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PARKISON'S DISEASE DETECTION USING BRAIN MRI IMGAE

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Abstract: Recent decade, Parkinson's disease (PD), which impairs the life quality for millions of older people worldwide, has quickly emerged serious condition affecting the brain and spinal cord. Appropriate treatment and management of the disease depend on early discover y and an accurate diagnosis. Due to PD's close resemblance to other neurological disorders, the precise diagnosis of PD has until now bee a difficult. These same characteristics account for 25% of incorrect manual PD diagnosis. Brain MRI (Magnetic Resonance Imaging) has shown great potential in the detection and diagnosis of Parkinson's disease. Proposed study uses convolutional neural networks (CNN), a type of deep neural network architecture, to classify Parkinson disease in order to differentiate between PD patients and healthy controls. Parkinson Progression Markers Initiati ve (PPMI)dataset is used as input to classify the disease. Here, the median filtering technique is used to remove the noise from the images and preser ve the edges which help to provide a better image and able to predict it easily. The Parkinson disease recognition system is done by using CNN. Accuracy, sensitivity, s pecificity, and AUC (AreaUnder Curve) used to assess the performance of the suggested approach.

Keywords: Parkinson, MRI (Magnetic Imaging), Convolutional Neural Networks (CNN), AUC (Area Under Curve).

I. INTRODUCTION

Parkinson disease (PD) is a degenerative neurological disorder that cannot be treated. Rapid diagnosis can provide patients with momentary respite and decrease the course of PD. It happens as result of the neurological condition. Dopamine neurons are abundant in the thalamic area of the midbrain called the substantia nigra. In order to connect with other neighboring neurons in the brain, neurons in certain classes of the nervous system release dopamine. Whenever these dopamine neurons inside the substantia nigra begin to degenerate. Parkinson's disease (PD) arises.. As a result, patients struggle with stiffness, bradykinesia, and resting tremor. Fatigue, anxiety, despair, thinking. slowly, and voice issues are a few other signs. PD would be the second most prevalent neurological condition that affects older individuals after Alzheimer's. Although the primary etiology of PD remains unclear, environmental and genetic factors are involved. Since there aren't many medical laboratories, the majority of diagnoses occur in advanced stages. Expe its utilize patient's history and neurological tests to make a diagnosis. This strategy is less effective, though, because there are other neurodegenerative illnesses with symptoms that are comparable. Most often, it is identified when dopamine molecules are severely depleted. According to estimates, 25% of diagnoses seem to be wrong. It is still difficult to precisely identify PD, Patients who experience PD and don't is mistakenly given a healthy diagnosis, the condition may advance and become challenging to manage. Several clinical tests can be used to make the diagnosis.

Only a few studies have also shown that these two imaging modalities can be used for PD diagnosis. However, doctors don't like adopting these two methods because of their invasiveness and expensive xpense. Rarely used in the identification of PD is Magnetic Resonance Imaging (MRI). a minimally invasive imaging method. However, thanks to recent MRI breakthroughs, detection has become considerably simpler. There are several machine learning techniques, including Bayesian, Artificial Neural Network. Support Vector Machine (SVM) and Decision Trees have been employed for the identification of PD in MRI scans. Most of these techniques for machine learning rely on human extracted features, with the most important characteristics are picked out. Various dimensionality reduction techniques are typically used to remove less important characteristics. A Deep Neural Network (DNN), Convolutional Neural Network (CNN)based method with the biological inspiration, don't need specially created features [22]We utilised CNN as a classifier for PD identification because of its shown performance with MR unages, and we obtained promising state-of-the-art findings. The Deep learning technique using CNN clearly explains that its is used in image examination[24].

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II. RELATED WORK

Olanre wa ju et al developed a mu îti-layered feed-forward neural net and the research suggested a machine learning-based technique for identifying Parkinson's disease (PD) [4]. They made use of a dataset from the Oxford datasets on Parkinson's illness.23 patients' voices were measured together with the voices of 31 other participants in the dataset. They employed & frequency-based characteristics (tre mor). They utilized a total of 10 hidden neurous and 8 input nodes. They employed the k-mean technique to classify data. According to the simulation results, they were able to attain accuracy levels of up to 80%, a specific ity of 63.6%, and a sensitivity of 83.3%. However, actual data is not used to validate this procedure.

