Micrographia-based parkinson's disease detection using Deep Learning

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Abstract: Parkinson's Disease (PD) is a disorder of the nervous system that is chronic and progressive, and affects millions of people around the globe. PD often manifests through symptoms like tremors or shaking, slowness of movement (Bradykinesia), freezing of gait, impaired posture, muscle stiffness, and others. The key focus is the early diagnosis of PD symptoms, which, if handled in their initial stage, can improve the quality of life for the patients. The fine motor control of PD-affected persons, particularly handwriting (Micrographia), can be used for PD diagnosis in patients. Deep Learning (DL) approaches, a subfield of machine learning research represent a useful tool for unsupervised feature learning because they employ a succession of layers, each of which is responsible for extracting different sorts of data. This research work utilises Convolutional Neural Networks (a deep learning algorithm) and focuses on Micrographia as the main diagnostic feature of PD. This work has achieved two main goals, i.e. utilizing CNN for PD diagnosis by learning features from handwriting, thereby improving, and assisting in PD detection, and enhancing overall diagnostic accuracy. The proposed system has achieved the following metrics: Accuracy of 96.67%, Precision of 96.67%, and Recall of 96.67%.

Keywords: Convolutional Neural Networks, Deep Learning, Parkinson's Disease, Micrographia.

1. Introduction

Parkinson's disease (PD) is a disorder of the nervous system that affects people all over the world. It causes slow movement, tremors, and muscle rigidity (Jankovic, 2008). Other major symptoms include small handwriting, tremors in muscles, loss of smell, trouble moving or walking, impaired posture, and balance, etc. It was first characterised by James Parkinson in the year 1817. The diagnosis of Parkinson's disease is notoriously challenging. Clinicians presently have no way of detecting Parkinson's disease before symptoms arise, and even once symptoms do appear, it can be difficult to distinguish them from a variety of other degenerative disorders. Manual detection is used in existing systems, which is inefficient and time-consuming. Handwriting alterations are common in patients with Parkinson's disease. Handwriting often becomes small and cramped and can become more difficult to control when writing for longer periods. Recent research also strongly implies that handwriting tests that reveal Micrographia often indicate PD (Gil-Martín et al., 2019).

PD mainly includes motor symptoms (a movement disorder) and non-motor symptoms like cognitive dysfunction (Meireles et al., 2012). As motor symptoms are concerned, four main signs are considered cardinal symptoms: resting tremor, rigidity, bradykinesia, and sometimes postural instability. About 70% of PD patients have a resting tremor which is between 3-5 Hz and it is characterized as an asymmetrical tremor. Another sign of PD is a feeling of resistance during joints' movements and it is called cogwheel rigidity (Samii et al., 2004). In other words, it is the converse of smooth movements (Khan Academy, 2015). Slowness of movement is the third sign, called bradykinesia; it is vivid for simple movements like handwriting. The fourth symptom is postural instability and this does not happen in the early stage of PD, in particular for younger patients it is related to balance, which makes the patient unstable on his feet and may lead to falls (Samii et al., 2004; Khan Academy, 2015).

The proposed work aims to assist physicians in diagnosing Parkinson's disease by utilizing CNNs to learn features from handwriting. CNNs can obtain accurate information from digitized versions of tests and then indicate the probability that a person is affected by PD or not based on the handwriting of that individual. The reason this work has become important is because of the issues in the existing detection system which are:

- Manual identification is the go-to tool for Parkinson's disease diagnosis, but it takes more time and is prone to errors;

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- Accurate detection of Parkinson's has a 25% probability of misdiagnosis;
- Traditional detection methods that utilize deep learning often use voice samples that are prone to noise and are usually harder to record on-site (hospitals etc.) (Gallicchio et al., 2018; Grover et al., 2018);
- Most existing methods do not take into consideration Micrographia, which is now considered one of the key determining symptoms of Parkinson's.

The problem this work addresses is the lack of effective, efficient, and accurate detection and diagnosis methods for Parkinson's Disease. Presently, there is no objective way to diagnose Parkinson's disease (Little et al., 2008). A complete PD diagnosis might take months and symptoms must be closely watched as they can be indicative of other degenerative disorders. Even then, the probability of making an incorrect diagnosis is about 25% (Jankovic, 2008). The symptoms of PD can overlap with those of other neurodegenerative diseases, such as essential tremor, multiple system atrophy, and progressive supranuclear palsy. Hence, it leads to misdiagnosis in most scenarios (ul Haq et al., 2022).

