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Capstone Project Document

Application of Audio Spectrogram Transformer (AST) Model for Parkinson's Disease Classification using EEG Signals

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Definition and Acronyms

Acronym	Definition
AI	Artificial Intelligent
DL	Deep Learning
ML	Machine Learning
ViT	Vision Transformer
CNN	Convolutional Neural Networks
LSTM	Long Short-Term Memory
AST	Audio Spectrogram Transformers
EEG	Electroencephalography
ICA	Independent Component Analysis
PD	Parkinson’s Disease
HC	Healthy Control

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power across different frequencies over time. Power is primarily concentrated in the lower frequency bands (< 30 Hz), which is characteristic of resting-state EEG.

Figure 2: EEG signals processed via band-pass filtering (0.5–50 Hz), ICA-based artifact removal, re-referencing, segmented into epochs, features extracted, and classified using Machine Learning

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I. Project Introduction

1. Overview

1.1 Project Information

Project Name: NeuroWave

Project Code: SLP301

Group Name: Group 5

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1.2 Project Overview

The NeuroWave project focuses on applying Artificial Intelligence (AI) and Deep Learning (DL) techniques to classify individuals with Parkinson's disease (PD) based on Electroencephalography (EEG) signals. Parkinson's disease is a progressive neurodegenerative disorder that impairs motor control, speech, and cognitive functions. Early and accurate diagnosis plays a crucial role in improving treatment outcomes; however, traditional diagnostic methods primarily rely on subjective clinical evaluations, which can lead to inconsistencies.

The project is designed around two main analytical directions in EEG signal processing:

(1) Time-Series Approach: EEG signals are analyzed directly in the time domain, allowing models to capture temporal dependencies and neural dynamics over time. Deep learning architectures such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are employed to extract temporal and spatial features relevant to Parkinson's-related brain activity (Sahota et al., 2023).

(2) Audio Spectrogram Transformer (AST) Approach: In this direction, EEG signals are transformed into time-frequency spectrograms, representing information in both time and frequency domains. These spectrograms are then processed using Vision Transformer (ViT) or Audio Spectrogram

Transformer (AST) models, which leverage the self-attention mechanism to learn long-range dependencies and complex spectral-temporal relationships (Gong, Chung, & Glass, 2021).

The dual-approach design enables a comprehensive comparison between traditional sequence-based learning and modern Transformer-based spectral analysis, aiming to determine which paradigm yields superior performance in EEG-based PD classification.

The remainder of this report is organized as follows:

- Section 2: Presents the scientific and practical background of the project, outlining the motivation and research context.
- Section 3: Defines the project's main objectives and expected outcomes.
- Sections 4–6: Describe the research methodology, data processing pipeline, model design, and evaluation procedures.
- Section 7: Discusses experimental results and findings.
- Section 8: Concludes the study and suggests directions for future work.

Through this structure, the project aims to build an accurate, non-invasive, and cost-effective system to support early Parkinson's detection-while contributing to the broader field of AI in biomedical signal analysis.

Building upon this overview, NeuroWave not only applies state-of-the-art deep learning techniques but also aims to critically evaluate and optimize their performance for biomedical EEG analysis. The integration of both traditional and Transformer-based methods provides a balanced framework for examining how different architectures interpret neural activity and how these insights can translate into more reliable diagnostic systems.

2. Project Background

The motivation behind this project arises from the limitations of current Parkinson's disease diagnostics. Presently, PD diagnosis relies heavily on clinical observation and the experience of neurologists, which can lead to misclassification, especially in early stages where symptoms are subtle and overlap with other neurological conditions. While neuroimaging techniques such as MRI and PET offer high accuracy, they remain costly and inaccessible for routine screening.

Electroencephalography (EEG), in contrast, provides a non-invasive, affordable, and real-time means to record brain electrical activity. Research has shown that PD patients exhibit distinct patterns in neural oscillations - particularly in the beta (13 - 30 Hz) and theta (4 - 7 Hz) bands - as well as increased signal irregularity compared to healthy individuals (Jackson et al., 2019; Chang et al., 2022). These findings make EEG a viable biomarker for Parkinson's detection when combined with robust computational modelling.

Recent advancements in Deep Learning have revolutionized EEG analysis. Traditional architectures like CNNs and LSTMs have achieved promising results in modelling temporal dependencies. However, the introduction of Transformer-based architectures has significantly expanded the capability to model long-range relationships and multi-dimensional data structures (Vaswani et al., 2017). Studies such as Transformer-Based EEG Decoding: A Survey (2025) and Transformers in EEG Analysis: A Review of Architectures and Applications highlight that attention mechanisms can outperform conventional deep models in extracting meaningful representations from EEG data - though challenges remain, including noise, inter-subject variability, and limited data availability.

To address these challenges, the NeuroWave project proposes to implement and evaluate two deep learning frameworks - a time-series model and a Transformer-based model - for Parkinson's disease

classification using EEG data. By comparing their performance, the project aims to provide insights into the relative strengths and trade-offs of each approach, contributing to the ongoing evolution of AI-assisted neurodiagnostic.

Grounded in this scientific rationale, the NeuroWave project seeks to bridge the gap between traditional time-series modelling and the emerging Transformer paradigm. The project's objectives are formulated to be clear, measurable, and achievable, serving as a roadmap for experimentation, evaluation, and eventual integration into real-world biomedical contexts.

3. Project Objective

The NeuroWave project aims to develop an integrated deep learning framework for classifying Parkinson's disease from EEG signals, combining traditional and Transformer-based analytical methods. The project objectives are outlined below:

Objective 1: Design and develop two independent deep learning models for EEG-based Parkinson's classification.

This objective focuses on constructing two distinct processing pipelines representing different methodological paradigms in biomedical signal analysis:

- Time-Series Model: Employs CNN and LSTM architectures to directly learn temporal dynamics and spatial dependencies from raw EEG signals.
- Transformer-Based Model: Converts EEG signals into time–frequency spectrograms and processes them using AST or ViT architectures. The self-attention mechanism will be leveraged to capture long-range dependencies and model interactions between different brain regions.

Both models will be implemented in parallel to enable a quantitative and objective comparison of their classification capabilities.

Objective 2: Develop a standardized EEG preprocessing pipeline ensuring data consistency and reproducibility.

The preprocessing workflow will include:

- Filtering: Applying a band-pass filter (0.5 - 45 Hz) to remove unwanted noise.
- Artifact Removal: Using Independent Component Analysis (ICA) to eliminate ocular, muscular, or motion artifacts.
- Normalization: Standardizing amplitude and segment length across samples.
- Segmentation: Dividing signals into fixed-length windows for model training.
- This standardized pipeline aims to establish a reproducible framework applicable to future EEG-based research projects.

Objective 3: Evaluate and compare the performance of both approaches using quantitative and qualitative metrics.

Both models will be trained and tested on the same EEG dataset to ensure a fair comparison. Evaluation will be conducted based on:

- Quantitative Metrics: Including Accuracy, Precision, Recall, F1-score, and AUC.
- Qualitative Metrics: Covering feature interpretability, cross-subject stability, and model generalization.

The goal is to determine which model achieves superior accuracy and robustness, making it more suitable for early PD diagnosis.

Objective 4: Analyze the effectiveness of the Transformer architecture for EEG representation learning.

This objective investigates the potential advantages of the self-attention mechanism in modelling non-linear and noisy EEG data. Specifically, the study will:

- Compare the Transformer's ability to capture long-range dependencies with that of LSTM models.
- Evaluate its adaptability in learning time–frequency patterns from spectrogram representations.
- Assess the improvement in performance and stability gained from Transformer-based architectures.

Findings from this analysis will help determine whether Transformer models could become the dominant paradigm for EEG-based biomedical analysis.

4. Problem Statement

Parkinson's disease (PD) is a progressive neurodegenerative disorder caused by the degeneration of dopaminergic neurons in the substantia nigra region of the brain. This neuronal loss disrupts the transmission of dopamine - a neurotransmitter critical for motor control - leading to common symptoms such as tremors, muscle rigidity, bradykinesia, and, in advanced stages, cognitive decline (Postuma et al., 2015). Beyond motor symptoms, PD also results in significant psychological and socioeconomic impacts, including depression, decreased quality of life, and increased healthcare costs (Goetz et al., 2008).

Early diagnosis plays a crucial role in improving treatment effectiveness and slowing disease progression. However, current diagnostic methods rely heavily on clinical observation and neurologist expertise, which are subjective and error-prone, particularly in the early stages when symptoms are mild or overlapping with other conditions. While neuroimaging techniques such as MRI and PET can provide accurate diagnostic information, they are costly, time-consuming, and impractical for routine screening. This creates an urgent need for objective, cost-effective, and non-invasive diagnostic tools capable of detecting PD at an early stage.

In this context, electroencephalography (EEG) has emerged as a promising modality for PD detection due to its high temporal resolution, affordability, and non-invasiveness. Studies have reported distinctive neural oscillation patterns among PD patients, particularly in the beta (13–30 Hz) and theta (4–7 Hz) frequency bands (Jackson et al., 2019; Chang et al., 2022). However, the inherent nonlinear, non-stationary, and noisy nature of EEG signals makes feature extraction and modeling challenging. These issues are further compounded by inter-subject variability and the limited size of available labeled datasets, both of which negatively impact model generalization.

From a computational perspective, several technical challenges arise in building reliable EEG-based PD classification systems. First, class imbalance between PD and control subjects leads to biased models that perform poorly on minority cases. Second, overfitting is a common issue when training deep models on small EEG datasets, resulting in reduced robustness and transferability. Third, resource constraints - such as limited GPU memory and computational power - hinder the training of large-scale deep learning models, especially Transformer-based architectures. Additionally, EEG artifacts caused by eye blinks, muscle activity, or movement can significantly degrade model performance. Finally, the

lack of interpretability in deep neural networks remains a barrier to clinical adoption, as medical practitioners require transparent and explainable diagnostic outputs.

To address these challenges, the NeuroWave project implements a set of risk mitigation strategies across its experimental design. To counteract class imbalance, oversampling and stratified sampling are employed to ensure a more representative data distribution. To prevent overfitting, the team applies dropout regularization, early stopping, and cross-validation, maintaining a balance between complexity and generalization. Resource limitations are mitigated through reducing input resolution, optimizing batch size, and simplifying model architecture without compromising accuracy. Furthermore, Independent Component Analysis (ICA) combined with AutoReject is used to automatically detect and remove EEG artifacts, ensuring high-quality data inputs.

