

Detection of Parkinson's Disease with Spiral images using Neural Networks

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Abstract—Parkinson's disease (PD) is a prevalent neurological condition affecting a significant number of people worldwide. Parkinson's disease (PD) is characterized by physical indications, including rigidity, shaking, and postural instability. Timely and precise diagnosis is crucial for effective intervention as well as disease management. However, Diagnosing Parkinson's disease (PD) and keeping track of its progression can be costly and inconvenient. Early-stage symptoms often manifest as handwriting disorders and changes in voice frequency. Detecting the disease based on handwriting could prove to be a superior technique, particularly utilizing spiral drawings. Spiral drawings are easily obtainable. We employ deep learning techniques with a primary focus on improving detection accuracy, particularly utilizing Feed forward Neural Networks (FNN) with Multilayer Perceptron (MLP) Architecture and HOG (Histogram of Oriented Gradients) Algorithm. Additionally, we have developed an interface that specifically requests input in the form of an individual's spiral drawing image.

Index Terms— Feedforward Neural Networks (FNN), MLP, HOG, tremors, rigidity.

I. INTRODUCTION

Parkinson's disease stands as a significant challenge in the field of neurodegenerative diseases as it affects the nervous system. This condition introduces a spectrum of symptoms, ranging from the distinctive tremors, bradykinesia, rigidity, posture instability, to subtle yet impactful alterations in speech and the loss of automatic movements. Early detection is essential for the best possible care and is the cornerstone of the management of Parkinson's disease. Prompt identification not only makes it easier to start appropriate medical procedures right away, but it also gives medical professionals the ability to more precisely and effectively customize treatment plans. Recognizing the critical importance of early-stage symptomatology, in particular the characteristic tremors frequently seen in the initial phases of the disorder. This work aims to make progress in the field by using cutting-edge deep learning techniques, with a special focus on neural networks. In this pursuit, we leverage a dataset of spiral drawings, a novel and targeted approach that aligns with the prominence of tremors in the initial stages of the disease.

Feed forward neural networks (FNNs), a type of deep learning, provide a data-driven method for analyzing complex patterns in medical imaging, particularly spiral pictures. To help diagnose Parkinson's disease (PD), FNNs identify minute variations in motor control that are represented in spiral images. Overall, FNNs with spiral image analysis hold the potential to improve patient outcomes by promoting individualized care and early PD detection.

II. LITERATURE REVIEW

The study uses speech recordings to identify Parkinson's disease. It employs a Convolutional Neural Network (CNN) architecture originally designed for image classification. The PC-GITA database's audio recordings were used by the researchers. The dataset included 100 people i.e, 50 were in good health and the other 50 had been diagnosed with Parkinson's disease. The audio recordings were transformed into spectrograms, treating them as image inputs. These spectrograms represented the frequency spectrum of the voice signal. A ResNet (Residual Neural Network) architecture was used for classification. This study used the PC-GITA database, which may have limitations in terms of diversity and size. A larger and more diverse dataset could enhance the model's generalization capabilities. Spectrograms are a representation of audio signals in the frequency domain. The resolution of spectrograms might impact the model's ability to capture fine-grained features [1].

The study leverages LightGBM, a gradient boosting framework, for accurate classification. Spiral patterns indicate irregularities associated with Parkinson's disease, making them helpful for diagnosis. The efficacy of LightGBM in differentiating between people with Parkinson's disease and those who do not is highlighted, along with its potential for early diagnosis and individualized treatment. However, the use of hand-drawn images increases unpredictability because different people have different drawing styles. To ensure robustness, additional validation on a variety of datasets is necessary [2].

This study explores to improve voice and speech analysis for the diagnosis and assessment of Parkinson's disease, focusing on phonatory and articulatory features. The review explores how these qualities can be used to create better diagnostic techniques. The importance of speech and voice patterns as possible potential indicators for Parkinson's disease is emphasized by the authors, who also stress the possibility of early identification. The study covers a range of technological techniques, such as signal processing and control strategies, that are used to evaluate Parkinson's disease via speech analysis. It also highlights how important these discoveries are to improving the state-of-the-art diagnostic instruments and furthering the field's research [3].

