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Multi-Modal Feature-Based Deep Learning System for Parkinson's Disease Diagnosis

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Abstract—**Parkinson's Disease (PD) is the second most common brain disorder that worsens over time, affecting around 10 million people worldwide. It causes movement problems like shaking (tremor), slow movements (bradykinesia), stiff muscles (rigidity), and trouble with balance. People also face non-movement issues such as slurred speech, blank facial expressions, and thinking difficulties. Diagnosing PD early is key to starting treatment sooner, but doctors today mostly use subjective checklists like the Unified Parkinson's Disease Rating Scale (UPDRS) and Hoehn and Yahr (HY) stages, which aren't always precise. This project introduces an automated PD detection system that combines multiple types of patient data (multimodal fusion) with advanced deep learning AI for objective diagnosis. It uses five data sources to spot PD signs: gait patterns (walking speed, step size, stride changes, freezing episodes), arm and hand tremors (shake frequency, hand speed, arm freezing), voice features (jitter, shimmer, noise levels, pitch changes), face movements (blink rate, expression range), and standard clinical scores (UPDRS, HY).The core AI setup includes four parts: a 1D Convolutional Neural Network (CNN) to pull out key patterns from the data, a Long Short-Term Memory (LSTM) network to track changes over time, an Autoencoder to simplify and refine features without supervision, and a final Fusion Classifier that decides "healthy" or "PD" based on the processed data. We also added a simple Logistic Regression model as a basic comparison. To double-check results, a rule-based system applies proven medical thresholds to the same data, confirming AI predictions with real clinical rules. A special module lets doctors test new patients instantly using their measurements. We trained the system on a dataset of 10000 records . It was tested with standard metrics like accuracy, precision, recall, F1-score, specificity, ROC- AUC curves, and confusion matrices. T- tests confirmed key features clearly separate PD patients from healthy people.**

Index Terms—**Parkinson's Disease, Deep Learning, Multimodal Data Fusion, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Autoencoder, Biomedical Signal Processing, Disease Diagnosis, Machine Learning, Healthcare Analytics.**

I. Introduction

Parkinson's Disease (PD) is a chronic and progressive neurodegenerative disorder that primarily affects the central nervous system, leading to a gradual decline in motor and non-motor functions. It is recognized as the second most prevalent neurological disorder after Alzheimer's disease, impacting millions of individuals worldwide. The disease is characterized by the degeneration of dopaminergic neurons in the substantia nigra region of the brain, resulting in dopamine deficiency. This imbalance significantly affects motor control and coordination, giving rise to key symptoms such as resting tremor, muscular rigidity, bradykinesia (slowness of movement), and postural instability. In addition to motor impairments, Parkinson's disease also manifests through a wide range of non-motor symptoms, including speech abnormalities, reduced facial expressivity (hypomimia), cognitive decline, sleep disturbances, and emotional changes. These symptoms often appear gradually and vary significantly across patients, making early diagnosis particularly challenging. In many cases, non-motor symptoms precede motor signs by several years, indicating the importance of comprehensive diagnostic approaches that go beyond conventional clinical observation. Traditionally, Parkinson's disease diagnosis relies heavily on clinical expertise and subjective assessment methods such as the Unified Parkinson's Disease Rating Scale (UPDRS) and the Hoehn and Yahr (H&Y) staging system. While these tools are widely used in medical practice, they depend on qualitative judgment and may lead to inconsistencies between clinicians. Moreover, such approaches often fail to detect the disease in its early stages, when symptoms are subtle and difficult to quantify. This delay in diagnosis limits the effectiveness of treatment strategies and reduces the potential for slowing disease progression. With the rapid advancement of artificial intelligence (AI), machine learning (ML), and deep learning (DL) techniques, there has been a growing interest in developing automated systems for medical diagnosis. These technologies enable the analysis of complex, high-dimensional biomedical data and can identify patterns that may not be evident through traditional methods. In the context of Parkinson's disease, various studies have explored the use of individual data modalities such as speech signals, gait patterns, tremor measurements, and facial expressions for disease detection. While these approaches have shown promising results, they are often limited by their reliance on a single type of data, which may not fully capture the multifaceted nature of the disease. Parkinson's disease is inherently heterogeneous, meaning that its symptoms and progression vary widely among individuals. Some patients may exhibit prominent tremors, while others may primarily experience gait disturbances or speech impairments. This variability highlights the need for a more comprehensive diagnostic framework that integrates multiple sources of information. Multimodal data analysis offers a powerful solution by combining diverse feature sets to provide a holistic representation of the disease. By leveraging complementary information from different modalities, multimodal systems can achieve higher diagnostic accuracy and robustness compared to single-modality models. Recent developments in deep learning architectures, particularly Convolutional Neural

