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An Efficient Approach Based on Medical Images for Parkinson's Disease Identification and Management

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Abstract: A progressive neurodegenerative condition that profoundly affects motor and cognitive abilities is Parkinson's disease (PD). Timely action and improved patient outcomes depend on an early and correct diagnosis. Two different models are used in this study's deep learning-based method for Parkinson's disease detection: Long Short-Term Memory (LSTM) networks for structured patient data classification and Convolutional Neural Networks (CNN) for handwriting picture analysis. In order to uncover patterns of motor impairment, the CNN model uses spatial features extracted from handwriting images, and the LSTM model analyses sequential patient data to find PD-related distinctive trends. Handwriting samples from both healthy and Parkinson's patients are included in the dataset, as are organized medical records with motor and cognitive test results.To improve model performance, preprocessing methods such data standardization, normalization, and image scaling are used.
Keywords: Parkinson's disease, Deep learning, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Handwriting analysis.

I. INTRODUCTION

Movement control is affected by Parkinson's disease (PD), a chronic neurological condition caused by a progressive loss of dopamine-producing neurons in the brain. Affecting millions of people globally, it is the second most prevalent neurological condition after the disease. Parkinson's disease is typified by tremors, muscle rigidity, postural instability, and bradykinesia, or slowness of movement. Nonmotor symptoms that affect patients' quality of life include mood disorders, sleep problems, and cognitive impairment. Early detection is difficult since clinical observations and patient history are frequently needed to make the diagnosis, even though there is no reliable test for Parkinson's disease.

Automated diagnostic techniques have demonstrated significant potential in supporting early identification and precise categorization of neurodegenerative illnesses, thanks to developments in deep learning and artificial intelligence (AI). Medical image analysis and sequential data processing have shown the effectiveness of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, respectively. While LSTM models may examine organized patient data over time to find anomalies, CNN models can extract spatial characteristics from handwriting and MRI images to find patterns suggestive of Parkinson's disease.

Preprocessing methods such as feature scaling, image resizing, and normalization are used to improve model performance.To guarantee robustness and generalization, the suggested system is trained and verified on various datasets.

II. RELATED WORK

Artificial intelligence research on Parkinson's disease (PD) detection has attracted a lot of interest lately. To enhance the early detection and categorization of PD patients, a variety of machine learning and deep learning techniques have been explored. Advances in AI-driven procedures have improved the accuracy and efficiency of PD detection, whereas traditional methods still rely on clinical assessments and motor function evaluations. Machine learning techniques, including Support Vector Machines (SVM), Random Forest, and k-nearest Neighbors (k-NN), have been used in several research studies to evaluate voice recordings, handwriting patterns, and biological signals to detect Parkinson's disease. Although these models make use of manually created features that are taken from sensor data, feature engineering and domain knowledge are frequently necessary for them to function well.

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For PD categorization, deep learning models—in particular, Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks—have gained acceptance. CNN showed encouraging outcomes in the analysis of MRI images and handwriting to detect motor problems and anatomical brain abnormalities. Conversely, LSTMs are highly effective at processing sequential clinical data, including gait analysis and motor scores, to identify temporal patterns linked to the advancement of disease. Recent studies have shown that LSTMs can predict temporal dependencies in structured medical records, whereas CNNs are effective at extracting spatial characteristics from image-based data. The diversity of datasets, generalization across populations, and real-time clinical implementation continue to be obstacles despite the success of AI-based PD identification. Larger datasets, improved feature representations, and more effective model designs are needed to overcome these constraints.