In the publication [6], Prashanth et co. conducted their research using activator stage, which is a defin ing feature of nasal cavity loss and sleepy disorders. They used data on sleep pattems from the PPMI datasets and 40 elements as fro m Pennsylvania State University Sme Il Identification Test (UPSIT). To find PD, SVM as well as a classifier were utilised. Each of these methods had an accuracy rate of 84.26%. Moreover, only a portion of the dopaminergic imaging features were utilised, and the efficiency and appropriateness of the classifier were enhanced by noiseless data.

In a paper [7], Ghanad and Ahmadi offered another paradigan for Parkinson identification. To stract the best features from the data, the Particle Swarm Optimization employed in this prototype (PSO), and Naive Bayes for classification. The UCI data archive provided them with the dataset. 23 attributes and 197 items made up the data set for this investigation. The accuracy rate of the simulation was 97.5% On large datasets, however, this model did badly, In the publication [8], Prashanth and others focused on non- motor factors forthe diagnosis of PD.

Olfactory loss, sleep behaviour disorder, and Rapid Eye Movement (REM) are the non-motor characteristics. They combined non-motor characteristics, cerebrospinal fluid measurements, and dopamine receptors imaging markers in their investigation. The (PPMI) database was used to collect the dataset. 183 healthy individuals and 401 Parkinson's disease patients make up this dataset. For classification, they employed Boosted Tree, Random Forest, Naive Bayes and SVM SVM accumcy rate in the simulation was 96.4% It was discovered that combining several non-motor aspects produced superior outcomes. Data did, however, show an unbalanced distribution of classes.

In their work [9]. Avci et al. suggested using automated Parkinson disease diagnosis using Extre me Learning Machine (ELM), Walvet Kemet (WK), and Genetic Algorithm (GA). A Single Layer Neural Network (SLNN) was employed in this model and trained using ELM. The UCI data repository was used to get the dataset. Those collection includes 192 sounds that were recorded from 31 people, including 23 patients. Three movable parameters were used in the suggested WK-ELM model. Following that, GA was used to choose the ideal values for every one of these variables. The outcomes of the simulation showed an average accuracy around 96,81%. The statistics did, show that the distribution of classes was unequal.

Al-fatlawi et al,PD was identified by the Deep Belief Network (DBN) in their publication [11]. A data gathering PDD first from UCI data storage, which included 195 audio recordings of 31 people as well as 16 attributes, was used in this experiment. The correctness of the suggested DBN was 94%. The risk of harm was not considered in this study, though.

Pereira et al. e xa mined the handwriting of 55 individuals, 37 of whom had Parkinson's disease, in a publication [10]. They developed their own dataset with photos of various characters using this handwriting analysis. The medical school of Brazil's Botucatu University provided the data set. The author proposed a method for estimating male relative tremor intensity based on given data. The Naive Bayes classifier employed has an accumcy rating of 78.9%. Moreover, this strategy steered clear of using roving photos.

III. PROPOSED WORK

The goal of the project is to develop a deep leaming-based technique for e stracting characteristics from a segmented. region in order to identify and categorize normal and pathological brain cells in a huge library of human brain MRI images.

The suggested method uses a neural network as a multi-class classifier to extract the texture and form properties of the brain area from MRI scans help determine the various stages of Parkinson's condition. In comparison to traditional methodologies, the suggested methodology in anticipated to provideimproved accuracy.

