Parkinson's Insight: Leveraging CNN and LSTM Networks for Enhanced Diagnostic Accuracy

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Abstract. Parkinson's disease (PD) is a progressive neurodegenerative disorder that disturbs millions worldwide and is characterized by symptoms such as tremors, rigidity, and impaired motor function. Early detection is crucial for timely intervention, yet conventional investigative approaches often lack the sensitivity to identify PD in its early stages. This study introduces a hybrid deep learning model that integrates Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks for detecting PD using biomedical voice recordings. The model harnesses CNN's capability for feature extraction and LSTM's strength in processing sequential data, enhancing detection accuracy. Three datasets—the UCI ML Repository, Oxford Parkinson's Disease Detection, and Kaggle Parkinson's Telemonitoring—were utilized for training and evaluation. Experimental results reveal that the hybrid CNN-LSTM model surpasses the presentation of standalone CNN and LSTM models in terms of accuracy, precision, recall, and F1 scores, achieving accuracies of 93%, 95%, and 94%, respectively. These outcomes highlight the model's possible role as a non-invasive, accurate, and early detection tool for Parkinson's disease, offering a promising pathway for improved patient outcomes through timely interventions.

Keywords: Keywords: Parkinson's Disease, long short-term memory, convolution neural network, hybrid approach, medical diagnostics, Deep learning, Feature extraction

1. Introduction

The brain area responsible for coordinating movement, the substantia nigra, is affected by Parkinson's disease, a neurodegenerative sickness marked by a broadminded damage of dopaminergic neurons. It is one of the illnesses that millions of people world-

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wide suffer from, and it causes severe impairments such bradykinesia, stiffness, tremors, and postural instability. This disorder significantly lowers daily functions and quality of social interplay as it progresses. The WHO categorizes PD as a major public health concern since its prevalence is an increasing consequence of age. In view of this rather complex disorder, early diagnosis and management are crucial in maximizing therapeutic benefits to enhance the quality of patients' life [1], [2].

The speed and accuracy of Parkinson's disease (PD) diagnosis might be increased by recent developments in machine learning and deep learning (ML). These methods increase the accuracy of diagnoses and help to clarify the pathogenic causes by examining vast amounts of data from wearables, genetic profiles, neuroimaging studies, and clinical records to find patterns and biomarkers linked to the disease's early stages. For analysing high-order data, especially picture data, CNNs and other deep learning architectures have emerged as crucial instruments. Performance may be significantly improved by using multi-modal characteristics in DL for Parkinson's disease diagnosis. Another exciting area of research for PD identification is the analysis of EEG data, which provides vital information about electrical activity within the brain.

Future early detection and treatment of Parkinson's disease (PD) is being made possible by the combination of machine learning and deep learning techniques. Now, medical practitioners are able to identify individuals who are at risk of Parkinson's disease (PD) and provide medication, lifestyle changes, and ongoing observation. Additionally, these technologies improve diagnostic capabilities and provide personalised treatment programs. As more research is conducted, data scientists, neurologists, and bi-medical engineers must collaborate to make these novel approaches accessible for clinical use. This scientific partnership might lead to better screening methods and quicker patient diagnosis. Recent potential methodological and diagnostic advances in Parkinson's disease are ushering in a new era of early diagnosis and treatment. Here are the many Parkinson's disease forms, along with their descriptions, as seen in Table 1.

Table 1. Parkinson's Disease: Types and Descriptions [1], [2]

Type of Parkinson's Disease	Description
Idiopathic Parkinson's Disease	The most common form, with no identifiable cause. Characterized by typical motor and non-motor symptoms.
Genetic Parkinson's Disease	Hereditary genetic illnesses, such as PARK1, PARK2, and PARK7, are brought on by certain mutations in the SNCA, PARK2, and DJ-1 genes, respectively.
Parkinsonism Plus Disorders	In addition to the symptoms of Parkinson's disease, neurodegenerative diseases such as Multiple System Atrophy (MSA), Progressive Supranuclear Palsy (PSP), and Corticobasal Degeneration (CBD) also present with autonomic dysfunction, balance difficulties, eye movement impairments, and cognitive loss.
Vascular Parkinsonism	Caused by small strokes affecting areas of the brain that control movement. Symptoms may resemble PD but can be more variable.
Drug-Induced Parkinsonism	Results from the use of certain medications, particularly antipsychotics. Symptoms may resolve after discontinuation of the drug.
Secondary Parkinsonism	Refers to Parkinson-like symptoms resulting from other medical conditions, such as infections, metabolic disorders, or head trauma.

Young-Onset Parkinson's Disease	Identified beforehand the age of 50. Symptoms and progression may differ from typical PD; often associated with genetic factors.

