PARKINSON'S DISEASE DETECTION FROM HANDWRITTEN SKETCHES USING DENSELY CONNECTED CONVOLUTIONAL NETWORKS

S.Sethu Subramaniyan
2nd year AIDS-B
Panimalar Engineering College
chennai,India

S.Sivanesan
2nd year AIDS-B
Panimalar Engineering College
chennai,India

G.Raakesh
2nd year AIDS-B
Panimalar Engineering College
chennai,India

***Abstract*—Parkinson's disease (PD) is a neurological condition that worsens over time and impairs motor skills, causing tremors, rigidity, and poor coordination. Early diagnosis of PD is essential for successful therapy, but existing diagnostic techniques can be time-consuming, expensive, and insufficiently accurate. When dealing with illnesses like Parkinson's, this cannot be allowed. Therefore, we offer a novel method for PD identification in this research that makes use of handwritten sketches and a densely connected convolutional network (DenseNet). Our method takes advantage of the distinctive qualities of handwritten sketches, such as the direction and curvature of the strokes, to spot PD symptoms before they become severe. We trained a DenseNet to distinguish between sketches made by people with and without PD using a dataset of sketches created by both groups of people. On our test set, we outperformed other state-of-the-art methods with an accuracy of over 97%. Our findings show that employing handwritten sketches as a low-cost, non-invasive strategy for PD identification has promise. Our method could be used to increase the usability and effectiveness of PD diagnosis in a variety of contexts, such as telemedicine and remote patient monitoring.**

Keywords—parkinson's disease, detection, diagnosis, dataset, model, accuracy

I. INTRODUCTION

A neurological condition called Parkinson's disease (PD) has a significant impact on society. According to [1], 6.1 million people worldwide were affected by Parkinson's disease in 2016, and the prevalence of the condition has been rising quickly over the previous 20 years. It is a degenerative condition that might have a long-term impact on the patients. Parkinson's disease is an age-related disease, with incidence and prevalence rising significantly with advancing years; nevertheless, it does not only afflict the elderly, as stated in [2]. In fact, 5-10% of those affected are under 50 years old, and over 25% of those affected are under 65[2]. Although both sexes are affected by PD, women appear to be less affected than males.

Rest tremor is one of the motor signs of Parkinson's disease (PD). Although PD cannot be cured, quality of life can be maintained with medication. The treatment of Parkinson's disease (PD) may be greatly aided by the early identification of these motor symptoms.

One such typical Parkinson's disease sign that can come before other motor symptoms is micrographia. The reduction in letter size in handwritten text is known as micrographia[3]. People with PD can be identified by looking for specific patterns in their handwriting sketches that result from micrographia. So we can classify and identify PD at an early stage by utilising a classification algorithm. Deep Convolutional Neural Networks are one such method of classification.

Tasks including segmentation, classification, and detection in medical image analysis have been successfully completed using Deep Convolutional Neural Networks (CNNs). The DenseNet architecture is one specific type of CNN that has grown in prominence in recent years.Huang et al.'s initial suggestion of DenseNet (Densely Connected Convolutional Networks) was made in 2016[4]. Each layer in a DenseNet is connected to every other layer in a feedforward fashion, creating a network with many connections. In comparison to conventional CNNs, this connectivity topology has better gradient flow and parameter efficiency [4]. Breast cancer metastasis prediction is one of the many tasks that DenseNet is utilised for in medical image analysis [5]. Additionally, it performed better than any other cutting-edge models

II. RELATED WORKS

The development of deep learning has given machine learning and AI technologies increased prominence in recent decades across a variety of disciplines. Additionally, a variety of medical areas have made extensive use of these technologies. Its reputation in the medical industry for disease forecasting and diagnosis has grown as a result of the expansion and development project in the fields of Artificial Intelligence, deep learning and Machine learning. Many symptoms, including speech patterns, handwriting tests, walking patterns, olfactory loss, and other motor skills tests, have been explored for the diagnosis of PD in a number of studies utilising a range of datasets.

