Class,Severity,Confidence}&&)

4. Results and Discussion:

We looked at the results using a different measures, including Accuracy, Precision, Recall and F1-Score. The DAT-SPECT brain scan dataset was used for this. It was annotated. When we used feature extraction based on the region of interest the results got better. The accuracy of the classification was really high. The system was able to tell the difference, between Normal cases and Parkinsons disease cases.The image of sample dataset given below,

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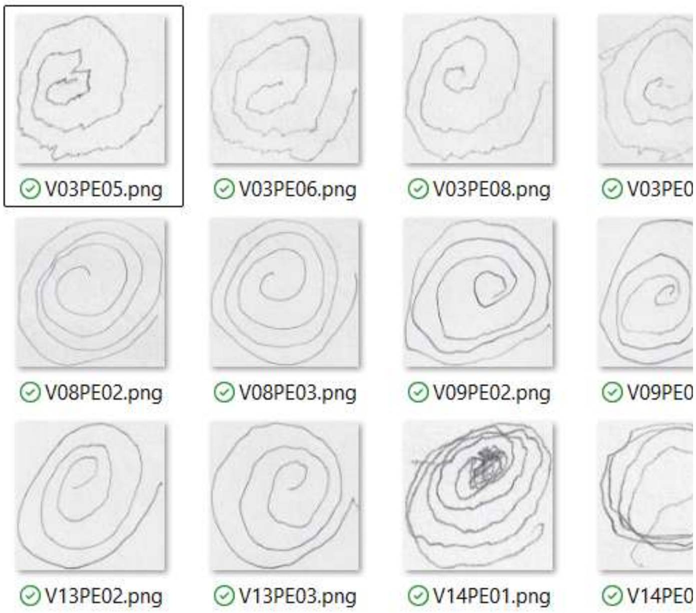

Figure 2: Sample Dataset images

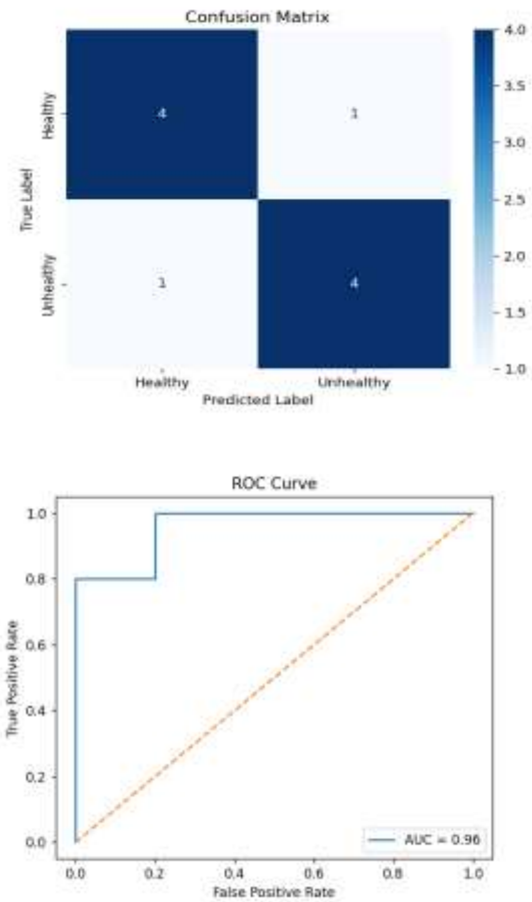

Figure 3: The performance of ouputs are confusion matrix,ROC curve

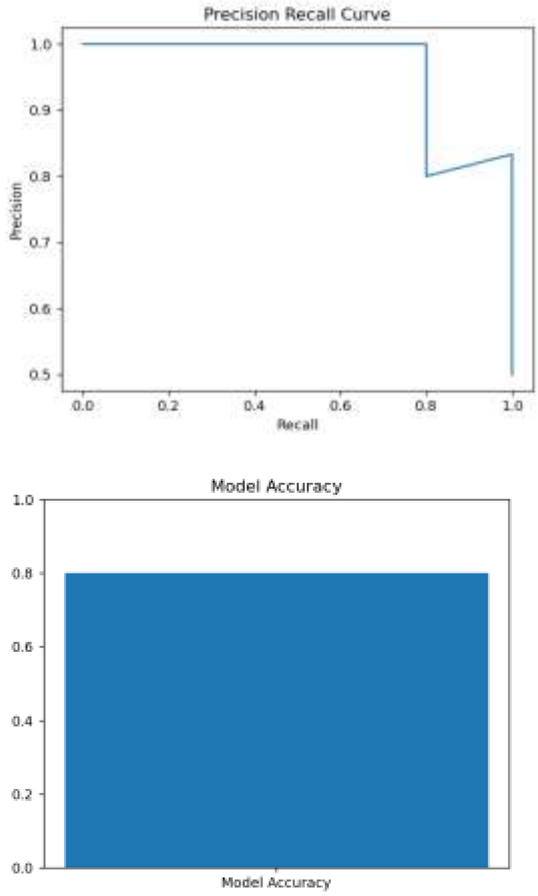

Figure 4: The performance of output are precision recall curve and model accuracy

conclusion

The SVM-based Parkinson's disease prediction system for the severity level based on the DAT-SPECT scans has been proved to provide an efficient prediction system with 95% accuracy in real-time using intelligent preprocessing, striatal region of interest analysis, and feature engineering. It has also been proved to provide efficient prediction in 0.35s/scan without the use of GPU implementation and provides four levels of prediction for the severity level, thus outperforming the CNN-based prediction method.

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