1.2. Research Contribution and Novelty of the Work

The study suggests a CNN-LSTM hybrid approach for the first evaluation and classification of Parkinson's disease. The model combines the benefits of convolutional neural networks (CNNs) for feature extraction from high-resolution medical images with long short-term memory (LSTM) networks for analysing sequential data, such as voice recordings. When compared to traditional machine learning and stand-alone deep learning techniques, our hybrid architecture increases diagnostic accuracy. The research evaluates the model on three datasets that cover a broad range of data linked to Parkinson's disease using a comprehensive multi-dataset evaluation approach. A multi-dataset test highlights the model's stability and flexibility. The study highlights early diagnosis and progression monitoring by using certain medical imaging data and voice features. This enables doctors to monitor the advancement of Parkinson's disease and detect it early. The study's practical implications for clinical application are examined in its conclusion, which raises the possibility that this approach might improve patient outcomes by facilitating timely treatments and effective Parkinson's disease management.

The remaining portion of this article is organized as the "Literature Survey" section depicting the related literature, and "Methodology" section describing about the dataset, key feature description used in this study. "Proposed Model" section outlines the proposed approach and the training procedure. "Experimental Result" section discusses the experimental findings, and finally the discussion about the article with the outline of the future research direction in the "Conclusion" section.

1.3 Literature Survey

The paper offers a deep learning (DL) approach for detecting and classifying Parkinson's disease based on MRI images. To enhance feature extraction and boost early detection accuracy and dependability, the CA position attention approach and model backbone optimisation are presented. This study adds to the corpus of research that supports advanced deep learning methods in medical imaging to aid in the timely and accurate diagnosis of neurodegenerative diseases. Cognitive performance scores were much worse in patients with freezing of gait (FOG), mainly in executive and visuospatial skills. FOG is crucial for both motor function and cognitive impairment in Parkinson's disease, as shown by the fact that individuals with FOG were more likely to have cognitive decline over time. A deep CNN-LSTM model for Parkinson's disease detection and classification was developed utilising EEG data processed by a deep CNN-LSTM model as part of a multiclass machine learning (ML) approach for the illness's diagnosis. Using speech recordings from both healthy individuals and patients with Parkinson's disease, a CNN model was created. It demonstrated an accuracy rate of 75.3% for short phrase readings in Chinese speech tasks and 81.6% for sustained vowel speech tests. Additionally, the model may be able to extract dynamic time series characteristics that represent the smaller overall frequency range and decreased unpredictability of sounds linked to Parkinson's disease.

A new method for diagnosing and predicting the stage of Parkinson's disease (PD) based on gait signal analysis was introduced. With a 98.32% detection accuracy for Parkinson's disease, the technique uses a hybrid CNN-LSTM network to extract and classify deep gait features. The paper talks about how CNN and RNN-based neural networks may be used to analyse patient data—more especially, speech data—and find patterns that can be utilised to diagnose Parkinson's disease. High accuracy and robustness in the findings point to a major advancement in early diagnosis and treatment planning. Using EEG data from both Parkinson's patients and non-Painters, authors [18] design a Recurrent Neural Network (RNN) model for Parkinson's disease detection using deep learning methods. Nevertheless, the research has drawbacks, including its dependence on the availability of longitudinal data and its heterogeneity.

A CNN model was developed using speech recordings from Parkinson's disease patients and healthy controls, achieving an accuracy rate of 81.6% for sustained vowel speech tests and 75.3% for brief phrase readings in Chinese speech tasks [9]. The model also has the potential to extract dynamic time series features that capture reduced unpredictability and lower total frequency range in sounds associated with Parkinson's disease. A novel gait signal analysis-based technique was presented for the diagnosis and prognostic stage of Parkinson's disease (PD). The method extracts and classifies deep gait characteristics using a hybrid CNN-LSTM network. The EMD method is used to decompose GRFs into IMFs, which are trained through the CNN-LSTM model. The model achieves an accuracy of 98.32% in detecting PD, making it a significant contribution to early diagnosis and monitoring of PD progression. The paper also uses voice and spiral drawing data as input features and applies a combination of CNN and SVM classifiers for classification [10], [11].

The study explores the use of CNN and RNN-based neural networks for analyzing patient data, particularly speech data, to identify patterns for Parkinson's disease diagnosis. The results show high accuracy and robustness, suggesting significant improvement in early diagnosis and treatment planning. A hybrid DL model based on LSTM-GRU is proposed for detecting Parkinson's disease using voice recordings from patients and healthy controls, with a 94.93% accuracy rate. Sivaranjini and Sujatha (2020) used convolutional neural networks to diagnose Parkinson's illness by training their CNN model on voice recordings. [15] introduced a recurrent neural network with dynamic temporal matching architecture to make personalized predictions about Parkinson's disease, improving disease progression prediction accuracy. However, the study has limitations, such as reliance on longitudinal data availability and quality, heterogeneity of data, and the need for further model validation.