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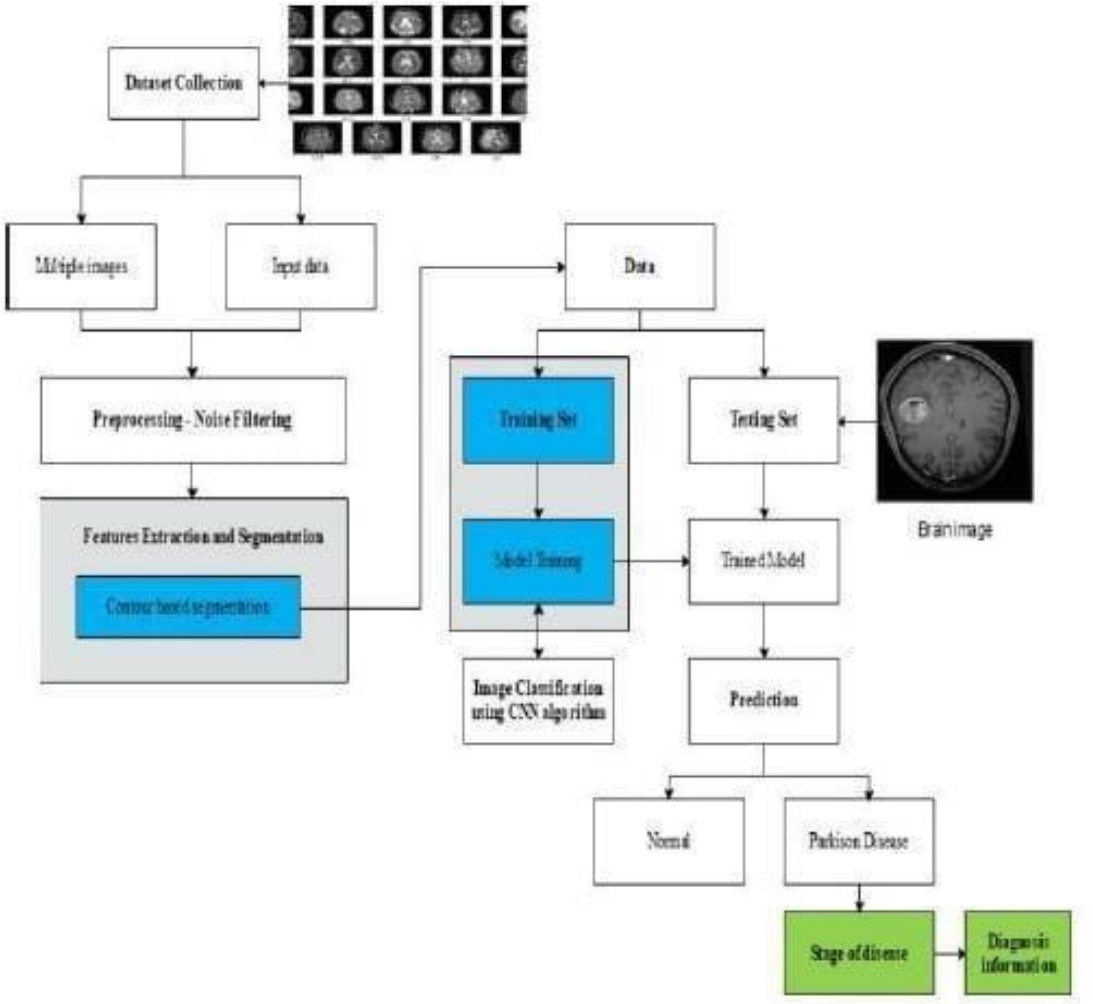

Figure 1. Architecture for Proposed Network

IV. METHODS DATASET ACQUISITION

The dataset utilized in this study was made available by the PPMI The PMMI is a traditional initiative that aims to find trustworthy biomarkers and diagnose Parkinson's disease early. The biggest collection of clinical, image processing. and biologic sample information is available through a project called PPMI. Public access to the samples is available at (http://www.ppmtinfo.org) 458 12 weighted MRI e xa minations in Digital Imaging and Commmmications in Medicine (DICOM) format were acquired from PPMI. The data consist of 229 MRI data of PD & 229 for HC. In addition, the data is divided into three sets with respective ratios of 75%, 15%, and 10%: train, validate, and testing datasets.