The authors of this paper investigate how to identify Parkinson's illness using evolutionary algorithms specifically the genetic algorithm (GA), in conjunction with the Support Vector Machine (SVM) classifier. Similar to a person's "black box," the voice signal has information hidden from view that can be retrieved to diagnose illnesses. Utilizing a discrete wavelet transform (DWT), the suggested model analyzes the signal in order to extract features. The accuracy obtained with the GA and SVM was 91.18%. It's crucial to recognize that there can be restrictions, such as the requirement for bigger and more varied datasets and possible difficulties with robustness and generalization [4].

In this paper, the authors suggest a novel method based on spiral and wave sketching patterns for detecting Parkinson's disease (PD). Convolutional neural networks (CNNs) are used in this method to analyze sketches in order to identify individuals who have Parkinson's disease (PD). With an accuracy of 93.3%, the CNN ensemble shows promise for early Parkinson's disease identification. The improvement of patient care and clinical diagnosis is greatly aided by this research. Recognizing limits is crucial, since they may include potential biases in the training data and the need for additional validation on bigger datasets [5].

III. METHODOLOGY

A. Data Acquisition

The data was collected from Kaggle which consists of spiral drawing images.

Then it is organized into training and testing sets for both healthy and Parkinson's cases. Later it undergoes augmentation and finally we got 1176 spiral images.

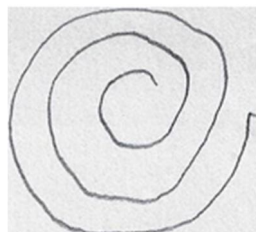


Figure 1: Healthy spiral image

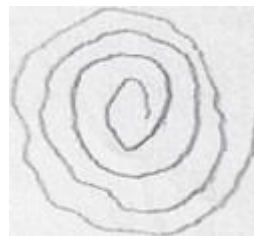


Figure 2: Parkinsoned Spiral image

B. Image Preprocessing

Each image in the dataset undergoes a series of preprocessing steps:

- Conversion to grayscale to simplify processing.
- Resizing to a standardized dimension of 200x200 pixels.
- Feature extraction using Histogram of Oriented Gradients (HOG), implemented using the skimage library.

The HOG algorithm, conceptualized by Navneet Dalal and Bill Triggs in 2005, serves as a pivotal feature descriptor in the realm of computer vision, particularly in the domain of object detection. Its methodology hinges on the meticulous calculation of gradient information within an image. This entails convolving the image with gradient filters to discern the magnitude and orientation of gradients at individual pixels. Subsequently, the algorithm proceeds to partition the image into minuscule, overlapping cells, from which histograms of gradient orientations are generated. These histograms effectively encapsulate the local texture characteristics of the image. To bolster its resilience against variations in lighting and contrast, the algorithm employs normalization techniques within larger blocks. The amalgamation of these normalized histograms culminates in the formation of the HOG descriptor, which serves as a comprehensive representation of the image's underlying structure.

C. Data Division

The data is gone through division into train and test sets through the utilization of the `train_test_split` function available in scikit-learn. The testing set comprises 20% of the total dataset, leaving the training set with 80%. We opted for a random state of 42 to set the seed for the random number generator used in the split.

D. Neural Network Architecture

The neural network comprises a total of four layers. Within this architecture, there exists an output layer, an input layer, and two hidden layers. Each one is as follows:

Input Layer:

It will be of 1024 neurons, representing the features extracted from the input data. Activation Function used here is - Rectified Linear Unit (ReLU). It acts as the initial layer for processing the input information.

It can be defined as:

In mathematical notation, the ReLU activation function $f(x)$ is equal to the maximum of zero and the input x .

$$f(x) = \max(0, x)$$

First Hidden Layer:

Following the input layer, a hidden layer consists of 512 neurons, employing the ReLU activation function.

iii. Second Hidden Layer:

Another hidden layer is added with 216 neurons. The utilized Activation Function for this layer is also same as previous.

iv. Output Layer:

The output layer has 2 neurons, each representing one of the classes: 'healthy' and 'parkinson'. Here we used Softmax.

It is a mathematical operation applied to a vector of real numbers, which then normalizes the vector into a probability distribution.

For an input vector z , the softmax function computes the output vector $\sigma(z)$ as follows:

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^J e^{z_j}}$$

Where:

- $\sigma(z)_i$ is the i^{th} element of the output vector.
- e is a constant (around 2.71828).
- z_j is the j^{th} element of z .