Using two datasets, Das et al. [11] assessed the effectiveness of various CNNs in their study. The Kaggle library provided the datasets under investigation. The

authors of [12] contributed the second dataset. Drawings of spirals and waves could be found in the first dataset, whereas cube and triangle graphics could be found in the second dataset. Two approaches were considered for the investigation. Both datasets were utilised to train CNNs such as MobileNet v2, Xception, VGG19, Inceptionv3, ResNet50 and Inception-ResNet-v2 in the first way, while transfer learning is employed in the second.

The scientists used manually drawn drawings to test the use of deep CNN in the identification of Parkinson's disease. Results from fine tuning were superior to those from the first two techniques. When ResNet50 and MobileNet-V2 models were examined, they performed better than other top CNN models.

To diagnose PD from handwriting, Gazda et al. [9] suggested an ensemble of deep learning models.CNN models make up the ensemble model that was generated.For this model, they employed the PaHaW and NewHandPD datasets. Transfer Learning was also used to increase the model's generalizability. The accuracy for each of the eight distinct handwritten tasks in PaHaW is determined using each CNN model and ensemble classifier, and then the results are compared. In order to reduce computing costs, the author of the work adopted a multiple fine-tuning method and used various CNN approaches for PD diagnosis. This strategy produced outcomes that were competitive.

S. M. Abdullah et al.'s method of early PD detection [10] also included handwritten records. With the help of optimised feature selection, they proposed a deep transfer learning model. The NewHandPD dataset was utilised by the author to train and test the model.It uses three transfer learning models to carry out feature extraction. Through the use of genetic algorithms and the K-Nearest Neighbour Technique, features are optimised. The suggested innovative model offers a detection accuracy more than 95%, precision greater than 98%, and area under the curve greater than 0.90 with just a loss of 0.12.

Using the UCI dataset and 5-fold cross-validation, Fang proposed an improved KNN method for detecting Parkinson's disease and compared it to other models with The researchers discovered that their improved KNN model outperformed conventional models based on entropy algorithms and had higher accuracy for detecting Parkinson's disease. This implies that the improved KNN method may be more impactful than the other models tested in the study. It should be noted, however, that the estimation was limited to a single dataset, and more research is needed to confirm the effectiveness of the improved KNN method in other contexts.

To evaluate and train their experimental setup, the researchers used a dataset of 204 photos with 102 spiral sketches and 102 wave sketches. The research was divided into three parts. In Section 1, you created spiral and wave images for a specific patient. Section 2 used a CNN architecture to extract feature representations from images. After that, the final dense layer was used to generate predictions for each image, which were then analyzed in Section 3. This section discusses several meta-classifiers that can predict probabilities and provide final predictions. The study's overall goal was to develop and test a method for accurately predicting patient diagnoses based on spiral and wave images.

Kuplan et al. created a novel system that uses MRI scans to categorize Parkinson's disease symptoms and evaluates the usefulness of artificial intelligence in diagnosis. The study comprised three evaluation tests for clinical stage, dementia severity, and Parkinson's disease motor abilities. The researchers employed a handmade topographical classifier, numerous feature selectors, patch-based learning, and IMV to describe each patient's present condition. On these principles, a new model was developed. The model scored well in each classification challenge, implying that artificial intelligence might increase the accuracy of Parkinson's disease diagnosis using MRI scans.

Nmm et al. conducted research with 34 volunteers, dividing them evenly into Parkinson's disease sufferers and regular persons. The life expectancy of the groups was 69 years, with a standard deviation of 4 years. The study collected patient data through writing and drawing tasks using customized software on an iPad Pro with a stylus. The researchers advocated using the Resnet architecture after data augmentation and improvement, which obtained a generations of 93%. These findings revealed the use of deep learning-based networks in the diagnosis of Parkinson's disease.

