AlzDetect: AI Analysis of EEG Signatures for Alzheimer's Diagnosis and Prognosis

REVOLUTIONIZING ALZHEIMER'S DIAGNOSIS WITH ACCESSIBLE AI-DRIVEN SOLUTIONS

SR-CBI-0162

Background	Goals
Alzheimer's disease affects 55 million people worldwide, with cases expected to double by 2050, placing a growing burden on healthcare systems. Traditional diagnostic tools, such as MRI and PET scans, are expensive, invasive, and often inaccessible, leading to delays in diagnosis and missed opportunities for early intervention. This highlights the urgent need for affordable, non-invasive solutions to enable widespread screening and timely treatment.	Developing a low-cost, non-invasive EEG-based system powered by AI offers a promising solution for the early detection and monitoring of cognitive decline. EEG technology provides a safe and accessible way to measure brain activity, while AI algorithms can analyze complex patterns to identify early signs of Alzheimer's disease with high accuracy. This approach has the potential to make early screening more widely available, enabling timely intervention and better management of cognitive health.

Problem Statement

Alzheimer’s disease (AD) is a progressive neurodegenerative disorder that can begin to affect the brain decades before any noticeable symptoms appear. These early changes, which include subtle disruptions in neural activity and connectivity, remain largely undetected using conventional diagnostic methods.

- The primary tools for diagnosing AD, such as magnetic resonance imaging (MRI) and positron emission tomography (PET) scans, are expensive, invasive, and not widely accessible—especially in resource-limited settings. These imaging techniques require specialized equipment and trained professionals, leading to high costs and long wait times for patients. Furthermore, the invasive nature of some diagnostic procedures, such as lumbar punctures for cerebrospinal fluid analysis, can deter individuals from seeking early screening. This lack of affordability and accessibility limits early diagnosis and intervention, leaving many individuals without the opportunity for preventative measures that could slow the disease's progression.
- The existing diagnostic approach predominantly focuses on symptomatic evaluation, meaning that diagnosis typically occurs only after significant cognitive impairment has already taken place. This symptomatic approach fails to identify the disease in its preclinical stages when interventions might be most effective.
- The absence of widespread, affordable screening tools leaves a critical gap in the healthcare system, preventing early detection strategies that could extend cognitive function and quality of life for patients.

RESEARCH QUESTION AND OBJECTIVES

Can custom-built EEG technology, combined with advanced AI algorithms, be used to detect early cognitive decline and predict Alzheimer's disease?

1. Design and build a lightweight, user-friendly, and affordable EEG headset that ensures reliable brainwave data collection in non-clinical settings such as homes and community healthcare centers. The device will incorporate high-quality signal acquisition components, noise reduction techniques, and wireless connectivity for seamless data transmission and accessibility.
2. Implement and optimize machine learning algorithms, including Multi-Layer Perceptron (MLP), Bayesian Logistic Regression Model, and Attention Transformers, to analyze EEG data and identify patterns associated with Alzheimer's disease. These models will leverage biological markers supported by scientific studies and interpret complex EEG features through Attention Transformers to enhance diagnostic accuracy.
3. Employ rigorous model training techniques, such as hyperparameter tuning, feature selection, and multiple cross-validation methods, to prevent overfitting and ensure the model generalizes well to unseen data. Techniques such as k-fold cross-validation and stratified sampling will be used to assess and improve the robustness of the system's predictive performance.
4. Develop a system that enables continuous, real-time EEG monitoring and prediction, allowing users to track cognitive health trends over time that will also incorporate cloud-based infrastructure to facilitate scalable data storage and processing.

AI and Machine Learning Models

Multi-Layer Perceptron

This model is a deep learning approach used to analyze EEG data and detect Alzheimer's disease by identifying complex, non-linear relationships within brainwave features. It processes various extracted features such as power spectral densities across frequency bands, entropy measures, and complexity metrics. The model consists of multiple layers of interconnected neurons that apply activation functions to uncover patterns in the data. During training, it adjusts weights using backpropagation and optimization techniques like gradient descent. The final output layer provides a probability score, indicating the likelihood of Alzheimer's presence. The MLP model's strength lies in its ability to accurately classify EEG signals by leveraging deep feature representations, making it a powerful tool for early detection.