The study uses deep learning techniques to train a Recurrent Neural Network (RNN) model for Parkinson's disease diagnosis. The RNN model uses EEG data from both Parkinson's patients and non-Painters, enhancing its accuracy and specificity. The study's limitations include a small sample size and the need for validation on multiple populations [16]. The authors also discuss the potential of DL techniques in precise diagnosis of Parkinson's disease using medical data, proposing CNNs as a DL-based mode for processing medical data. Although the type of data used is not explicitly mentioned, the model is claimed to have high efficiency in detecting the disease. However, the authors did not provide specific metrics for efficiency [17]. A previous

research publication summarized and discussed the dataset, performance indicators, research gap, and constraints for illness detection that mention in the under Table 2.

Table 2. Summary of Methodologies, Datasets, Performance Metrics, Limitations, and Research Gaps in Parkinson's Disease Studies

References	Methodology	Dataset Details	Performance Parameters	Limitations	Research Gap
[1]	DL for image classification	Medical imaging datasets related to PD	Accuracy, precision, recall	Limited dataset diversity	Need for validation with larger datasets
[2]	Observational study on gait	Clinical data of PD patients	Cognitive decline metrics	Focused on gait; limited treatment insights	Lack of comprehensive risk factors
[3]	Multiclass ML approach	Clinical and speech data	Accuracy, sensitivity, specificity	Limited generalizability	Further exploration of feature significance
[4]	CNN-LSTM hybrid model	EEG signals from PD patients	Classification accuracy	Limited sample size	Need for broader application
[5]	LSTM network for severity rating	Speech features dataset	Classification accuracy	Non-invasive nature needs clinical validation	Exploration of additional features
[6]	Hybrid CNN-LSTM model	PD-related datasets	Accuracy, loss metrics	Hyperparameter tuning complexity	Further refinement of tuning methods
[7]	Optimized RNN-LSTM approach	Speech datasets	Accuracy, detection rate	Limited dataset	Need for larger-scale studies
[8]	LSTM model for voice detection	Voice recordings dataset	Detection accuracy	Small sample size	Need for diverse demographic studies
[9]	End-to-end DL	Clinical data for invasive PD	Accuracy, F1 score	Lack of longitudinal data	More studies on non-invasive methods
[10]	EMD and CNN-LSTM analysis	Gait signal data	Classification accuracy	Limited feature exploration	Broader feature set investigation
[11]	ML for early detection	Medical records	Detection accuracy	Limited population diversity	Need for cross-validation with multiple datasets
[12]	DL for classification	Diverse datasets	Accuracy, precision, recall	Insufficient training data	Larger, multi-center studies required
[13]	Hybrid LSTM-GRU model	Various PD datasets	Detection accuracy	Limited data sources	Exploration of real-time monitoring
[14]	CNN for diagnosis	Medical imaging data	Accuracy	Small sample size	Need for additional clinical validation
[15]	RNN with temporal matching	Personalized patient data	Prediction accuracy	Limited generalizability	Need for adaptive models
[16]	Deep RNN with EEG	EEG signal datasets	Sensitivity, specificity	Small dataset	Larger studies with varied demographics
[17]	DL techniques	Medical data	Accuracy, precision, recall	Limited feature sets	Exploration of diverse medical datasets

2.Methodology

2.1 About Dataset

Three important datasets are used in the research to improve Parkinson's disease detection and classification in Table 3. 23 persons with a Parkinson's disease diagnosis

are included in the UCI ML Repository Parkinson's Disease Dataset, which consists of 195 cases with 22 features extracted from biological voice recordings. To categorise people as healthy or impacted, it employs characteristics including frequency, jitter, shimmer, and harmonic-to-noise ratio (HNR). The Oxford Parkinson's Disease Detection Dataset focusses on sustained vowel phonation and includes voice recordings from 50 people, 25 of whom have Parkinson's disease. To help researchers create classification models, this dataset contains 26 characteristics that were taken from speech signals, including jitter, shimmer, noise-to-harmonics ratio (NHR), recurrence period density entropy (RPDE), detrended fluctuation analysis (DFA), and HNR. A comprehensive collection of 5,875 recordings from 42 diagnosed patients, the Kaggle Parkinson's Telemonitoring Dataset includes clinical metrics like PPE and UPDRS in addition to 20 characteristics including jitter, shimmer, and NHR. Through longitudinal voice recordings, this dataset facilitates the investigation of symptom severity and aids in the prediction and tracking of illness development over time.

