Parkinson's Disease Detection using Deep Learning Techniques

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Abstract **- Parkinson's Disease (PD) is a progressive neurological disorder that affects movement and motor control, making early diagnosis both important and challenging. Traditional diagnostic methods are often time-consuming, subjective, and not always accurate, especially in the early stages. To address this, we explored a deep learning approach that uses hand-drawn spiral images to help detect PD in a faster and more reliable way. Our study compares three different models-CNN, MobileNetV2, and ResNet50, each chosen for their unique strengths in feature extraction and classification. The dataset used was collected from Kaggle and includes drawings by both individuals with Parkinson's and healthy controls. After preprocessing and augmenting the data, we trained the models using binary classification with standard evaluation metrics like accuracy, precision, recall, and F1-score. The results showed that deep learning models, especially MobileNetV2 and ResNet50, can effectively distinguish between healthy and PD-affected individuals based on simple hand-drawn inputs. This approach has the potential to become a non-invasive, accessible screening tool to support early diagnosis and ongoing monitoring of Parkinson's Disease. Future work will focus on improving accuracy further and deploying the system in real-time applications, such as mobile or web platforms.**

Keywords: Deep Learning, Convolutional Neural Network, MobileNetV2, ResNet50, Spiral image Dataset, Flask framework, MySQL.

INTRODUCTION

Parkinson's disease is a progressive neurological disorder that affects motor functions and worsens over time. PD is considered a malison for mankind for several decades. Existing Methods involve clinical assessments and neurological examinations and can lead to inaccurate, high time resolution and difficult to detect PD. Early and accurate diagnosis is crucial for effective treatment and management. This entails a need for fast automated screening tool and high accurate model, so we propose a deep learning approach for the detection of PD using handwritten spiral and wave images which is sourced from Kaggle. Many existing models focus on singular modality or have a cursory analysis of multiple modalities. This encouraged us to provide a comparative literature study of four main modalities signifying major symptoms used for the detection of PD, namely, tremor at rest, bradykinesia, rigidity, and voice impairment. The system utilizes Convolutional Neural Network (CNN), MobileNetV2 and ResNet50 to automatically extract and analyze features from hand-drawn spiral and wave images. The models are trained on a dataset of spirals drawn by Parkinson's individuals and healthy individuals. The dataset undergoes preprocessing, augmentation, normalization to improve model generalization.

For feature extraction, CNN captures local tremor-induced distortions, MobilenetV2 provides fast and efficient PD detection while being lightweight for real-world applications and ResNet50 leverages deep learning residual learning for high accuracy. The models are trained using binary cross-entropy loss function and optimized using the Adam optimizer. The model performance is evaluated using accuracy, precision, recall and F1-Score.

The results shows that deep learning models can effectively identify Parkinson's-related tremors from spiral and wave images, achieving high classification accuracy. The proposed system can serve as a fast, non-invasive automated screen tool for Parkinson's detection, aiding medical professionals in diagnosis and monitoring. Future improvements may involve fine-tuning, larger datasets and real-time deployment in mobile or web applications for practical use.

LITERATURE SURVEY

[1]. Adams, WR. "The detection of hand tremor through the characteristics of finger movements while typing." Posted August 5, 2018. bioRxiv 385286; doi: https://doi.org/10.1101/385286. Accessed online September 17, 2018., 2018. Parkinson's Disease (PD) is a neurodegenerative movement disease affecting over 6 million people worldwide. Current diagnosis is based on clinical and observational criteria only, resulting in a high misdiagnosis rate. Approximately 75% of people with PD have hand tremor, which can precede clinical diagnosis by up to 6 years. Previous studies have shown that early PD can be accurately detected from keystroke features while typing, and this study investigated whether tremor can be detected as well. Typing data from 76 subjects, with and without PD, including 27 with PD and 15 with tremor, was analysed and showed that hand tremor in PD can be detected from keystroke features. This novel technique has not been used before and was able to achieve an overall sensitivity of 67% and a specificity of 80% and was also able to differentiate PD tremor from essential tremor. This means that the diagnosis of early PD through typing can achieve the clinical requirement of at least two cardinal features being present (bradykinesia and tremor). Less than half a page of typing is needed, the technique does not require any specialised equipment, and can take place in the patient's home as they type normally on a computer.