Bayesian Logistic Regression

This machine learning model offers an interpretable and probabilistic method for predicting Alzheimer's disease by assigning weights to each EEG feature based on its significance in the classification process. It applies a logistic function to the weighted features, producing a probability score for Alzheimer's detection. The Bayesian approach introduces prior knowledge into the model, allowing it to adapt as more data is added and providing an estimate of uncertainty in predictions. This interpretability makes BLR especially valuable for medical applications where understanding the influence of individual features is crucial. Additionally, its regularization properties help prevent overfitting, making it a reliable complement to the MLP by offering explainable insights into the decision-making process.

Attention Transformer

The transformer plays a crucial role in enhancing feature extraction from EEG data by identifying significant temporal dependencies across brain signals. Using a self-attention mechanism, it analyzes relationships between different time segments of the EEG recordings, assigning attention scores to highlight the most relevant patterns. Unlike traditional feature extraction methods, which rely on predefined statistical measures, the Transformer autonomously identifies meaningful characteristics indicative of Alzheimer's disease. The extracted features from the Transformer model provide a more refined and informative input for the classification models, improving their overall accuracy and robustness. Its ability to capture long-term dependencies in brainwave activity makes it an essential component in the system.

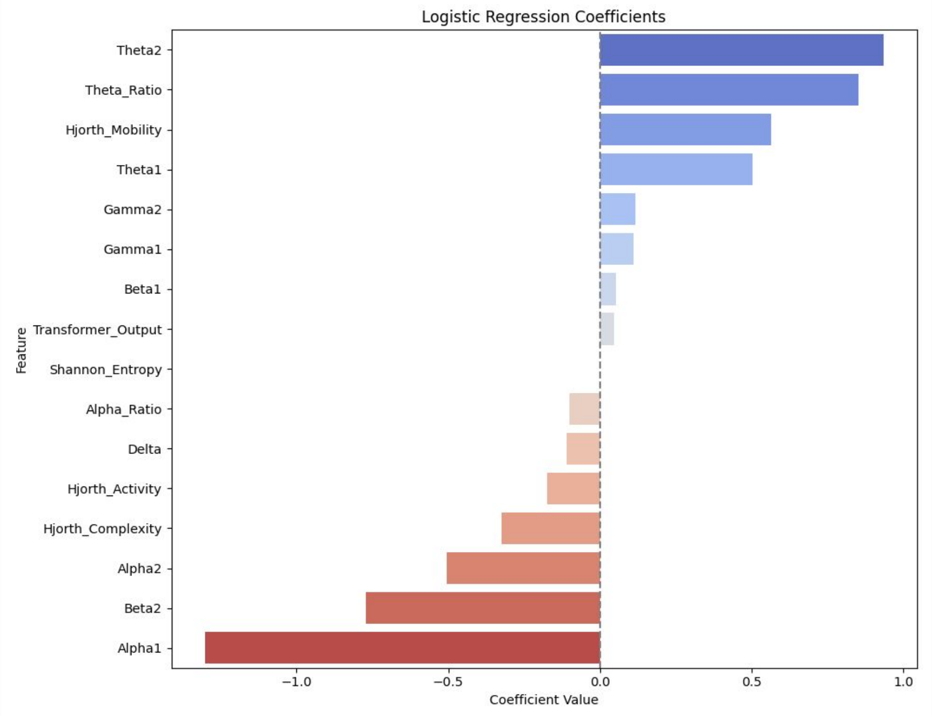
Methods and Data Collection

- This project utilized two publicly available EEG datasets, ds004504 and ds003800, to train and evaluate machine learning models for Alzheimer's detection. The datasets contain EEG recordings from individuals diagnosed with Alzheimer's Disease (AD) and healthy controls, with standardized electrode placements following the 10-20 international EEG system. Key channels such as Fp1, Fp2, C3, and C4 were analyzed, and data sampling rates ranged from 256 Hz to 500 Hz. To prepare the data for analysis, preprocessing steps included band-pass filtering (0.5–100 Hz) to isolate relevant frequency bands, Independent Component Analysis (ICA) to remove artifacts like muscle movements and eye blinks, and resampling to a consistent rate of 256 Hz. Additionally, the EEG recordings were segmented into 1-second epochs with 50% overlap to facilitate efficient feature extraction and model training.