III. PROPOSED SYSTEM

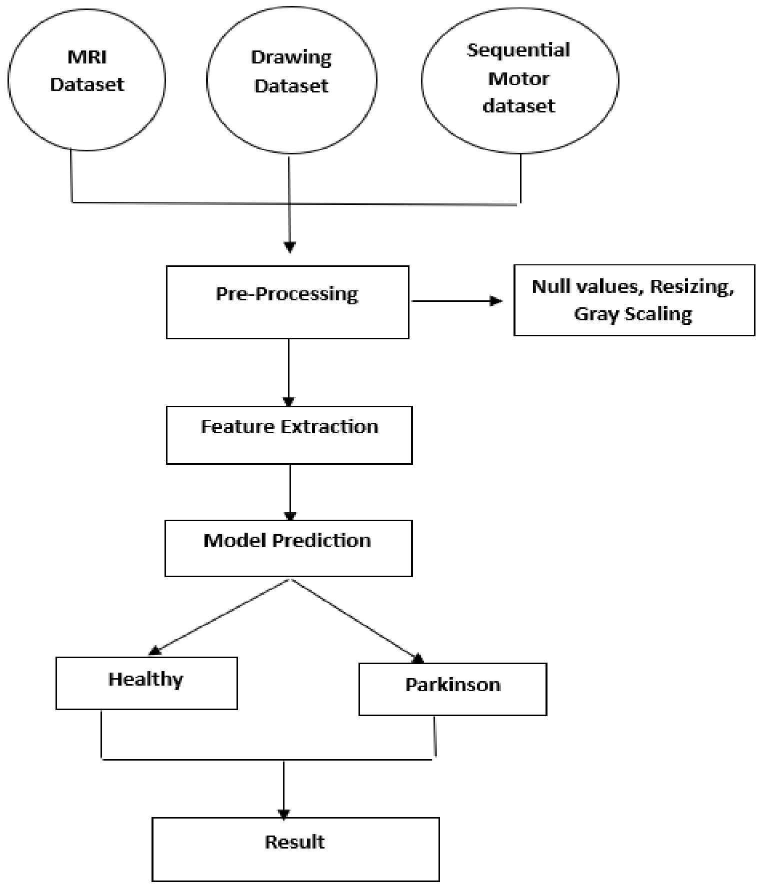

Figure 1: Process of Proposed System

This work suggests a CNN and LSTM model-based deep learning-based Parkinson's disease diagnosis method. The CNN model is intended to extract spatial patterns suggestive of neurodegeneration from MRI scans and handwriting images. In contrast, the LSTM model captures temporal connections in motor and cognitive evaluations while processing organized clinical records. This method seeks to increase the accuracy of Parkinson's disease categorization and early diagnosis by combining image-based and sequential data processing.

MRI scans, handwriting images, and structured patient data gathered from both healthy people and Parkinson's sufferers make up the dataset. Preprocessing methods such as feature scaling, image resizing, and normalization are used to improve model performance. Using cross-entropy loss and the Adam optimizer, the CNN and LSTM models are trained independently. Accuracy, precision, recall, and F1-score are among the evaluation metrics. To guarantee robustness and generalization, the suggested system is tested on various datasets. Future research will concentrate on real-time deployment for clinical applications, dataset growth, and the incorporation of extra biomarkers like speech analysis.

IV. METHODOLOGY

To detect Parkinson's disease, this study uses deep learning models in an organized manner. The five main phases of the methodology are performance evaluation, training and evaluation, model creation, preprocessing, and data gathering. To make sure the models function well and generalize well to new data, each step is carefully planned.

A. Data Collection

Three different forms of data were employed in this study: structured medical records, MRI scans, and handwriting images. Images of handwriting are gathered from both healthy people and Parkinson's sufferers since handwriting deterioration is a major sign of motor dysfunction. MRI scans offer comprehensive information about the neurodegenerative alterations in the brain that are frequently linked to Parkinson's disease. A thorough picture of the course of the disease is provided by the numerical data included in the structured patient records, which comprise clinical history, motor function scores, and cognitive evaluations. The MRI pictures and handwriting are taken from clinical trials, research studies, and medical sources to guarantee data trustworthiness. Research projects on Parkinson's disease and hospital databases provide structured patient data. Data gathering is conducted with rigorous adherence to ethical principles, such as patient identity and data privacy.

B. Data Preprocessing

The dataset is pre-processed to improve its consistency and quality before it is put into deep learning models. Resizing all photos to 128×128 pixels, turning them to grayscale to lower computational complexity, and normalizing pixel values to increase learning efficiency are all part of the preparation process for handwriting and MRI images. To prevent overfitting and enhance the diversity of the dataset, image augmentation techniques like rotation, flipping, and contrast alterations are utilized. Min-max scaling is used to normalize numerical features, mean or median imputation is used to handle missing values and categorical variables are encoded where appropriate in structured patient records. A fair distribution of Parkinson's and non-Parkinson's cases is also guaranteed by data balancing procedures, which avoid biased model projections. To properly evaluate the model, the dataset is subsequently divided into subsets for training (80%) and testing (20%).

C. Model Development

The two deep learning models employed in this study are a Convolutional Neural Network (CNN) for handwriting and MRI image processing and a Long Short-Term Memory (LSTM) network for structured patient data classification. The CNN model, which consists of many convolutional layers, can extract spatial information from MRI scans and handwriting. Max-pooling layers to reduce dimensionality, dropout layers to prevent overfitting, and fully linked layers for classification come after these layers. The CNN model's ultimate output is a probability score that indicates whether the image depicts a healthy individual or someone who has Parkinson's disease. Finding temporal relationships in sequential patient data is the aim of the LSTM model.

