EXPLAINABLE TEMPORAL TRANSFORMER FOR DISEASE PROGRESSION PREDICTION USING ATTENTION AND SHAP ANALYSIS

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CANDIDATE'S DECLARATION

I Ajitesh Chhibber hereby certify that the work which is being presented in the thesis entitled **"Explainable Temporal Transformer for Disease Progression Prediction using Attention and SHAP Analysis"** in partial fulfillment of the requirements for the award of the Master of Technology Degree, submitted in the Department of Computer Science and Engineering, Delhi Technological University is an authentic record of my own work carried out during the period from August 2025 to May 2026 under the supervision of **Prof. Vinod Kumar**

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

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CERTIFICATE

I hereby Certified that **Ajitesh Chhibber (24/CSE/31)** has carried out their research work presented in this thesis entitled **"Explainable Temporal Transformer for Disease Progression Prediction using Attention and SHAP Analysis"** for the award of Master of Technology from Department of Computer Science and Engineering, Delhi Technological University, Delhi, under my supervision.

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ABSTRACT

Keywords— Parkinson's Disease, Disease Progression Prediction, Explainable Artificial Intelligence, Temporal Transformer, FAETT, SHAP Analysis, Deep Learning, Attention Mechanism, Parkinson Telemonitoring Dataset.

Parkinson's disease (PD) is a progressive neurodegenerative disorder characterized by the gradual deterioration of motor functions, significantly affecting the quality of life of patients. Accurate prediction of disease progression is essential for timely clinical intervention, treatment planning, and personalized patient management. Traditional machine learning approaches often treat clinical observations as independent samples, limiting their ability to capture the temporal dynamics inherent in longitudinal patient data. Although deep learning models such as Long Short-Term Memory (LSTM) networks have demonstrated improved temporal modeling capabilities, they may struggle to effectively capture long-range dependencies present in disease progression trajectories.

This thesis presents an Explainable Feature-Aware Enhanced Temporal Transformer (FAETT) framework for predicting Parkinson's disease progression using longitudinal voice-based biomarkers from the Parkinson Telemonitoring dataset obtained from the UCI Machine Learning Repository. The proposed framework integrates temporal sequence modeling with self-attention mechanisms to learn complex relationships across historical patient observations. A comprehensive preprocessing pipeline involving data cleaning, feature scaling, temporal sequence generation, and patient-wise train-test partitioning is employed to ensure robust model development and unbiased evaluation.

To assess the effectiveness of the proposed approach, FAETT is compared against three baseline models: Random Forest (RF), Long Short-Term Memory (LSTM), and a standard Transformer architecture. Model performance is evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). Experimental results demonstrate that the proposed FAETT model achieves superior predictive performance, attaining an MAE of 1.2688, RMSE of 1.6457, and R^2 score of 0.9754, outperforming the baseline approaches. The findings indicate that the incorporation of feature-aware temporal attention significantly enhances the model's ability to capture disease progression patterns.

To address the interpretability requirements of clinical decision-support systems, SHAP (SHapley Additive exPlanations) analysis is integrated into the framework. The explainability analysis identifies the most influential vocal biomarkers contributing to disease progression prediction and provides transparent insights into model behavior. Correlation analysis, residual diagnostics, and prediction-performance visualizations further validate the robustness and reliability of the proposed framework.

The results demonstrate that the proposed FAETT architecture effectively combines predictive accuracy with model interpretability, making it a promising tool for explainable disease progression forecasting in Parkinson's disease. The study highlights the potential of attention-based temporal learning and explainable artificial intelligence techniques for advancing data-driven healthcare applications.

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Chapter 1

INTRODUCTION

1.1 Introduction

Parkinson's Disease (PD) is one of the most common neurodegenerative disorders affecting millions of people worldwide [1]. It is characterized by the progressive degeneration of dopaminergic neurons in the substantia nigra region of the brain, resulting in impaired motor and non-motor functions. Common symptoms include tremors, rigidity, bradykinesia, postural instability, speech impairment, and cognitive decline. As the disease advances, patients experience increasing difficulty in performing routine daily activities, significantly affecting their quality of life.

Accurate prediction of disease progression is essential for effective clinical management, treatment planning, and personalized healthcare interventions. Traditionally, neurologists assess Parkinson's disease severity using clinical examinations and standardized rating scales such as the Unified Parkinson's Disease Rating Scale (UPDRS) [1, 2]. Although these assessments provide valuable information, they are often subjective, time-consuming, and dependent on periodic hospital visits.

The rapid growth of Artificial Intelligence (AI) and Machine Learning (ML) has created new opportunities for developing automated systems capable of predicting disease progression using biomedical and voice-based biomarkers. Such systems can assist clinicians in monitoring patients remotely and identifying disease trends at an early stage. However, many traditional machine learning approaches treat patient observations as independent samples and fail to capture the temporal relationships that exist in longitudinal medical data.

Recent advances in Deep Learning, particularly Transformer-based architectures, have demonstrated remarkable success in sequence modeling tasks [3] due to their ability to learn long-range dependencies through self-attention mechanisms. In addition, Explainable Artificial Intelligence (XAI) techniques have emerged as an important research area [6, 7] for improving the transparency and interpretability of predictive models in healthcare applications.

In this thesis, an Explainable Feature-Aware Enhanced Temporal Transformer (FAETT) framework is proposed for Parkinson's disease progression prediction using longitudinal telemonitoring data. The proposed framework combines temporal sequence modeling with SHAP-based explainability to achieve both high predictive accuracy and transparent decision-making. The effectiveness of the proposed model is evaluated and compared with baseline approaches including Random Forest (RF), Long Short-Term Memory (LSTM), and a standard Transformer architecture.

1.2 Motivation and Problem Statement

Parkinson's disease (PD) is a progressive neurodegenerative disorder that affects millions of people worldwide and significantly impacts motor and non-motor functions. Accurate prediction of disease progression is essential for effective clinical management, treatment planning, and personalized healthcare interventions. The increasing availability of telemonitoring technologies and biomedical data has created opportunities for developing intelligent systems capable of forecasting disease severity using machine learning and deep learning techniques.

Traditional machine learning approaches such as Random Forest, Support Vector Machine, and Decision Trees have demonstrated promising performance in analyzing Parkinson's disease data. However, these methods generally treat patient observations as independent samples and fail to capture the temporal dependencies present in longitudinal healthcare datasets. As a result, their ability to model disease progression patterns over time remains limited.

Deep learning architectures, particularly Long Short-Term Memory (LSTM) networks, have improved temporal modeling by learning sequential relationships among patient observations. Nevertheless, LSTM-based approaches often face challenges in capturing long-range temporal dependencies and require sequential processing, which increases computational complexity. Furthermore, many deep learning models operate as black-box systems, providing limited insight into the factors influencing their predictions.

Transformer-based architectures have recently emerged as powerful alternatives for sequence modeling due to their self-attention mechanisms, which enable the learning of long-range temporal relationships while supporting parallel computation. Despite their strong predictive capabilities, standard Transformer models generally lack sufficient interpretability, which restricts their adoption in healthcare environments where transparency and trust are essential.

Therefore, there is a need for an advanced predictive framework capable of:

1. Capturing temporal dependencies present in longitudinal patient observations.
2. Learning complex nonlinear relationships among voice-based and clinical biomarkers.
3. Providing interpretable predictions that can support clinical decision-making.
4. Achieving superior predictive performance compared to conventional machine learning and deep learning approaches.

To address these challenges, this research proposes an Explainable Feature-Aware Enhanced Temporal Transformer (FAETT) framework for Parkinson's disease progression prediction. The proposed framework integrates Transformer-based temporal learning with SHAP-based explainability to achieve both high predictive accuracy and transparent decision-making, thereby enhancing the practical applicability of artificial intelligence in healthcare environments.

1.3 Research Objectives

The primary objective of this research is to develop an explainable deep learning framework for predicting Parkinson's disease progression using longitudinal telemonitoring data.

The specific objectives are:

1. To preprocess and analyze the Parkinson Telemonitoring dataset obtained from the UCI Machine Learning Repository.

2. To generate temporal sequences from longitudinal patient observations for disease progression modeling.

3. To implement and evaluate baseline models including Random Forest, Long Short-Term Memory (LSTM), and Transformer architectures.

4. To develop the proposed Feature-Aware Enhanced Temporal Transformer (FAETT) model.

5. To compare the predictive performance of all models using MAE, RMSE, and R^2 evaluation metrics.

6. To incorporate SHAP-based explainability for interpreting model predictions and identifying influential biomarkers.

1.4 Scope of the Study

This study focuses on predicting Total UPDRS scores using the Parkinson Telemonitoring dataset. The work compares Random Forest, LSTM, Transformer, and the proposed FAETT model. Performance is evaluated using MAE, RMSE and R^2. SHAP analysis is used to interpret predictions. The study does not address diagnosis, treatment recommendation or clinical deployment.

1.5 Research Contributions

The major contributions of this thesis are summarized as follows:

1. Development of a novel Feature-Aware Enhanced Temporal Transformer (FAETT) framework for Parkinson's disease progression prediction using longitudinal patient data.

2. Design and implementation of a temporal sequence generation pipeline for capturing disease progression patterns from historical patient observations.

3. Comprehensive comparative analysis of Random Forest, LSTM, Transformer, and the proposed FAETT model using standard regression performance metrics.

4. Integration of SHAP-based explainability to provide transparent and interpretable predictions suitable for healthcare applications.

5. Identification of the most influential voice-based biomarkers contributing to disease progression prediction through feature importance analysis.

6. Demonstration of improved predictive performance and generalization capability of the proposed FAETT model compared with conventional machine learning and deep learning approaches. “‘

1.6 Thesis Organization

The remainder of this thesis is organized as follows:

- **Chapter 2: Literature Review** presents a review of existing studies related to Parkinson’s disease progression prediction, machine learning techniques, Transformer architectures, and explainable artificial intelligence methods.