- EEG features play a crucial role in understanding brain activity and detecting cognitive decline associated with Alzheimer's disease. **Delta waves (0.5–4 Hz)** are linked to deep sleep and unconscious brain activity, often associated with cognitive decline in Alzheimer's patients. **Theta1 (4–6 Hz)** is related to drowsiness and early-stage cognitive processes, playing a role in memory consolidation and early impairment detection, while **Theta2 (6–8 Hz)** represents deeper cognitive engagement, with increased activity potentially indicating cognitive disruptions. **Alpha1 (8–10 Hz)** and **Alpha2 (10–12 Hz)** waves reflect relaxation and alertness, with reductions in power often linked to cognitive impairment and memory deficits. The **Beta1 (12–20 Hz)** and **Beta2 (20–30 Hz)** bands are associated with active thinking, concentration, and high-level cognitive functions, where reduced activity may signal slowed cognitive processing or dysfunction. **Gamma1 (30–50 Hz)** and **Gamma2 (50–100 Hz)** waves are linked to attention, memory, and fast cognitive processing, with alterations often observed in neurodegenerative conditions. Additionally, ratio-based features such as the **Theta Ratio**, which compares theta power to other frequency bands, can be used to detect cognitive slowing, while the **Alpha Ratio** assesses cognitive alertness by measuring the proportion of alpha wave activity. Other key EEG features include **Hjorth parameters**, with **Hjorth Activity** measuring the signal's variance to represent overall power, **Hjorth Mobility** describing frequency dynamics to indicate signal variability, and **Hjorth Complexity**, which provides insights into the complexity of brainwave patterns. Lastly, **Shannon Entropy** quantifies the randomness or disorder in EEG signals, where lower entropy values suggest more predictable and less complex brain activity, potentially indicating neurological decline.
- To enhance feature representation, an Attention Transformer model was employed to capture complex temporal dependencies within the EEG data, providing additional high-level features for model input. Machine learning models, including Multi-Layer Perceptron (MLP) and Bayesian Logistic Regression (BLR), were trained using a combination of traditional and Transformer-extracted features. Cross-validation techniques such as k-fold cross-validation were implemented to prevent overfitting and ensure the models' ability to generalize effectively across different EEG recordings.
- The project enables real-time EEG data processing using a custom-built system with an **OpenBCI Ganglion board** and four dry electrodes placed according to the 10-20 EEG system. The board transmits brainwave signals via Bluetooth to a local device running the **board_client.py** script, which handles data acquisition, preprocessing, and transmission to the server in small chunks to maintain real-time performance. On the processing side, the **server.py** script receives the EEG data, applies preprocessing and feature extraction, and runs trained machine learning models—MLP and BLR—to predict the likelihood of Alzheimer's disease. Once a 20-second data window is collected, features such as power spectral densities, entropy, and transformer-derived embeddings are extracted. The system outputs JSON-formatted predictions, including confidence scores and feature values for further analysis