D. Model Training and Evaluation

Supervised learning methods are used to train each model independently. Whereas the LSTM model is developed using structured patient records, the CNN model is trained using handwritten and MRI image data. For binary classification problems, the binary cross-entropy loss function is minimized using the Adam optimizer. To guarantee steady convergence and better generalization, training is carried out across several epochs using batch normalization. Metrics including accuracy, precision, recall, and F1-score are used to assess the models' classification performance. The CNN model is judged on how effectively it can differentiate between Parkinson's and non-Parkinson's cases in image data, whereas the LSTM model is judged on how well it can spot patterns in the evolution of the disease in structured records. For optimal performance, hyperparameter tuning is used to optimize dropout rates, learning rates, and layer configurations.

E. Performance Assessment and Future Enhancements

To confirm that the trained models can generalize, they are checked against distinct test datasets. The measurement of the model’s sensitivity and specificity is done through Receiver Operating Characteristic (ROC) curves, and matrices are constructed for scrutinizing misclassifications of positive and negative instances. The results have been compared with traditional machine learning models such as decision trees and support vector machines (SVM) to illustrate the advantages of deep learning in identifying Parkinson's disease.

For further studies, the dataset will be enriched by including a more extensive and diverse population, additional biomarkers such as voice and gait analysis will be incorporated, and the deep learning models will be refined for use in clinical settings. Other research will focus on interpretable model design to explain and justify their foretelling, increasing trust and usability for healthcare providers.

V. RESULT OVERVIEW

Using sequential clinical data and handwriting images (waves and spirals), the framework created in this study may accurately diagnose Parkinson's disease. A thorough diagnostic approach is provided by the dataset's integration of time-series motor assessments and spatial handwriting patterns. Subsequent subsections address the classification performance of CNN and LSTM models, their outcomes, and how well data visualization methods enhance interpretability.

A. *Handwriting and MRI Image Dataset (CNN-Based Analysis)*

Table 5.1.1 Summary of Handwriting Image Dataset (Pre-processed Features)

Feature	Min Value	Max Value	Mean	Standard Deviation
Stroke Width Variability	0.21	1.07	0.64	0.18
Line Smoothness	0.32	0.89	0.58	0.14
Loop Closure Consistency	0.15	0.92	0.48	0.16
Pressure Consistency	0.40	0.88	0.62	0.11

Brain scans from both healthy people and Parkinson's patients make up the MRI image dataset used in this investigation. Convolutional Neural Networks (CNNs) were used to preprocess and analyze these MRI data in order to identify significant spatial patterns suggestive of Parkinson's disease. Finding structural anomalies in the brain that are associated with the advancement of Parkinson's disease is the aim of this investigation.

Table 5.1.2 Sample MRI Image Dataset (Pre-processed Features)

Image ID	Brain Region	Voxel Intensity	Gray Matter Density	White Matter Density
MRI_001	Basal Ganglia	75.2%	48.3%	51.7%
MRI_002	Substantia Nigra	82.1%	55.6%	44.4%
MRI_003	Thalamus	79.5%	52.4%	47.6%
MRI_004	Motor Cortex	84.2%	57.1%	42.9%

B. *Sequential Motor Data (LSTM-Based Analysis)*

Multiple time points of motor and cognitive evaluation scores make up the organized dataset. Over time, this sequential data aids in monitoring the development and intensity of Parkinson's symptoms.

Table 5.2.1 Sample Sequential Motor Data for Parkinson's Classification

Time Step	Hand Tremor Score	Gait Speed	Reaction Time	Cognitive Function Score
T1	3.2	0.85	1.1	2.4
T2	4.1	0.78	1.5	2.1
T3	4.5	0.72	1.9	1.9
T4	5.0	0.65	2.4	1.7

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C. Classification Accuracy Results

Conventional machine learning classifiers like SVM and Random Forest are compared with the CNN and LSTM models' classification outcomes. The findings demonstrate that when it comes to identifying Parkinson's illness, deep learning models perform noticeably better than traditional methods.