- **Chapter 3: Dataset Description and Preprocessing** describes the Parkinson Telemonitoring dataset, data preprocessing procedures, exploratory data analysis, and temporal sequence generation methodology.

- **Chapter 4: Proposed Methodology** presents the architecture and components of the proposed Feature-Aware Enhanced Temporal Transformer (FAETT) framework along with the SHAP-based explainability mechanism.

- **Chapter 5: Experimental Setup** discusses the implementation details, experimental environment, hyperparameter settings, training strategy, and evaluation metrics used in this study.

- **Chapter 6: Results and Discussion** presents the experimental results, comparative performance analysis, visualization studies, SHAP explainability analysis, and discussion of findings.

- **Chapter 7: Conclusion and Future Work** summarizes the major contributions of the research, highlights key findings, discusses limitations, and outlines potential directions for future work.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

Parkinson's disease (PD) is a progressive neurodegenerative disorder that affects both motor and non-motor functions. Advances in Artificial Intelligence (AI) and the increasing availability of healthcare data have encouraged the development of predictive models for disease diagnosis, severity assessment, and progression forecasting. Machine learning and deep learning techniques have demonstrated significant potential in analyzing biomedical data and identifying complex patterns associated with disease progression.

Over the years, various approaches ranging from traditional machine learning algorithms to advanced deep learning architectures have been applied to Parkinson's disease prediction. More recently, Transformer-based models and Explainable Artificial Intelligence (XAI) techniques have attracted considerable attention due to their ability to improve predictive performance and model interpretability. This chapter reviews the existing literature related to Parkinson's disease progression prediction, machine learning methods, deep learning architectures, Transformer-based models, and explainability techniques, and identifies the research gap addressed by the proposed FAETT framework.

2.2 Parkinson's Disease Prediction Using Machine Learning

Machine learning techniques have been widely employed for Parkinson's disease diagnosis and progression prediction using clinical and voice-based biomarkers. Algorithms such as Support Vector Machines (SVM), Random Forests (RF), Decision Trees (DT), and Gradient Boosting Machines (GBM) have demonstrated promising performance in identifying disease patterns and estimating disease severity.

Little et al. demonstrated the effectiveness of voice-based biomarkers, including jitter, shimmer, and harmonic-to-noise ratio, for monitoring Parkinson's disease progression [1, 2]. Subsequent studies reported that ensemble learning approaches such as Random Forest provide robust predictive performance and can effectively model nonlinear relationships among biomedical features [5, 8]. Despite their effectiveness, traditional machine learning approaches generally treat observations as independent samples and fail to capture temporal dependencies present in longitudinal patient data. Consequently, their ability to model disease progression trends over time remains limited, motivating the adoption of advanced deep learning architectures for temporal healthcare analytics.

2.3 Deep Learning Approaches for Parkinson's Disease Prediction

The success of deep learning in healthcare analytics has encouraged researchers to apply neural network architectures for Parkinson's disease prediction [9]. Deep learning models are capable of automatically learning complex feature representations and capturing nonlinear relationships among biomedical variables [9], often outperforming traditional machine learning approaches on large datasets.

Various deep learning architectures, including feedforward neural networks, recurrent neural networks, and attention-based models, have been explored for disease severity estimation and progression forecasting. These models provide improved predictive capabilities by learning hierarchical patterns directly from data without extensive manual feature engineering.

Despite their strong performance, many deep learning models suffer from limited interpretability, making it difficult to understand the factors influencing their predictions. Furthermore, conventional neural network architectures may not effectively capture long-range temporal dependencies present in longitudinal healthcare data. These limitations have motivated the development of specialized sequential models such as Long Short-Term Memory (LSTM) networks and Transformer-based architectures.

2.4 Long Short-Term Memory Networks

Long Short-Term Memory (LSTM) networks are a specialized form of Recurrent Neural Networks (RNNs) designed to model sequential data and overcome the vanishing gradient problem associated with traditional RNNs [4]. By utilizing memory cells and gating mechanisms, LSTMs can preserve relevant information over extended time intervals and learn temporal dependencies from longitudinal healthcare data.

In Parkinson's disease research, LSTM networks have been widely applied for disease progression prediction using sequential clinical observations and telemonitoring data [4]. Their ability to capture temporal patterns enables improved forecasting performance compared with conventional machine learning techniques that treat observations independently.

Despite their effectiveness, LSTM networks have certain limitations. Their sequential processing nature restricts parallel computation and increases training complexity. In addition, LSTMs may struggle to capture very long-range dependencies present in longitudinal patient trajectories. These limitations have motivated the exploration of attention-based architectures such as Transformers for healthcare time-series analysis.

2.5 Transformer-Based Models

Transformer architectures have emerged as powerful sequence modeling frameworks due to their ability to capture long-range dependencies using self-attention mechanisms [3]. Unlike recurrent neural networks, Transformers process sequence elements in parallel, enabling efficient training and improved scalability for large datasets.

Recent studies have demonstrated the effectiveness of Transformer models in healthcare applications [11–13, 15], including disease diagnosis, medical time-series forecasting, electronic health record analysis, and patient outcome prediction. Their ability to learn global temporal relationships makes them particularly suitable for modeling disease progression trajectories from longitudinal patient data [11, 13].

Despite their strong predictive performance, standard Transformer architectures often require domain-specific adaptations for healthcare applications. Furthermore, their decision-making process is generally difficult to interpret, which may limit their adoption in clinical environments where transparency and trust are essential. These challenges highlight the need for explainable Transformer-based frameworks capable of providing both accurate predictions and interpretable insights.

2.6 Explainable Artificial Intelligence in Healthcare

Explainable Artificial Intelligence (XAI) techniques are increasingly employed in healthcare to improve the transparency and trustworthiness of predictive models [7, 9]. Among the available approaches, SHAP (SHapley Additive exPlanations) is widely used for quantifying feature contributions and interpreting model predictions [6]. Several studies have successfully applied SHAP analysis to identify influential biomarkers and support explainable decision-making in clinical applications.

2.7 Comparative Analysis of Existing Studies

Table 2.1 summarizes key research studies related to Parkinson's disease prediction, machine learning, deep learning, Transformer architectures, and explainable artificial intelligence techniques.

The studies summarized in Table 2.1 highlight the evolution of Parkinson's disease prediction methods from traditional machine learning approaches to deep learning and Transformer-based architectures [16–21].

The literature survey indicates that traditional machine learning techniques provide strong baseline performance but fail to model temporal dependencies present in longitudinal patient observations. Deep learning approaches such as LSTM improve temporal modeling capabilities; however, they often struggle to capture long-range relationships effectively. Transformer-based architectures offer superior sequence learning performance but generally lack sufficient interpretability for healthcare applications. Furthermore, only a limited number of studies have combined temporal Transformer architectures with explainable artificial intelligence techniques for Parkinson's disease progression prediction.

Therefore, there exists a significant research gap in the development of an explainable temporal modeling framework that simultaneously achieves high predictive accuracy and transparent decision-making. The proposed Feature-Aware Enhanced Temporal Transformer (FAETT) model aims to address this gap by integrating Transformer-based temporal learning with SHAP-based explainability.

The studies summarized in Table 2.1 indicate a progressive transition from traditional machine learning approaches toward Transformer-based and explainable AI frameworks for healthcare analytics [5, 11–13, 15].

2.8 Research Gap Analysis

The literature review reveals that traditional machine learning approaches fail to capture temporal dependencies present in longitudinal patient data. Although LSTM-based models improve sequential learning, they often struggle with long-range temporal relationships and computational efficiency. Transformer architectures provide superior temporal modeling capabilities; however, their application to Parkinson's disease progression prediction remains limited, and most existing approaches lack interpretability. Furthermore, few studies have combined Transformer-based temporal learning with SHAP-based explainability for disease progression forecasting. Therefore, there exists a need for an explainable temporal modeling framework that can achieve both high predictive accuracy and transparent decision-making.

Table 2.1: Comparative Analysis of Existing Literature

Authors	Year	Method	Dataset	Performance	Limitation
Sakar et al.	2019	Machine Learning Classifiers	UCI Parkinson Dataset	High classification accuracy	Focused on diagnosis only
Aich et al.	2020	Random Forest	Voice Biomarker Dataset	Robust prediction performance	Ignores temporal dependencies
Mitra et al.	2020	Support Vector Machine	Clinical Dataset	Good classification accuracy	Limited scalability
Shinde et al.	2021	Deep Neural Networks	Parkinson Speech Dataset	Improved feature learning	Black-box predictions
Wang et al.	2021	LSTM Networks	Longitudinal Health Data	Effective sequence modeling	Difficulty with long-range dependencies
Zhang et al.	2021	Bi-LSTM	Clinical Time-Series Data	Enhanced temporal learning	High computational complexity
Li et al.	2022	GRU Networks	Healthcare Time-Series Dataset	Faster training than LSTM	Reduced interpretability
Khan et al.	2022	CNN-LSTM Hybrid Model	Parkinson Dataset	Improved prediction accuracy	Complex architecture
Vaswani et al.	2017	Transformer Architecture	Sequence Data	Superior sequence modeling	Limited explainability
Liu et al.	2022	Healthcare Transformer	Electronic Health Records	Strong temporal modeling	Interpretability concerns
Chen et al.	2023	Temporal Transformer	Medical Time-Series Data	High forecasting accuracy	Black-box behavior

2.9 Need for the Proposed Work

The limitations of existing machine learning, deep learning, and Transformer-based approaches highlight the need for a framework capable of accurately modeling disease progression while maintaining interpretability. Parkinson's disease progression forecasting requires effective learning of temporal patterns from longitudinal patient observations together with transparent explanations of prediction outcomes. Therefore, this research proposes an Explainable Feature-Aware Enhanced Temporal Transformer (FAETT) framework that integrates attention-based temporal learning with SHAP-based explainability to achieve both high predictive performance and interpretable decision-making for Parkinson's disease progression prediction.