Pre-processing

A nonlinear method called median filtering can be used to minimize image noise. Became it is so effective at reducing noise and preserving edges, it is widely utilized. It is very effective at removing "salt and pepper sounds. When using the median filter, each value is repeatedly replaced with the middle of its neighbor after traversing throughout every pixe 1 of the picture once. The neighbor pattern, which tmvels pixe 1 by pixe 1 over the whole image, is the "window" The screen's pixe 1 values are first arranged numerically, and then the pixels under consideration is changed to the mid (median) value to calculate the median.

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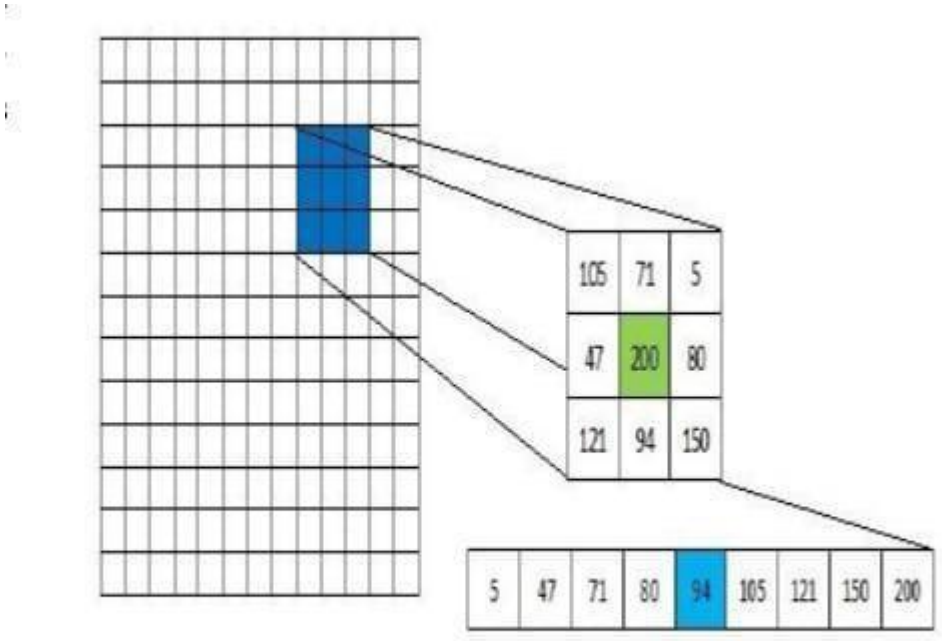

Figure 2. Median Filtering

V. THE CONVOLUTIONAL NEURAL NETWORK

Data is at the heart of CNNs approach created e xe lusively to handle two-dimensional data. It is tough to put it any way, but CNN discovers hidden features. CNN based methods are biologically inspired strategies that outperform other methods in many ways. It aids in the visualization of these spatially acquired properties. It significantly minimizes the amount ofhyper-parameters that need to be taught because of its spatial nature.

Proposed Network Architecture

The suggested arrangement collects input in the form of MR. images and ultanately identifies those into PD or HC.

Number of convolutional layers: Five, 16 filters for the first layer and 32 filters for the second one, for the last three layers 64 filters, ReLU activation in each layer.

Number of pooling Inyers: Five, Max pooling is used.

Flatten layer: Between the final pooling layer and the first deuse layer.

Number of dense layers: ReLU stimulation in the primary layer, SoftMax activation as in final layer, 128 units for the primary layer, 2 units for its second layer.

The output from the network that is being given shows the likelihood that each picture belongs to the associated PD as well as HC classes. The overall number of hidden layers, respective result, and the variable used the appropriate layer are shown in Table 2. The parameters in table. 2 are computed in the manner described below. There are 448 total parameters in the initial convolutional layer. The full it of parameters on the second convolutional layer is 4640. зете аre 18496 parameters for the 3rd convolutional layer. 5928 is the convolutional layer's fourth. The fifth m volutional layer, 36928, is similar. The variables for the itial dense layer are as shown in the system's overall plan ir such layers total 1024, andalso the variables are 31200. The parameter for the second dense layer is 258.