Table 5.3.1LSTM Model Classification Report

Class	Precision	Recall	F1-Score
Healthy (0)	0.96	1.00	0.99
Parkinson’s (1)	1.00	0.96	0.98
Overall Accuracy	98.0%	-	-

Table 5.3.2CNN Model Classification Report

Class	Precision	Recall	F1-Score
Healthy (0)	1.00	0.98	0.99
Parkinson’s (1)	0.98	1.00	0.99
Overall Accuracy	99.02%	-	-

Table 5.3.3 Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score
SVM (Traditional ML)	85.4%	83.2%	86.1%	84.6%
Random Forest (Traditional ML)	90.0%	87.5%	87.9%	87.7%
CNN (MRI Image Analysis)	99.02%	98.00%	99.00%	99.00%
LSTM (Sequential Data Analysis)	98.0%	100.00%	96.10%	98.01%

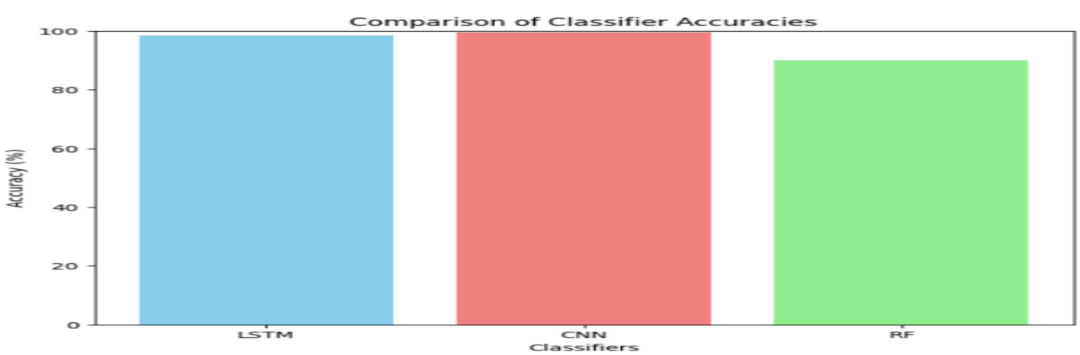


Figure 2:Classification accuracy results

VI. CONCLUSION

This work proposes a deep learning approach for identifying Parkinson's disease using two distinct models: CNN for analyzing spiral and wave handwriting images and LSTM for evaluating sequential motor assessment data. The CNN model achieved an accuracy of 99.2% in recognizing spatial patterns in handwriting, while the LSTM model achieved 98% accuracy for temporal trends in clinical data. Both models demonstrated superiority over traditional classifiers, illustrating the potential of deep learning for the accurate and early diagnosis of Parkinson's disease.

REFERENCES

[1] Sangeetha, S., Baskar, K., Kalaivaani, P.C.D., and Kumaravel, T.: Deep Learning-Based Early Parkinson's Disease Detection from Brain MRI Image. Proceedings of the 7th International Conference on Intelligent Computing and Control Systems (ICICCS), IEEE, pp. 490–495, India (2023).

[2] Kumar, K., and Ghosh, R.: Parkinson's Disease Diagnosis Using Recurrent Neural Network Based Deep Learning Model by Analyzing Online Handwriting. Multimedia Tools and Applications, Springer, vol. 83, no. 4, pp. 11687–11715 (2024).

[3] Govindu, A., and Palwe, S.: Early Detection of Parkinson's Disease Using Machine Learning. Procedia Computer Science, Elsevier, vol. 218, pp. 249–261 (2023).

[4] Jovanovic, L., Damaševičius, R., Matic, R., et al.: Detecting Parkinson's Disease from Shoe-Mounted Accelerometer Sensors Using CNNs Optimized with Metaheuristics. PeerJ Computer Science, vol. 10, p. e2031 (2024).

[5] Vyas, T., Yadav, R., Solanki, C., et al.: Deep Learning-Based Scheme to Diagnose Parkinson's Disease. Expert Systems, Wiley, vol. 39, no. 3, p. e12739 (2022).