Brain MRI scans, speech tests, handwriting analyses, and sensory data are all within CNN's capabilities. Compared to clinical observations or a patient's medical history, this data can better reflect the subtle and varied changes in brain structure and function caused by PD (Ramzan et al., 2020). Convolutional Neural Networks can help reduce the rate of misdiagnosis of PD for two reasons. First, CNNs can learn features that are not easily visible to the human eye. This means that CNNs may be able to identify subtle signs of PD that would be missed by other diagnostic methods. Second, CNNs can learn from many data points. This means that CNNs can be trained on a dataset of images that includes both PD patients and patients with other neurodegenerative diseases. This allows CNNs to learn the subtle differences between PD and other conditions, which can help to reduce the risk of misdiagnosis (Tanveer et al., 2022).

CNNs are a type of deep learning algorithms that is particularly well-suited for image classification tasks. This is because CNNs can learn the spatial relationships between features in an image (Shamshirband et al., 2021). Moreover, in the proposed approach, the input dataset includes handwritten images (Micrographia) pertaining to Healthy and Unhealthy persons. Then these images are sent to the neural network model to train it to produce predictions. Hence, CNN has been considered as the suitable prediction model for the proposed approach.

The contributions of this research work are the following:

- Increasing the CNN layers (including the number of epochs used), hence increasing the accuracy of the system;
- Designing a user-friendly and trustworthy method for Parkinson's disease prediction;
- Using Micrographia (a recently developed/novel symptom in diagnosing) as base diagnostic factor instead of more traditional voice samples;
- To further help increase accuracy, data augmentation techniques are used which in turn results in a higher accuracy.

The remainder of this paper is structured as follows. In Section 2, the brief overview of existing research works related to this work are discussed. In Section 3, the proposed system is presented along with the system architecture and methodology. Section 4 sets forth the implementation details and the analysis of obtained results. In Section 5, a conclusion is drawn, and future work is discussed.

2. Related work

Machine learning models can aid in PD prediction in the early stages. The accuracy is good and time consumption is lower, but the learning speed is found to be very low in these models. (Little et al., 2008) have shown the practical significance of existing conventional and nonstandard tests for differentiating healthy persons from PD-affected individuals by diagnosing Dysphonia. Persistent phonation from 31 participants is recorded, 23 of whom had Parkinson's disease.

The Support Vector Machine (SVM) has achieved better results when there is a considerable margin of separation between classes, but the SVM does not achieve good results when there exists more noise in the dataset i.e. when target classes are overlapping. When the number of features for each data point exceeds the number of training data samples, the SVM will underperform. Challa et al. (2016) indicated that Parkinson's disease has motor and non-motor symptoms, and more studies are being carried out to predict Parkinson's disease based on non-motor symptoms that occur before the motor ones, such as Rapid Eye Movement and Sleep Behaviour Disorder.

Shivangi et al. (2019) introduced two neural network-based models, the VEGFR (Vascular Endothelial Growth Factor Receptor) Spectrogram Detector and the Voice Impairment Classifier. These models aid in the early detection of Parkinson's disease. A comprehensive empirical evaluation of Convolutional Neural Networks was performed to predict the disease based on large-scale image classification and deep dense Artificial Neural Networks on voice recordings. In terms of accuracy, the experimental findings show that the suggested model outperformed other existing models. The VEGFR Spectrogram Detector has an accuracy of 88.1 percent, while the Voice Impairment Classifier has an accuracy of 89.15 percent. The accuracy is better than that of other existing models, but the clarity of the image was not very high in this model.

Mohamad et al. (2022) intend to assist in the diagnosis of Parkinson's disease by separating healthy patients from PD patients using Convolutional Neural Networks (CNN). In this work, the Naive Bayes classifier is used for this purpose. The Naive Bayes is simple to use and efficient, which also allows the model to outperform others. The main limitation of Naive Bayes is the assumption of independent predictors. LeCun et al. (1998) have shown that if the correct network design is provided, Gradient-based learning methods can be used to compile a complicated decision surface that can categorize patterns of high dimensions such as handwritten characters with minimal pre-processing. The research examines and analyses various approaches for handwritten character recognition using a standard handwritten digit recognition problem. It is quite accurate for visual recognition tasks, but the CNN does not encode the position and orientation of objects.