Chapter 3

Dataset Description and Preprocessing

3.1 Introduction

This chapter describes the Parkinson Telemonitoring dataset and the preprocessing procedures employed in this study. The preprocessing pipeline includes data cleaning, feature normalization, temporal sequence generation, and train-test partitioning. These steps transform the raw telemonitoring data into a structured format suitable for machine learning and deep learning models.

3.2 Parkinson Telemonitoring Dataset

The dataset used in this study is the Parkinson Telemonitoring dataset obtained from the UCI Machine Learning Repository. It contains longitudinal voice measurements collected from Parkinson's disease patients during telemonitoring sessions. The objective of the dataset is to predict disease severity using biomedical voice-based biomarkers. In this study, the Total UPDRS score is considered as the target variable for disease progression prediction. The general characteristics of the dataset are summarized in Table 3.1.

3.2.1 Dataset Characteristics

Table 3.1 presents the general characteristics of the dataset used in this study.

Table 3.1: Dataset Overview

Attribute	**Value**
Dataset Name	Parkinson Telemonitoring Dataset
Source	UCI Machine Learning Repository
Number of Patients	42
Number of Records	5875
Number of Features	22
Target Variable	Total UPDRS
Task Type	Regression
Data Type	Longitudinal Time-Series

3.2.2 Feature Description

The dataset contains demographic, clinical, temporal, and voice-based biomarkers extracted from speech recordings. These features capture frequency variations, amplitude perturbations, noise characteristics, and nonlinear voice dynamics that are associated with Parkinson's disease severity. The major feature categories used in this study are summarized in Table 3.2.

Table 3.2: Feature Categories in the Parkinson Telemonitoring Dataset

Category	**Features**
Demographic Features	Age, Sex
Temporal Feature	Test Time
Clinical Feature	Motor UPDRS
Jitter Features	Jitter(%), Jitter(Abs), Jitter:RAP, Jitter:PPQ5, Jitter:DDP
Shimmer Features	Shimmer, Shimmer(dB), Shimmer:APQ3, Shimmer:APQ5, Shimmer:APQ11, Shimmer:DDA
Noise Features	NHR, HNR
Nonlinear Features	RPDE, DFA, PPE

3.3 Exploratory Data Analysis

Exploratory Data Analysis (EDA) was performed to examine the statistical characteristics of the dataset and identify relationships among variables. The analysis indicated that several voice-based biomarkers exhibit meaningful associations with Parkinson's disease severity, supporting their use for disease progression prediction.

3.4 Correlation Analysis

Correlation analysis was performed using the Pearson correlation coefficient to examine relationships among features and their association with the target variable, Total UPDRS. The resulting correlation matrix is visualized in Figure 3.1. Several voice-based biomarkers exhibited moderate to strong correlations with disease severity, indicating their potential relevance for disease progression prediction.

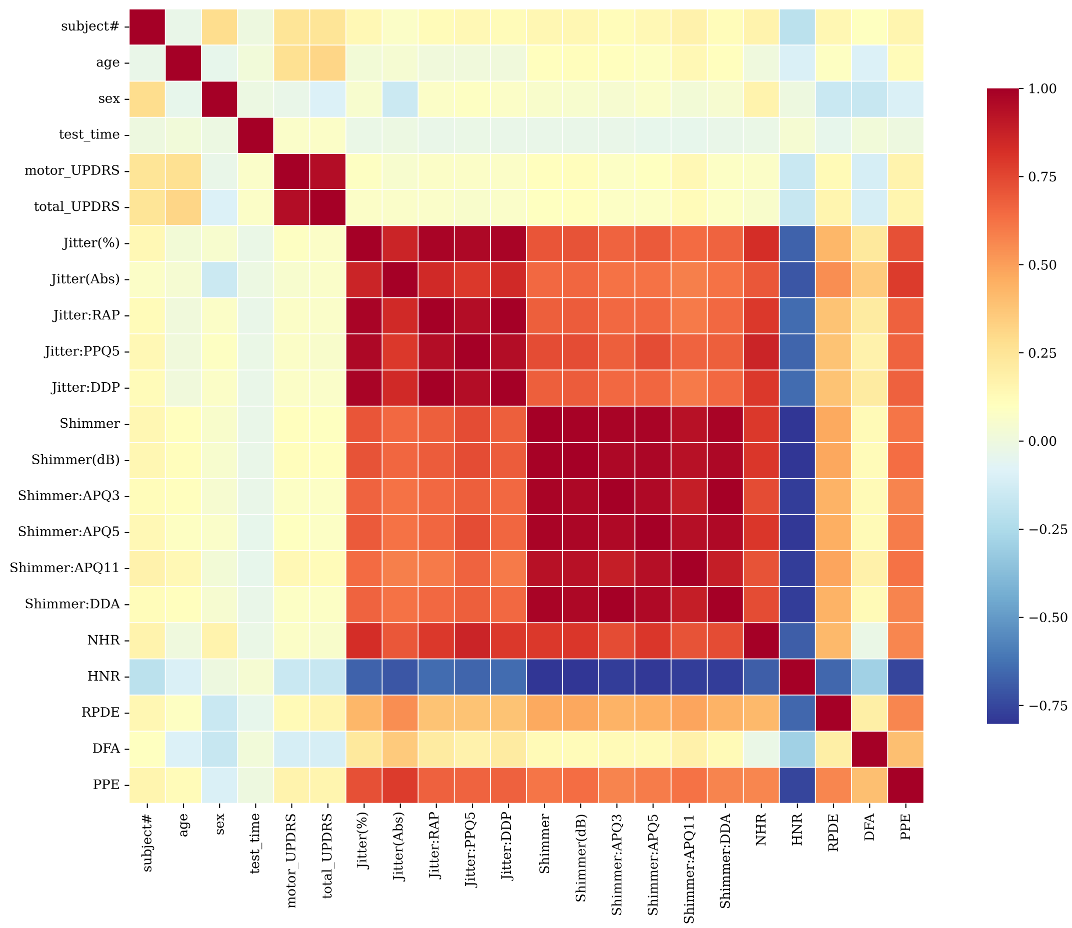

Figure 3.1: Correlation Heatmap of Parkinson Telemonitoring Features

3.5 Data Cleaning

Data cleaning was performed to ensure the quality and consistency of the dataset prior to model development. The preprocessing steps included verification of missing values, removal of non-predictive attributes, and validation of feature formats. No significant missing values or inconsistencies were observed in the dataset; therefore, extensive imputation procedures were not required.

3.6 Feature Normalization

To ensure uniform feature scaling and improve model training stability, StandardScaler normalization was applied to all input features. The transformation is defined as:

$$z = \frac{x - \mu}{\sigma} \tag{3.1}$$

where x is the original feature value, μ is the feature mean, and σ is the standard deviation.

3.7 Temporal Sequence Generation

To capture disease progression patterns, the longitudinal patient records were transformed into temporal sequences using a sliding window approach. For each patient, observations were first sorted according to the *test_time* attribute to preserve chronological order. A sequence length of 10 was selected, enabling the model to utilize information from the previous ten observations to predict the subsequent Total UPDRS value.

3.7.1 Sliding Window Method

The sliding window technique was used to transform the chronological patient records into fixed-length temporal sequences suitable for sequence learning models.

$$X = \{x_1, x_2, x_3, \ldots, x_n\} \tag{3.2}$$

For a window size of 10, the input sequence is defined as:

$$S_i = \{x_i, x_{i+1}, \ldots, x_{i+9}\} \tag{3.3}$$

and the corresponding target value is:

$$y_i = x_{i+10} \tag{3.4}$$

where S_i represents the input sequence and y_i denotes the prediction target associated with the subsequent observation.

3.8 Sequence Dataset Construction

After sequence generation, the dataset was transformed into a three-dimensional tensor suitable for sequence learning models:

$$X \in \mathbb{R}^{N \times T \times F} \tag{3.5}$$

where N denotes the number of samples, T represents the sequence length, and F denotes the number of input features.

For the generated dataset:

$$X \in \mathbb{R}^{5455 \times 10 \times 19} \tag{3.6}$$

$$y \in \mathbb{R}^{5455} \tag{3.7}$$

3.9 Train-Test Partitioning

To evaluate model generalization performance, the generated sequences were divided into training and testing subsets using an 80:20 split ratio. The training set was used for model development and parameter optimization, while the testing set was reserved exclusively for performance evaluation. The resulting dataset dimensions are summarized in Table 3.3.

Table 3.3: Training and Testing Dataset Dimensions

Dataset	**Shape**
Training Input (X_{train})	(4364, 10, 19)
Testing Input (X_{test})	(1091, 10, 19)
Training Target (y_{train})	(4364,)
Testing Target (y_{test})	(1091,)

The training dataset was used for model development and parameter optimization, while the testing dataset was reserved exclusively for performance evaluation.

3.10 Preprocessing Pipeline

The complete preprocessing workflow adopted in this study is illustrated in Figure 3.2. The pipeline includes data cleaning, feature normalization, temporal sequence generation, dataset partitioning, and model training. These steps transform the raw telemonitoring data into a structured format suitable for machine learning and deep learning models used for disease progression prediction.

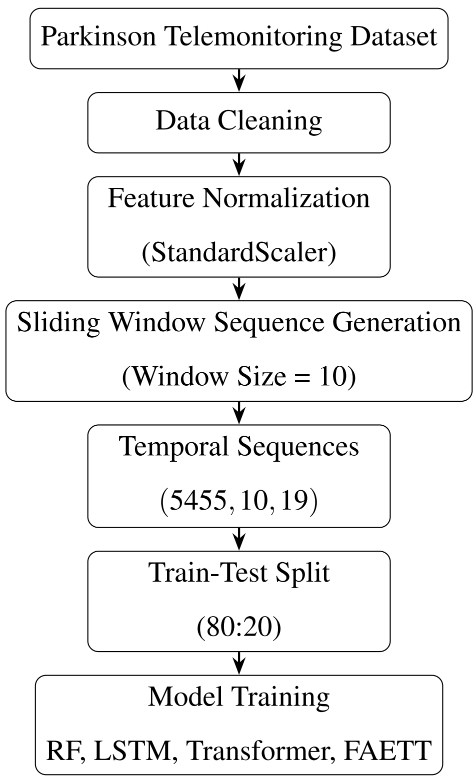

Figure 3.2: Data Preprocessing and Sequence Generation Pipeline

Chapter 4

Proposed Methodology

4.1 Introduction

This chapter presents the methodology adopted for Parkinson's disease progression prediction. The proposed Feature-Aware Enhanced Temporal Transformer (FAETT) framework integrates Transformer-based temporal learning with SHAP-based explainability to model longitudinal patient observations and provide interpretable predictions. The chapter describes the overall framework, baseline models, proposed architecture, training strategy, and explainability mechanism.