[2] akmak, Y. O¨. ; O¨ lc¸ek, S.C.; O¨ zsoy, B.; Go¨kc¸ay, D." Quantitative Measurement of Bradykinesia in Parkinson's Disease Using Commercially Available Leap Motion." Bio-Signals, Proceedings of the 11th International Joint Conference on Biomedical Engineering Systems and Technologies; Funchal: Madeira, Portugal, 2018; Volume 3, pp. 227–232. 2018. Parkinson's Disease (PD) is a neurodegenerative disease caused by the depletion of dopamine in the brain. Tremor, bradykinesia, rigidity and postural stability are the four major symptoms. Like other symptoms, bradykinesia causing unnatural stillness/slowness in motions affects the daily life of the patients. The levels of these symptoms are clinically assessed by a scoring system based on Unified Parkinson's Disease Rating Scale (UPDRS). However, UPDRS relies on the visual observations of physicians rather than a test based on quantitative measurements. This makes it not only difficulty to repeat but also subjective. Because of these two major disadvantages, researchers build custom devices for their studies. But this leads to the reliability issues and non-standard measurements. Thus, 24 PD patients were bilaterally UPDRS III (motor subsection) scored and recorded for finger motion (pinching) by using commercially available off-the-shelf (COTS) product called Leap Motion. The various features extracted from recordings and UPDRS III scores were analyzed for correlation. After the analysis, a linear model was created to estimate UPDRS III score. The study revealed that Leap Motion, a COTS device, can be used to estimate bradykinesia of a patient with PD.

[3] Lonini, L., Dai, A., Shawen, N. et al. "Wearable sensors for Parkinson's disease: which data are worth collecting for training symptom detection models." npj Digital Med 1, 64 (2018) doi:10.1038/s41746-018-0071-z., 2018. Deep learning algorithms that use data streams captured from soft wearable sensors have the potential to automatically detect PD symptoms and inform clinicians about the progression of disease. However, these algorithms must be trained with annotated data from clinical experts who can recognize symptoms, and collecting such data are costly. Understanding how many sensors and how much labeled data are required is key to successfully deploying these models outside of the clinic. Here we recorded movement data using 6 flexible wearable sensors in 20 individuals with PD over the course of multiple clinical assessments conducted on 1 day and repeated 2 weeks later. Participants performed 13 common tasks, such as walking or typing, and a clinician rated the severity of symptoms (bradykinesia and tremor). We then trained convolutional neural networks and statistical ensembles to detect whether a segment of movement showed signs of bradykinesia or tremor based on data from tasks performed by other individuals. Our results show that a single wearable sensor on the back of the hand is sufficient for detecting bradykinesia and tremor in the upper extremities, whereas using sensors on both sides does not improve performance. Increasing the amount of training data by adding other individuals can lead to improved performance, but repeating assessments

with the same individuals—even at different medication states—does not substantially improve detection across days. Our results suggest that PD symptoms can be detected during a variety of activities and are best modeled by a dataset incorporating many individuals.