Lamba et al. (2021) proposed an approach based on speech signals thereby providing early detection of Parkinson's disease. A variety of feature selection techniques/approaches and classification algorithms were tested before designing the model and the best combination was used. To create various combinations, several feature selection methods as well as numerous classifiers were used. Camps et al. (2017) present a novel method for detecting Freezing of Gait (FoG), the evaluation is done on 15 patients who manifested FOG, and it has achieved a validation accuracy of 88%. Nagasubramanian & Sankayya (2021) introduced acoustic-based DL techniques for diagnosing Parkinson's disease symptoms. The suggested system uses Deep multivariate vocal data analysis. It has been created and developed with the help of an Acoustic deep neural network, an Acoustic deep recurrent neural network, and an Acoustic deep convolutional neural network.

Cantürk & Karabiber (2016) proposed a machine-learning approach for classifying People with Parkinson's Disease (PwP) based on speech data. Feature selection algorithms, classifiers, and validation methods were used in the system to accurately classify PwP. The proposed model also calculates specificity, accuracy, and Matthew's correlation coefficient for the results. Lei et al. (2019) have proposed a hierarchical stacked DPN (Deep Polynomial Network) to improve the effective diagnosis of PD patients as it is very difficult to diagnose PD with the help of neuroimaging techniques due to mutation of genes in the patients. In the next stage, correlative information between different segmentations is extracted by different combinations of feature pairs. The method has achieved remarkable and superior results compared to other related methods.

Wrobel et al. (2022) suggested a novel method for diagnosing Parkinson's disease, based on hand-drawn spirals and features generated from them. Both ill and healthy patients used a drawing tablet to create spirals that were analysed. The study showed that the proposed set of features enables the effective diagnosis of Parkinson's disease. This work proposed a method for diagnosing Parkinson's disease based on hand-drawn spirals and the features generated using them. There is a preponderance of records from people with Parkinson's, which means that some classifiers may have the ability to favour the more numerous classes.

Reyes et al. (2022) mentioned a transformer encoder-based model to classify PD patients from Healthy Controls (HC) based on their genotype. This method is designed to effectively model complex global feature interactions and enable increased interpretability through the learned attention scores. The proposed framework outperformed traditional machine learning and deep learning baseline models. The restricted sample size issue might be solved by novel training approaches including pretraining and domain adaption techniques (Nancy Noella et al., 2023). When diagnosing Alzheimer's disease (AD) and Parkinson's disease (PD) using Positron Emission Tomography (PET), Nancy Noella et al. (2023) described various effective machine learning techniques that are used to analyse their behaviours. The PET image dataset used in this work consists of 1050 images with AD, PD, and Healthy Brain images. The diagnosis of AD and PD with reference to the healthy brain is carried out using different machine learning algorithms such as Bagging Ensemble, Decision Tree, Naïve Bayes, and Multiclass Classification Using Support Vector Machine (SVM) (Tripathi et al., 2022).

To detect PD in an ecologically valid data-gathering setting at the subjects' homes, Tripathi et al. (2022) suggested a new set of characteristics based on keystroke dynamics, i.e. the time necessary to press and release keyboard keys during typing. On a sizable keystroke dynamics PD dataset obtained by observing participants for 22 months and extracting around 5 months' worth of active typing data in an uncontrolled setting at the subjects' homes, they have presented a benchmark of published approaches (Arora et al., 2022).

To distinguish between PD and healthy controls in two situations, namely off- and on-medication, Aljalal et al. (2022) suggested an effective Discrete Wavelet Transform (DWT)-based technique. First, the EEG signals are pre-processed to remove major artefacts before being decomposed into several EEG sub-bands (approximate and detailed) using DWT. Regarding EEG channel selection, results show that the frontal region channels contribute the most to classification performance compared with other regions. However, using the forward-addition method, it was found that selecting a suitable small number of channels from several regions could improve the classification accuracy.

Through this literature survey, the new approaches and techniques used to further improve detection and diagnosis are identified. For example, the new OPF (Optimum-Path Forest) approach introduced by Spadoto et al. (2010) has proved to be faster than traditional techniques, and LeCun et al. (1998) have shown that the Gradient-based learning methods can be used to synthesize complicated decision surfaces, which provide high accuracy in image recognition. It can also be observed from the work of Shivangi et al. (2019) that the VEGFR (Vascular Endothelial Growth Factor Receptor) Spectrogram Detector and the Voice Impairment Classifier developed by them provide a novel approach to PD diagnosis.