4.2 Overall Proposed Framework

The overall framework adopted in this study is illustrated in Figure 4.1.
The proposed Feature-Aware Enhanced Temporal Transformer (FAETT) framework is designed to predict Parkinson's disease progression from longitudinal telemonitoring data. The framework consists of five major stages: data preprocessing, temporal sequence generation, feature embedding, Transformer-based temporal learning, and SHAP-based explainability. The final output corresponds to the predicted Total UPDRS score, while SHAP analysis provides insights into feature contributions. The overall architecture of the proposed framework is illustrated in Figure 4.1.

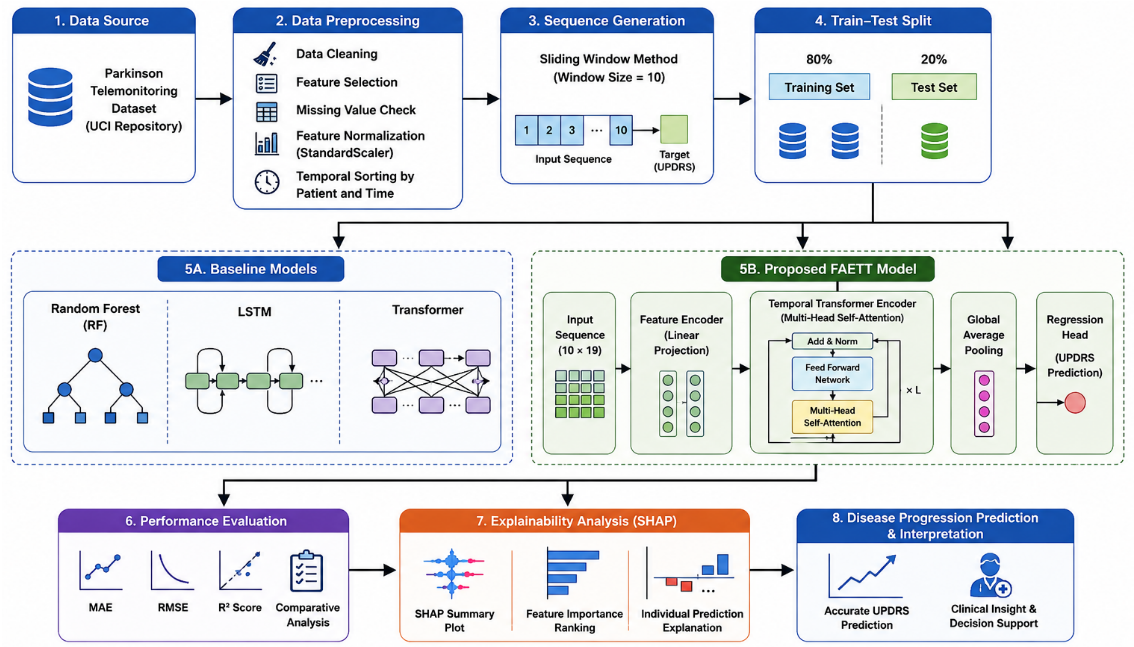

Figure 4.1: Overall Framework of the Proposed Study

4.3 Baseline Models

To evaluate the effectiveness of the proposed FAETT framework, three baseline models were implemented: Random Forest (RF), Long Short-Term Memory (LSTM), and Transformer. These models represent traditional machine learning, recurrent neural network-based learning, and attention-based sequence modeling approaches, respectively. Performance comparisons between the baseline models and the proposed framework provide insights into the benefits of enhanced temporal learning and explainability.

4.3.1 Random Forest

Random Forest was employed as a traditional machine learning baseline for disease progression prediction [5]. The model utilizes an ensemble of decision trees and generates predictions by averaging the outputs of individual trees. Random Forest provides a strong benchmark for evaluating the effectiveness of deep learning and Transformer-based approaches.

4.3.2 Long Short-Term Memory Network

Long Short-Term Memory (LSTM) networks were implemented as a sequential learning baseline. LSTM models are capable of capturing temporal dependencies through memory cells and gating mechanisms, making them suitable for longitudinal healthcare data. The model was trained using the generated temporal sequences for disease progression prediction [4].

4.3.3 Transformer Model

A standard Transformer model was implemented [3] as an attention-based baseline. The model employs self-attention mechanisms to learn temporal relationships among sequence elements and serves as a direct benchmark for evaluating the improvements introduced by the proposed FAETT framework.

4.4 Proposed FAETT Architecture

The proposed Feature-Aware Enhanced Temporal Transformer (FAETT) framework is designed to model temporal dependencies in longitudinal Parkinson's disease data while providing interpretable predictions. The architecture consists of a feature embedding layer, multi-head self-attention mechanism, feed-forward network, temporal aggregation layer, and a regression output layer. Figure 4.2 illustrates the overall architecture of the proposed model.

4.4.1 Architecture Overview

The overall architecture of the proposed FAETT model is illustrated in Figure 4.2.

4.4.2 Temporal Input Representation

The generated temporal sequences are represented as a three-dimensional tensor:

$$X \in \mathbb{R}^{N \times T \times F} \tag{4.1}$$

where N denotes the number of samples, T represents the sequence length, and F corresponds to the number of input features.

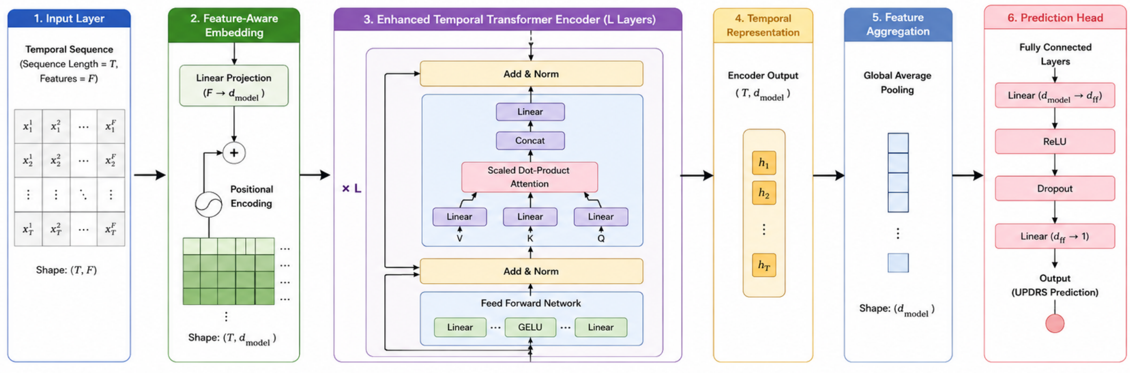

Figure 4.2: Architecture of the Proposed Feature-Aware Enhanced Temporal Transformer

4.4.3 Feature Embedding Layer

The input features are projected into a higher-dimensional latent space using a learnable embedding layer:

$$Z = XW_e + b_e \tag{4.2}$$

where W_e and b_e denote the embedding weights and bias, respectively.

4.4.4 Multi-Head Self-Attention

The embedded features are transformed into query, key, and value representations:

$$Q = ZW_Q \tag{4.3}$$

$$K = ZW_K \tag{4.4}$$

$$V = ZW_V \tag{4.5}$$

The attention mechanism is computed as [3]:

$$\text{Attention}(Q,K,V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{4.6}$$

The outputs from multiple attention heads are combined as [3]:

$$\text{MultiHead}(Q,K,V) = \text{Concat}\left(\text{head}_1,\ldots,\text{head}_h\right)W_O \tag{4.7}$$

4.4.5 Residual Connection and Normalization

Residual connections and layer normalization are applied to stabilize learning:

$$H_1 = \mathrm{LayerNorm}\left(Z + \mathrm{MultiHead}(Z)\right) \tag{4.8}$$

4.4.6 Feed Forward Network

The attention output is refined through a position-wise feed-forward network [3]:

$$\mathrm{FFN}(x) = W_2\big(\mathrm{ReLU}(W_1 x + b_1)\big) + b_2 \tag{4.9}$$

$$H_2 = \mathrm{LayerNorm}\left(H_1 + \mathrm{FFN}(H_1)\right) \tag{4.10}$$

4.4.7 Temporal Aggregation Layer

Global average pooling is employed to obtain a fixed-length sequence representation:

$$G = \frac{1}{T}\sum_{t=1}^{T} H_t \tag{4.11}$$

4.4.8 Output Layer

The final prediction is generated through a regression layer:

$$\hat{y} = W_o G + b_o \tag{4.12}$$

4.5 SHAP-Based Explainability

To enhance model interpretability, SHAP [6]SHapley Additive exPlanations) was integrated with the proposed FAETT framework. SHAP quantifies the contribution of each input feature to the prediction outcome and provides both local and global explanations. This enables the identification of influential biomarkers associated with Parkinson's disease progression.

4.5.1 SHAP Additive Explanation Model

SHAP explanations are based on an additive feature attribution model defined as [6]:

$$g(x') = \phi_0 + \sum_{i=1}^{M} \phi_i x'_i \tag{4.13}$$

where ϕ_0 denotes the baseline prediction and ϕ_i represents the contribution of the i-th feature.

4.5.2 Global Feature Importance

Global feature importance was computed using the mean absolute SHAP values:

$$\text{Importance}_j = \frac{1}{N} \sum_{i=1}^{N} |\phi_{ij}| \tag{4.14}$$

where ϕ_{ij} denotes the SHAP value of feature j for sample i.