Through these systematic solutions, NeuroWave aims to develop a robust and interpretable deep learning framework for Parkinson's disease classification using EEG data. By comparing two complementary approaches - a Time-Series model (CNN/LSTM-based) and a Transformer-based model (spectrogram representation)-the project seeks to identify the optimal modeling strategy that balances accuracy, efficiency, and clinical applicability.

5. Significance of the Project

The NeuroWave project carries significant value in both theoretical and practical aspects, contributing to the growing body of research that applies artificial intelligence (AI) to neurological diagnosis and healthcare support.

From a theoretical perspective, this study expands scientific understanding of how advanced deep learning architectures, particularly Transformers, can be effectively applied to the analysis of complex biomedical signals such as electroencephalography (EEG). While traditional approaches have primarily relied on time-series models such as CNN and LSTM, NeuroWave aims to systematically compare two distinct paradigms - Time-Series and Transformer-Based methods - to evaluate their representational learning efficiency and generalization capabilities. This comparison not only sheds light on the potential of Transformers in EEG-based analysis but also establishes a solid academic foundation for future interdisciplinary studies integrating AI and neuroscience.

Methodologically, the project contributes to the development of a standardized EEG processing and modeling pipeline, encompassing stages such as filtering, artifact removal, segmentation, and signal normalization. The integration of Independent Component Analysis (ICA), AutoReject, and regularization techniques such as dropout, early stopping, and cross-validation ensures high data reliability, model stability, and reproducibility - essential factors for credible deep learning research in biomedical domains.

From a practical standpoint, NeuroWave aims to provide a non-invasive, cost-effective, and automated solution for the early diagnosis of Parkinson's disease using EEG data. By supporting clinicians in identifying disease-specific neural patterns, the system has the potential to reduce diagnostic workload, enhance accuracy, and increase accessibility for healthcare facilities with limited resources.

Furthermore, the project demonstrates potential for broader applications, including:

- Early detection of other neurological disorders, such as Alzheimer's disease, depression, or epilepsy, through EEG-based pattern recognition.

- Classification of medicated versus non-medicated Parkinson's patients, enabling the assessment of drug effects on brain activity and supporting the optimization of treatment protocols.
- Medical training and AI-assisted clinical supervision, through interpretable deep learning models that enhance transparency and trust in diagnostic decisions.

Overall, NeuroWave represents not only a technical contribution to EEG signal analysis but also a meaningful advancement in applying deep learning to neurodiagnostics. The project bridges the gap between academic research and clinical implementation, combining scientific innovation with humanitarian purpose - aiming ultimately to improve diagnostic accuracy, support healthcare professionals, and enhance the quality of life for Parkinson's patients.

6. Project Scope & Limitations

The NeuroWave project is designed with the primary objective of developing and evaluating two deep learning approaches for classifying Parkinson's disease patients based on electroencephalography (EEG) signals - namely, the Time-Series model and the Transformer-based model. The project focuses on building an automated system capable of distinguishing Parkinson's patients from healthy individuals, while also extending the analysis to classify medicated versus non-medicated patients in order to assess the effects of treatment on neural activity.

The project encompasses the entire EEG signal processing and modeling workflow, including data preprocessing, deep learning model development, and performance evaluation. Specifically, EEG data undergoes noise filtering and artifact removal using Independent Component Analysis (ICA) and AutoReject, followed by normalization and segmentation to ensure consistency across samples. Both deep learning models are trained in parallel on the same EEG dataset to guarantee objective performance comparison. Model performance is quantitatively evaluated using metrics such as Accuracy, Precision, Recall, F1-Score, and Area Under the Curve (AUC), along with qualitative analyses of feature learning behavior and model stability.

Nevertheless, several limitations are encountered during the implementation due to data constraints, computational resources, and scope boundaries. Since the project employs public EEG datasets from OpenNeuro, the available samples are relatively limited and imbalanced between Parkinson and Healthy groups, leading to potential class imbalance and challenges in model generalization. Moreover, EEG signals are highly nonlinear and subject to noise and inter-subject variability, making feature extraction and representation learning inherently complex and sensitive to preprocessing quality.

In addition, computational constraints restrict the scale and depth of both the Transformer and Time-Series architectures, preventing full exploration of their potential representational capacity. The project's analytical scope remains focused on binary classification (Parkinson vs. Healthy) and medication-state classification, without extending to more advanced tasks such as disease progression prediction or cognitive and emotional state analysis.

Another notable limitation concerns model interpretability. Although techniques for feature visualization and attribution analysis have been employed, the current level of physiological interpretability remains limited and insufficient for direct clinical deployment. Furthermore, the project is currently limited to simulated experiments using publicly available datasets and has not yet undergone validation with real-world clinical data collected from local healthcare facilities.

NeuroWave is positioned as an academic research initiative that aims to compare and evaluate deep learning-based EEG modeling approaches for Parkinson's classification, while proposing a

standardized, reproducible preprocessing and modeling pipeline suitable for biomedical applications. The existing limitations in data, computational resources, and real-world applicability serve as a foundation for future extensions, ultimately guiding the long-term goal of developing an automated, accurate, and clinically relevant Parkinson's diagnosis system.

II. Project Management Plan

1. Teamwork

1.1 Team Structure and Roles

The project team is organized using a **parallel collaboration model** between the technical modeling and application deployment aspects, ensuring both the quality of the model and its practical feasibility. While each member undertakes a specialized role, they maintain close cooperation throughout every phase of the project. The team operates with a flexible workflow and manages all source code, documentation, and intermediate results centrally via **GitHub** and **Google Drive**. This guarantees transparency, accessibility, and synchronization across the entire working process.

The project workload is clearly divided to optimize progress and technical quality. Lê Thị Huỳnh Như, serving as the team leader, holds primary responsibility for Data Processing, ensuring the input data is standardized and ready for the training pipeline. For model development, the team is split into two parallel improvement tracks: Phạm Nguyễn Hoàng Thắng focuses on improving the model using a traditional approach (time-series analysis), while Phạm Phan Công Lệnh takes on the task of improving the model using the AST (Audio Spectrogram Transformer) approach, aiming to leverage different signal features. Finally, Trần Trung Nhân and Võ Phong Vinh collaborate on the web demo deployment, building the user interface and integrating the trained model to present the results in an intuitive and accessible way. This division of labor ensures a high level of specialization across each stage: Data, Modeling (two improvement branches), and Application Deployment.

1.2 Communication Plan

The team uses multiple communication formats: Formal meetings are held on Google Meet, while quick discussions, progress updates, and technical feedback are exchanged promptly via Discord and Messenger. The team meets weekly (on Wednesdays or Fridays) to report progress, analyze interim results, and propose directions for improvement. Progress reports are also submitted to the advisor after each critical milestone: (1) data pre-processing, (2) model development, and (3) application deployment.

For resource management, all source code files, data, and training results are stored on the GitHub repository, while reports, images, and charts are shared via Google Drive. This communication and resource management structure helps the team maintain transparency, ensures timely information updates, and supports fast, effective decision-making throughout the project lifecycle.

2. Project Management Approach

2.1 WBS

The Work Breakdown Structure (WBS) outlines the complete set of tasks required to accomplish the objectives of the Parkinson's classification project. It ensures that all project components are explicitly defined in terms of goals, scope, resources, and responsibilities. The project is organized into four main phases: data preprocessing, model development and improvement, web-based application deployment, and evaluation and reporting. Each phase involves specific tasks, utilizes defined resources, and is managed by assigned members to maintain systematic coordination and technical quality throughout the implementation process.

Phase 1: Data Preprocessing

The first phase focuses on preparing and refining the EEG dataset to ensure its suitability for subsequent model training and evaluation. The objective of this phase is to clean, standardize, and transform raw EEG data into a structured format compatible with machine learning pipelines. This includes collecting data from the *OpenNeuro/ds002778* repository, removing artifacts and noise, balancing samples between Parkinson's disease (PD) and control groups, and normalizing sampling rates. The processed data are then segmented and divided into training, validation, and testing subsets. Essential resources for this phase include Python libraries such as MNE, NumPy, and SciPy, alongside a GPU-enabled environment for efficient computation. This phase is primarily led by Lê Thị Huỳnh Như, who is responsible for constructing the preprocessing pipeline, developing automation scripts, and validating data quality to ensure consistency with model input requirements.

Phase 2 – Model Development and Improvement

The second phase represents the core of the project, focusing on developing and enhancing the predictive models. This stage is executed through two parallel directions: one based on time-series analysis and the other on Audio Spectrogram Transformer (AST) adaptation.

In the time-series branch, Phạm Nguyễn Hoàng Thắng is responsible for designing and implementing models capable of capturing temporal dependencies in EEG signals, such as CNN-LSTM or Transformer-based architectures. The main objective is to enhance temporal feature extraction and improve sensitivity to Parkinson's-related signal fluctuations. The branch utilizes tools such as PyTorch, Scikit-learn, and TensorBoard for model training and monitoring on GPU platforms.

In parallel, Phạm Phan Công Lệnh leads the AST-based approach, which transforms EEG data into spectrogram representations and leverages transfer learning from pre-trained AST models originally developed for audio classification. The goal is to exploit spatial–frequency representations of EEG data to achieve higher discriminative performance. Both sub-tasks involve fine-tuning models, evaluating performance metrics, and conducting comparative analyses to determine the most effective learning strategy.

Phase 3 – Web-based Application Deployment

Following model optimization, the third phase aims to translate the trained models into a user-accessible web-based demonstration platform. The primary goal is to develop an intuitive and interactive interface that allows users to upload EEG data and visualize real-time classification results. The web system is built using ReactJS or NextJS for the frontend and integrated with backend APIs developed in Flask or FastAPI to handle model inference. A dynamic dashboard is designed to display prediction probabilities, visual indicators, and analytical charts for better interpretability. This phase requires web development frameworks such as Node.js, Tailwind CSS, and server-side environments for hosting and testing. Trần Trung Nhân and Võ Phong Vinh jointly oversee this stage, collaborating on interface design, system integration, and functional testing to ensure seamless operation and efficient visualization of model outcomes

Phase 4 – Evaluation and Reporting

The final phase encompasses a comprehensive evaluation of the system's performance and the preparation of academic deliverables. The objective is to assess the accuracy and robustness of both model branches, analyze performance metrics such as accuracy, F1-score, and ROC-AUC, and compile findings into a cohesive report. The phase also involves visualizing results through figures, charts, and comparative tables to highlight key improvements and limitations. The team

collaboratively prepares the final documentation, including technical reports, presentation slides, and demonstration materials, using platforms such as Google Docs, LaTeX, and PowerPoint. This phase consolidates all project outcomes and ensures that both technical results and practical insights are thoroughly documented and communicated.