There are many issues in the existing works, one of them being manual identification, which is a tool for Parkinson’s disease diagnosis, but it takes more time and is prone to errors. Accurate detection of Parkinson’s has a 25% probability of misdiagnosis. Traditional detection methods that utilize deep learning often use voice samples that are prone to noise and are usually harder to record on-site (hospitals etc.) (Lamba et al., 2021) Most of the existing methods do not take into consideration Micrographia, which is now considered one of the key determining symptoms of Parkinson’s. To address these issues, the proposed system incorporates the CNN algorithm with more layers to provide a higher accuracy. This research work also addresses the issue of voice samples by replacing them with images drawn by patients and finally, it addresses Micrographia.

3. Methodology

In the proposed approach, Convolutional Neural Network (CNN) has been used, which takes an image as input and learns several properties of that image using filters. It comprises four phases: Data Collection, Data Preprocessing, Model Training, and Model Evaluation as it is shown in Figure 1.

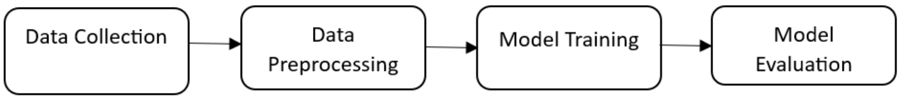

Figure 1. Methodology flow diagram (Codeacademy, 2021)

CNN is used to classify and predict the image as an image pertaining to a healthy person or to a person with Parkinson's. The dataset is split up into two sections: the training dataset and the testing dataset in a 70:30 ratio. In the training module, the model is trained on images in the training dataset by adding different layers of CNN, for example, the max-pooling layer, flatten layer, convolutional layer, dense layer, and image augmentation are used to prevent overfitting and enhance the accuracy of the model. The testing module runs the model on images in the testing dataset. This further leads to the prediction aspect of the system, where a threshold value of 0.5 is set for prediction and the result is decided based on this value. Using CNN, the prediction process is carried out to detect whether a person is affected by Parkinson's disease or not as it is shown in Figure 2.