4.5.3 SHAP Summary Plot

A SHAP summary plot was generated to visualize the overall contribution of features across the test dataset.

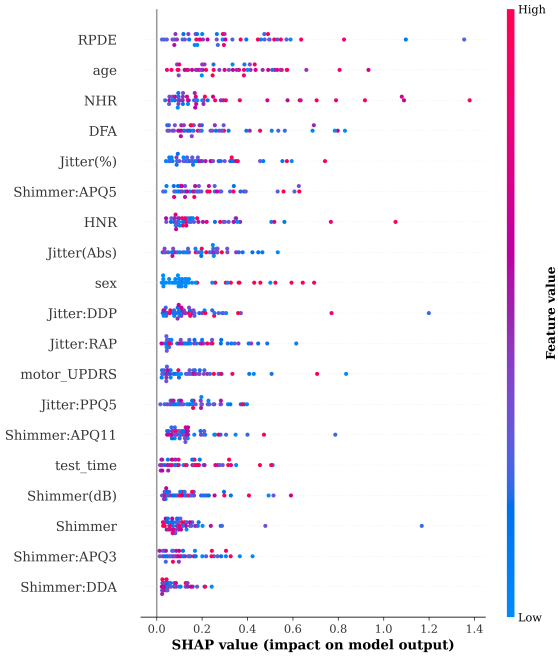

Figure 4.3: SHAP Summary Plot for the Proposed FAETT Model

The summary plot simultaneously displays:

- Feature importance ranking,
- Distribution of SHAP values,
- Direction of feature influence,
- Variability of feature contributions.

This visualization provides a comprehensive overview of model behavior and feature relevance.

4.6 Model Training and Optimization

The proposed FAETT model was trained using supervised learning to minimize prediction error between the actual and predicted Total UPDRS scores. Mean Squared Error (MSE) was employed as the loss function, while the Adam optimizer was used for parameter optimization.

Chapter 5

Experimental Setup

5.1 Introduction

This chapter describes the experimental environment, implementation settings, hyper-parameter configuration, and evaluation metrics used to assess the performance of the proposed FAETT framework and baseline models.

5.2 Experimental Environment

All experiments were conducted using Python and TensorFlow in the Google Colab environment. The implementation was executed on a system equipped with GPU acceleration to facilitate efficient model training. The software and hardware specifications used in this study are summarized in Table 5.1.

Table 5.1: Experimental Environment

Component	**Specification**
Programming Language	Python 3.x
Framework	TensorFlow / Keras
Development Platform	Google Colab
Processor	Intel/AMD Processor
GPU	NVIDIA GPU (Colab)
Operating System	Linux Environment

5.3 Dataset Configuration

The Parkinson Telemonitoring dataset was used for all experiments. Following preprocessing and temporal sequence generation, the final dataset consisted of 5455 temporal sequences, each containing 10 historical observations and 19 predictive features.
The dataset dimensions are summarized in Table 5.2.

Table 5.2: Dataset Dimensions After Sequence Generation

Dataset Component	**Shape**
Input Sequences	(5455, 10, 19)
Target Values	(5455,)
Training Input	(4364, 10, 19)
Testing Input	(1091, 10, 19)
Training Target	(4364,)
Testing Target	(1091,)

5.4 Hyperparameter Configuration

The hyperparameters used for training the baseline models and the proposed FAETT framework were selected empirically based on preliminary experiments. The final configuration employed in this study is summarized in Table 5.3.

5.5 Evaluation Metrics

Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). These metrics quantify prediction accuracy and assess the ability of the models to explain variations in the target variable.

5.5.1 Mean Absolute Error

Mean Absolute Error (MAE) is defined as:

Table 5.3: Hyperparameter Configuration

Parameter	**Value**
Sequence Length	10
Batch Size	32
Epochs	100
Learning Rate	0.001
Optimizer	Adam
Loss Function	Mean Squared Error
Embedding Dimension	64
Number of Attention Heads	4
Dropout Rate	0.2
Train-Test Split	80:20

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{5.1}$$

5.5.2 Root Mean Squared Error

Root Mean Squared Error (RMSE) is computed as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{5.2}$$

5.5.3 Coefficient of Determination

The coefficient of determination (R^2) is given by:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{5.3}$$

Chapter 6

Results and Discussion

6.1 Introduction

This chapter presents the experimental results obtained using Random Forest (RF), Long Short-Term Memory (LSTM), Transformer, and the proposed Feature-Aware Enhanced Temporal Transformer (FAETT) framework. Comparative performance analysis, visualization studies, and SHAP-based explainability results are discussed to evaluate the effectiveness of the proposed approach.

6.2 Exploratory Data Analysis Results

Prior to model training, exploratory data analysis was conducted to understand feature relationships and identify patterns within the dataset.

6.3 Random Forest Results

Random Forest was implemented as a traditional machine learning baseline model.

6.3.1 Actual vs Predicted Analysis

The scatter plot demonstrates a strong agreement between actual and predicted values, indicating the capability of Random Forest to model nonlinear relationships present in the dataset.

6.3.2 Residual Analysis

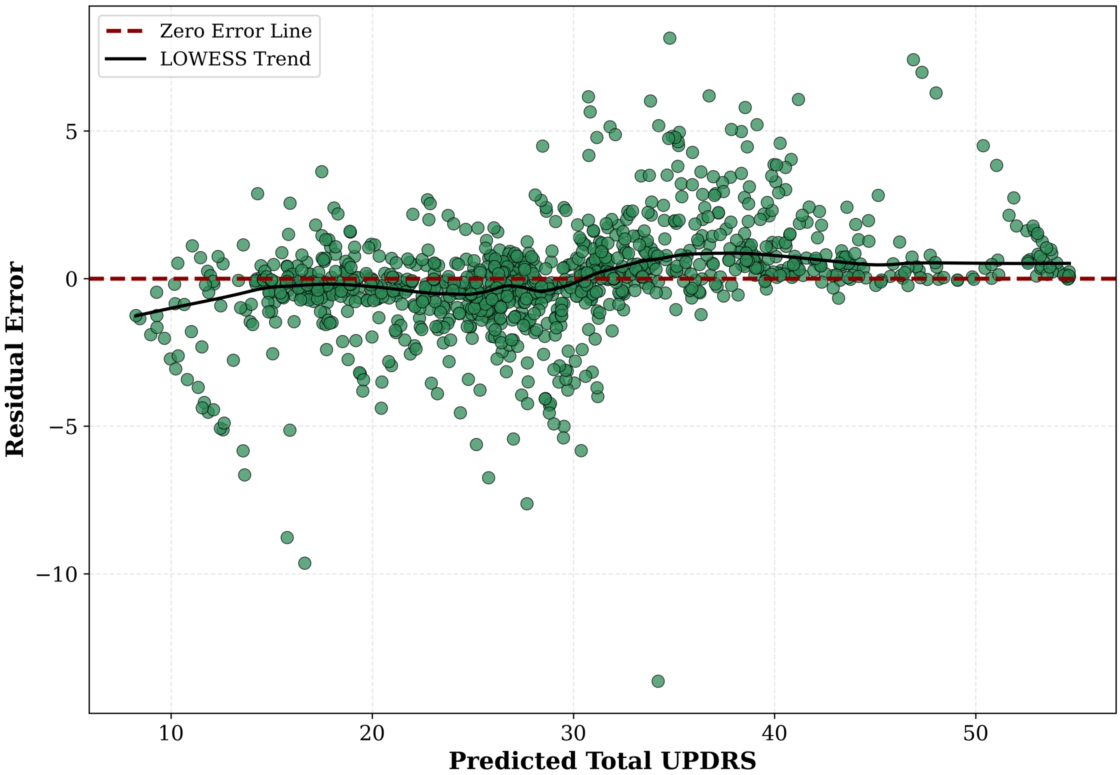

Figure 6.2: Residual Analysis of Random Forest

The residual plot shows that prediction errors are reasonably distributed around zero, suggesting satisfactory generalization performance.

6.4 LSTM Results

The Long Short-Term Memory model was implemented to capture temporal dependencies within longitudinal patient observations.

6.4.1 Actual vs Predicted Analysis

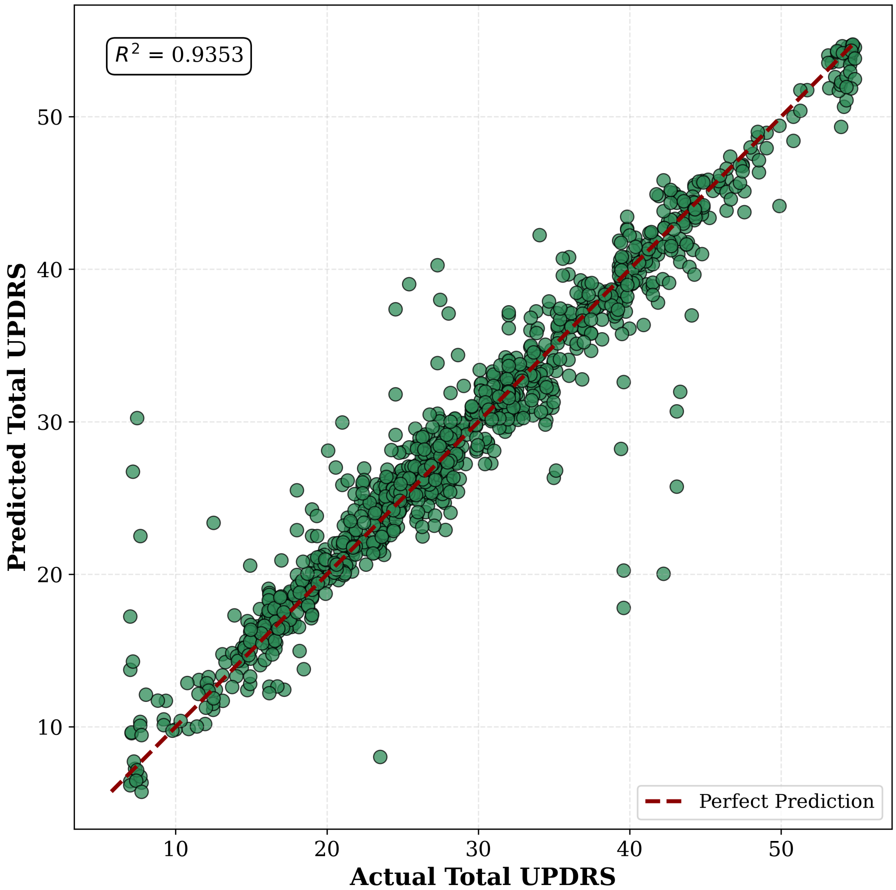

Figure 6.3: Actual vs Predicted Total UPDRS Values using LSTM

6.4.2 Residual Analysis

The LSTM model successfully captures temporal information; however, its performance is limited by difficulties in modeling long-range dependencies across patient visits.