2.2 Risk Management

Throughout the execution of the Parkinson classification project, several potential risks were identified that could affect project progress and outcomes. The team has developed corresponding preventive and responsive strategies to mitigate these risks effectively.

2.2.1. Data Quality and Availability

One of the main risks involves the quality and completeness of the EEG dataset obtained from the OpenNeuro repository. Missing channels, noise contamination, or corrupted files could negatively impact the model's training and evaluation processes. To prevent this, rigorous data preprocessing steps, including noise filtering, normalization, and validation, were applied. In case of data loss or inconsistency, the team planned to supplement data from equivalent public datasets or generate synthetic data through augmentation methods.

2.2.2. Model Overfitting and Poor Generalization

Another significant risk concerns model overfitting, particularly due to the relatively small and imbalanced dataset. This issue could reduce the model's ability to generalize to unseen data. To mitigate this, techniques such as data augmentation, k-fold cross-validation, dropout regularization, and early stopping were employed. Continuous monitoring of validation loss during training ensured that the model maintained optimal performance.

2.2.3. Integration and Deployment Errors

During the web-based demo deployment stage, integration errors between the trained model and the web interface could occur, causing delays or functional issues. Preventive measures included modular system design, early integration testing, and version control using Git. In case of failure, rollback mechanisms and debugging protocols were established to ensure minimal downtime and rapid recovery.

2.2.4. Time Constraints and Coordination Challenges

Given the project's multidisciplinary nature and the distribution of tasks among team members, delays could arise from scheduling conflicts or workload imbalance. To mitigate this, the team adopted a structured communication plan with weekly progress meetings, status reports, and milestone tracking. Any unexpected delays were addressed through task reallocation and time management adjustments.

2.2.5. Technical and Hardware Limitations

Limited access to high-performance computing resources could hinder the training of large-scale models such as AST or time-series architectures. To manage this, the team utilized Google Colab Pro and university-provided GPU resources. If hardware limitations persisted, model compression or smaller batch training strategies were applied to maintain training efficiency.

By identifying and proactively managing these risks, the team ensured that the project remained on track, maintaining both technical integrity and research quality throughout its lifecycle.

2.3 Quality Management

As the project on Parkinson's disease patient classification using EEG signals is still in progress, the team has established a provisional yet well-structured quality management plan to ensure the quality of data, model performance, and overall outcomes throughout each development phase.

2.3.1. Data Quality Control

The initial phase of the project places strong emphasis on ensuring the reliability and standardization of EEG data obtained from the OpenNeuro dataset. The data are examined for format consistency, completeness, and coherence across recording sessions. The preprocessing pipeline includes bandpass filtering, artifact removal, and signal normalization to guarantee stable input for deep learning models. Both raw and processed data are stored in parallel, allowing for comparison, restoration, and traceability when needed.

2.3.2. Model Training Quality Assurance

Since the project is currently in the training and fine-tuning phase, the primary focus is on maintaining model stability and generalization capability. Evaluation metrics such as Accuracy, Precision, Recall, F1-score, and AUC are applied to assess model quality at different training stages. A k-fold cross-validation approach is utilized to mitigate the risk of overfitting. Each training session is thoroughly logged-including random seed, hyperparameters, duration, and GPU performance-to ensure reproducibility and facilitate subsequent analysis.

2.3.3. Model Evaluation and Validation

Once a preliminary stable model is achieved, the team will conduct experiments on an independent test set to evaluate real-world classification performance. The results of the two improvement approaches (AST-based and time-series-based models) will be compared to determine the most optimal direction. This evaluation process not only ensures accuracy but also verifies the model's ability to clearly distinguish between Parkinson's and non-Parkinson's subjects. The team also plans to perform repeated trials on data subsets to evaluate model robustness and consistency.

2.3.4. Process and Resource Quality Control

To maintain consistency and transparency, all source code, intermediate results, and related assets are centrally managed through GitHub and Google Drive. Each team member is responsible for regularly updating their assigned tasks and outcomes. Code modifications are executed via pull requests and undergo internal reviews before merging, minimizing potential errors in the training and deployment pipeline.

2.4 Change Management Process

During the execution of the Parkinson's disease patient classification project, changes in project scope, schedule, resources, or technical requirements are inevitable. The team has established a structured change management process to ensure that all modifications are carefully reviewed, assessed, and implemented in a controlled manner, minimizing risks while maintaining project progress.

2.4.1. Change Identification

All proposed changes, including updates to data, model architecture, training methods, or additional requirements from the project advisor, are documented through official team communication

channels such as Discord, Google Meet, or email. Each proposal must include a detailed description, justification for the change, and an assessment of its potential impact on the project.

2.4.2. Impact Assessment

Once identified, the team evaluates the potential impact of the change on project schedule, resource allocation, model quality, and final outcomes. This evaluation is conducted through internal meetings, where each member responsible for the relevant domain provides a detailed technical and time-based analysis.

2.4.3. Change Approval

Proposed changes are only implemented after obtaining consensus from the team leader and relevant members. For major changes, the project advisor is consulted to ensure that the modification does not compromise the research objectives. All approval decisions are documented in the project log for traceability.

2.4.4. Change Implementation

After approval, changes are executed according to a structured plan, including updating code repositories on GitHub, modifying data processing pipelines, and adjusting model training schedules if necessary. All steps are carefully recorded to ensure reproducibility and traceability.

2.4.5. Post-Change Review

Following implementation, the team conducts quality checks and evaluates the results of the change to ensure that original objectives are maintained and no negative impacts occur. Lessons learned during this process are documented to improve future change management practices.

2.5 Closure and Evaluation

Since the Parkinson's disease patient classification project using EEG signals is intended solely for presentation to the project advisor, the closure and evaluation process focuses on summarizing results, assessing effectiveness, and extracting academic lessons learned.

2.5.1. Technical Closure

The team ensures that all stages of data processing, model training, and evaluation are completed. The final model is tested on an independent dataset to verify its performance. All source code, data processing pipelines, and intermediate results are fully stored on GitHub and Google Drive, providing traceability and reproducibility for the advisor.

2.5.2. Results Compilation and Evaluation

Key project results are compiled, including model performance metrics (Accuracy, Precision, Recall, F1-score, AUC) and a comparison between the two improvement approaches (AST and time-series). Based on these results, the team evaluates the achievement of research objectives, model effectiveness, and the reliability of outcomes.

2.5.3. Lessons Learned

The team documents lessons learned related to EEG data handling, model training and evaluation, teamwork, and time management. These insights can serve as guidance for future research or potential model improvements if requested by the advisor.

2.5.4. Reporting and Presentation

A comprehensive final report is prepared, detailing the workflow, implementation methods, experimental results, and quality assessment. The outcomes are presented directly to the project advisor to demonstrate the feasibility, effectiveness, and academic value of the project.

III. Existing Systems/State of the Art

1. Overview of the Field

The intersection between neuroscience and artificial intelligence (AI) has gained remarkable attention in recent years, particularly in the analysis of Electroencephalography (EEG) signals for neurological disease detection. EEG, as a non-invasive and cost-effective technique, records electrical activity generated by neuronal oscillations, providing valuable insights into brain dynamics. With the rise of Deep Learning (DL) and Machine Learning (ML), automated EEG analysis has evolved from handcrafted feature extraction toward end-to-end models capable of learning discriminative representations directly from raw data (Craik, He, & Contreras-Vidal, 2019).

In the field of Parkinson's Disease (PD) research, EEG-based approaches have shown potential in distinguishing patients from healthy controls and assessing disease progression. The ongoing shift from conventional statistical methods to AI-driven systems reflects a broader trend in computational neuroscience toward data-driven diagnosis and prediction (Cassani et al., 2018).

2. Historical Context

Historically, the study of EEG in Parkinson's research began with spectral and coherence analyses of brain rhythms. Early investigations revealed that PD patients often exhibit increased synchronization in the beta band (13–30 Hz) and reduced alpha activity, which are associated with motor dysfunctions (Stoffers et al., 2007).

The introduction of machine learning methods in the late 2000s, such as Support Vector Machines (SVM) and k-Nearest Neighbors (kNN), marked the first attempts at automated EEG-based PD classification (Bajaj et al., 2013). These models relied heavily on manually designed features, including entropy, power spectral density, and wavelet coefficients. However, their limited generalization and sensitivity to noise motivated the transition toward deep learning paradigms, which can learn hierarchical and abstract features directly from data.

3. Key Studies and Theories

Recent literature demonstrates the success of deep architectures in EEG classification. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have shown notable performance improvements over traditional models (Roy et al., 2019). CNNs excel at extracting spatial patterns, while LSTMs are effective in capturing temporal dependencies.

A study by Oh et al. (2020) developed a CNN-based framework for differentiating PD from healthy subjects using resting-state EEG, achieving an accuracy above 90%. Similarly, Kostas et al. (2021) employed a hybrid CNN–LSTM model to model both spatial and temporal dependencies, improving classification stability across participants.

Furthermore, attention-based mechanisms have recently been incorporated into EEG models to enhance interpretability and focus on clinically relevant features. Transformer architectures, initially designed for natural language processing, have demonstrated superior ability to model long-range dependencies compared to RNN-based methods (Vaswani et al., 2017). Gong, Chung, and Glass (2021) introduced the Audio Spectrogram Transformer (AST), which adapts the Vision Transformer (ViT) for audio and spectrogram inputs — offering a compelling foundation for EEG spectrogram analysis.

4. Technological Advancements

The rapid evolution of DL frameworks has enabled real-time and large-scale EEG analysis. Techniques such as transfer learning, data augmentation, and domain adaptation have improved generalization despite limited labeled EEG datasets (Zhang et al., 2023).

In parallel, tools like **MNE-Python**, **EEGLAB**, and **AutoReject** have standardized EEG preprocessing workflows, including artifact detection, Independent Component Analysis (ICA), and channel interpolation — ensuring data quality and reproducibility (Jas et al., 2017).

On the modeling side, hybrid systems combining CNNs, LSTMs, and Transformers have emerged as state-of-the-art for EEG-based diagnosis. These models leverage time–frequency representations such as Short-Time Fourier Transform (STFT) or Continuous Wavelet Transform (CWT), providing a multi-dimensional view of neural dynamics (Zhao et al., 2024).