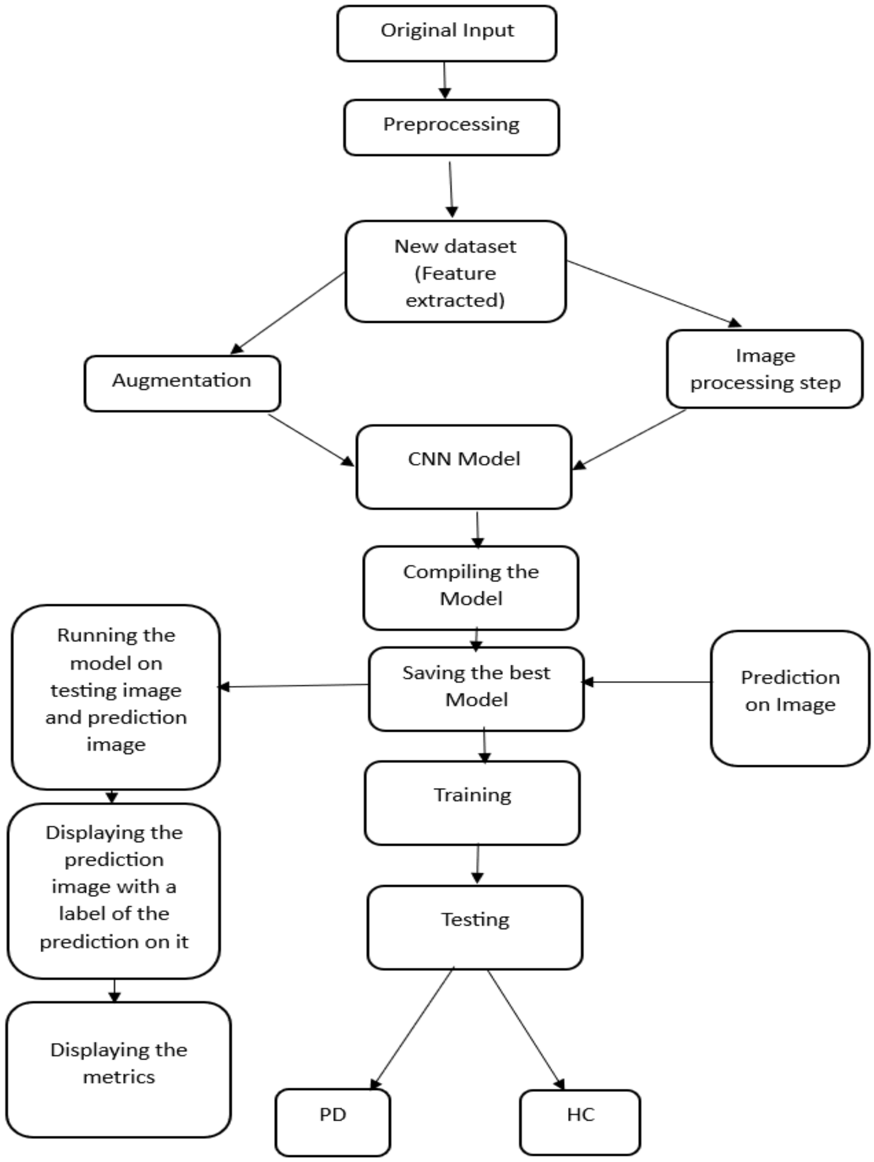

Figure 2. Proposed System Overview

3.1. Dataset collection

The images of healthy persons and patients with Parkinson's disease (drawing of spirals and waves) have been taken and the images are further divided into training and testing sets. The image dataset has been taken from Kaggle and it contains 204 images out of which 102 are images pertaining to healthy persons and 102 belong to persons with Parkinson's. The proposed work uses 70% and 30% of the images taken from the primary datasets for training and testing purposes, respectively. Image Augmentation is used for pre-processing data, to prevent overfitting.

3.2. Data pre-processing and model training

The dataset has been divided into two folders, one is for training and the other one is for testing. The training folder images are used to train the model and the validation accuracy is calculated based on the testing dataset. Both are considered for selecting the best model. The first step is building the neural network which consists of a convolution layer along with max-pooling layers, Flatten and Dense layers. The last dense layer has used a sigmoid activation function to make the final output fit in the interval from 0 to 1.

In the next step as it is shown in Figure 2, data augmentation has been carried out by converting the images from coloured to grayscale images. Thereafter, the training and testing dataset is prepared from the selected directory by specifying the batch size, class mode, directory, and target size. The next stage involves compiling the model and choosing the loss function along with the optimizer for the model (the Adam optimizer). As this was a binary classification problem, the loss function chosen was binary cross-entropy. The final step is fitting and saving the model as well as plotting the graph for training accuracy, validation accuracy, and loss.

3.3. Testing and prediction

In this phase, another folder has been created to store the prediction images so that the saved classifier is made to run on the testing dataset and the prediction image as it is shown in Figure 2. As in the training module, the final output is between 0 and 1 in the final layer of the neural network. Therefore, a threshold value of 0.5 is set for identifying the Parkinson's drawn image (an image drawn by a patient suffering from Parkinson’s).

If the final threshold output is higher than 0.5, then it is a Parkinson's drawn image, or else (if the output is lower than 0.5) it is a healthy person-drawn image. A confusion matrix has also been constructed, from which recall, precision and accuracy have been calculated. As a result, the prediction of the image with a label of being healthy or being affected by PD is made. Subsection 3.4. also discusses the accuracy, precision, and recall metrics.

3.4. System model

Figure 3 shows the CNN model taken for the proposed approach. Using previously unseen images from a testing dataset, the model was put to the test as a classifier to distinguish between healthy persons and patients after training. In supervised mode, CNN models employ distinct datasets for training and testing. 70% and 30% of the samples were taken from the primary datasets for training and testing. Each group was given a different set of samples at random. This technique enables one to assess the framework's accuracy.

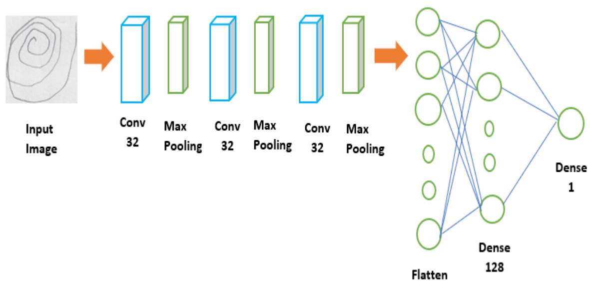

Figure 3. The employed CNN Model

3.4.1. Model training

Here, the neural network is initialized as a sequential network. After initializing the network, it uses convolutional 2D layers to perform convolution operations on training images. Since it works on images that are 2D arrays, it has used convolutional 2D layers. The output of the convolution of an image matrix with a filter matrix is called a ‘Feature Map’. Following the convolution operation on the image, a pooling operation on the generated feature maps is required. It will shrink the image as much as feasible (lower the number of nodes for subsequent layers) without losing the features discovered during convolution. Max pooling returns the maximum pixel value in each region. Flattening converts all the pooled images into a continuous vector. In this step, the 2D array is taken and converted into a one-dimensional single vector. Then, a fully connected layer is created using the dense layer, and the set of nodes that were achieved after the flattening step is given as input to these layers.