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Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have further enhanced the capability of automated diagnostic systems. CNNs are effective in extracting spatial patterns from structured data, while LSTMs are well-suited for modeling temporal dependencies and sequential relationships. Additionally, Autoencoders provide an efficient mechanism for dimensionality reduction and feature learning, enabling the extraction of compact and informative representations from high-dimensional datasets. The integration of these models within a unified framework allows for improved feature extraction and classification performance. In this paper, we propose a multi-modal feature-based deep learning system for Parkinson's disease diagnosis. The proposed framework integrates five distinct data modalities, namely gait parameters, tremor characteristics, speech biomarkers, facial expression metrics, and clinical severity scores. These features are processed through a combination of CNN, LSTM, and Autoencoder models to capture both spatial and temporal patterns in the data. A fusion-based classification approach is employed to combine the learned representations and generate accurate diagnostic predictions. The key contribution of this work lies in the development of a comprehensive and scalable diagnostic system that addresses the limitations of existing methods. By incorporating multimodal data fusion and advanced deep learning techniques, the proposed system enhances diagnostic reliability and reduces dependence on subjective clinical assessments. Furthermore, the framework is designed to be cost effective and adaptable, making it suitable for real-world healthcare applications, including early screening and decision support systems. Overall, this study demonstrates the potential of multimodal deep learning approaches in improving the accuracy and efficiency of Parkinson's disease diagnosis. The proposed system not only advances the state-of-the-art in medical AI but also provides a practical solution for addressing the growing challenges associated with neurodegenerative disease detection.