Fratello et al. conducted a research with 22 healthy people and 9 Parkinson's disease patients, all of whom were anyways and aged 25 to 60. They created an app that used a tablet to gather scribbled data in order to find connections that may be used to diagnose Parkinson's illness. The study offered three models for different types of handwritten data, with the Mann-Whitney test used to extract highly identifying characteristics. The first two models utilised a linear SVM method, whereas the third used a medium KNN method. The accuracy of the first two models was found to be 71.6% and 75.5%, respectively, while the accuracy of the proposed example was determined to be 77.5%.

Khatamino et al. [19] used a CNN-based technique to evaluate the HW dataset. The dataset was separated into spiral and spiral picture components, and spiral drawings were promote the software's 2D properties. The signals were reduced, homogenized, and converted into square matrices before being input into the proposed CNN model.

The SST and DST datasets supplied a total of 72 images, comprising 57 Parkinson's disease patients and 15 healthy individuals. To avoid a reduction in coefficient of determination, the researchers incorporated early stopping.

According to the researchers, a CNN based on K-fold cross validation and LOOVC would be appropriate for the retrieved features. They were able to get greater accuracy with fewer features, and the model's accuracy approached 88%.

A. Our Contributions

Our research advances the understanding of Parkinson's disease detection by showing how well DenseNet analyzes handwritten doodles. According to our findings, adopting

DenseNet for feature extraction and classification has a number of benefits, such as increased accuracy, decreased overfitting, and better scalability. Because of these advantages, DenseNet is a good option for medical image processing jobs requiring little training data. To fully explore the potential of DenseNet and other deep learning models for diagnosing Parkinson's disease using various forms of input data, we do realize that more research is necessary.

III. MODEL PROPOSED

In this study , we proposed a DenseNet model which is pretrained using transfer learning and it uses augumented dataset.

A. Model Architectures

In this study, we employed the 121-layer Densely Connected Convolutional Network (DenseNet)[4] for the classification process. The DenseNet-121 architecture has multiple dense blocks, each with convolutional and pooling layers. Each layer in a dense block receives feature maps from all preceding layers and passes on its own feature maps to subsequent layers. This connectivity pattern improves feature reuse and performance. Transition layers connect the dense blocks and include batch normalization, convolution, and pooling operations to reduce spatial dimensions and increase channel numbers. This reduces parameters and improves computational efficiency.A global average pooling layer and a fully linked layer with a softmax activation mechanism are included in the subsequent rounds, producing class probabilities. The global average pooling layer aggregates spatial information and produces a single feature vector for each channel. The Fig 1 demonstrates the architecture of the DenseNet model.

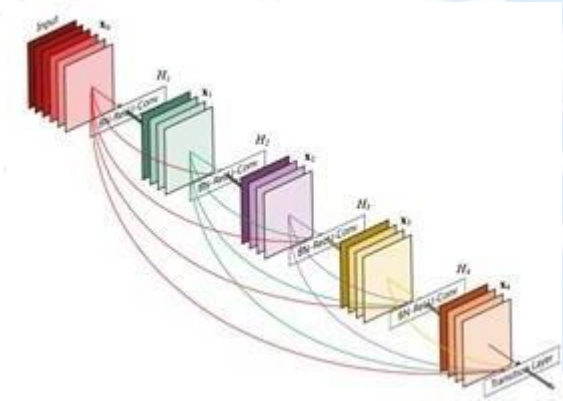

Fig 1. .Architecture of DenseNet model[4]

B. Transfer Learning

In transfer learning, a pre-trained model can be used as the starting point for a new task, which saves time and resources that would be needed to train the network from scratch. Transfer learning with DenseNet-121 involves taking a pre-trained model and replacing the last layers with new ones tailored for a specific task. For example, when classifying images, the last layer can be replaced by a new layer that produces the desired number of classes. The network may be taught in this manner to use a new dataset with fewer labeled examples, since the pre-trained weights already capture the important features. The advantages of using DenseNet-121 transfer learning in research include faster training and better performance on new datasets. Finally, tuning a pre-trained model can further improve its performance by adapting it to the specifics of a new task. Overall, DenseNet-121 and transfer learning are promising techniques to achieve high performance in computer vision tasks and can be valuable tools in research

C Augmentation of image data

Another method for handling a tiny training set is image data augmentation. This method is applied to the current training set of photographs. As a result, both the diversity and the number of examples in the training set increase.