6.5 Transformer Results

The Transformer model was evaluated to investigate the effectiveness of self-attention mechanisms for disease progression prediction.

6.5.1 Training Convergence

The loss curve indicates stable convergence throughout training and demonstrates the effectiveness of attention-based learning.

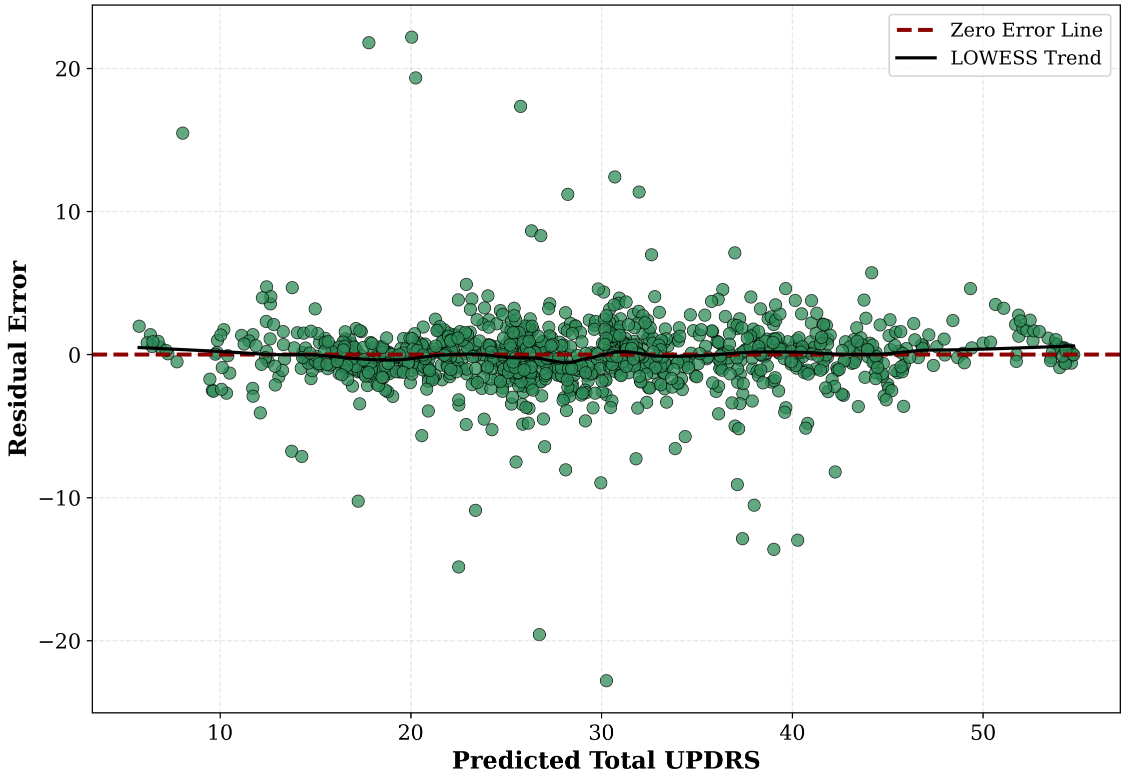

Figure 6.4: Residual Analysis of LSTM

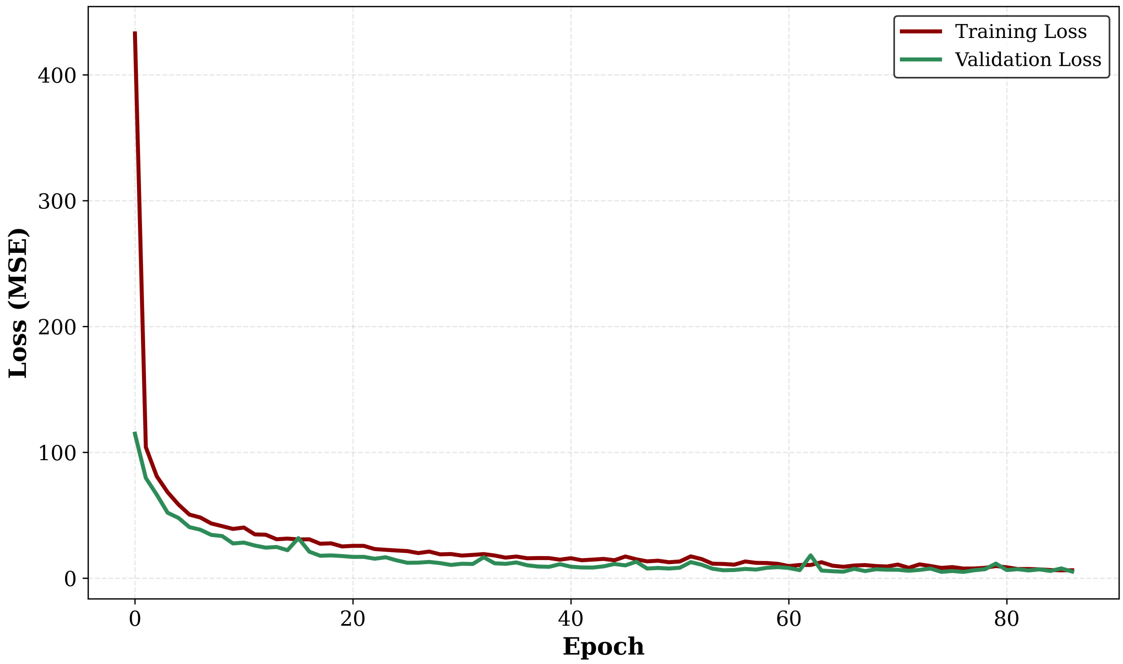

Figure 6.5: Training and Validation Loss Curve of Transformer

6.5.2 Actual vs Predicted Analysis

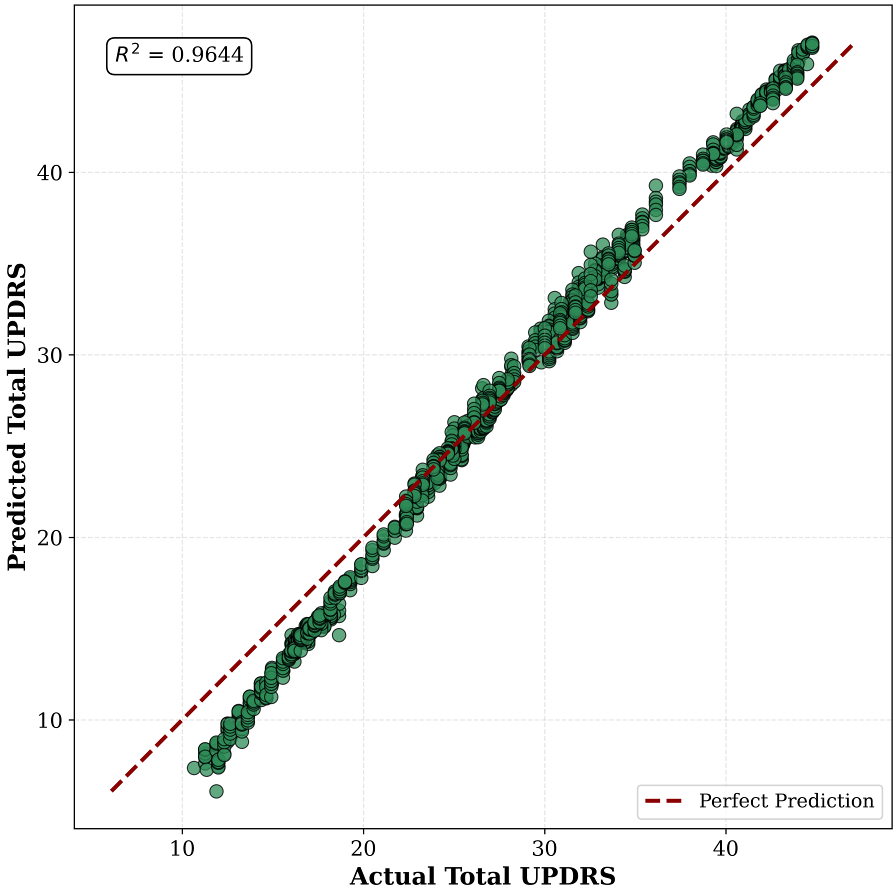

Figure 6.6: Actual vs Predicted Total UPDRS Values using Transformer

6.5.3 Residual Analysis

The Transformer model achieves superior performance compared with LSTM due to its ability to capture long-range temporal dependencies through self-attention mechanisms.

6.6 Proposed FAETT Model Results

The proposed Feature-Aware Enhanced Temporal Transformer (FAETT) model was evaluated using the same experimental settings employed for the baseline models. The objective was to determine whether the integration of temporal attention mechanisms and feature-aware learning could improve disease progression prediction performance.