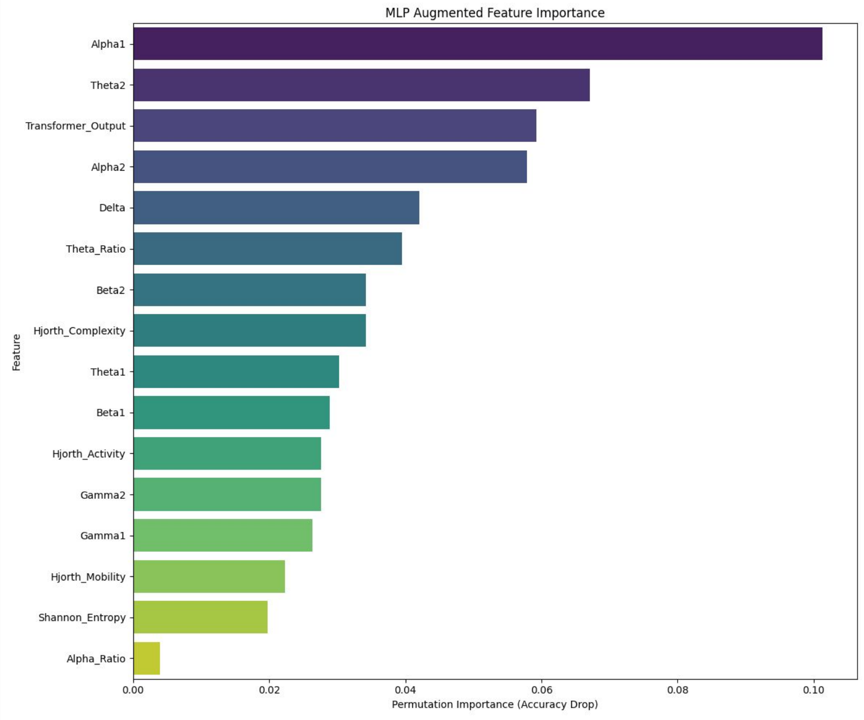
Feature Importance and Significance

The logistic regression coefficient plot reveals that **Theta 2, Theta Ratio, and Hjorth Mobility** have the most significant positive contributions to Alzheimer's detection, indicating their strong association with cognitive decline. Conversely, features such as **Alpha 1 and Beta 2** contribute negatively, suggesting they may be more characteristic of healthy brain activity. However, the model chose not to utilize the transformer-derived features..

BLR Feature Importance



MLP Feature Importance



The MLP feature importance plot, based on permutation importance, further validates the significance of specific frequency bands and complexity measures. Features related to **Delta, Theta, and Alpha power** were found to play a critical role in distinguishing Alzheimer's from control cases. Additionally, the inclusion of Transformer-derived features, labeled as **Transformer_Output**, provided added value by capturing intricate patterns.

Control Mean/Alzheimer Mean: The average feature values for control and Alzheimer's groups, indicating potential differences in brainwave activity. **Control Std/Alzheimer Std:** The standard deviation, showing the variability of the feature within each group.

T-statistic: Measures the degree of difference between the two groups; higher values indicate greater separation. **P-value**: Indicates the statistical significance of the feature's difference; lower values suggest strong evidence against the null hypothesis (i.e., the feature is relevant for distinguishing between groups).

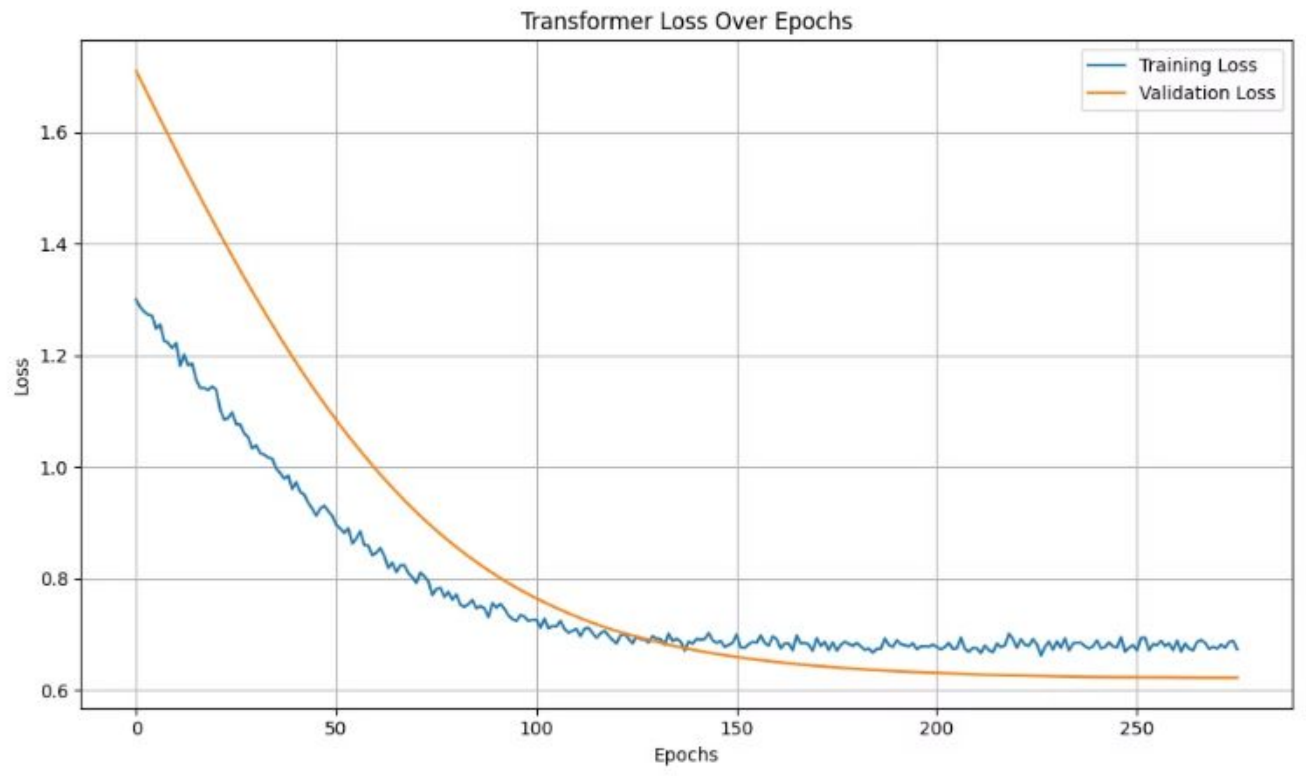
Below are the most significant features.