In the last step, the output layer is initialized and it contains only one node. This single node will provide a binary output indicative of whether the person is affected by Parkinson's disease or not i.e. whether the image belongs to a healthy or unhealthy person. All these steps are visually summarized in Figure 3. Before fitting CNN to the image dataset, the images are pre-processed to prevent overfitting by performing some image augmentations on them, Binary cross-entropy loss function has been used as it is a binary classification task because the image selected for prediction will be either a healthy or a Parkinson's affected person image. For the optimization process, the Adaptive Moment Estimation (Adam) algorithm is applied. It is an optimization technique that can be used to iteratively update network weights using training data.

As it is shown in Figure 4, the graph plots accuracy along the y-axis and epochs along the x-axis. As it can be seen from Figure 4, when the number of epochs is 10, the training accuracy is 54% and validation accuracy is 60% and when the number of epochs reaches 80, the training and validation accuracy increase and go beyond 90 percent.

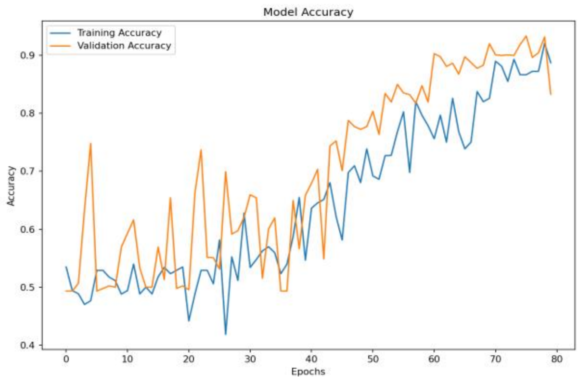

Figure 4. Graph showing Model Accuracy

The loss function is a measure of how well the model is performing on the training data. A lower loss indicates that the model is performing better. The most common loss function for convolutional neural networks is the binary cross-entropy loss function. The binary cross-entropy loss is computed as follows.

$$LOSS = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot \log\left(p(y_i)\right) + \left(1-y_i\right)\cdot \log\left(1-p(y_i)\right) \quad (1)$$

Where,

y_i is the ground truth table for i^{th} training example

$p(y_i)$ is the predicted probability for the i^{th} training example

N is the number of training examples

When the model's output is a probability, like in a classification task, the binary cross-entropy loss function performs well. When predicted probabilities are very near to the ground truth labels, the loss function is minimised. As it is shown in Figure 5, the graph plots loss along the y-axis and epochs along the x-axis. As it can be observed from Figure 5, when the number of epochs is 10, the training and validation loss is 70 percent, and when the number of epochs reaches 80 the training and validation loss decreases and goes below 30 percent. This shows that this model is properly trained.

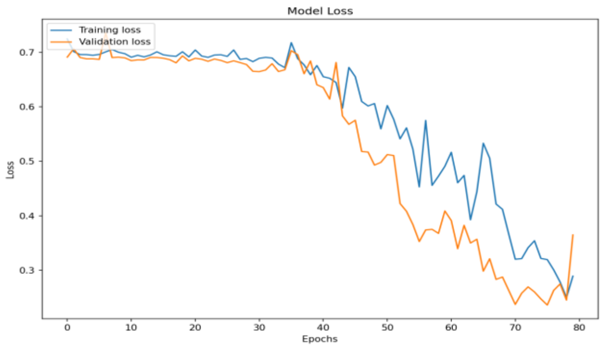

Figure 5. Graph showing Model Loss

3.4.2. Model testing and prediction

In this phase, a folder has been created to store the image on which the prediction has to be made. The model is created by the name of parkinson_model.h5. The saved classifier model is made to run on the prediction image. As in the training module, the final output is between 0 and 1 in the final layer of the neural network. Therefore, a threshold value of 0.5 is set to identify whether the image is drawn by a Parkinson-affected person (if the threshold value > 0.5) or a healthy person (if the threshold value < 0.5). The saved classifier model contains the configuration, weight, and the model optimizer's state. This enables us to restart training where it was left. Hence, this model predicts whether the person who has drawn the image is healthy or affected by Parkinson's.