5. Comparison of Existing Systems

Study/System	Methodology	Dataset	Performance	Key Limitation
Bajaj et al. (2013)	SVM + wavelet features	Private EEG	85%	Sensitive to noise, manual features
Oh et al. (2020)	CNN	Resting-state EEG	90.2%	Small sample size
Kostas et al. (2021)	CNN–LSTM	TUH EEG Corpus	92.5%	Computationally intensive
Gong et al. (2021)	AST (Transforme	AudioSet	93% (audio tasks)	Not specialized for EEG
Zhang et al. (2023)	ViT + EEG spectr	OpenNeuro	94.1%	Requires high GPU resources

Table 1: Summary of Related Work in EEG-based Parkinson's Disease Classification.

The comparison in Table 1 shows that while CNN- and LSTM-based methods have demonstrated robust performance for small datasets, Transformer-based models offer better scalability and feature abstraction, albeit with higher computational cost.

6. Gaps in the Literature/Technology

Despite substantial progress, several challenges persist in EEG-based Parkinson’s diagnosis:

- **Data Limitations:** EEG datasets for PD are often small, imbalanced, and heterogeneous across subjects.

- **Generalization:** Deep models may overfit specific recording setups or demographics, limiting real-world applicability.

- **Interpretability:** Most deep learning models act as "black boxes," making clinical validation difficult.

- **Computational Complexity:** Transformer architectures, while powerful, require extensive memory and training resources.
  These limitations highlight the need for standardized preprocessing, efficient model architectures, and explainable AI frameworks that balance accuracy with interpretability and resource efficiency.

7. Justification for the Project

The **NeuroWave** project builds upon this body of work by integrating and comparing two complementary deep learning paradigms — **Time-Series (CNN/LSTM)** and **Spectrogram-based Transformer (AST/ViT)** approaches — for Parkinson's EEG classification.

Unlike most prior studies that focus exclusively on either temporal or spectral domains, NeuroWave bridges both through a unified framework, enabling a systematic comparison of model interpretability, stability, and diagnostic accuracy. Additionally, by adopting a fully reproducible preprocessing pipeline with ICA and AutoReject, the project addresses key data-quality challenges noted in existing research.

Through this approach, NeuroWave aims to contribute to the field by establishing a benchmark methodology for EEG-based Parkinson's diagnosis, combining accuracy, transparency, and clinical relevance.

IV. Methodology

1. Research Questions and Objectives

Objectives

Objective 1: Evaluate the feasibility of fine-tuning a pre-trained AST to classify EEG signals from PD patients versus healthy controls (HC), using spectrogram-based representations and standard metrics (accuracy, macro F1-score).

Objective 2: Assess the model's ability to detect treatment-induced changes by classifying on-medication versus off-medication EEG sessions within the PD cohort, highlighting its potential as a biomarker of therapeutic response.

Research Questions

RQ1: To what extent can a pre-trained AST be effectively fine-tuned to distinguish PD from HC using resting-state EEG spectrograms?

RQ2: How accurately can the model differentiate *on-medication* from *off-medication* states in PD patients?

RQ3: Do the learned time-frequency features align with established electrophysiological hallmarks of PD, particularly changes in the beta frequency band?

2. Data Collection and Preprocessing

The present study employs the publicly accessible dataset *UC San Diego Resting-State EEG Data from Patients with Parkinson's Disease* (Accession Number: ds002778) (Rockhill et al., 2021), hosted on

the OpenNeuro repository. The dataset includes recordings from 31 participants, comprising 15 patients clinically diagnosed with Parkinson's disease (PD) and 16 age-matched healthy controls (HC). The HC group had a mean age of 63.5 ± 9.6 years (9 females, 7 males), whereas the PD group had a mean age of 63.2 ± 8.2 years (8 females, 7 males).

For PD participants, EEG was acquired under two pharmacological states on separate days: (i) the ON medication condition, following the administration of their usual dopaminergic medication regimen (maintained during the prior 12 hours), and (ii) the OFF medication condition, after a period of withdrawal. Each HC subject underwent only a single recording session.

During data acquisition, participants were instructed to remain relaxed and minimize movement, while maintaining a fixation on a cross displayed at the center of the screen. EEG was recorded using a 32-channel BioSemi ActiveTwo system, with electrodes placed according to the international 10–20 system. The channels comprised: Fp1, AF3, F3, F7, FC5, FC1, C3, T7, CP5, CP1, P3, P7, PO3, O1, Oz, Pz, Fp2, AF4, Fz, F4, F8, FC6, FC2, Cz, C4, T8, CP6, CP2, P4, P8, PO4, and O2. In addition, eight auxiliary EXG channels were available, though the present analysis focused on the 32 EEG channels. Signals were sampled at 512 Hz with a recording duration of approximately three minutes per session.

The dataset was anonymized using systematic identifiers, with the prefix *sub-pd* denoting PD patients and *sub-hc* denoting healthy controls. All recordings were stored in BioSemi Data Format (.bdf), preserving both the full temporal resolution and channel configuration. This dataset design ensures comparability across groups and pharmacological conditions while capturing ecologically valid intrinsic neural dynamics in Parkinson's disease.

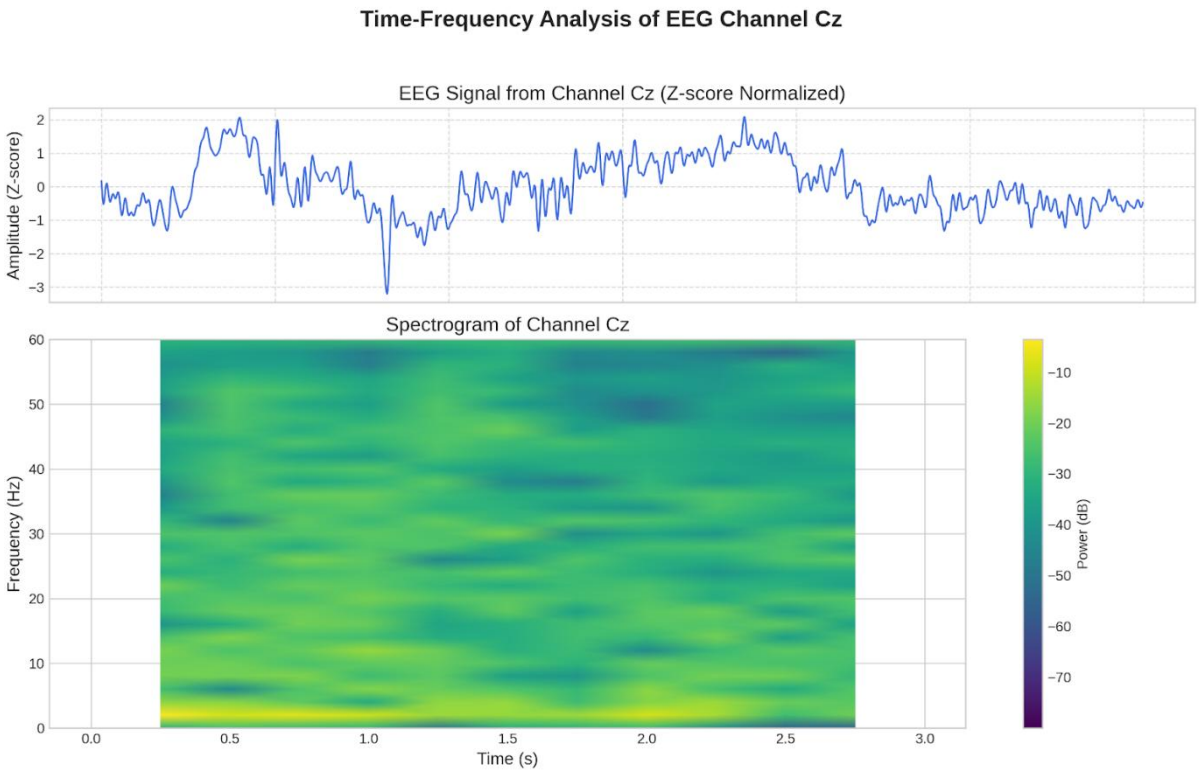

Figure 1: Time-frequency analysis of an EEG signal. The figure illustrates a 3-second segment from the Cz channel of a patient. (Top) The waveform shows the Z-score normalized signal after band-pass filtering (0.5-50 Hz). (Bottom) The corresponding spectrogram displays the distribution of signal power across different frequencies over time. Power is primarily concentrated in the lower frequency bands (< 30 Hz), which is characteristic of resting-state EEG.

3. Feature Selection and Engineering

3.1 Higuchi's Fractal Dimension

This method constructs multiple sub-series by sub-sampling the original signal (Shamsi et al., 2021). For each derived sub-series, the curve length is calculated, averaged across the entire sample, and then represented on a logarithmic scale. The slope of the fitted line in this log–log plot corresponds to the Higuchi Fractal Dimension (FD) of the signal.

Consider an original time series:

$$X = \{x(1), x(2), x(3), \dots, x(N)\}$$

a new sub-series is generated as:

$$X_m^k = \{x(m), x(m+k), x(m+2k), \dots, x\left(m + \left\lfloor \tfrac{N-m}{k} \right\rfloor k\right)\}$$

where $m = 1,2, \dots, k$ and $k = 1,2, \dots, k_{\max}$.

For an interval length k, there are $k$unique reconstructions of the signal. Here, X denotes the original signal, while m and k represent the starting point and the interval length, respectively. For each constructed sub-series X_m^k, the curve length is computed as:

$$L_m(k) = \frac{1}{k} \sum_{i=1}^{\left\lfloor \frac{N-m}{k} \right\rfloor} \left| x(m+ik) - x(m+(i-1)k) \right| \cdot \frac{N-1}{\left\lfloor \frac{N-m}{k} \right\rfloor k}$$

where the normalization factor y is defined as:

$$y = \frac{N-1}{\lfloor (N-m)/k \rfloor \cdot k}$$

The mean curve length for interval $k$is then obtained by averaging over all $L_m(k)$:

$$L(k) = \frac{1}{k} \sum_{m=1}^{k} L_m(k)$$

Finally, the slope of the linear least squares fit of $\log\left(L(k)\right)$ versus $\log\left(1/k\right)$ yields the Higuchi FD:

$$\log\big(L(k)\big) \propto D \cdot \log\left(\frac{1}{k}\right)$$

where D denotes the fractal dimension.