Feature	Control Mean	Control Std	Alzheimer's Mean	Alzheimer's Std	T-statistic	P-Value
Theta_Ratio	0.112	0.0236	0.173	0.102	-3.886231	0.000282
Alpha_2	0.0	0.0	0.0	0.0	3.851396	0.000369
Hjorth_Activity	0.0	0.0	0.0	0.0	3.493524	0.000916
Delta	0.0	0.0	0.0	0.0	3.263033	0.002008
Alpha_1	0.0	0.0	0.0	0.0	3.325452	0.002223
Hjorth_Mobility	0.129	0.0141	0.172	0.0871	-3.215901	0.002284
Shannon_Entropy	7.03	0.129	6.86	0.36	2.947424	0.004493
Beta1	0.0	0.0	0.0	0.0	2.355998	0.023524
Hjorth_Complexity	5e-06	1e-06	5e-06	2e-06	2.193272	0.032075
Beta_2	0.0	0.0	0.0	0.0	1.563313	0.125362

Results—Transformer

The Transformer model was evaluated using loss metrics across multiple training epochs to assess its learning progress and generalization capability. The loss curve demonstrates a steady decline in both training and validation loss, indicating effective learning and convergence over time. While there is a slight gap between the training and validation loss, it remains within an acceptable range, suggesting that the model is capturing meaningful patterns without significant overfitting. Regularization techniques such as dropout and weight decay were applied to enhance generalization, ensuring the model can perform well on unseen data. The Transformer's ability to process raw EEG signals holistically allows it to capture complex temporal dependencies that traditional methods might miss. The Transformer model outputs numerical feature embeddings, such as `[0.56, 1.23, -0.78, ...]`, which represent compressed, high-dimensional representations of EEG signals. These values encode critical information about brainwave patterns, such as frequency changes and temporal correlations, that may indicate cognitive decline associated with Alzheimer's. When combined with traditional EEG features, such as power spectral densities and entropy measures, these Transformer-derived features enhance the performance of the classification models. The Multi-Layer Perceptron (MLP) and Bayesian Logistic Regression (BLR) models utilize these embeddings to make more informed predictions, improving accuracy and robustness in distinguishing Alzheimer's cases from healthy controls. The integration of Transformer-based features offers a more comprehensive approach to EEG analysis, leveraging both deep learning insights and established statistical measures.