The softmax function normalizes the output vector into a probability distribution, where each element represents the probability of the corresponding class. These probabilities sum up to 1, ensuring that the output vector represents a valid probability distribution. Softmax activation is employed to convert the raw output scores into probability distributions, indicating the likelihood of each class.

A feedforward neural network (FNN), also referred to as a multilayer perceptron (MLP), represents a foundational architecture within artificial neural networks. It operates on a unidirectional flow of information, moving from input nodes through intermediary hidden layers to output nodes. Every node, excluding the input

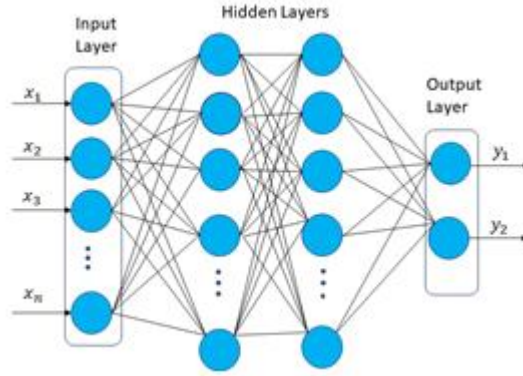


Figure 3: FNN Architecture

ones, applies a nonlinear activation function to the weighted sum of its inputs, facilitating the network's capacity to comprehend intricate data relationships.

Table I: Architecture of FNN

Layer (type)	Output	Param#
dense_1 (Dense)	(None, 1024)	18433024
dense_2 (Dense)	(None, 512)	524800
dense_3 (Dense)	(None, 216)	110808
dense_4 (Dense)	(None, 2)	434

In the above Table I. Param# denotes the quantity of parameters, encompassing both weights and biases, present within each layer. Every connection linking neurons is assigned a weight, while each neuron possesses a bias. The total number of parameters is the sum of all weights and biases in the layer.

E. Model Compilation

The Adam optimizer is utilized in the compilation of the model, with categorical_crossentropy serving as the loss function. The metric for evaluation is accuracy. The formula for categorical_crossentropy loss is:

$$categorical_crossentropy = -\frac{1}{N} \sum_{i=1}^N \sum_{j=1}^C y_{ij} \cdot \log \hat{y}_{ij}$$

Where:

C represents count of Classes.

N represents the count of Samples.

The term 'accuracy' is used as the metric, which measures the percentage of correctly classified samples. During training, the accuracy metric will be calculated and displayed after each iteration or epoch.

F. Training the Model

Utilizing a batch size of 32, the model undergoes training for 20 epochs on the training dataset (trainX and trainY). In the context of neural network training, an epoch signifies a single complete iteration of the overall training dataset. Within a single epoch, the model goes through all training examples once, computes the loss, and adjusts the model parameters (weights and biases) based on the gradients calculated. Additionally, a 20% validation split is taken to assess the performance of model.

G. Model deployment

This phase involves making the model accessible to end-users through a user- friendly interface. We deployed the model into flask. Then an interface is created.

The above diagram represents the overall methodology in brief saying that the data is collected first followed by preprocessing. After preprocessing, model is developed using FNN. Then the model is deployed into the flask. Finally, the interface is created followed by analysis of results.

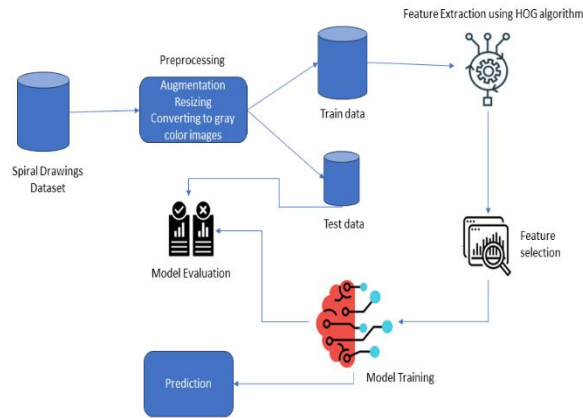


Figure 4: Proposed Methodology Architecture

IV. RESULTS

The model was successfully trained and evaluated for the detection of Parkinson's disease using the drawings of spiral. The results demonstrated a notable accuracy of 94.7% nearly 95%, confirming the model's efficiency in distinguishing between persons with Parkinson's disease and those without.