Data augmentation also lessens overfitting, which is another benefit.

The geometry enhancement was carried out as follows:

- The picture was rotated at random angles between 0 and 360 degrees.
- Flipping involves flipping the picture along either the x or y axes.
- The picture was translated either horizontally or vertically. (or both). Images were randomly translated vertically or horizontally within certain width and height limits (as a percentage of the overall width or height).
- Cropping took away a portion of the picture.
- Scaling is used to either increase or decrease the image's size.

IV. TRAINING SETTING AND MODEL IMPLEMENTATION

A. Dataset Description

In the experimental phase of the research, the authors utilized the publicly available NewHandPD [20] dataset, which includes handwritten samples that are relevant to their study. The data was collected using a tablet and a smart pen. The NewHandPD dataset was created by Pereira et al. [20], and it builds upon the HandPD dataset [21]. The total number of images in the dataset is 594, of which 160 are male and 104 are female. The dataset comprises of two groups, the Healthy Group and the Patient Group, with 315 and 279 samples, respectively, including both males and females. The data is categorized into three types of drawings, namely, circle, meadow, and spiral, based on the type of drawing the participant was asked to produce. We trained and tested our model using the Spiral dataset.

B. Data Preprocessing

It is standard practice to compress datasets to 256x256 pixels and convert them to grayscale to boost the accuracy and efficacy of deep learning models. Also, to decrease data complexity, the number of pixels are often scaled to lie within the range of 0 to 1. This pixel value range has been proven to be especially useful for increasing the performance of deep learning models.

C. *Train Setting And Model Implementation*

Using the Sequential API in Keras, a new model is constructed on top of a pre-trained DenseNet121 model as the base model. A Flatten layer, a dense layer with ReLU activation, a Dropout layer to prevent overfitting, and a final dense layer with a softmax activation function to output class probabilities to make up the new model. It starts with the DenseNet base model. The Adam optimizer and categorical cross-entropy loss function are used to build the DenseNet base model, and the layers are frozen to prevent their weights from changing during training.
The below formula is used to find the weights for adaptive moment estimation

$$\theta t + 1 = \theta t + \Delta\theta t \qquad (1)$$

The categorical cross-entropy loss function is also employed in this investigation. The overfitting is reduced using L2 regularisation. Pre-trained weights from the ImageNet dataset were used to launch the suggested model. This made it possible for this investigation to use the pretrained model.

The flowchart of our model is shown in Fig 2. First the DenseNet-121 model is loaded. In order to initialize the weights, this model was trained using ImageNet. The penultimate layer was eliminated, and a softmax with two neurons that can individually predict whether or not someone will have Parkinson's disease was installed in its stead. The NewHandPD[20] dataset was then used to refine and retrain the model. This trained model's prediction performance was assessed during testing.