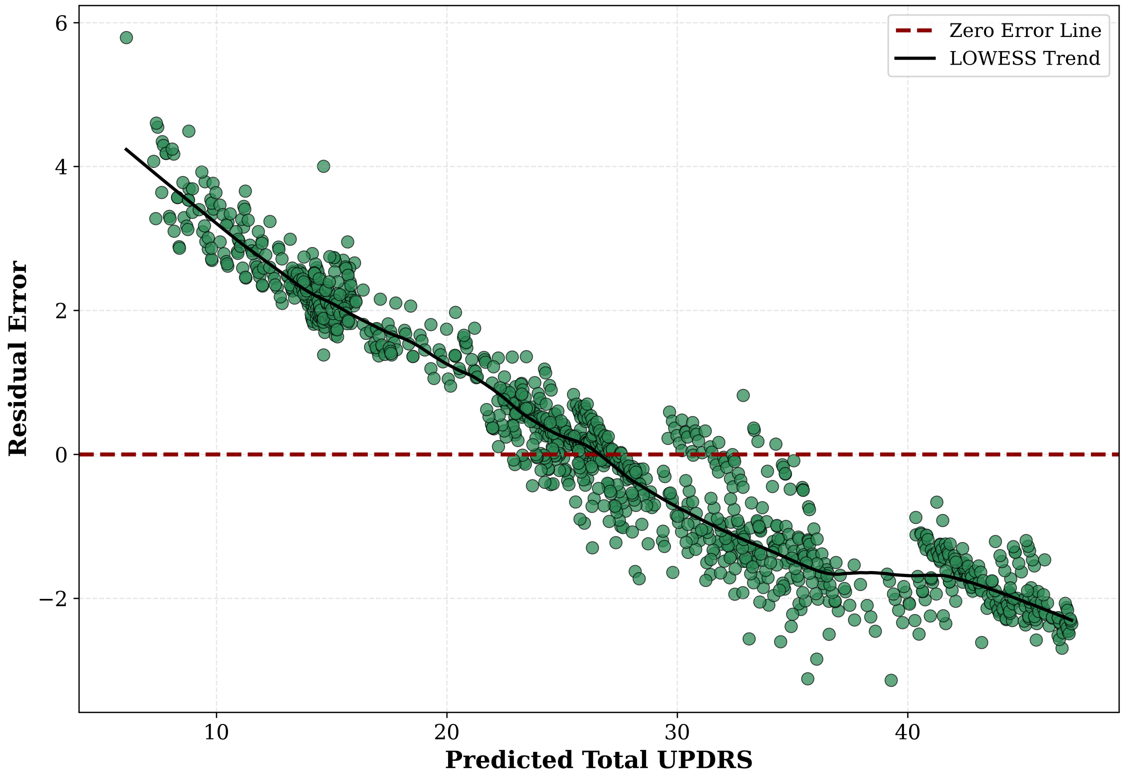

Figure 6.7: Residual Analysis of Transformer

6.6.1 Training and Validation Loss Analysis

Figure 6.8 presents the training and validation loss curves obtained during model optimization.

The loss curves indicate stable convergence throughout training. The validation loss follows the training loss closely, suggesting good generalization performance and limited overfitting.

The gradual reduction in loss demonstrates the effectiveness of the optimization strategy and confirms that the model successfully learned meaningful temporal patterns from historical patient observations.

6.6.2 Actual vs Predicted Analysis

Figure 6.9 illustrates the relationship between actual and predicted Total UPDRS values.

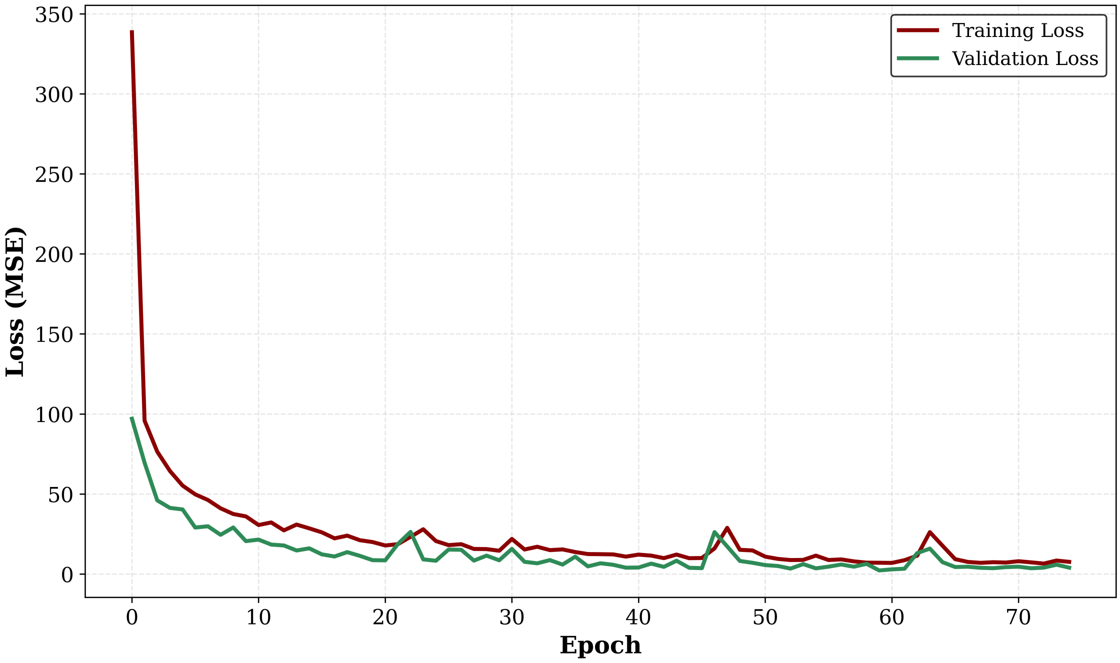

Figure 6.8: Training and Validation Loss Curve of the Proposed FAETT Model

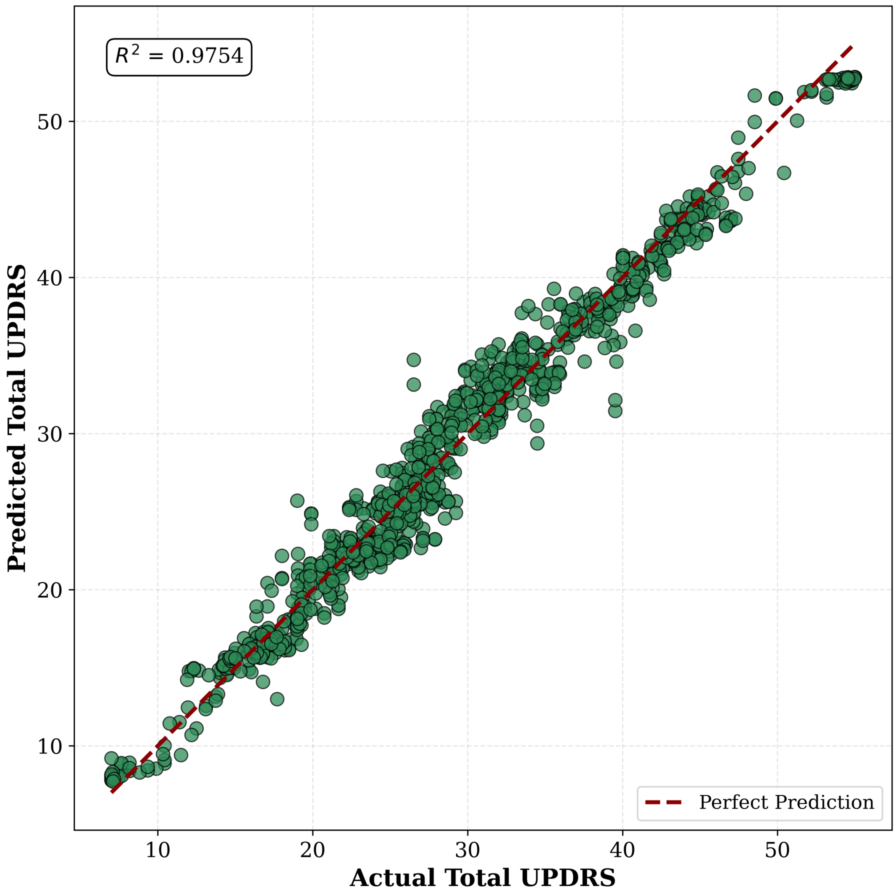

Figure 6.9: Actual versus Predicted Total UPDRS Values using FAETT

The points are closely distributed around the ideal prediction line, indicating strong agreement between predicted and actual values. This demonstrates the ability of the proposed model to accurately capture disease progression trends.

6.6.3 Residual Analysis

Figure 6.10 presents the residual distribution of the proposed model.