[4] Yao, L., Brown, P., Shoaran, M., "Resting Tremor Detection in Parkinson's Disease with Deep Learning and Kalman Filtering.", 2018 IEEE Biomedical Circuits and Systems Conference (BioCAS). doi:10.1109/biocas.2018.8584721, 2018. Adaptive deep brain stimulation (aDBS) is an emerging method to alleviate the side effects and improve the efficacy of conventional open-loop stimulation for movement disorders. However, current adaptive DBS techniques are primarily based on single-feature thresholding, precluding an optimized delivery of stimulation for precise control of motor symptoms. Here, we propose to use a Deep learning approach for resting-state tremor detection from local field potentials (LFPs) recorded from subthalamic nucleus (STN) in 12 Parkinson's patients. We compare the performance of state-of-the-art classifiers and LFP-based biomarkers for tremor detection, showing that the high-frequency oscillations and Hjorth parameters achieve a high discriminative performance. In addition, using Kalman filtering in the feature space, we show that the tremor detection performance significantly improves ($F_{(1,15)}$=32.16, $p<0.0001$). The proposed method holds great promise for efficient on-demand delivery of stimulation in Parkinson's disease.

EXISTING SYSTEM

Currently, Parkinson's Disease (PD) is diagnosed by neurologists through physical examinations and evaluation of symptoms such as tremors, stiffness, and slowness of movement. These assessments are largely subjective and often detect PD only in its later stages. Diagnostic tools like motor function tests and DatScans may assist, but they are not definitive. Imaging tests like MRI or CT scans and blood tests are typically used to rule out other conditions, not to confirm PD. Due to the lack of objective and early-stage biomarkers, here is a growing need for accurate, non-invasive, and automated diagnostic tools to support early detection and monitoring.

DISADVANTAGES OF EXISTING SYSTEM

- Detection of Parkinson's disease is difficult.
- Results are not accurate.
- It takes more time to give results.
- High time resolution.
- High variation in results
- Low efficiency.

PROPOSED SYSTEM

The proposed system for Parkinson's Disease Detection using Deep Learning techniques utilizes advanced deep learning algorithms such as Convolutional Neural Network(CNN), MobileNetV2, ResNet50. These algorithms are applied to large datasets of handwritten images of spirals which are taken from the medical reports of various individuals to effectively detect patterns, features and enabling accurate detection of Parkinson's disease which is crucial for correct treatment.

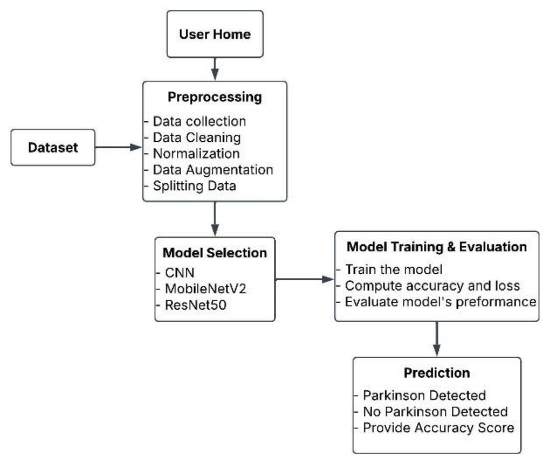

Fig:[1] Architecture of Proposed System

ALGORITHMS OF PROPOSED SYSTEM

CNNs(Convolutional Neural Networks) are a core deep learning model used for image classification. They work by scanning an image with small filters to pick up patterns like edges, textures, and shapes. In our project, we used CNNs to detect differences in spiral drawings- like shakiness or uneven curve- that could indicate Parkinson's disease. These models are great at learning important features from images without needing manual input, which made them a solid starting point for training on our dataset. CNN served as our baseline model and helped us understand how well basic deep learning could perform on this task.

MobileNetV2 is a lightweight and efficient model built for mobile and embedded systems. It uses a clever technique called depth-wise separable convolutions to keep the model small and fast, while still delivering strong accuracy. For our project, MobileNetV2 was a perfect choice for real-time image classification, especially in situations where hardware resources are limited. It was able to analyze the spiral images quickly and accurately, which makes it a great fit for future use in mobile health apps or portable diagnostic tools.