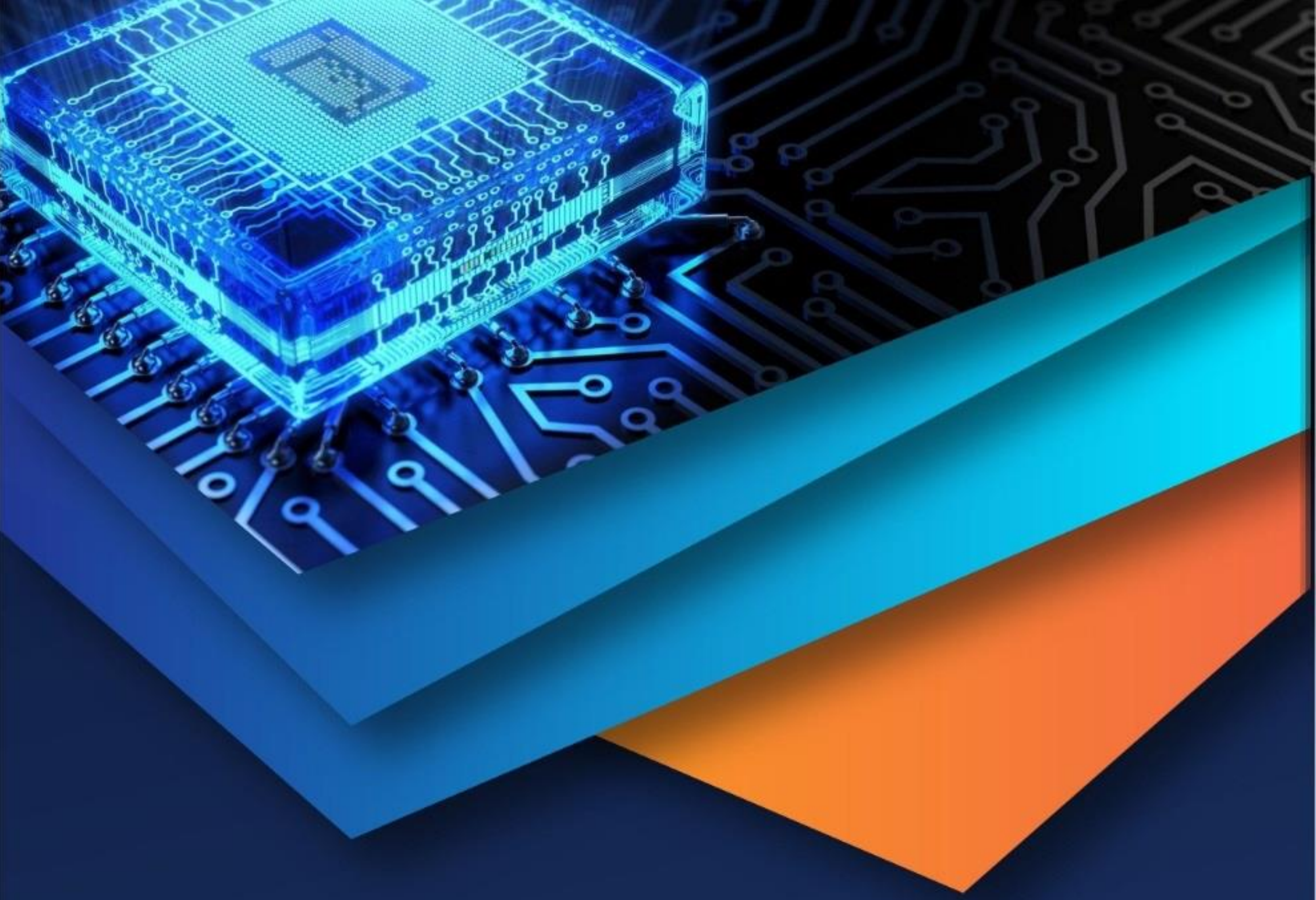
[6] Sahu, L., Sharma, R., Sahu, I., et al.: Efficient Detection of Parkinson's Disease Using Deep Learning Techniques Over Medical Data. Expert Systems, Wiley, vol. 39, no. 3, p. e12787 (2022).

[7] Dentamaro, V., Impedovo, D., Musti, L., et al.: Enhancing Early Parkinson's Detection through Multimodal Deep Learning and Explainable AI. Scientific Reports, Nature, vol. 14, no. 1, p. 20941 (2024).

[8] Shaban, M.: Deep Learning for Parkinson's Disease Diagnosis: A Short Survey. Computers, MDPI, vol. 12, no. 3, p. 58 (2023).

[9] Islam, M.A., Majumder, M.Z.H., Hussein, M.A., et al.: Review of Machine Learning and Deep Learning Algorithms for Parkinson's Detection Using Handwriting and Voice Datasets. Heliyon, Elsevier, vol. 10, no. 3 (2024).

[10] Sayed, M.A., Tayaba, M., Islam, M.D., et al.: Parkinson's Disease Detection Through Vocal Biomarkers and Advanced Machine Learning Algorithms. arXiv preprint arXiv:2311.05435 (2023).



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