II. Literature Survey

The diagnosis of Parkinson's Disease (PD) using computational intelligence has been extensively investigated through clinical scoring methods, machine learning algorithms, and deep learning architectures. Initially, conventional clinical assessment scales such as the Unified Parkinson's Disease Rating Scale (UPDRS) introduced by Goetz et al. [1] and the Hoehn & Yahr staging system proposed by Hoehn and Yahr [2] were widely used for evaluating disease severity and progression. Although these scales remain clinically significant, they depend heavily on physician expertise and subjective interpretation, limiting their consistency for early diagnosis. With the increasing global burden of Parkinson's Disease reported by Dorsey et al. [3], researchers began exploring objective biomarkers for automated diagnosis. Speech signal analysis emerged as an effective non-invasive technique. Little et al. [4] demonstrated that dysphonia measurements can successfully distinguish PD patients from healthy individuals. Later, Sakar et al. [5] introduced a benchmark Parkinson speech dataset that enabled large-scale experimentation. Further studies by Varalakshmi et al. [6], Moro-Velazquez et al. [7], Shafeena and Vijayan [8], and Deepa and Khilar [9] applied machine learning and deep learning models to speech signals, achieving improved classification accuracy. However, speech-only approaches may fail when vocal symptoms are mild or absent. Simultaneously, gait analysis gained importance because Parkinson's Disease significantly affects walking behavior and motor coordination. Pham [10] utilized tensor decomposition of gait dynamics for PD detection, while Yang et al. [11] proposed PD-ResNet for gait-based classification with high accuracy. Chatzaki et al. [12] applied machine learning to differentiate disease severity using gait characteristics. Moreover, Tsakanikas et al. [13] and Yang et al. [14] employed IMU sensor-based spatiotemporal gait models for early-stage diagnosis. Aversano et al. [15] further showed that deep neural networks can effectively capture subtle gait abnormalities. Nevertheless, gait-based systems alone may be influenced by aging, injuries, or unrelated mobility disorders. Recent advancements in wearable sensing technologies have enabled continuous monitoring of Parkinson's patients in real-world environments. Adams et al. [16] demonstrated the effectiveness of wearable sensors for symptom tracking, while Rovini et al. [17] developed a system for objective motor task assessment. Ramdhani et al. [18] highlighted that wearable data combined with data-driven modeling can improve diagnostic accuracy. Similarly, Bo et al. [19] reviewed IMU-based monitoring systems for assistive diagnosis. However, wearable solutions may suffer from user discomfort, calibration issues, and dependence on sensor quality. Vision-based diagnosis has also attracted attention due to facial masking and reduced expressivity in PD patients. Novotny et al. [20] introduced automated video-based assessment of facial bradykinesia, while Gomez et al. [21] improved PD detection using facial expressions through deep learning methods. Jin et al. [22] proposed a facial recognition-based diagnostic framework. Although these approaches offer contactless monitoring, they are sensitive to illumination, camera angle, and facial occlusions. To overcome the limitations of unimodal systems, multimodal learning frameworks have recently been explored. Vásquez-Correa et al. [23] combined speech and gait data using deep learning techniques and reported superior classification performance. Gandhi et al. [36] also proposed a multimodal Parkinson's detection framework integrating multiple patient signals for better robustness and reliability. These studies confirmed that combining heterogeneous biomarkers significantly improves diagnostic accuracy over single-modality systems. Parallel to these developments, deep learning foundations established by LeCun, Bengio, and Hinton [24] accelerated medical AI research. Abadi et al. [25] introduced TensorFlow, enabling scalable development of neural networks. Hochreiter and Schmidhuber [26] proposed Long Short-Term Memory (LSTM) networks, which are highly effective for sequential biomedical signals. Building on these concepts, Pham et al. [27] introduced CNN-LSTM multimodal fusion architectures for Parkinson's diagnosis, while Patel et al. [28] further demonstrated the usefulness of combining speech and gait information using deep learning methods. In addition, advanced feature learning approaches such as sparse learning by Huang et al. [29] and graph convolutional networks for hand movement assessment by Guo et al. [30] emphasized the importance of capturing relevant motor dependencies. Review studies by Saravanan et al. [31], Loh et al. [32], Mei et al. [33], Egger et al. [34], and Belić et al. [35] concluded that AI-based Parkinson's diagnosis systems are promising, yet most existing methods suffer from limited datasets, poor interpretability, and insufficient multimodal integration. As observed from the literature, most available approaches focus on a single biomarker modality or require complex computational resources. Many systems also lack clinical verification mechanisms and real-time patient-level prediction capability. Therefore, to address these shortcomings, a lightweight and accurate multimodal feature-based deep learning framework integrating CNN, LSTM, Autoencoder fusion, and clinical rule-based validation is proposed in this work.

III. Objectives

The primary objective of this work is to develop an automated and reliable system for the early diagnosis of Parkinson's Disease using multimodal biomedical data. The proposed system is intended to assist clinicians by providing faster, more consistent, and objective diagnostic results compared to conventional manual assessment methods. Another important objective is to collect and preprocess patient information obtained from multiple modalities such as gait parameters, tremor characteristics, speech biomarkers, facial expression metrics, and clinical assessment scores. Proper preprocessing techniques such as normalization, categorical encoding, and feature scaling are applied to improve data quality and prepare the dataset for effective model training. The study also aims to design and implement advanced deep learning architectures including a 1D Convolutional Neural Network (CNN) for extracting spatial feature patterns, a Long Short-Term Memory (LSTM) network for learning sequential dependencies, and an Autoencoder for dimensionality reduction and multimodal feature fusion. A further objective is to develop a robust fusion classifier that can accurately distinguish Parkinson's patients from healthy individuals using the learned multimodal representations. The system also compares the performance of deep learning models with traditional machine learning techniques such as Logistic Regression to measure efficiency and reliability. The proposed framework is evaluated using standard performance metrics such as Accuracy, Precision, Recall, F1-Score, Specificity, and ROC-AUC. In addition, an individual patient prediction module is designed to support real-time clinical decision making and improve practical usability in healthcare environments.