ResNet50((Residual Network 50 layers) is a deeper neural network that stands out because of its *skip connections*, which help the model learn better by avoiding common training issues like vanishing gradients. This allows it to go deeper and pick up on finer details in images. In our case, ResNet50 helped the system detect more subtle patterns in the spiral drawings-small clues that might signal early Parkinson’s symptoms. Thanks to its depth and accuracy, ResNet50 boosted the overall performance of the system and made it more reliable for complex or borderline cases.

METHODOLOGY OF PROPOSED SYSTEM

Data Collection: The collection encompasses images of hand-drawn spirals that classified into both healthy and diseased groups. All images are sourced from Kaggle and from medical databases. Generally, the class labeling process is automated by extracting indicators from the folder names of each image.

Data Preprocessing: The dataset is preprocessed using ImageDataGenerator, where all dataset images are resized to 224×224 pixels and normalized to the [0,1] range to improve training stability. Data augmentation techniques are applied to improve the model’s generalization. The dataset is split into training and validation, ensuring a balanced approach to learning and evaluation.

Model Selection: A combination of deep learning algorithms, including CNN, MobileNetV2 and ResNet50, is used to enhance PD detection. These models collectively improve accuracy, robustness, and efficiency.

Model Training & Testing: In model training, we use three models such as CNN, MobileNetV2 and ResNet50. During training, the model learns to distinguish between Parkinson’s and healthy spirals by adjusting its internal parameters., and while testing ensures the accuracy of models and check whether the fine-tuning is required or not.

Model Evaluation: Metrics such as accuracy, precision, F1-Score and recall are used to measure the model’s effectiveness.

Evaluation metrics such as Accuracy, Precision, Recall, and F1-Score are used to measure the effectiveness of the models. These metrics ensure reliable classification and validate the system's ability to detect ASD accurately. Confusion matrices are also used to visualize misclassifications and understand where the model is failing.

Prediction & Deployment: The trained model is deployed via Flask application which is used to connect both frontend and backend parts. To store the user’s data, we use MySQL by using Xampp server. The user should be registered for using the application by giving their details such as name, email, contact number, address, password. Through user-friendly web application, user can upload image after login and user have access to select model among the three models and view the results whether the individual is healthy or PD.

ADVANTAGES OF PROPOSED SYSTEM

- Low time resolution and High efficiency.
- Low variation in results.
- Complexity is low.
- Detection of Parkinson’s disease is easy.
- Results are accurate.