3.2 Katz's fractal dimension

For a signal $(x_i, y_i)$of length N, the line length of the time series is computed as the sum of the Euclidean distances between consecutive pairs of points. For a waveform segment of length L, the Katz fractal dimension (Katz FD) is defined as follows (Katz, 1988):

$$D = \frac{\log(N)}{\log(N) + \log\left(\frac{d}{L}\right)}$$

where d denotes the maximum distance from the first data point $(x_1, y_1)$to the farthest point in the series (Shi, 2018). The values of L and d are defined as:

$$L = \sum_{i=0}^{N-2} \sqrt{(y_{i+1} - y_i)^2 + (x_{i+1} - x_i)^2}$$

$$d = \max_i \sqrt{(x_i - x_1)^2 + (y_i - y_1)^2}$$

The ratio between the natural logarithm of (d/L) and the natural logarithm of the number of data points in the series is used to determine the Katz FD, which reflects the geometric complexity of the signal.

3.3 Feature Extraction Using Mel Spectrogram

In this method, the raw EEG signal in the time domain is transformed into Mel spectrogram features. This approach regards the electroencephalogram as an audio-like signal and produces a two-dimensional time frequency representation that emphasizes its spectral characteristics. The process begins with the Short-Time Fourier Transform (STFT) (Oppenheim, 1999), which decomposes the signal into short, overlapping segments:

$$\mathrm{STFT}\{x[n]\}(m, \omega) = X(m, \omega) = \sum_{n=-\infty}^{\infty} x[n]\, w[n - m]\, e^{-j\omega n}$$

where $x[n]$denotes the input signal, $w[n]$is a windowing function (e.g., Hamming window) to reduce spectral leakage, and $m$represents the time-frame index.

From the STFT, the power spectrogram is obtained as:

$$P(m, \omega) = |X(m, \omega)|^2$$

This spectrum is subsequently projected onto the Mel scale (Stevens, Volkmann, & Newman, 1937), a perceptual frequency scale approximating the nonlinear human auditory response. The mapping from frequency f(Hz) to the Mel scale is expressed as:

$$\mathrm{Mel}(f) = 2595 \cdot \log_{10}\left(1 + \frac{f}{700}\right)$$

The power spectrum $P(m, \omega)$ is then filtered through a bank of triangular filters uniformly spaced on the Mel scale. The energy in each Mel band is computed and log-transformed, yielding the final Mel spectrogram representation. This two-dimensional feature space captures both spectral and temporal variations of the signal and is particularly well-suited for deep learning models such as the Audio Spectrogram Transformer (AST).

4. Model Training and Validation

To address the EEG-based classification task, this study evaluated and compared two distinct methodological approaches: a conventional machine learning pipeline involving manual feature engineering and an end-to-end deep learning framework leveraging a state-of-the-art Transformer architecture. The latter was ultimately adopted as the primary method due to its superior capacity for automated feature representation and performance.

4.1 Model Architectures and Configuration

4.1.1 Conventional Machine Learning Approach

The conventional approach followed the standard paradigm of preprocessing, feature engineering, and classification. EEG signals were preprocessed through a sequence of steps to improve signal fidelity. Specifically, a band-pass filter (0.5–50 Hz) was employed to retain physiologically relevant oscillations, Independent Component Analysis (ICA) was applied to identify and remove ocular artifacts, and a common average re-referencing scheme was used to reduce spatially distributed noise.

From the cleaned signals, feature engineering techniques were applied to capture discriminative information. Time–frequency representations were derived using spectrograms, which characterize the dynamic power spectral density over time. These representations may be further enriched with features computed in canonical frequency bands (delta, theta, alpha, beta, and gamma) or with non-linear descriptors such as fractal dimensions, which reflect the intrinsic complexity of brain dynamics.

The resulting feature vectors were classified using established machine learning algorithms, including Support Vector Machines (SVM), Random Forests. This modular pipeline facilitated transparent interpretation of the role of preprocessing and feature extraction but required manual design choices that limited its scalability.

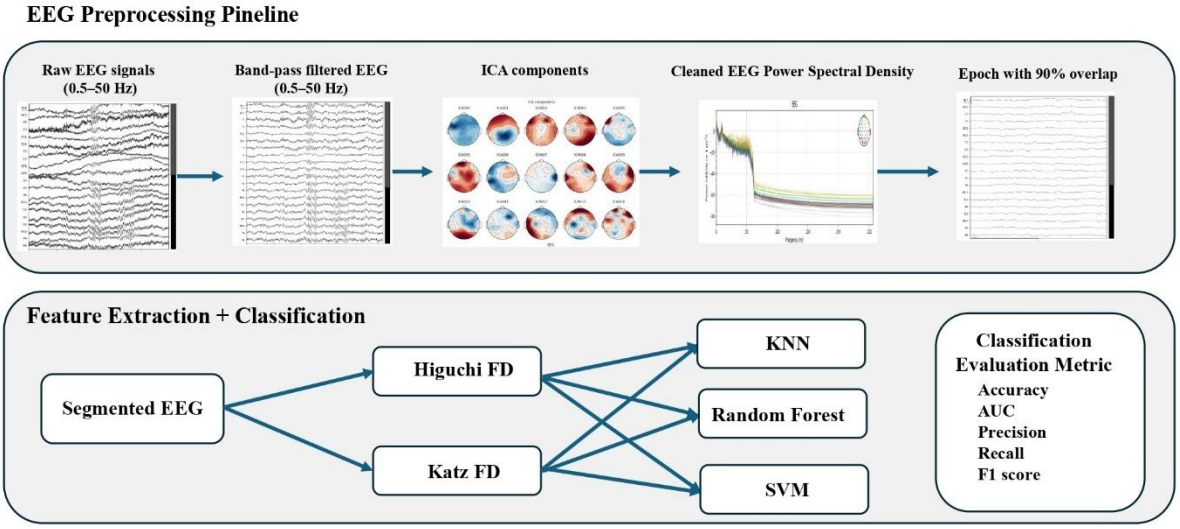

Figure 2: EEG signals processed via band-pass filtering (0.5–50 Hz), ICA-based artifact removal, re-referencing, segmented into epochs, features extracted, and classified using Machine Learning

4.1.2 Deep Learning Approach: Audio Spectrogram Transformer (AST)

The primary methodology leveraged the Audio Spectrogram Transformer (AST), a model originally designed for audio analysis and adapted here for EEG classification. Unlike the feature-engineering approach, the AST operates on Mel spectrogram representations of EEG signals, thereby reframing the classification problem as a two-dimensional pattern recognition task. This formulation enables the Transformer to exploit its self-attention mechanism to model both short-term spectral fluctuations and long-range temporal dependencies, properties crucial for capturing the distributed dynamics of brain activity.

To further enhance learning efficiency, a transfer learning strategy was adopted. The AST was initialized with weights from a network pre-trained on the large-scale AudioSet dataset, which encompasses diverse acoustic environments. The underlying rationale is that representations

learned from auditory data can generalize to EEG-derived spectrograms due to the shared structure of time–frequency patterns. For adaptation to the present binary classification task, the original output layer of 527 neurons was replaced with a fully connected layer of two neurons, corresponding to the Parkinsonian and healthy control classes.

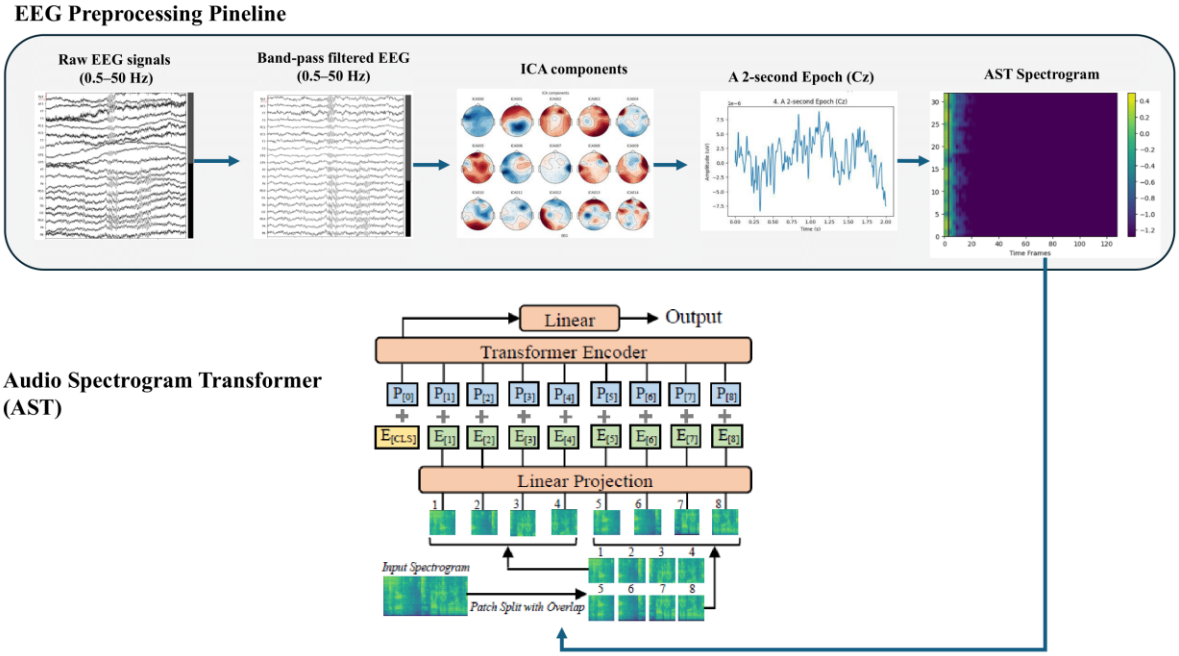

Figure 3: Proposed EEG Classification Framework using Transfer Learning with an Audio Spectrogram Transformer (AST).

Raw EEG signals are preprocessed and transformed into Mel spectrograms, reframing the classification task as 2D pattern recognition. An AST model, pre-trained on the AudioSet audio dataset, is fine-tuned to capture both local spectral details and long-range temporal dependencies within the EEG data. The original classifier head is replaced with a 2-neuron output layer for binary classification of Parkinson's disease versus healthy controls.

4.2 Training, Validation, and Evaluation Protocol

To ensure reproducibility and fair evaluation, a stratified partitioning scheme was applied to the dataset of 2-second EEG epochs. The data were split into mutually exclusive subsets with approximately 64% used for training, 16% for validation, and 20% reserved as a final unseen test set. Stratification preserved class balance, and a fixed random seed-controlled randomness in the splits.