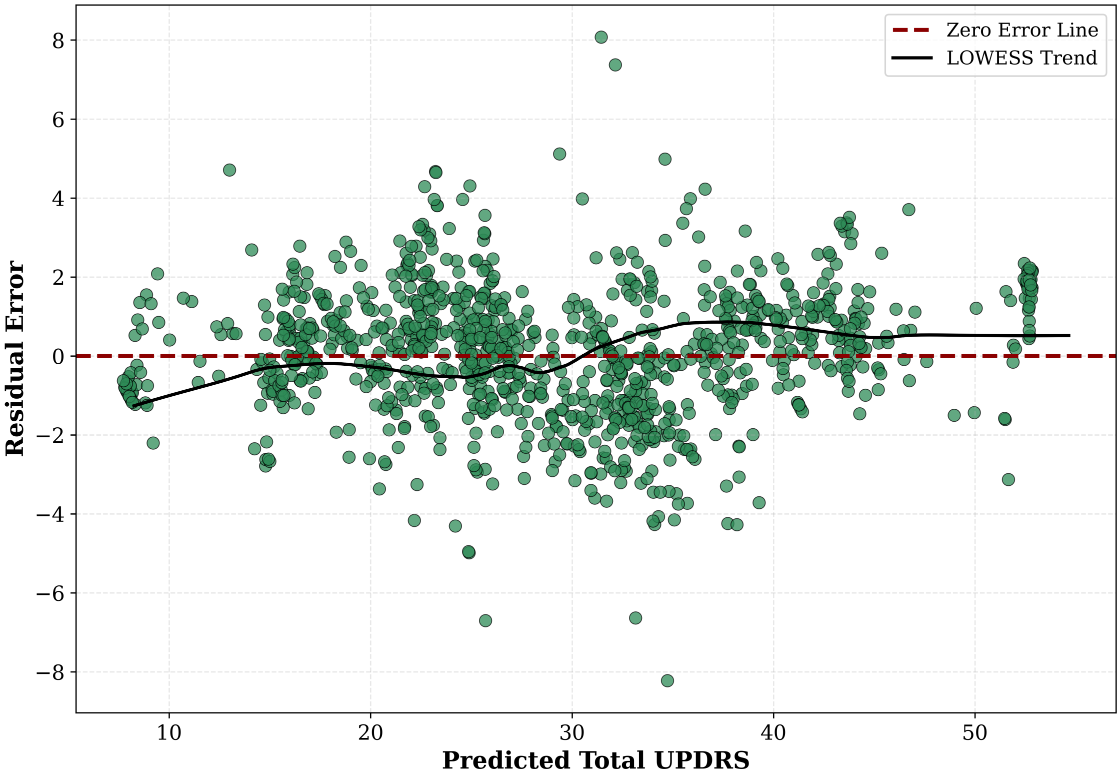

Figure 6.10: Residual Analysis of the Proposed FAETT Model

The residuals are randomly distributed around zero without noticeable systematic patterns. This behavior indicates that the model predictions are unbiased and that the learned relationships generalize effectively to unseen data.

6.7 SHAP Explainability Analysis

Although deep learning models often achieve high predictive performance, their adoption in healthcare applications requires interpretability and transparency. Therefore, SHAP analysis was performed to explain the predictions generated by the proposed FAETT model.

6.7.1 SHAP Summary Plot

Figure 6.11 presents the SHAP summary plot.

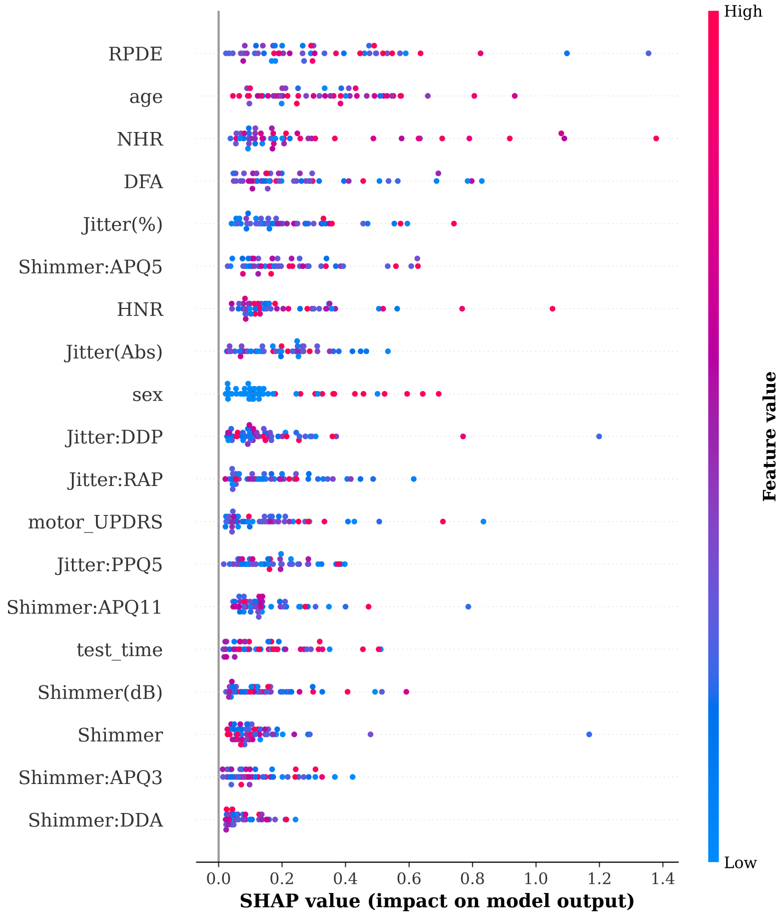

Figure 6.11: SHAP Summary Plot of the Proposed FAETT Model

The summary plot ranks features according to their influence on model predictions while simultaneously illustrating the direction and magnitude of feature contributions.

6.7.2 SHAP Feature Importance Analysis

Figure 6.12 presents the global feature importance obtained from SHAP analysis.

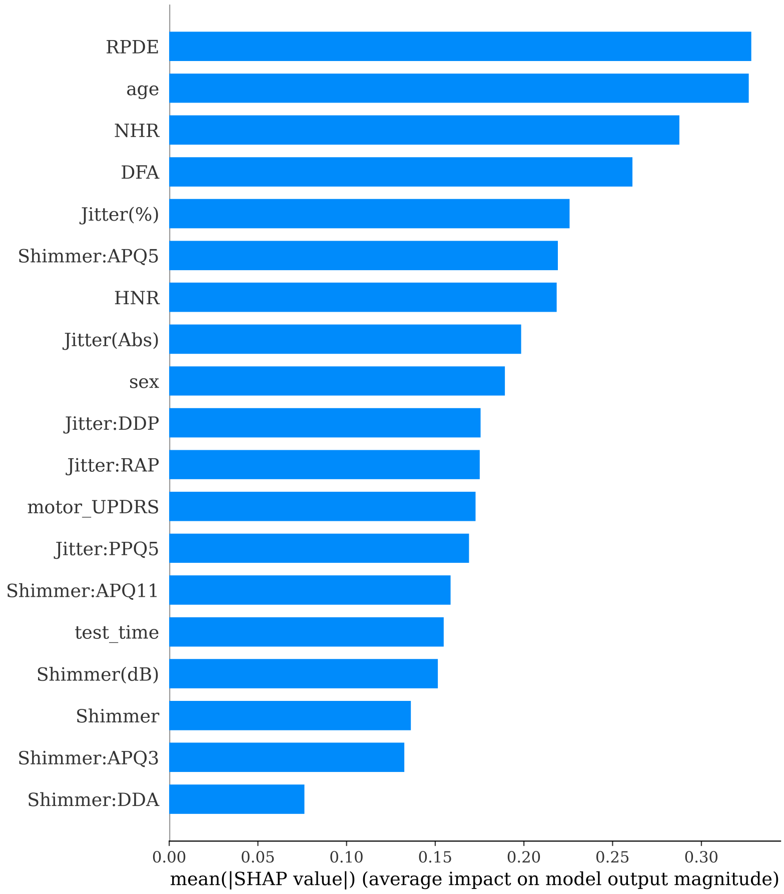

Figure 6.12: Global Feature Importance Based on SHAP Values

The feature importance ranking highlights the biomarkers that contribute most significantly to disease progression prediction. These findings provide valuable clinical insights regarding the factors associated with Parkinson's disease severity.

The integration of SHAP analysis improves the transparency of the proposed framework and increases confidence in the generated predictions.

6.8 Quantitative Performance Comparison

Table 6.1 presents the performance of all evaluated models. The proposed FAETT framework achieved the lowest prediction errors and the highest coefficient of determination, demonstrating its effectiveness for Parkinson's disease progression prediction.

Table 6.1: Comparative Performance of Evaluated Models

Model	**MAE**	**RMSE**	R^2
LSTM	1.4992	2.6445	0.9353
Transformer	1.5725	2.2892	0.9515
Random Forest	1.315	1.774	0.9709
FAETT	**1.2688**	**1.6457**	**0.9754**

6.9 Discussion

The experimental results demonstrate that the proposed FAETT framework effectively captures temporal dependencies in longitudinal Parkinson's disease data. Compared with Random Forest, LSTM, and standard Transformer models, FAETT achieved superior predictive performance while maintaining interpretability through SHAP analysis. The combination of temporal attention mechanisms and explainable AI techniques makes the proposed framework suitable for healthcare forecasting applications.

Chapter 7

Conclusion and Future Work

7.1 Conclusion

This research presented a Feature-Aware Enhanced Temporal Transformer (FAETT) framework for Parkinson's disease progression prediction using longitudinal voice-based telemonitoring data. The proposed model integrates Transformer-based temporal learning with SHAP-based explainability to achieve both accurate and interpretable predictions. Experimental evaluation was conducted using the Parkinson Telemonitoring dataset, and the performance of the proposed framework was compared with Random Forest, LSTM, and standard Transformer models. The results demonstrated that FAETT achieved superior predictive performance in terms of MAE, RMSE, and R^2, indicating its effectiveness in modeling disease progression patterns.

Furthermore, SHAP analysis provided insights into the contribution of individual biomarkers, enabling transparent interpretation of model predictions. The findings suggest that the proposed framework can serve as a reliable and interpretable approach for healthcare forecasting applications involving longitudinal patient data.

7.2 Major Contributions

The major contributions of this research are summarized as follows:

1. Developed a Feature-Aware Enhanced Temporal Transformer (FAETT) framework for Parkinson's disease progression prediction.

2. Utilized temporal sequence generation to model longitudinal patient observations effectively.

3. Integrated SHAP-based explainability to provide interpretable predictions and identify influential biomarkers.

4. Conducted a comparative evaluation against Random Forest, LSTM, and Transformer models.

5. Demonstrated improved predictive performance and enhanced interpretability using the proposed framework.

7.3 Limitations

Although the proposed framework demonstrated promising performance, the study was limited to a single publicly available dataset. In addition, the model was evaluated in an offline experimental setting and was not validated in real-world clinical environments. Future studies involving larger and more diverse datasets may further improve the generalizability of the proposed approach.

7.4 Future Work

Future research may explore the integration of multimodal healthcare data, including speech, clinical, imaging, and wearable sensor information, to improve disease progression prediction. Additional investigations may focus on lightweight Transformer architectures, real-time monitoring systems, and clinical validation of explainable AI frameworks for practical healthcare deployment.

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