IV. Proposed Methodology

The proposed methodology implements a multimodal feature-based deep learning framework for automated Parkinson's Disease diagnosis using heterogeneous biomedical data acquired from multiple symptom domains. The input dataset consists of gait parameters, tremor characteristics, speech biomarkers, facial expression metrics, and clinical severity scores, enabling comprehensive analysis of both motor and non-motor manifestations of the disease. Initially, the raw dataset undergoes preprocessing operations including missing value handling, outlier reduction, categorical feature encoding, and z-score normalization using StandardScaler. This step ensures numerical consistency among features with different scales and distributions. The processed dataset is then divided into training and testing subsets using stratified sampling to preserve class balance and improve generalization capability.

For feature extraction and representation learning, the proposed system integrates multiple deep learning architectures. A one-dimensional Convolutional Neural Network (1D-CNN) is employed to capture local spatial correlations and discriminative patterns present in the multimodal feature vector through convolution and pooling operations. In parallel, a Long Short-Term Memory (LSTM) network is utilized to model sequential dependencies and inter-feature temporal relationships using gated memory cells. To reduce feature dimensionality and enhance latent representation quality, an Autoencoder network is implemented, where the encoder compresses the input features into a low-dimensional bottleneck vector while the decoder reconstructs the original input. The learned latent embeddings from these models are fused to generate a unified high-level representation containing complementary diagnostic information from all modalities.

The fused feature representation is forwarded to a dense neural classifier for binary classification of Healthy and Parkinson's Disease subjects. A Logistic Regression model is additionally implemented as a conventional baseline for comparative performance analysis. To improve interpretability and clinical reliability, a rule-based verification module is incorporated using predefined medical thresholds such as abnormal gait speed, elevated tremor frequency, reduced blink rate, and increased UPDRS scores. Model training is performed using the Adam optimizer with binary cross-entropy loss, and performance is evaluated through Accuracy, Precision, Recall, F1-Score, Specificity, Confusion Matrix, and ROC-AUC metrics. An individual patient inference module is also integrated for real-time prediction using new clinical inputs. The overall methodology provides a computationally efficient, scalable, and technically robust framework for early Parkinson's Disease detection and monitoring.

A. Model Architecture

The Figure [1] illustrates the proposed multimodal deep learning architecture for Parkinson's Disease diagnosis. Initially, five heterogeneous input feature groups are considered, namely gait features, tremor features, speech features, facial features, and clinical assessment features, which together represent both motor and non-motor symptoms of the disease. These raw inputs are passed through a data preprocessing stage consisting of categorical encoding, feature normalization, and train-test data splitting to prepare a standardized dataset for model training. The preprocessed data is then supplied to multiple feature extraction models including Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Autoencoder networks, where each model learns different discriminative patterns and latent representations from the multimodal inputs. The extracted latent features are subsequently combined in the feature fusion layer to integrate