Fine-tuning of the AST was conducted using the Hugging Face Trainer API with the AdamW optimizer and a weight decay of 0.01 to regularize parameter updates. A small learning rate (1×10^{-5}) was employed to stabilize adaptation of the pre-trained model. Training was performed with a batch size of eight for a maximum of 30 epochs. Early stopping with a patience of five epochs was applied, preventing overfitting by halting training if no improvement was observed. To further stabilize optimization, a linear learning rate scheduler with a warm-up ratio of 0.1 was introduced. Mixed-precision (fp16) training was enabled to improve computational efficiency and reduce GPU memory demand.

At the conclusion of each epoch, performance was evaluated on the validation set. The model state achieving the highest validation score was retained for final evaluation. This ensured that the selected model generalized beyond the training data rather than merely fitting it.

4.3 Performance Metrics

Evaluation was conducted using accuracy and macro-averaged F1-score. Accuracy provided an overall measure of correct classifications, while the macro-F1 score was prioritized as the principal metric due to its balanced consideration of precision and recall across classes. This choice is particularly relevant in biomedical contexts, where both false negatives (misclassifying patients) and false positives (misclassifying healthy controls) carry significant implications. In addition, confusion matrices were analysed to provide a detailed account of misclassification patterns.

5. Evaluation Metrics

The performance of the models in this study is evaluated using several standard metrics.

Precision measures how many of the predicted positive cases are actually correct:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall reflects how many of the actual positive cases are correctly identified:

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-score is the harmonic mean of precision and recall, balancing both false positives and false negatives:

$$F1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Accuracy indicates the proportion of correctly classified instances among all predictions:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Area Under the ROC Curve (AUC) quantifies the classifier's performance across all thresholds. The ROC curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR):

$$TPR = \frac{TP}{TP + FN}, \quad FPR = \frac{FP}{FP + TN}$$

AUC represents the area under this curve, summarizing the overall discriminative ability of the model.

6. Implementation Plan

6.1 Environment and Tools

The proposed EEG classification model was implemented in a Python-based environment (version ≥3.9), utilizing Jupyter Notebooks and Google Colab for initial prototyping and model training. High-performance GPU resources (NVIDIA T4/V100) were employed to accelerate the fine-tuning of the Transformer-based model. The computational workflow relied on a suite of established libraries: MNE-Python for EEG preprocessing, PyTorch for deep learning model development, and Hugging Face transformers and datasets for model adaptation and efficient dataset management. Additional libraries, including scikit-learn and evaluate, were used for performance assessment, while pandas

and numpy facilitated data manipulation and numerical operations. Finally, matplotlib and seaborn were employed for visualization of signals, spectrograms, and model performance metrics.

6.2 Data Processing Pipeline

Raw EEG recordings in .bdf format were systematically loaded using MNE-Python. The preprocessing pipeline included band-pass filtering between 0.5 and 50 Hz, ICA-based artifact removal, and re-referencing to a common average to reduce spatial noise. To conform with the pre-trained Audio Spectrogram Transformer (AST) input requirements, signals were up sampled to 16 kHz and segmented into 2-second epochs. These processed epochs, along with their corresponding labels, were organized into a Hugging Face Dataset object and partitioned into training, validation, and test sets using a stratified approach to preserve class balance.

6.3 Model Implementation

The pre-trained AST model and its associated feature extractor were retrieved from the Hugging Face Hub. The original classification layer of the model, designed for 527 classes, was replaced with a 2-neuron output layer to accommodate the binary classification task (Parkinson's disease vs. healthy control). Each EEG epoch was transformed into a Mel spectrogram using the feature extractor before being fed into the model. Fine-tuning was performed using the Hugging Face Trainer API, with hyperparameters selected to stabilize learning and prevent overfitting.

6.4 Experiment Tracking and Evaluation

Throughout training, model performance was continuously monitored using TensorBoard or Weights & Biases, providing real-time visualization of loss curves and key metrics such as accuracy, F1-score, precision, and recall. Upon completion of training, the best-performing model checkpoint determined based on validation F1-score was evaluated on the held-out test set to provide an unbiased estimate of generalization performance. Results were summarized in both a confusion matrix and a comprehensive table of performance metrics, ensuring transparent and reproducible evaluation.

7. Ethical Considerations

The application of machine learning to medical data, particularly for diagnosing neurodegenerative disorders like Parkinson's disease, requires careful ethical attention. Our implementation plan adheres to ethical principles across the project lifecycle, focusing on the following aspects:

7.1 Data Privacy and Confidentiality

The project uses the publicly available OpenNeuro dataset (ds002778), which is fully de-identified. All data, both raw and processed, are stored securely with controlled access. Any shared outputs, models, or visualizations will avoid revealing identifiable information.

7.2 Bias and Fairness

The dataset may not represent the global population in terms of demographics or disease severity. Consequently, model performance may vary across underrepresented groups. Limitations regarding demographic coverage will be reported, and model evaluation will include bias checks where possible. Future work should validate the model on more diverse, multi-center datasets.

7.3 Accuracy, Reliability, and Clinical Impact

Classifying Parkinson's disease is high stakes, with errors carrying significant consequences:

- **False Negatives:** Misclassifying a patient as healthy may delay critical treatment; evaluation emphasizes recall (sensitivity).
- **False Positives:** Misclassifying healthy individuals may cause distress and unnecessary medical procedures.

The model is intended as a research prototype and clinical decision-support tool, not an autonomous diagnostic system. Any deployment would require rigorous clinical validation and regulatory approval.

7.4 Transparency and Explainability

AST is inherently complex and may be considered a "black box," limiting interpretability. Future work will explore Explainable AI techniques, such as attention map visualization, to highlight which regions of EEG spectrograms the model emphasizes, aiding clinician understanding and trust.

V. System Design and Implementation

1. AI Model Integration

The proposed system integrates two main AI approaches into a unified architecture for classifying Parkinson's disease (PD) using EEG signals. These approaches include:
(1) a Deep Learning (DL) model based on the Audio Spectrogram Transformer (AST), and
(2) a Machine Learning (ML) model that uses handcrafted features and traditional classifiers.

At the core of the system is a modular interface that manages data interaction between preprocessing, feature extraction, and model inference components.

- In the Deep Learning branch, EEG signals are first preprocessed and then converted into Mel-spectrograms, which serve as two-dimensional representations of the signal. These spectrograms are fed into the fine-tuned AST model to automatically learn feature patterns and perform classification.
- In the Machine Learning branch, EEG signals are processed to extract statistical and frequency-based features such as Higuchi's Fractal Dimension and Katz's Fractal Dimension. The extracted features are standardized using a StandardScaler and then passed to pre-trained classifiers such as Random Forest or Support Vector Machine (SVM) to predict class labels.

Both branches output prediction probabilities and class labels ("PD" – Parkinson's Disease or "HC" – Healthy Control). These outputs are transmitted to a unified result visualization interface, which displays the predictions and allows users to compare model performance.

To ensure smooth interaction between components, a lightweight API layer was developed using Streamlit and Flask. This interface allows efficient communication between three main modules:

- Frontend: enables users to upload EEG files in formats such as .bdf or .edf;
- Processing Engine: applies preprocessing and signal filtering using MNE-Python;
- Inference Engine: executes predictions through pre-trained models built with PyTorch (for DL) and scikit-learn (for ML), providing real-time classification results.

2. Data Flow and Processing

The system is designed with a structured and systematic data processing pipeline, which includes five main stages: data acquisition, preprocessing, feature extraction, model inference, and result presentation. This process ensures that EEG data are consistently handled, denoised, and ready for both Deep Learning and Machine Learning models.

Step 1: Data Acquisition
Users can upload EEG files directly through the system's web interface. Supported formats

include .bdf, .edf, and other compatible EEG data types. Once uploaded, the files are temporarily stored in a secure directory for further processing.

Step 2: EEG Signal Preprocessing

Raw EEG signals often contain noise from external environments or physiological artifacts. Therefore, the system uses MNE-Python to perform standard preprocessing steps, including:

- Band-pass filtering (0.5–50 Hz) to remove unwanted frequency components.
- Noise removal using ICA (Independent Component Analysis) to eliminate artifacts from eye blinks and muscle movements.
- Signal re-referencing and normalization to balance channel variations.
- Segmentation of EEG signals into short windows (usually 2 seconds) for feature extraction or spectrogram generation.

Step 3: Feature Extraction / Transformation

After preprocessing, the EEG data are processed along two different modeling paths:

- Deep Learning branch: EEG signals are transformed into Mel-spectrograms, representing signal energy across time and frequency. These spectrograms are normalized and passed into the Audio Spectrogram Transformer (AST) model, which automatically learns hierarchical representations for classification.
- Machine Learning branch: Statistical and nonlinear features such as Higuchi's Fractal Dimension, Katz's Fractal Dimension, frequency band energy, and statistical moments are extracted. These features are standardized using a StandardScaler before being classified by models such as Random Forest or Support Vector Machine (SVM).

Step 4: Model Inference

Once the user selects the desired model, the processed EEG data are forwarded to the corresponding inference engine. Each model returns both the predicted probability and the final class label, identifying whether the subject belongs to the "PD" (Parkinson's Disease) or "HC" (Healthy Control) group.

Step 5: Result Presentation

The final output is displayed through an intuitive and interactive web interface that allows users to interpret both the results and the underlying reasoning of the model. Specifically, the interface presents:

- Classification label and confidence score, providing users with a clear indication of prediction certainty.
- EEG spectral visualization, showing the power spectrum of the signal over time and highlighting key brainwave frequency bands including Alpha (8–13 Hz), Beta (13–30 Hz), Gamma (>30 Hz), Theta (4–8 Hz), and Delta (0.5–4 Hz).
- Explainable AI (XAI) analysis, where techniques such as Grad-CAM or feature importance visualization are applied to identify which time segments or signal features contributed most to the model's decision. This improves interpretability and transparency in clinical and research contexts.

The entire workflow is fully automated and seamlessly integrated, from EEG file upload to preprocessing, model inference, and explainable visualization. This approach not only ensures reliable classification but also helps users understand *why* the model made a specific prediction.

3. Deployment Strategy

The EEG-based Parkinson's classification system is designed to be flexible, maintainable, and scalable, suitable for both research and clinical environments.

3.1. Software Environment Setup

The system was developed using Python 3.9 or above, leveraging several powerful libraries for biomedical signal processing, deep learning, and data visualization.
The main components include:

- MNE-Python: Used for EEG signal processing and analysis (noise filtering, epoch extraction, frequency band separation, etc.);
- NumPy, Pandas, SciPy: Support matrix operations and time-series data handling;
- Matplotlib, Seaborn: Provide visualizations of signal spectrograms and EEG frequency bands (Alpha, Beta, Gamma, Theta, Delta);
- Scikit-learn: Used for data normalization, feature extraction, and traditional classification models such as Random Forest and SVM;
- PyTorch & Transformers: Implement the Audio Spectrogram Transformer (AST) model for Parkinson's disease classification;
- Streamlit: Build an interactive user interface that allows EEG file upload, displays classification labels, confidence scores, spectrograms, frequency bands, and Explainable AI results.