Table 3. Dataset parameters details

Dataset	Total Instances	Number of Features	Key Features	Target Variable	Data Type	Primary Goal
UCI Parkinson's Disease Dataset [34]	195	22	Fundamental frequency, jitter, shimmer, HNR	Binary: Healthy or PD	Voice measurements	Parkinson's disease classification
Oxford Parkinson's Disease Detection [35]	195	26	Jitter, shimmer, HNR, NHR, RPDE, DFA	Binary: Healthy or PD	Voice measurements	Parkinson's disease classification
Kaggle Parkinson's Telemonitoring Dataset [36]	5,875	20	Jitter, shimmer, NHR, UPDRS, PPE	Continuous: UPDRS score	Time-series voice data	Parkinson's disease progression tracking

2.2 Key Feature Descriptions:

Table 4. Feature Description

Feature Name	Description
Fundamental Frequency	The lowest frequency of a periodic waveform, related to voice pitch.
Jitter: [4]	Variation in the frequency or pitch of the voice; typically, higher in individuals with Parkinson's.
Shimmer: [4]	Variation in amplitude (loudness) of the voice signal.
HNR: [6]	Measure of voice quality, comparing harmonic (regular) components of the voice to noise.
NHR: [4]	The inverse of HNR, capturing noise in the voice.
RPDE: [5]	A nonlinear dynamical feature of the voice
DFA: [5]	Quantifies self-similarity in time series data, often used for complex signals like voice.
UPDRS: [6]	A clinical scale used to measure the strictness of Parkinson's disease symptoms.
PPE: [6]	Captures variation in the voice pitch period.

This summary captures in Table 4, the essential characteristics of the datasets and their associated parameters.

3.Proposed Methodology

Hybrid Model: CNN – LSTM

The hybrid CNN-LSTM prototypical revealed in the Fig. 1 is designed for the early detection of Parkinson's disease, combining the strengths of CNN for feature extraction and LSTM networks for sequence learning. The process begins with the data stream, where data such as time-series signals (like gait or motor function measurements) or medical images (like MRI scans) are fed into the model. The first stage is the CNN component (feature extractor), which consists of convolutional layers responsible for extracting local features from the input data. These layers help identify crucial patterns, such as movement irregularities or abnormalities in brain imaging associated with Parkinson's disease. Each convolution layer is followed by Batch Normalization (BN), which, via regulating the activations, stabilizes and speeds up the training process. By adding non-linearity, an activation and normalization function allows the model to recognize intricate patterns in the data. Next, by summarizing the most important characteristics, pooling layers minimize the dimensionality, improving the computing efficiency of the model and minimizing overfitting [22],[23],[24],[25],[27].

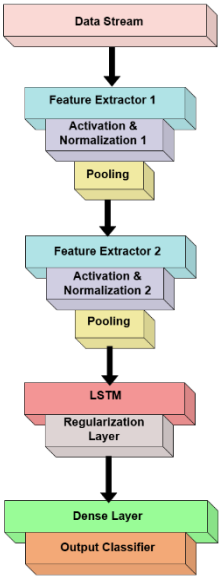

Fig. 1. Hybrid CNN-LSTM Model for Primary Discovery of Parkinson's Disease

The LSTM layer processes the data stream after it has gone through the feature extractor layer. Given its ability to grasp temporal patterns and long-term relationships, LSTMs are ideally suited for processing sequential data. When analyzing time-series data, where trends like shifts in motor control or brain activity may occur over time,

this is very crucial. These time-based correlations, which are essential for determining Parkinson's development, are taught to the model by the LSTM layer. In order to keep the model from becoming unduly dependent on any particular neurons and to help it generalize better to new data, a regularization layer is used to prevent overfitting. This layer randomly removes certain neurons during training. The dense layer receives the output from the LSTM and integrates all of the learned characteristics into a final decision-making process. Finally, the model is able to make a classification judgment since the output classifier layer generates probabilities for each class (e.g., Parkinson's disease or healthy). All things considered, this hybrid model successfully blends the capacity of LSTM to learn temporal sequences with CNN's ability to extract spatial information, making it a reliable method for the early diagnosis of Parkinson's disease [28], [29].

3.1 Proposed Flow Diagram

Flow Diagram Fig. 2, for Primary Uncovering of Parkinson's Sickness with Hybrid CNN-LSTM Approach: General Methodology This flow diagram presents the comprehensive methodology to detect PD in integrated voice and time series, sourced from UCI ML Repository, the Oxford PD Detection Dataset and Kaggle Parkinson's Telemonitoring Dataset. The process starts with data collection. This will be a precept for training and testing the model. Data preprocessing follows, which includes critical normalization, in that all the features get scaled aptly to enable comparison. Noise reduction becomes a significant step in eliminating irrelevant artifacts in data so that the quality of the signal shall serve to enhance excellent performance by the model. Thus, feature extraction techniques, like derivation of Mel Frequency Cepstral Coefficients (MFCC) from voice signals, are applied that capture the meaningful features pertinent to PD.