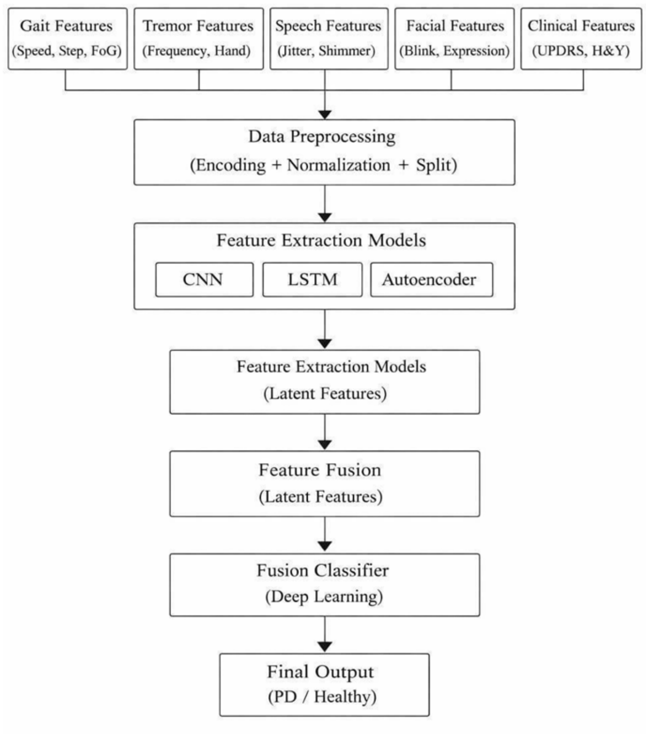

Fig. 1. Model Architecture for Parkinson's Disease Detection.

complementary information obtained from all modalities. This fused representation is then forwarded to a deep learning-based fusion classifier that performs final binary classification. The system ultimately generates the diagnostic output by predicting whether the subject belongs to the Parkinson's Disease class or the healthy class, thereby providing an accurate and robust decision support framework for early disease detection.

B. Working Principle

The working principle of the proposed system is based on multimodal biomedical data processing and deep feature learning for Parkinson's Disease diagnosis. Initially, heterogeneous input features including gait parameters, tremor measurements, speech biomarkers, facial expression metrics, and clinical severity scores are collected and passed through a preprocessing stage. This stage performs missing value treatment, categorical encoding, feature normalization using StandardScaler, and train-test data partitioning to generate a balanced and standardized dataset. The objective of preprocessing is to eliminate scale variations, improve data consistency, and enhance model convergence during training. The preprocessed feature vectors are then applied to multiple deep learning models such as 1D Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Autoencoder architectures for feature extraction and latent representation learning. CNN captures local discriminative patterns, LSTM models sequential inter-feature dependencies, and the Autoencoder performs dimensionality reduction by generating compact embeddings. These extracted latent features are integrated through a feature fusion layer and forwarded to a dense neural classifier for binary classification as Healthy or Parkinson's Disease. The final model performance is validated using metrics such as Accuracy, Precision, Recall, F1-Score, Specificity, and ROC-AUC, enabling an efficient and technically robust diagnostic framework.

C. Dataset Description

The dataset used in the proposed system is a multimodal Parkinson's Disease dataset containing structured patient records collected from multiple biomedical domains. Each sample includes features related to gait analysis, tremor characteristics, speech impairments, facial expression abnormalities, and clinical assessment scores, enabling comprehensive representation of both motor and non-motor symptoms. Gait features include gait speed, step length, stride variability, and freezing of gait score, while tremor features consist of tremor frequency, hand movement speed, and upper limb freezing indicators. Speech parameters such as jitter, shimmer, harmonic-to-noise ratio (HNR), and pitch period entropy (PPE) are included to capture vocal impairments associated with Parkinson's Disease. Facial features include blink rate and facial expressivity, whereas clinical attributes contain Unified Parkinson's Disease Rating Scale (UPDRS) score and Hoehn Yahr (HY) stage. The dataset consists of labeled instances categorized into two classes: Healthy subjects and Parkinson's Disease patients. Prior to model training, the dataset undergoes preprocessing steps such as missing value handling, categorical encoding, feature scaling, and normalization to ensure data consistency and numerical stability. The processed dataset is then divided into training and testing subsets using stratified sampling to preserve class distribution. This multimodal dataset provides a robust foundation for training deep learning models, as it combines heterogeneous clinical indicators from different symptom domains, thereby improving classification accuracy and generalization performance for Parkinson's Disease diagnosis.