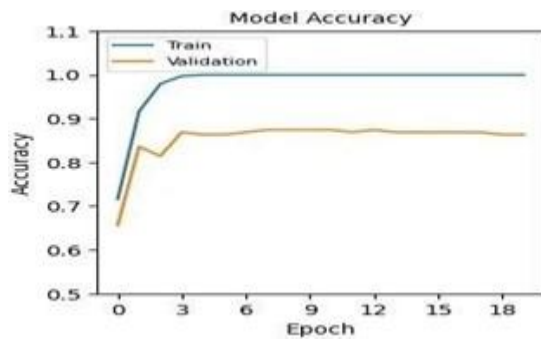


Figure 5: Accuracy graph

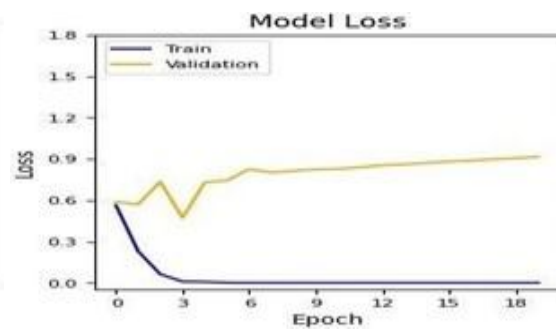


Figure 6: Loss graph

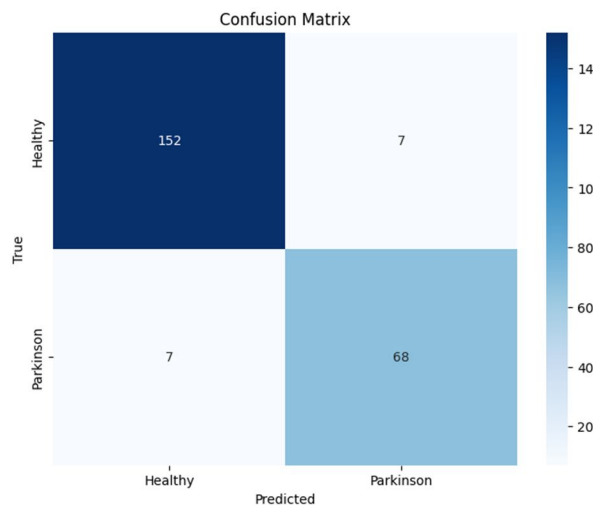


Figure 7: Confusion Matrix

Figure 7. represents the confusion matrix (152, 7, 7, 68). It achieved the true positive value as 152 showing the accuracy of the model. It achieved 68 true negatives, 7 false positives, and 7 false negatives.

TABLE II: EVALUATION METRICS

	Precision	Specificity	F1-Score	Accuracy
Proposed System	0.97	0.97	0.88	0.95

The Table II. Shows the specific values of evaluation metrics like precision, specificity, F1-Score and Accuracy. The interface we created is as follows:

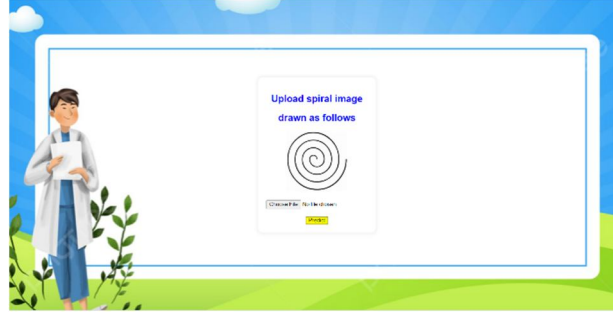


Figure 8: Interface

V. CONCLUSION

The developed model of Parkinson's disease detection using spiral images has shown promising results in accurately classifying people into two divisions: those with disease and those in good condition. The integration of deep learning techniques, particularly feedforward neural networks, has demonstrated the system's ability to extract significant data from spiral drawings and has aided in the early diagnosis of the disease. The project successfully tackled challenges related to data quality, model interpretability, and generalization, resulting in the creation of a robust and efficient diagnostic tool. The integration of an interface has significantly improved the system's accessibility and usability, enabling users to effortlessly upload spiral images for analysis. The user-friendly design promotes seamless interaction with the model, establishing it as a practical tool for both healthcare professionals and individuals interested in assessing their risk of Parkinson's disease.

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