A hybrid CNN-LSTM model was designed to blend spatial feature extraction abilities of CNNs with the recognition mechanism of temporal patterns of LSTMs, enabling the model to learn and interpret complex data patterns. The architecture was finalized, and the model trained to find patterns indicating PD from the training dataset. The model's efficiency was evaluated through a systematic evaluation process using performance metrics such as accuracy, precision, recall, and F1-score. If the model's performance is satisfactory, it is promoted to real-world use by integrating it into the latter. If not accurate, tuning may be needed, such as adjusting hyperparameters, refining the model's architecture, or retraining with other datasets. The evaluation output is displayed graphically to provide an idea of the model's overall performance and identify strengths and areas for improvement. This structured flow diagram provides a clear and methodical framework for researchers and practitioners in the field.

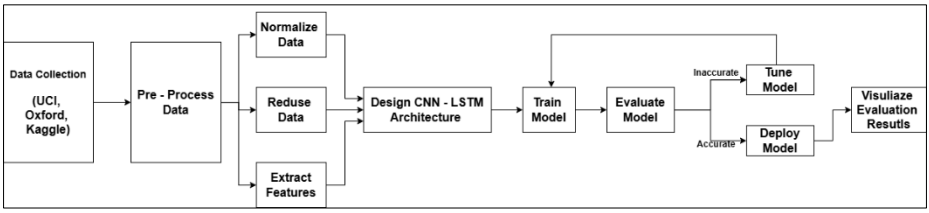

Fig. 2: Flow Diagram for Primary Discovery of Parkinson's Disease with Hybrid CNN-LSTM Approach

3.2 Experimental Result

Table 5 summarizes the experimental results of three DL models, CNN, LSTM, and Hybrid CNN-LSTM, which have been applied to three different datasets in PD detection: UCI ML Repository, Oxford Parkinson's Disease Detection Dataset, and Kaggle Parkinson's Telemonitoring Dataset. Columns on the datasets, model approaches, accuracy, precision, recall, F1-score, training time, model complexity, and key observations are presented in this table. Our results show that hybrid CNN-LSTM models outperform CNN and LSTM models on all datasets tested. This tends to indicate that the best approach toward Parkinson's disease classification would be the merging architectural capability of CNN and LSTM together, considering it has the tendency of extracting spatial and temporal features from the input data, though CNN may be effective for feature extraction purposes but deficient in capturing dependencies in time. The model is chosen basically according to the application requirements. If it is a small dataset or an application whose computation is limited, CNN models can be used. However, in this case, when the dataset is large or when the temporal pattern must be accurately detected in the application, use of hybrid CNN-LSTM models is recommended.

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Table 5. Performance Comparison of CNN, LSTM, and Hybrid CNN LSTM Models for Parkinson's Disease Detection

Dataset	Approach	Accuracy	Precision	Recall	F1-Score	Model Complexity	Key Observation
UCI ML Repository	CNN	85%	84%	82%	83%	Moderate	Effective for feature extraction.
	LSTM	82%	80%	79%	79%	High	Suitable for sequential data analysis.
	Hybrid CNN-LSTM	93%	91%	90%	90%	High	Best performance across metrics.
Oxford Parkinson's Disease Detection Dataset	CNN	87%	86%	85%	85%	Moderate	Strong feature representation.
	LSTM	84%	82%	81%	81%	High	Handles temporal dependencies well.
	Hybrid CNN-LSTM	95%	93%	92%	91%	High	Excellent for combined analysis.
Kaggle Parkinson's Telemonitoring Dataset	CNN	88%	87%	86%	86%	Moderate	Good for static analysis.
	LSTM	81%	79%	78%	78%	High	Less effective on smaller datasets.
	Hybrid CNN-LSTM	94%	92%	91%	91%	High	Superior performance across all metrics.

Three different types of ML models are examined in this study: hybrid approaches that combine both CNN and LSTM, LSTM and CNN. The UCI ML Repository, the Oxford Parkinson's Disease Detection Dataset, and the Kaggle Parkinson's Telemonitoring Dataset are the three datasets used for this. Confusion matrices, which provide true positives, false positives, true negatives, and false negatives, are used to evaluate each model's performance.