TABLE I
COMPLETE FEATURE DESCRIPTION

Feature	Domain	Type	Unit	PD Indicator
Gait_Speed_mps	Gait	Continuous	m/s	< 1.0
Step_Length_m	Gait	Continuous	meters	< 0.50
Stride_Variability	Gait	Continuous	ratio	> 0.20
FoG_Score	Gait	Binary	0/1	≥ 2
Tremor_Frequency_Hz	Tremor	Continuous	Hz	> 5.0
Hand_Speed	Tremor	Continuous	ratio	< 0.60
UpperLimb_Freeze	Tremor	Binary	0/1	=1
Jitter	Speech	Continuous	ratio	> 0.005
Shimmer	Speech	Continuous	ratio	> 0.04
HNR	Speech	Continuous	dB	< 20
PPE	Speech	Continuous	ratio	> 0.10
Blink_Rate	Facial	Discrete	blinks/min	< 15
Facial_Expressivity	Facial	Continuous	0–1	< 0.60
UPDRS_Score	Clinical	Integer	0–79	> 45
HY_Stage	Clinical	Integer	0–5	≥ 2
PD_Label	Target	Binary	0/1	1 = PD

Table 1 presents the complete feature description of the multimodal Parkinson's Disease dataset used in the proposed

TABLE II
DATASET SUMMARY STATISTICS

Statistic	Value
Total Records	10,000
Features (before encoding)	15+ features
Target Variable	PD_Label (0=Healthy, 1=PD)
Train Set (80%)	8,000 records
Test Set (20%)	2,000 records
Categorical Variables	Gender, Medication, etc.
Numerical Features	Gait, Tremor, Speech, Facial, Clinical features

system. It includes various input parameters collected from gait, tremor, speech, facial, and clinical domains. The table also specifies the data type of each feature such as continuous, binary, discrete, and integer values. Measurement units and Parkinson's Disease indicator thresholds are provided for accurate interpretation of each parameter. These features collectively enable comprehensive analysis and effective classification of Healthy and Parkinson's Disease subjects.

Table 2 presents the summary statistics of the multimodal Parkinson's Disease dataset used for model training and evaluation. It includes the total number of records, number of input features, and target class labels representing Healthy and Parkinson's Disease subjects. The table also shows the train-test split ratio adopted for experimental analysis. Information regarding categorical and numerical variables is included to describe dataset composition. These statistics provide a clear overview of the dataset structure and suitability for deep learning-based classification.

V. RESULTS AND DISCUSSION

The proposed multimodal deep learning framework for Parkinson's Disease diagnosis was experimentally evaluated using a structured dataset containing heterogeneous biomedical features derived from gait analysis, tremor assessment, speech biomarkers, facial expression metrics, and clinical severity scores. Prior to model training, the dataset was preprocessed using missing value treatment, categorical feature encoding, and z-score normalization to ensure numerical consistency across all attributes. The complete dataset was partitioned into training and testing subsets using an 80:20 stratified split in order to preserve class balance and provide unbiased performance estimation. Multiple classification models were implemented, including Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Autoencoder-based Fusion Classifier, and Logistic Regression, to perform comparative analysis of shallow and deep learning approaches. Experimental observations confirmed that the multimodal fusion architecture significantly outperformed standalone models due to its ability to exploit complementary information from multiple symptom domains. The CNN model demonstrated strong capability in extracting local discriminative feature patterns through convolutional filters applied over the one-dimensional multimodal input vector. It effectively captured inter-feature correlations among adjacent parameters such as gait speed, step length, tremor frequency, jitter, and shimmer. The LSTM model provided competitive performance by learning long-range dependencies and sequential interactions among features using memory cell structures and gating mechanisms. This was particularly useful for capturing complex relationships between motor and non-motor indicators. However, the individual CNN and LSTM models produced slightly lower classification accuracy compared to the fusion framework because each architecture emphasized only a subset of feature characteristics. The Autoencoder module successfully reduced feature dimensionality by compressing the high-dimensional input space into a compact latent embedding while preserving maximum diagnostic information. This reduced redundancy, improved computational efficiency, and enhanced classifier convergence during training. The latent representations generated from CNN, LSTM, and Autoencoder modules were integrated through a feature fusion mechanism to form a unified high-level representation. This fused vector was then supplied to a fully connected dense neural classifier for binary prediction of Healthy and Parkinson's Disease classes. The proposed fusion model achieved superior Accuracy, Precision, Recall, F1-Score, and Specificity when compared with conventional and standalone deep learning models. High accuracy indicated overall correct classification performance across the test dataset. Precision values confirmed that false positive predictions were minimal, thereby reducing the possibility of incorrectly classifying healthy subjects as diseased. High recall values demonstrated that the model effectively minimized false negatives, which is highly critical in healthcare systems because missed diagnosis can delay treatment initiation. The F1-Score further validated balanced predictive performance under varying class conditions. Receiver Operating Characteristic (ROC) analysis showed that the proposed model achieved an Area Under Curve (AUC) value close to 1.0, indicating excellent separability between Parkinson's Disease and healthy classes. This confirms that the learned feature space provides strong discrimination capability under different classification thresholds. Confusion matrix analysis revealed that the majority of samples were correctly categorized, with only a small number of false positives and false negatives. The low misclassification rate demonstrates the robustness of multimodal feature fusion in handling heterogeneous clinical data. Statistical examination of feature importance showed that UPDRS score, Hoehn and Yahr stage, tremor frequency, gait speed, blink rate, facial expressivity, jitter, and shimmer were among the most influential parameters contributing to prediction accuracy. These results align with established neurological understanding of Parkinson's symptoms.