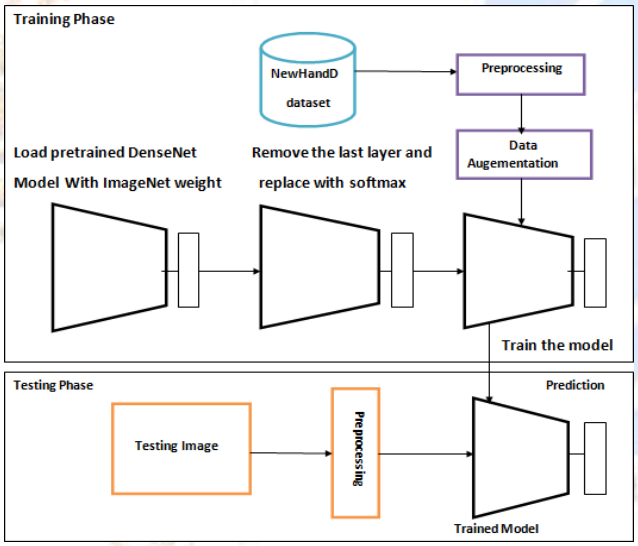

Fig 2. Flowchart for the proposed model

V. PERFORMANCE RESULTS

D. *Accuracy*

Our suggested method can obtain a maximum accuracy of 97.91% before it overfits and completely stops learning. Accuracy improves with each algorithm iteration. After reaching its peak at and after epoch 25, the algorithm then behaves steadily. It is displayed in the Fig 3.

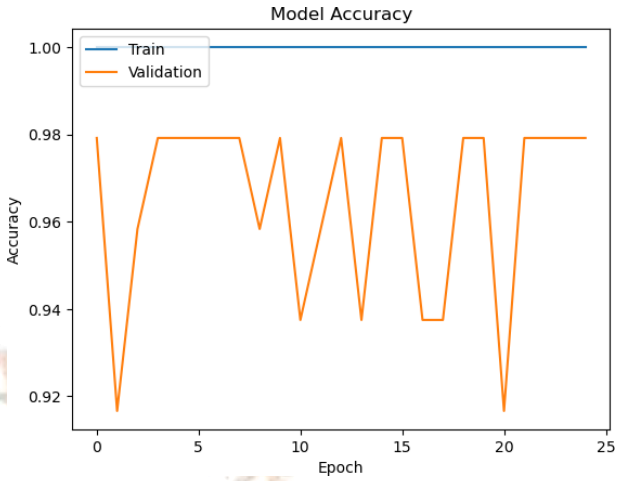

Fig 3. Training and testing accuracy of the model

E. *Loss*

The validity of the feature map is verified at each learning step using the instructional loss, which is calculated by multiplying the best vector generated for each population by the train dataset. The generated feature map is then used to build the DenseNet121 model, which is subsequently validated against the test data. The test loss is computed using the test dataset to assess variations in the training epoch and test loss. Importantly, the attained similar mean loss was 0.11, which is less than the minimum training loss of 0.16. It is is shown in the Fig 4.

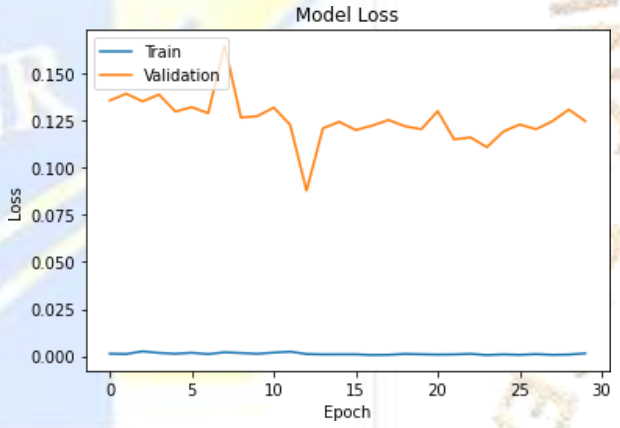

Fig 4. Training and testing loss of the model

VI. CONCLUSION

This study's goal was to provide a fresh framework for the data from a shared NewHandPD dataset that can be used for the accurate and rapid diagnosis of Parkinson's disease.
To save training time, we used DenseNet-121 as the basis infrastructure for our current plan, and the results demonstrate that our model surpasses several recently investigated strategies in terms of classification accuracy. Furthermore, our model obtained an astonishingly modest loss and excelled in other operation conditions, such as accuracy.

Our proposed model has been validated through analyses of experimental data and performance comparisons, which demonstrate its higher accuracy in detecting Parkinson's disease.

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