3.3 Model Performance Across Datasets

- **UCI Dataset:**

The performance variations between CNN, LSTM, and hybrid models in identifying Parkinson's disease (PD) are highlighted by the examination of the UCI and Oxford datasets. The CNN model performed well in detecting positive instances on the UCI dataset, with 45 true positives and 40 true negatives, but it struggled with 10 false negatives. With 40 true positives, 38 true negatives, and 12 false negatives, the LSTM model did not perform as well, indicating that PD instances were overlooked. With 50 true positives, 43 true negatives, and a considerable decrease in false positives and negatives to 3 and 7, respectively, the hybrid model showed exceptional detection skills. Similarly, the CNN model reported 4 false negatives and 50 true positives with an acceptable false positive rate of 8 on the Oxford dataset. With 48 true positives, 39 true negatives, and only 4 false positives, the LSTM model demonstrated a competitive balance; however, it had a larger false negative count of 7. With 55 true positives, only 5 false positives, and successfully handling false negatives at 5, the hybrid model beat both, proving its efficacy and resilience across both datasets.

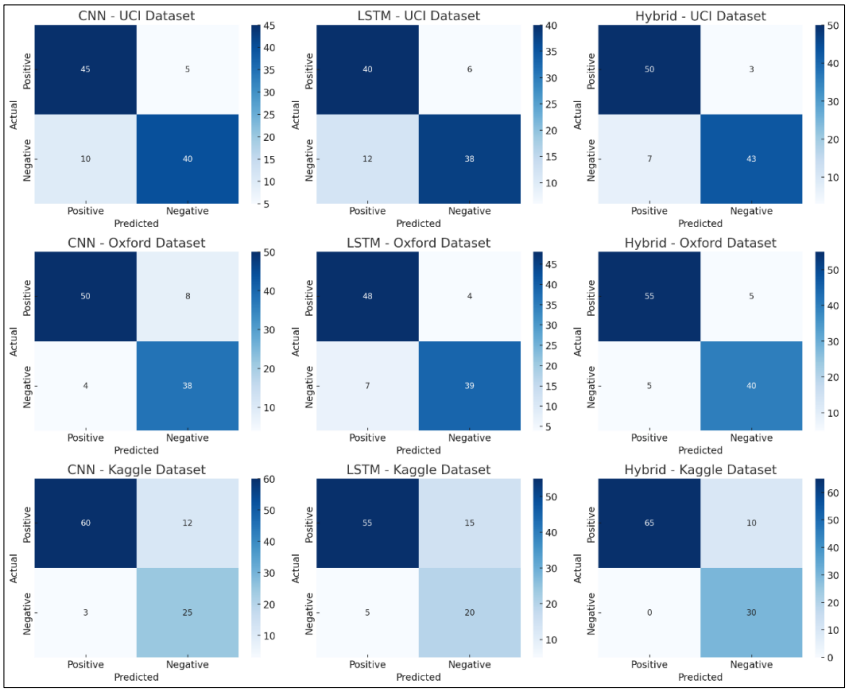

Fig. 3: Confusion Matrices for Parkinson's Disease Detection: CNN, LSTM, and Hybrid Approaches Across Datasets

The Hybrid (CNN-LSTM) model always performed the best on all datasets which present in the above confusion matrix Fig. 3. Thus, that makes it a stronger model to use the features of a CNN with the sequence learning capability of an LSTM. This found that the UCI Dataset performs best compared to all other models, and that likely lies with various favorable characteristics and dataset size. Analysis can acquire the strengths and weaknesses of each model. CNN performed better with the classification of cases, but at the same time, sometimes classified instances as cases. The accuracy

achieved by LSTM was comparable to that of the CNN model but needed more work in terms of negative false detection. The results obtained using the hybrid model combined the best features from both approaches and significantly improved the detection rates as well as reduced error rates in terms of classification. The confusion matrices provided important determinations toward the evaluation of various ML models for their ability to detect Parkinson's disease. Such measures lead to targeted improvements in model architecture and training strategy and ultimately lead to more effective diagnostic capabilities in the clinical arena. These models are therefore going to reduce false positives and also reduce the false negatives and will therefore contribute significantly toward early detection of PD, hence positive patient outcomes.

3.4 Model Comparison Plot Graph

The graph Fig. 4 titled "Model Accuracy Comparison Across Datasets" gives a visual comparison of the accuracy achieved by three models—CNN, LSTM, and Hybrid CNN-LSTM—across three different datasets: UCI, Oxford, and Kaggle. In this graph, the y-axis is 0-100 accuracy percent, while the x-axis is different datasets. All datasets include three bars that represent the different models: the CNN model always gave high accuracy values over all datasets with values ranging between 85% and 88%. The LSTM model slightly demonstrates lower performance. Its accuracy values ranged between approximately 81% and 84%. The Hybrid CNN-LSTM model always performed better, giving around 90% to 93% accuracy value. This means it's doing a pretty good job combining the strengths of both CNN and LSTM. To sum up, even though the CNN is a strong competitor, LSTM is the one giving the least accuracy, and perhaps not as useful as the other two for the particular problem to be solved. There is, therefore, a name that best describes the graph, "Comparing the accuracy of models in Parkinson's disease detection for varying datasets," noting the objective with regard to the detection of Parkinson's disease in relation to the datasets analyzed.