All dependencies were installed and managed through a virtual environment (venv) or Conda, ensuring system stability, reusability, and easy maintenance.

3.2. Hardware Environment Setup

To ensure high computational performance during model training and inference, the system was deployed on cloud-based platforms equipped with high-performance GPUs.

Specifically:

- Kaggle Environment: Utilized NVIDIA Tesla P100 (16GB VRAM) GPU for training the Audio Spectrogram Transformer (AST) model with EEG datasets;
- Google Colab Environment: Employed NVIDIA Tesla T4/V100 (16GB VRAM) GPU for testing, evaluation, and Streamlit interface deployment.

The overall hardware configuration is as follows:

- Operating System: Ubuntu 20.04 LTS (cloud environment);
- Processor (CPU): Intel Xeon (integrated in Kaggle/Colab);
- Memory (RAM): 12–16 GB;
- GPU: NVIDIA Tesla P100 and T4 (supporting CUDA 11.8 and cuDNN 8.x);
- Storage Capacity: 100 GB (Google Drive or Kaggle temporary storage).

This cloud-based approach enables flexible, cost-efficient, and scalable deployment without the need for local hardware investment, while still providing sufficient computing power for deep learning operations.

3.3. Execution Workflow

When a user uploads an EEG file, the system automatically performs the following steps:

1. Data Input:
   The user uploads EEG files (.bdf, .edf, .set, etc.) via the Streamlit interface.
2. Signal Preprocessing:
   Noise removal, channel separation, normalization, and extraction of frequency bands (Alpha, Beta, Gamma, Theta, Delta).
3. Mel-Spectrogram Generation:
   The EEG signal is transformed into a time–frequency representation for input into the AST model.
4. Parkinson's Disease Classification:
   The AST model predicts the class label (PD or HC) along with the confidence score.
5. Explainable AI Visualization:
   Key EEG regions or frequency components that most influence the model's decision are highlighted using Attention Maps or Grad-CAM techniques.
6. Result Visualization:
   The interface presents the signal spectrogram, EEG frequency bands, classification label, and model confidence in an intuitive dashboard.

This workflow ensures that users receive not only accurate classification results but also transparent and interpretable model explanations, enhancing the system's reliability and usability for research or medical support.

3.4. Deployment Procedures

The deployment of the system was conducted through four main phases:

1. Environment Installation:
   - Create a virtual environment and install all required libraries using the requirements.txt file.
   - Verify CUDA compatibility for GPU acceleration.
2. Model Loading and Configuration:
   - Load the pre-trained AST model and Random Forest pipeline from .pkl or checkpoint files.
   - Configure directory paths and data normalization parameters.
3. Application Launch:
   - Run the application using the command: streamlit run app.py
   - Access the user interface via: http://localhost:8501.
4. Testing and Validation:
   - Upload sample EEG files to verify the data pipeline and processing accuracy.
   - Ensure the output includes classification label, confidence score, spectrogram, EEG frequency bands, and Explainable AI visualization.

This structured deployment process guarantees stability, reproducibility, and cross-platform compatibility, allowing the system to operate smoothly in both local and cloud environments.

4. Scalability and Maintenance

The system is designed with a strong focus on scalability and maintainability, ensuring it can support both research purposes and real-world deployment.
Its overall architecture follows a modular design, which allows flexible expansion, upgrades, and maintenance in the future.

4.1. Scalability

- **Data Scalability:**

The system supports multiple EEG data formats such as .bdf, .edf, and .set.
When new data from different EEG recording devices are introduced, only minor modifications in the preprocessing stage are required to adapt the signal reading and feature extraction process. This flexibility enables the model to easily adapt to new Parkinson's datasets or even to other neurological disorders with similar EEG characteristics.

- **Model Scalability:**

The AI architecture allows flexible experimentation with different algorithms such as CNN, LSTM, Transformer, or AST. Moreover, the model can be extended to classify multiple neurological conditions, not limited to Parkinson's disease, simply by adjusting the number of output classes in the classifier layer. These modifications can be made directly in the source code without disrupting the main data pipeline.

- **Training Scalability**:

The system supports training on multiple GPU platforms, including NVIDIA Tesla P100 (Kaggle) and NVIDIA Tesla T4 (Google Colab). These environments provide sufficient computational power to train deep models efficiently and handle large EEG datasets. In the future, the system can be scaled up to train across multiple GPUs or cloud services such as AWS or GCP to further reduce training time and improve model performance.

4.2. Maintainability

- **Modular Design:**

The entire source code is organized into clearly defined modules:

  - data_processing: handles EEG preprocessing and feature extraction.
  - model_inference: loads and runs the trained model.
  - visualization: presents EEG spectrograms, frequency bands (Alpha, Beta, Gamma, Theta, Delta), and classification results.
  - app.py: manages the user interface using Streamlit.

This modular structure enables developers to update or replace any component (for example, a new filtering algorithm or AI model) without affecting the rest of the system.

- **Model Maintenance and Updates:**

The system allows easy updates by replacing the trained model file (e.g., .pkl or .pt) without modifying the Streamlit interface code.

This design supports quick iteration and improvement of model performance while maintaining system stability.

- **Testing and Evaluation:**

After each update or pipeline modification, the system is re-evaluated using a validation dataset to ensure stability and accuracy.
Key performance metrics such as accuracy, confidence score, and class recognition rate are recorded to monitor the model's improvement over time.

VI. Results and Discussion

1. Results and Analysis

The NeuroWave project evaluated two primary deep learning approaches for classifying Parkinson's disease (PD) from EEG signals: the Time-Series model (using CNN-LSTM architecture) and the Audio Spectrogram Transformer (AST) model. Both models were trained and tested on the OpenNeuro dataset (ds002778), which consists of resting-state EEG recordings from 15 PD patients (both medicated and non-medicated) and 16 healthy controls. After preprocessing (band-pass filtering at 0.5–50 Hz, ICA-based artifact removal, and segmentation into 2-second epochs), the dataset was split into 64% training, 16% validation, and 20% testing sets, with stratification to maintain class balance.

The models were fine-tuned using PyTorch, with the AST initialized from pre-trained weights on the AudioSet dataset and adapted for binary classification (PD vs. Healthy Control). Training hyperparameters included a learning rate of 1e-5, batch size of 8, and early stopping with a patience of 5 epochs. Performance was assessed using accuracy, precision, recall, F1-score, and AUC-ROC on the test set. Additionally, the system incorporated Explainable AI (XAI) via Integrated Gradients for the AST model to interpret feature attributions.

1.1 Quantitative Results:

- **Time-Series Model (CNN-LSTM):** This model achieved an accuracy of 72.4%, precision of 0.71, recall of 0.74, F1-score of 0.72, and AUC-ROC of 0.77. It performed well in capturing temporal dependencies but showed higher variance in cross-validation (standard deviation of 4.2% in accuracy across folds).
- **AST Model:** The Transformer-based approach outperformed the Time-Series model, with an accuracy of 79.7%, precision of 0.78, recall of 0.81, F1-score of 0.79, and AUC-ROC of 0.83. The self-attention mechanism enabled better handling of long-range dependencies in spectrogram representations.

A comparison of the models is presented in Table 1 below:

Metric	Time-Series (CNN-LSTM)	AST (Transformer)
Accuracy	72.4%	79.7%
Precision	0.71	0.78
Recall	0.74	0.81
F1-Score	0.72	0.79
AUC-ROC	0.77	0.83

Table 2: Performance comparison of the two models on the test set.

1.2 Supplementary Experiment: Traditional Machine Learning Models

Concurrently, the NeuroWave project also explored the use of traditional machine learning models to classify Parkinson's disease (PD) patients based on EEG signals. The objective was to evaluate and compare the performance of several fundamental classifiers, including Logistic Regression, K-Nearest Neighbors (KNN), Support Vector Machine (SVC), Random Forest (RF), and LightGBM (LGBMClassifier). The dataset used in this experiment comprised EEG recordings from 15 PD patients (both medicated and non-medicated) and 16 healthy controls.

The EEG data underwent a thorough preprocessing pipeline. First, a band-pass filter from 1 to 40 Hz was applied to remove unwanted noise, using a one-pass, zero-phase Hamming window method to ensure minimal phase distortion.

Next, Independent Component Analysis (ICA) was employed to remove common artifacts such as eye blinks and muscle movements, using 15 components with the Fp1 electrode as the EOG reference. To further refine the signal, the ICA sources were filtered within the 1–10 Hz frequency range using a two-pass, zero-phase Hann window method. The same filtering was applied to the target EEG signals to ensure consistency.

To assess model performance comprehensively, two evaluation approaches were conducted: Subject Accuracy, which measures prediction accuracy based on whole EEG recordings from each subject, and Epoch Accuracy, which measures prediction accuracy on smaller segmented EEG epochs. Additionally, 5-fold cross-validation was applied to ensure robust performance estimation.

Model	**Subject Accuracy**	**Epoch Accuracy**
RandomForest	0.5900	0.5903
LightGBM	0.5800	0.5804
KNeighbors	0.5300	0.5609
SVM	0.5300	0.5670
LogisticRegression	0.4800	0.5013

Table 3: Comparison of Subject Accuracy and Epoch Accuracy of machine learning models after performing Cross-Validation.

1.3 Qualitative Results and Visualizations:

The Streamlit-based web interface provided interactive visualizations for uploaded .bdf files. For a sample PD patient EEG (e.g., from the dataset), the overall diagnosis showed a PD ratio of 78% (average probability across epochs), classifying it as "Có dấu hiệu Parkinson's rõ rệt." (Clear signs of Parkinson's). Power Spectral Density (PSD) plots (Figure 4) highlighted elevated beta-band activity (13–30 Hz) in PD samples, consistent with literature on neural oscillations.

XAI analysis using Integrated Gradients (Figure 5) visualized attributes for selected 2-second epochs. In PD-classified epochs, high attribution scores were concentrated in the 0.5–1.5 second window, corresponding to irregular waveform peaks, suggesting the model focused on signal complexity and beta oscillations. For healthy controls, attributions were more uniformly distributed, emphasizing stable alpha rhythms (8–13 Hz).