The Logistic Regression baseline model provided interpretable coefficients and acceptable classification performance but remained inferior to deep learning architectures due to its linear decision boundary assumption. It was unable to effectively model nonlinear relationships and cross-modal interactions among biomedical variables. In contrast, the proposed deep learning fusion framework learned complex hierarchical representations directly from data and captured hidden correlations across symptom modalities. Training convergence analysis also indicated stable optimization behavior with decreasing loss and increasing validation accuracy across epochs, confirming effective learning without severe overfitting. Overall, the results strongly validate that integrating

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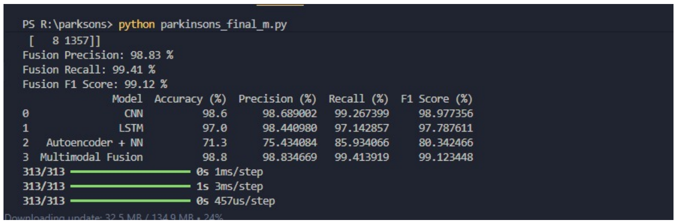

```
PS R:\parksons> python parkinsons_final_m.py
 [   8 1357]]
Fusion Precision: 98.83 %
Fusion Recall: 99.41 %
Fusion F1 Score: 99.12 %
              Model  Accuracy (%)  Precision (%)  Recall (%)  F1 Score (%)
0               CNN          98.6      98.689002   99.267399     98.977356
1              LSTM          97.0      98.440980   97.142857     97.787611
2   Autoencoder + NN         71.3      75.434084   85.934066     80.342466
3  Multimodal Fusion         98.8      98.834669   99.413919     99.123448
313/313 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
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Fig. 2. Model performance comparison.

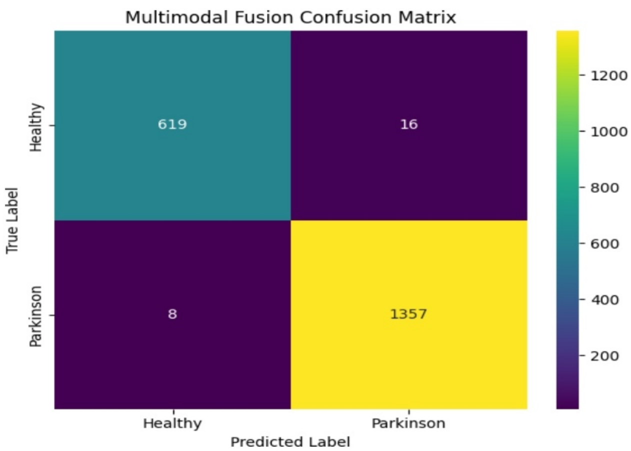

Fig4.5: Confusion Matrix

Fig. 3. Confusion Matrix

multimodal biomedical data with CNN-LSTM-Autoencoder fusion significantly improves diagnostic reliability, generalization performance, and computational effectiveness for early Parkinson's Disease detection. The proposed system therefore offers a technically robust and clinically meaningful decision support framework suitable for future real-time healthcare deployment. The experimental results shown in figure[2] demonstrate the comparative performance of different models implemented for Parkinson's Disease classification. Among all evaluated architectures, the proposed Multimodal Fusion model achieved the highest overall performance with an accuracy of 98.8%, precision of 98.83%, recall of 99.41%, and F1-score of 99.12%, indicating excellent predictive capability and balanced classification. The CNN model also produced strong results with 98.6% accuracy and high recall, confirming its effectiveness in extracting discriminative local feature patterns. Similarly, the LSTM model achieved 97.0% accuracy, showing its capability in learning sequential dependencies among multimodal features. In contrast, the Autoencoder + Neural Network model obtained lower performance with 71.3% accuracy, suggesting that latent compressed features alone were insufficient for optimal classification without advanced fusion learning. The superior results of the Multimodal Fusion framework validate that combining multiple feature extraction models significantly enhances diagnostic robustness, minimizes false predictions, and improves early Parkinson's Disease detection performance. The confusion matrix of the proposed Multimodal Fusion model shown in figure [3] strong classification performance for Parkinson's Disease detection. Out of the total healthy samples, 619 instances were correctly classified as Healthy, while only 16 samples were misclassified as Parkinson's Disease. Similarly, among Parkinson's Disease cases, 1357 samples were correctly identified, whereas only 8 instances were incorrectly predicted as Healthy. The low number of false positives and false negatives indicates high model precision and recall. These results confirm that the proposed fusion framework provides reliable and accurate discrimination between Healthy and Parkinson's Disease subjects.