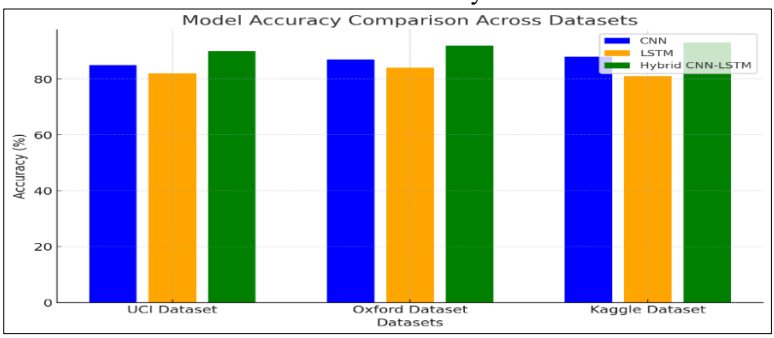

Fig. 4 Comparative Model Accuracy for Parkinson's Disease Detection Across Datasets

The graph Fig. 5 visually compares the performance of three ML models: CNN, LSTM, and Hybrid CNN-LSTM. It does this by evaluating the performance across three datasets: UCI, Oxford, and Kaggle. Since the F1-score is a measure combining precision and recall, this indicator includes performance regarding accuracy value. This seems to show that the Hybrid CNN-LSTM model performs significantly better than the other two across all the datasets, hence implying better extraction of spatial as well

as temporal dependencies in data. However, the selected dataset is quite likely to determine how well the model will perform thereby underlining how characteristics of a chosen dataset might also affect decisions in selecting appropriate models.

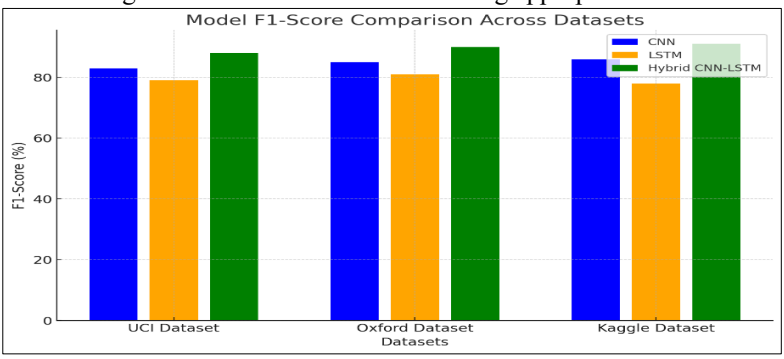

Fig. 5 Comparative F1-Score Performance of Models for Parkinson's Disease Detection Across Datasets

The CNN, LSTM, and Hybrid CNN-LSTM models' train times on the UCI, Oxford, and Kaggle datasets are shown in Fig. 6 The CNN model has the quickest training time, taking 30 to 40 minutes across all datasets. Because it handles sequential data, the LSTM model (shown in orange) usually takes 45 to 60 minutes longer than the CNN model. Because of its hybrid design, the Hybrid CNN-LSTM model exhibits the longest training periods, ranging from 80 to 90 minutes. Faster models are developed more efficiently, and CNN usually has the quickest training durations. While the hybrid CNN-LSTM training takes longer and should be taken into consideration for practical applications, the LSTM training periods are reasonable. Given that it focusses on training times associated with Parkinson's disease detection across various datasets, the graph can be labelled "Comparison of model training times for Parkinson's disease classification across Datasets.