RESULTS

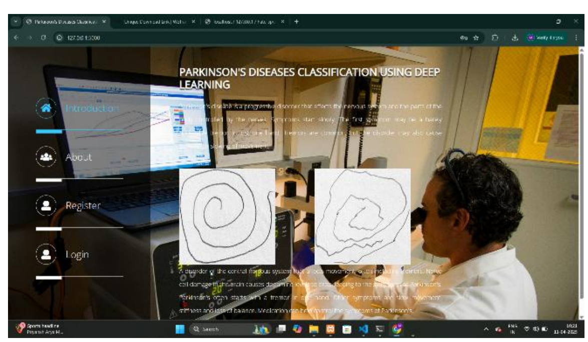

Fig:[2] Home Page

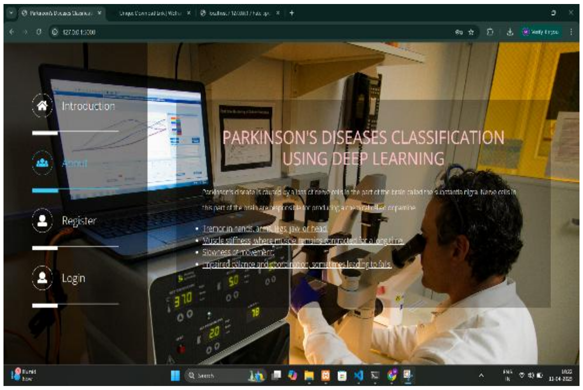

Fig:[3] About Page

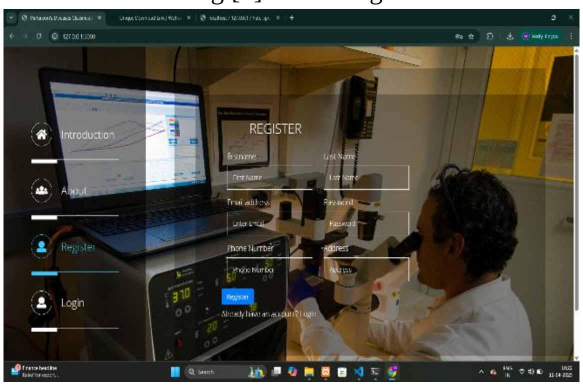

Fig:[4] Registration Page

Fig:[5] Login Page

Fig:[6] Upload Page

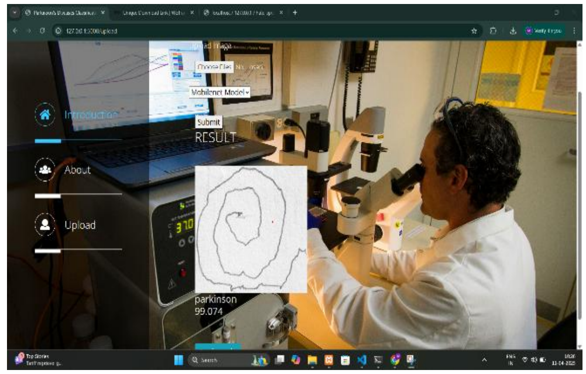

Fig:[7] Prediction Result Page 1

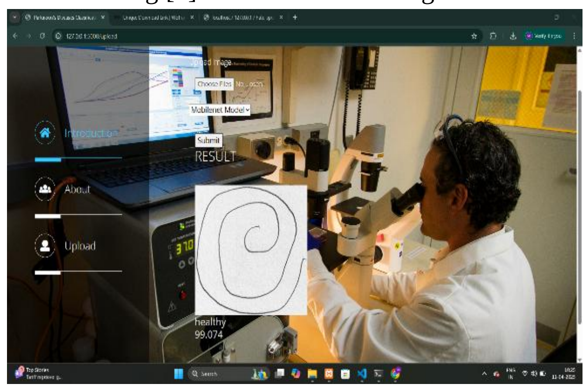

Fig:[8] Prediction Result Page 2

CONCLUSION

In this project, we leveraged transfer learning to classify images related to Parkinson's disease, distinguishing between those affected and unaffected by the condition. We trained and evaluated several deep learning models including CNN, MobileNetV2, and ResNet50 on a curated dataset to improve accuracy while keeping training time and computational demands manageable. MobileNetV2 was especially useful due to its lightweight architecture, making it well-suited for mobile and embedded systems where real-time performance is critical. ResNet50, with its powerful residual connections, allowed us to train deeper networks and capture more complex and subtle features in the images key for detecting early signs of Parkinson's. CNNs were used as our baseline model and proved effective in extracting spatial features such as textures and patterns that are essential for accurate classification. Each of these algorithms brought unique strengths to the table, contributing to a more robust and reliable system. The combination of these models enabled us to classify test images with promising accuracy, even identifying potential types or stages of Parkinson's disease. Overall, the results highlight the practical value of deep learning and transfer learning in medical image analysis, showing strong potential for assisting in early diagnosis and improving patient outcomes in real-world healthcare settings.

FUTURE SCOPE

The future scope lies in the integration of multi-modal deep learning techniques to enhance the accuracy and efficiency of Parkinson's disease (PD) detection systems. By combining tremor analysis, bradykinesia assessment, rigidity detection, and voice impairment recognition into a unified framework, researchers can develop more comprehensive and robust diagnostic models. Additionally, advancements in wearable sensor technology and data fusion methodologies hold promise for real-time monitoring and personalized treatment strategies, ultimately improving patient outcomes in the management of Parkinson's disease.

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