As it is shown in Figure 6, 60 images have been tested for prediction and the True Positive (TP) value came out as 29, True Negative (TN) value as 29, False Positive (FP) value as 1, and False Negative (FN) value also as 1.

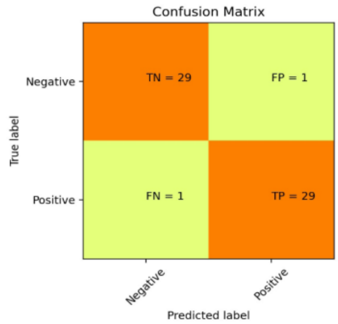

Figure 6. Confusion Matrix

Accuracy, Precision, and Recall metrics are calculated as follows:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \times 100 = \frac{(29 + 29)}{(29 + 29 + 1 + 1)} = 96.67\% \quad (2)$$

$$Precission = \frac{TP}{TP + FP} \times 100 = \frac{29}{209 + 1} = 96.67\% \quad (3)$$

$$Recall = \frac{TP}{TP + FP} \times 100 = \frac{20}{29 + 1} = 96.67\% \quad (4)$$

The proposed system has achieved the following metrics: Accuracy of 96.67%, Precision of 96.67%, and Recall of 96.67% as it can be observed from equations (2), (3), and (4). The accuracy that has been obtained in the proposed work is better than those reported in previous works that have used different datasets but also spiral drawings. Mohamad et al. (2022) obtained an accuracy of 93.5 % while Gil-Martín et al. (2019) obtained an accuracy of 96.5% using a digitizing tablet considering pressure points as a parameter. While considering previous works over the same dataset, research by Yuvnish Malhotra and AI Technology and Systems (2021) recorded an accuracy of 83%.

4. Experimental settings and results

The proposed model uses Python (Python 3.7 or higher) and PyCharm (an IDE used for the Python scripting language). Several Python and deep learning libraries are used such as OpenCV (an open-source library used for machine learning and image processing), Matplotlib (a comprehensive library for interactive visualizations in Python), Sklearn (a library for machine learning and statistical modelling), Keras (open-source deep-learning library for Python), NumPy (a Python library used for working with arrays), PIL (a Python library used for image processing), etc.

As it is shown in Table 1, the various works written in this field are compared and it is evident from Table 1 that the dataset used in the proposed work is larger in comparison with others and the accuracy obtained in the proposed work is 96.67%, better than those obtained in previous works.

Table 1. Datasets and images used by related research works in PD diagnosis using Deep Learning (Gil-Martin et al., 2019)

Existing Works and Proposed Work	**Datasets**	**Tests**	**Methodology & algorithms used**	**Accuracy**	**Details**
(Kotsavasiloglou et al., 2017)	24 PD 20 Healthy	Line Drawing	Naive Bayes Algorithm	88.6%	Line drawing (2s approx.)
(Zham et al., 2017)	31 PD 31 Healthy	Archimedean spiral	Naive Bayes Algorithm	93.3%	Segments between Pen up and down (2s approx.)
(Gallicchio et al., 2018)	62 PD 15 Healthy	Spiral drawings	Deep Echo State Networks	89.3%	Drawings (>10s)
(Khatamino et al., 2018)	62 PD 15 Healthy	Spiral drawings	Convolution Neural network	72.5%	Drawings (>10s)
(Yuvnish Malhotra, 2021)	102 PD 102 Healthy	Spirals and Waves drawing	Convolution Neural network	83%	Drawings (>10s)
(Mohamad et al., 2022)	58 PD 29 Healthy	Pentagon and Cube Drawing	Convolution Neural network	93.53%	Drawings (>10s)
Proposed work	102 PD 102 Healthy	Spirals and Waves drawing	Convolution Neural network	96.67%	Drawings (>10s)

Table 2. Datasets used by different authors and types of tasks (Mohamad et al., 2022)

Year	**Authors**	**Number of Subjects**	**Tasks**
2016	Pereira et al.	32	Meander & Spiral Drawing
2017	Afonso et al.	32	Meander & Spiral Drawing