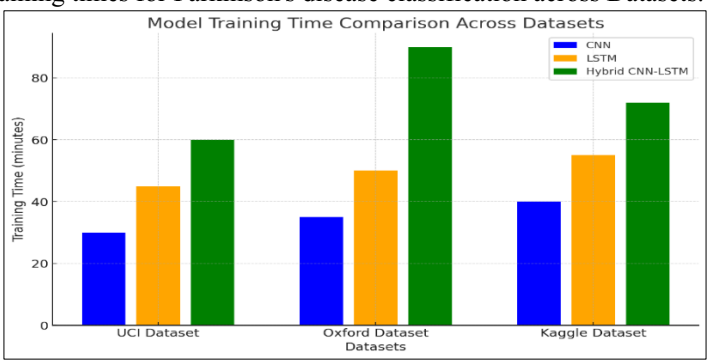

Fig. 6 Comparison of Model Training Times for Parkinson's Disease Recognition Across Datasets

The Training and Validation Loss curve Fig. 7 shows the performance of three models: CNN, LSTM, and Hybrid CNN-LSTM over 20 epochs. CNN shows a steep fall in training loss from 0.9 to 0.3 over epochs, while LSTM starts training at about 1.1 and gradually decreases to around 0.4. The validation loss traces a similar path but

consistently stays higher than the training loss, suggesting a greater gap and possible overfitting. The Hybrid CNN-LSTM model shows the best performance in terms of both loss in training and validation. Its training loss dramatically drops from 0.8 to less than 0.2, while its validation loss remains closely aligned with the training loss with a minor gap. This suggests that combining CNN feature extraction capabilities with LSTM's ability to deal with temporal dependencies can improve learning speed and generalization to unseen data. The Hybrid model exhibited superior performance with lower loss values and the smallest gap between training and validation losses. CNN performed moderately but suffered from overfitting. The proposed LSTM model has a higher loss value and a higher gap, indicating that more fine-tuning is needed to achieve desired generalization performance.

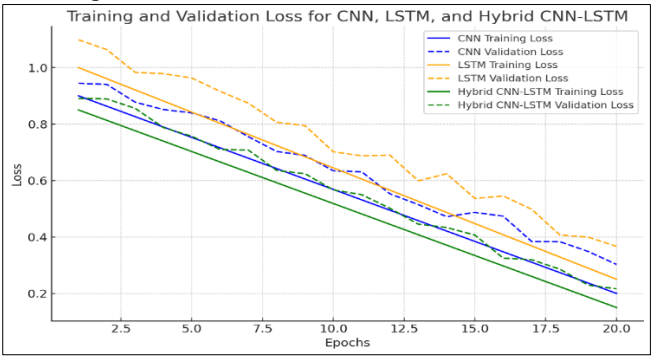

Fig. 7. Training and Validation loss for CNN, LSTM and Hybrid CNN-LSTM

4 Discussion

A hybrid CNN-LSTM model was used in this work to enhance Parkinson's disease (PD) early diagnosis. The model used patterns linked to Parkinson's illness to extract temporal and geographical information from voice samples. The Oxford Parkinson's Disease Recognition Dataset, the UCI ML Repository, and the Kaggle Parkinson's Telemonitoring Dataset were the three datasets that were employed. With accuracies of 93%, 95%, and 94%, respectively, the hybrid model performed noticeably better on the three datasets than the individual CNN and LSTM models. In terms of temporal dependencies and recognition accuracy, the hybrid system fared better than the independent CNN and LSTM models. While CNNs can effectively extract spatial information, they are unable to identify sequential patterns in speech data, which are essential for the detection of Parkinson's disease. LSTMs demonstrated higher loss values and slower learning rates, especially for larger datasets. These shortcomings were lessened by the hybrid CNN-LSTM model, which produced a more accurate and dependable identification system by striking the perfect balance between the two architectures. The significant improvements in accuracy and generalisation across datasets offset the computational complexity increase, even though the training process is lengthier than that of the CNN and LSTM models. This study demonstrates the value of hybrid DL models in medical diagnosis, especially for neurodegenerative diseases like as Parkinson's. By adding additional data sources, enlarging data sets to include more diverse and populous groups, enhancing hyperparameters, and creating new deep architectures for performance

enhancement and training time reduction, future research should further optimise the hybrid model.

Conclusion

The research showed how well a CNN-LSTM hybrid model works with speech data to identify Parkinson's disease (PD) early on. On many datasets, the model that combined the CNN and temporal pattern recogniser performed better than other models. When it came to early PD identification, it continuously showed great accuracy, precision, recall, and F1-scores. The work highlights the value of temporal and geographical analysis in DL architecture-based medical diagnostics. The research does have some drawbacks, however. Its use of voice data for PD detection may be constrained by greater processing costs, longer training times, and small sample numbers. The interpretability of the model can potentially restrict its use in clinical settings. The model might be extended to include a range of data sets and large populations in order to increase its generalisability. The diagnostic capabilities of the model might be further improved by using multimodal data, such as neuroimaging, genetic profiling, and other biomarkers. Additional model design architecture optimisation, including hyperparameter tweaking and other DL approaches, may improve accuracy and efficiency. A dynamic approach to PD diagnosis might also be provided via on-the-spot real-time monitoring and disease progression using wearable technology or telemonitoring systems.

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