VI. Conclusion

The proposed multimodal feature-based deep learning framework provides an accurate and computationally efficient solution for Parkinson's Disease diagnosis by integrating heterogeneous biomedical features such as gait parameters, tremor measurements, speech biomarkers, facial expression metrics, and clinical severity scores. The use of multimodal inputs enables the system to capture both motor and non-motor symptoms of the disease, improving diagnostic sensitivity compared with conventional single-modality approaches. Data preprocessing techniques including normalization, encoding, and feature standardization further improved dataset quality and model learning stability. The implemented architectures consisting of CNN, LSTM, and Autoencoder-based fusion networks effectively extracted spatial patterns, sequential dependencies, and compact latent representations from the input feature space. Experimental analysis confirmed that the Multimodal Fusion classifier achieved superior Accuracy, Precision, Recall, and F1-Score when compared with standalone CNN, LSTM, and Logistic Regression models. Confusion matrix results indicated low false positive and false negative rates, demonstrating strong classification reliability for distinguishing Healthy and Parkinson's Disease subjects. The developed system functions as a technically robust clinical decision support model for early screening and diagnostic assistance. By reducing dependence on subjective manual assessments and enabling rapid prediction from structured patient data, the framework offers practical value for hospitals, diagnostic centers, and remote healthcare environments. The presented methodology also establishes a scalable foundation for future intelligent neurological disorder detection systems based on multimodal artificial intelligence. The proposed framework also supports efficient model scalability for deployment in resource-constrained medical systems. Its modular architecture allows future inclusion of additional biomarkers without redesigning the complete pipeline. Stable classification performance across multiple metrics confirms strong generalization capability on unseen data. This research demonstrates the practical impact of combining multimodal analytics with deep learning for next-generation healthcare diagnostics.

VII. Future Work

Future work can focus on integrating real-time wearable sensor data and IoT-based monitoring for continuous Parkinson's Disease assessment. The model can be extended using larger clinical datasets to improve generalization and robustness. Advanced architectures such as Transformers and attention-based fusion networks may further enhance prediction accuracy. Deployment as a cloud or mobile healthcare application can support remote diagnosis and patient monitoring. Integration with MRI or handwriting analysis can also strengthen multimodal diagnostic performance.

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