2018	Pereira et al.	92	Meander & Spiral Drawing
2018	Gallicchio et al.	77	Spiral Drawing
2018	Khatamino et al.	77	Spiral Drawing
2018	Moetesum et al.	72	Spiral Drawing
2018	Vásquez-Correa et al.	84	Spiral, circle, and cube drawing
2019	Afonso et al.	35	Meander & Spiral Drawing
2019	Ribeiro et al.	35	Meander & Spiral Drawing
2019	Gil-Martín et al.	77	Spiral Drawing
2019	Diaz et al.	72	Spiral Drawing
2020	Afonso et al.	35	Meander & Spiral Drawing
2020	Szumilas et al.	64	Circle Drawing
2020	Cantürk	40	Spiral Drawing
2020	Naseer et al.	75	Spiral Drawing
2021	Shenoy et al.	87	Spiral pentagon Drawing

Table 2 shows in a concise manner the different tests and datasets used by different research works in this field (Parkinson's detection using machine learning). It illustrates the number of subjects used and the type of figures (spirals, lines, etc.) the subjects were asked to draw. It can also be observed that a maximum of 92 subjects were used in the research work of Pereira et al. (2018) (this is the highest number for all the research works shown in Table 2). The proposed system however uses over 200 subjects, which outnumbers the subjects in the research that was carried out before it by far. The proposed research work has significant achievements in terms of accuracy and usability.

It can be noticed that the research conducted by Yuvnish Malhotra, AI Technology and Systems (2021), features a training and validation accuracy below 85 percent as it is shown in Figure 7, which is much lower than what was attained by the proposed work as it is illustrated in Figure 4 (which depicts the accuracy of the model proposed in this paper), this work has higher accuracy of 96.67%.

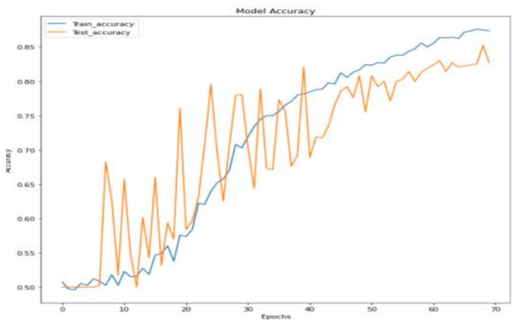

Figure 7. Graph showing Model Accuracy for the research conducted by Yuvnish Malhotra, AI Technology and Systems (2021) (Accuracy - y-axis; Epoch - x-axis)

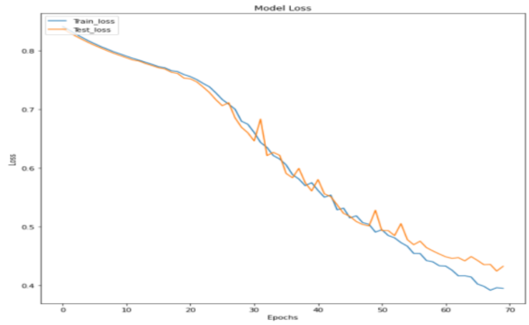

Figure 8. Graph showing Model loss for the research conducted by Yuvnish Malhotra, AI Technology and Systems (2021) (Loss - y-axis; Epoch - x-axis)

As it can be seen in Figure 8, it features a training and validation loss above 35 percent, which is again higher than the loss for the model proposed in this paper, which is illustrated in Figure 5 (which depicts the proposed work's Model loss).

5. Conclusion

The proposed system used the Deep Learning approach and investigated the potential of using drawing movements to detect Parkinson's disease. Micrographia, which is an early major motor symptom found in persons affected by Parkinson's disease is considered in this work which can prove to be very helpful in the early detection of Parkinson's disease. The accuracy of the results obtained in this study reached 96.67 percent. These findings encourage the use of sketching motions in the development of medical-decision support tools for PD detection. Unlike other approaches in this field, most of which use voice samples to determine the outcome, are inefficient and time-consuming and sometimes also use digitized tablets for drawing, this study will help with a better and early diagnosis of Parkinson's disease and also provide a higher accuracy and credibility for the obtained results and allow patients to know the status of their disease in the comfort of their own home as these patients face a lot of difficulties in making any movement.

In future work, the aim will be to explore other Deep Learning models like RNN. There is also a need to see if the generated models could provide more information about the stages of this illness such as the ability to distinguish between individuals with and without cognitive impairment. Also, this work can be utilized to see if one can extract relevant information from trained deep learning models in order to better understand the basis for discriminating PD from other similar disorders by evaluating the attributes that the models used for identifying patients affected by Parkinson's disease.

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