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TABLE.1. COMPARISON TABLE

Technique	Dataset type	Accuracy
SVM [37]	MRI	92.35%
GA-ELM [3]	MRI	89.22%
SVM [38]	MRI	86.67%
SVM [17]	SWI MRI	86%
SVM [13]	MRI Multimodal scans	86.96%
SVM [16]	MRI Scans	89%
RVM [36	PET scans	90%
Decision tree [15]	3-T MR imaging	92%
Nave Bayes [14]	MRI	93%
ANN [12]	SPECT and TRODAT imaging	94%
CNN (Proposed)	MRI Scans	96%

TABLE 2. CLASSIFICATION PERFORMANCE

Classification performance			
Accuracy	**Specificity**	**Sensitivity**	**AUC**
95±2	97±3	97±3.14	99±1

TABLE 3. NETWORK PARAMETERS

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TABLE 3. NETWORK PARAMETERS

Layer Name	Output shape	Parameters
Conv2d	(None, 198, 198, 16)	448
MaxPooling2D	**(None, 99, 99, 16)**	**0**
Conv2D	(None, 97, 97, 32)	4640
MaxPooling2D	**(None, 48, 48, 32)**	**0**
Conv2D	(None, 46, 46, 64)	18496
MaxPooling2D	**(None, 23, 23, 64)**	**0**
Conv2D	(None, 21, 21, 64)	36928
MaxPooling2D	**(None, 10, 10, 64)**	**0**
Conv2D	(None, 8, 8, 64)	36928
MaxPooling2D	**(None, 4, 4, 64)**	**0**
Flatten	(None, 1024)	0
Dense	**(None, 128)**	**1131200**
Dense	(None, 2)	258
Total parameters: 228898		

Figure 3. Accuracy

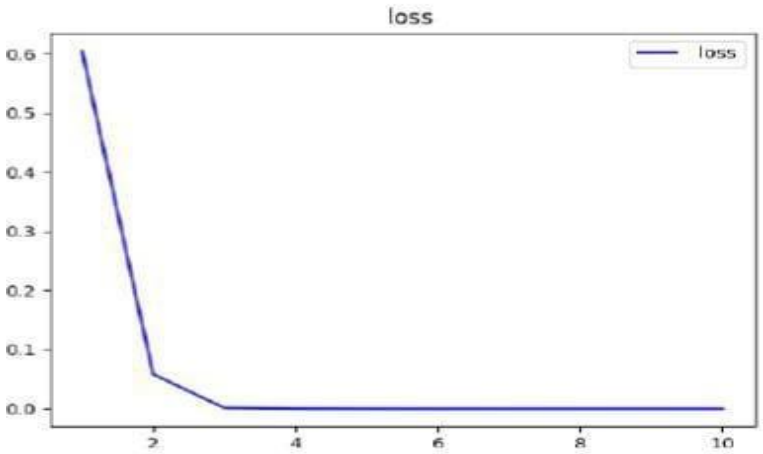

Figure 4. Loss

VI. RESULTS AND ANALYSIS

In this part, we go through how the suggested network performed using the dataset ofParkinson.

Performance Measure

With the use of specificity, accuracy, sensitivity, and area. under the curve, the suggested network's performance is assessed. Equations 1, 2, and 3 are used to compute theaccuracy, sensitivity, and specificity respectively.