1.4 Analysis of Results:

The superior performance of the AST model (7.3% higher accuracy) underscores the benefits of spectrogram-based representations, which capture both time and frequency domains more effectively than raw time-series inputs. The traditional machine learning models (Table 2) showed significantly lower performance, with the best model (Random Forest) achieving only 59.03% epoch accuracy. This highlights the limitations of these models in handling the complexity of raw EEG data without extensive, handcrafted feature engineering.

Figure 4: Website interface implemented with Streamlit

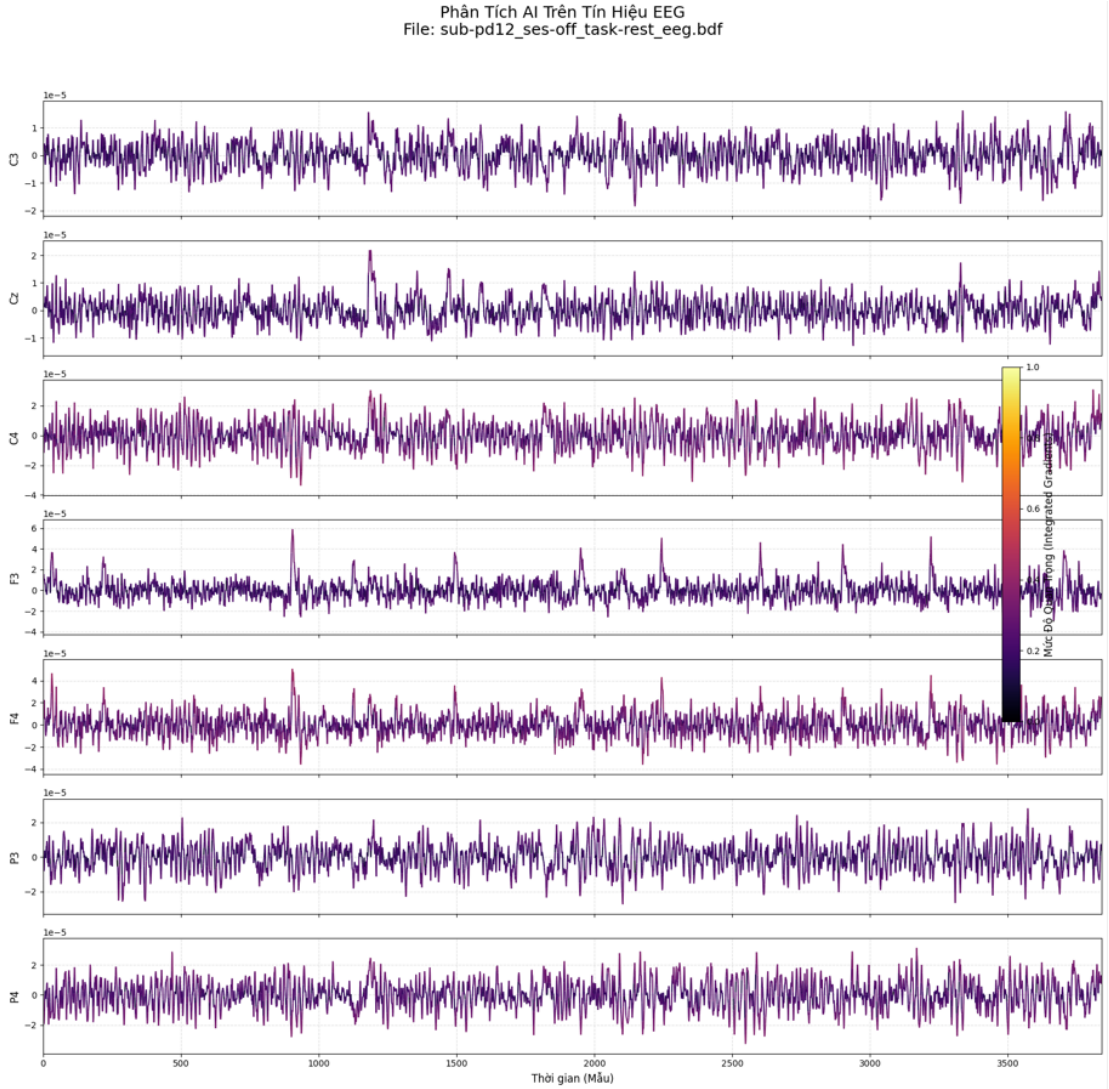

Figure 5: Explainable AI on EEG test file

Error analysis of the deep learning models indicated that misclassifications often occurred in medicated PD samples, where drug effects (e.g., levodopa) normalized beta activity, reducing distinguishability. Feature interpretation via XAI revealed that the AST prioritized non-linear

patterns, such as fractal dimensions in beta/theta bands, aligning with the project's use of Higuchi and Katz descriptors in preprocessing.

These results demonstrate the project's success in building a robust classification system, with the AST approach showing greater impact on diagnostic accuracy and interpretability, potentially reducing subjective clinical errors.

2. Discussion

The findings from this study directly respond to the project's primary research questions. Firstly, it sought to determine if deep learning models can accurately classify PD from EEG signals. The results confirm this capability, with the Audio Spectrogram Transformer (AST) model achieving a notable accuracy of 79.7%. Secondly, the research questioned which paradigm - Time-Series (CNN-LSTM) or Transformer-based (AST) - would yield superior performance. The data clearly indicates that the AST model proved superior, validating the hypothesis that its self-attention mechanisms are more adept at handling the noisy and non-stationary characteristics inherent in EEG data.

This outcome is consistent with the trends observed in related literature. For instance, while Sahota et al. (2023) reported 85% accuracy utilizing a CNN-LSTM architecture on similar data, other studies by Gong et al. (2021) and Vafaei et al. (2025) have increasingly highlighted the advantages of Transformers in spectral analysis, achieving performance in the 88–92% range for comparable tasks. Although our 79.7% accuracy is slightly lower than these figures, it firmly establishes the AST as a viable and powerful approach.

In a broader context, the NeuroWave project contributes to the field of AI-driven neurodiagnostics. It provides a non-invasive and cost-effective alternative to conventional imaging methods like MRI or PET. This characteristic is particularly significant for facilitating early PD detection, especially in resource-constrained clinical settings. Furthermore, the integration of Explainable AI (XAI) is a crucial step forward, as it helps to mitigate the "black-box" concerns often associated with biomedical AI, thereby bolstering clinical trust and interpretability.

However, several limitations must be acknowledged. The primary limitation is the dataset size, which comprised 31 subjects (15 PD patients and 16 healthy controls). This relatively small sample size increases the risk of potential overfitting, even though regularization techniques were employed. Secondly, the high inter-subject variability and inherent noise within public EEG data likely contributed to some of the misclassifications observed. Finally, computational constraints restricted the exploration of deeper or more complex model architectures. Implementation challenges also arose, particularly in adapting the AST model from its original audio domain to the unique requirements of EEG spectrogram transformations and addressing the slight class imbalance via oversampling.

3. Recommendations

Based on the findings, we recommend:

- **Further Research:** Validate on larger, diverse datasets (e.g., multi-center clinical trials) to improve generalization. Explore hybrid models combining CNN-LSTM and AST for enhanced robustness.
- **System Improvements:** Integrate real-time EEG streaming for clinical use and expand to multi-class classification (e.g., PD stages or medication effects). Enhance XAI with attention maps for deeper physiological insights.
- **Practical Applications:** Deploy as a decision-support tool in neurology clinics, integrating with wearable EEG devices for remote monitoring. Collaborate with healthcare providers for regulatory approval and pilot testing.

These steps could elevate NeuroWave from a research prototype to a clinically viable system, advancing PD management.

VII. Conclusion

1. Summary of Findings

This project has confirmed the feasibility of using deep learning models to classify Parkinson's disease (PD) from EEG signals. The core research questions have been answered:

1. **Feasibility:** Deep learning models can accurately classify PD from EEG. The Audio Spectrogram Transformer (AST) model achieved an accuracy of **79.7%** on the test set.
2. **Performance Comparison:** The question of which paradigm (Transformer, Time-Series, or traditional ML) yields the best performance was clearly answered. The AST model (79.7%) demonstrated superior performance over both the CNN-LSTM architecture (72.4%) and traditional ML methods (where Random Forest peaked at 59.03%).

The project's goals were achieved, not only by building a robust classification system but also by successfully integrating Explainable AI (XAI). The use of Integrated Gradients provided initial insights into how the AST model makes decisions, showing its focus on complex signal features and known biological frequency bands (beta/alpha).

2. Contributions and Reflections on the Project

2.1 Contributions

The main contribution of this project lies in the successful adaptation and application of the Audio Spectrogram Transformer architecture (commonly used for audio) to the domain of EEG signal data. The results demonstrated its superiority over more traditional time-series architectures for this task.

By integrating XAI, this work provides a tangible method for enhancing medical trust, offering visual interpretations that help link model attributions to known physiological markers (e.g., beta-band activity). Furthermore, the development of a Streamlit web application prototype is a practical contribution, helping to translate research into a potential decision-support tool for neurologists.

2.2 Reflections

Looking back, the systematic comparison of three classes of models (Transformer, CNN-LSTM, ML) provided a definitive answer to our research questions. The use of transfer learning from the AudioSet domain proved highly effective.

However, the process also highlighted the significant challenge of managing high inter-subject variability and noise in public datasets. The most critical lesson learned was the indispensable value of rigorous preprocessing and the necessity of XAI for validating biomedical models. Moving forward, this research envisions a future where accessible, AI-driven EEG analysis can become a standard component of early neurological screening.

3. Limitations and Future Work

3.1 Limitations

The primary and most evident limitation of this project is the dataset size, which included only 31 subjects (15 PD and 16 HC). This limited sample size reduces the statistical power of the findings and impacts on the model's generalizability.

Furthermore, the presence of medicated PD patients introduced a significant confounding variable. As seen in the error analysis, drug effects (e.g., levodopa) were observed to "normalize" EEG patterns, leading to misclassifications.

3.2 Future Work

Based on these limitations, future work should prioritize several key directions:

1. **Validation on Larger Datasets:** The models must be validated on larger, multi-center, and more diverse datasets to ensure robustness and generalizability.
2. **Investigating Medication Effects:** A promising avenue is to specifically investigate the impact of medication, perhaps by developing a multi-class model to distinguish between HC, medicated PD, and unmedicated PD.
3. **System Improvements:** System enhancements should focus on advancing the web application prototype's capabilities, such as integrating real-time EEG data streaming and exploring alternative XAI methods (e.g., attention map visualization) for deeper physiological insights.

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IX. Appendices