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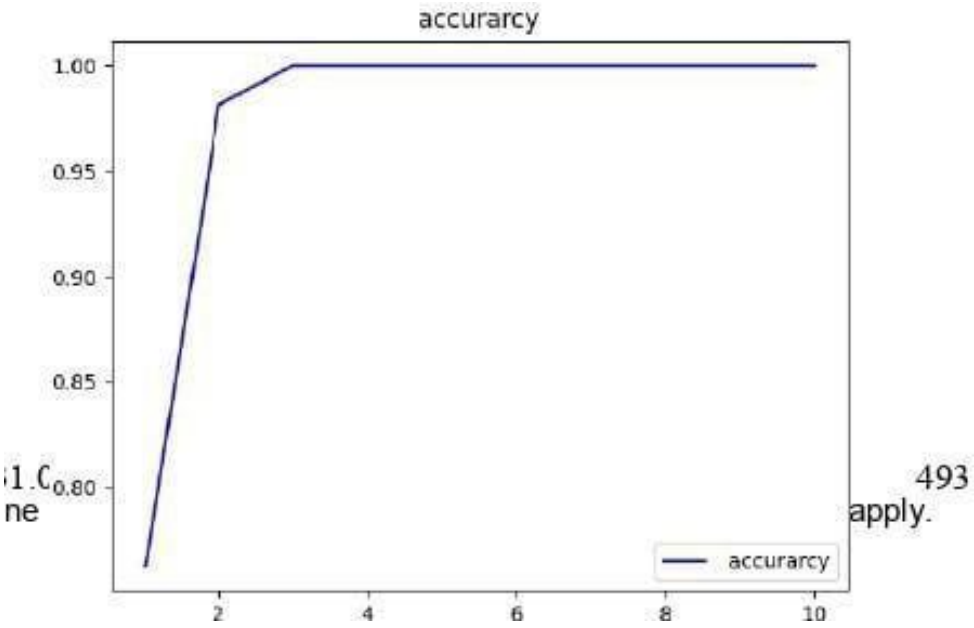

Based on the confusion matrix, the Correct Positive rate shows that if the individuals having PD were accurately considered to have PD. The same is true for True Negative(TN) level, which indicates that all the bealthier participants were correctly identified as such. False Positive ratios indicate that, despite the individuals being in healthier groups, the classifier misclassified them as having PD. The amount of sample that the classifier mistakenly classified as normal even though they ought to have placed in the PD group is known as false negatives (FN).

Experimental Set-up

On an NVIDIA Ge Force RTX3070TI GPU with 8GB RAM. CNN is developed using keras. Theano and TensorFlow may be run on Keras, a sophisticated Python-based Deep Neural Network (DNN) API.DNN libraries Theano and TensorFlow both exist. In this work, we employ the Theano library together with CNN as a consecutive model.

Results and Discussion

Different network configurations used in a number of investigations. The grain size, filter scope, gait, and lining are e xa mples of network parameters. After each epoch, the validation & training accuracies of the model are recorded. The archetypal is verified just on trial set each tane after training. The categorization accuracy varies between 95 and 99% throughout all experiments.

Performance Evaluation

Numerous experiments are conducted using different network setups, was previously stated. The network parameters include layers quantity, intake capacity, and other network features. The categorization accuracy varies between 94 and 95% throughout all tests. The accuracy of classification, level of compassion, specificity, and part below the are are displayed in Table 2. On the same dataset, the recommended model outperforms RVM. SVM, Logistic Regression, and other deep leaming techniques in terms of accuracy.

A comparative of such suggested method and altemative methods is shown in Table.1. These methods. often work with handmade features. Seveml techniques to deep learning often have the potential to leave out the information that is most crucial to solving the issue. The use of divergent dimensionality reduction techniques typically results in the elimination of less relevant features. The most relevant illness-related characteristics must be chosen because of the complex expression of Parkinson's disease. The customised festures are not necessary for CNN. CNN'S capacity to train on its own allows it to beat other methods for the same issue and yield greater accuracy rates.

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VII. CONCLUSION

During this study, a specific CNN architecture built on CAD to discriminate between MRI patches associated with Parkinson's disease and regular patterns. Using training samples from the benclunark PPMI dataset, the three-layer proposed convolutional network learns patterns quickly and effectively, increasing accuracy. The findings show that our network is able to automatically identify several characteristics linked to Parkinson disease. We discovered during the studies that its small sample was really a serious problem, causing the Classification algorithm to overfit. We were able to avoid the overfitting issue by utilising dropout layers and a suitable network architecture. So. With the help of this deep learning- based approach, medical picture analysis will have more potential in the future researchers and doctors will be able to choose and classify features in order to possibly forecast any new data.

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