Validation and Training Loss vs. Epochs Analyzed



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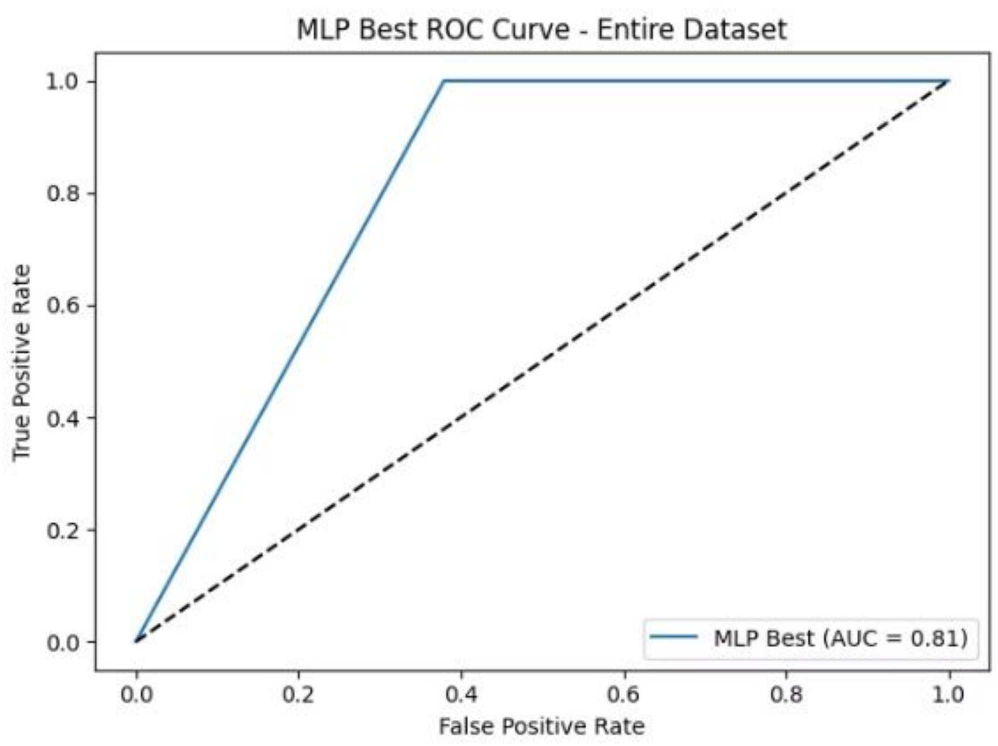
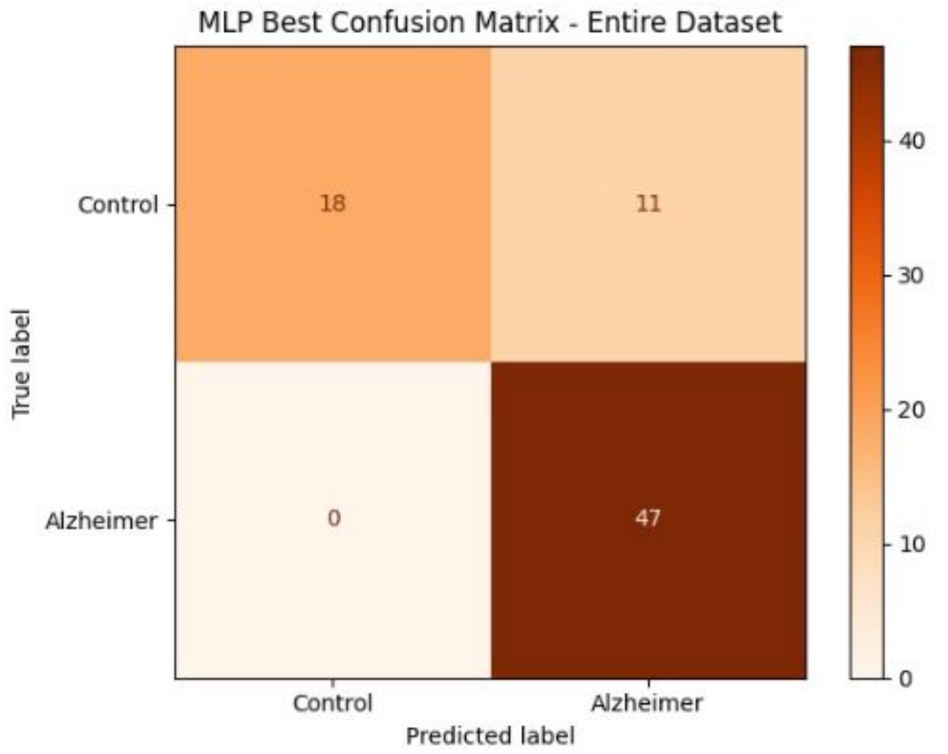
Results—Multi-Layer Perceptron (MLP)



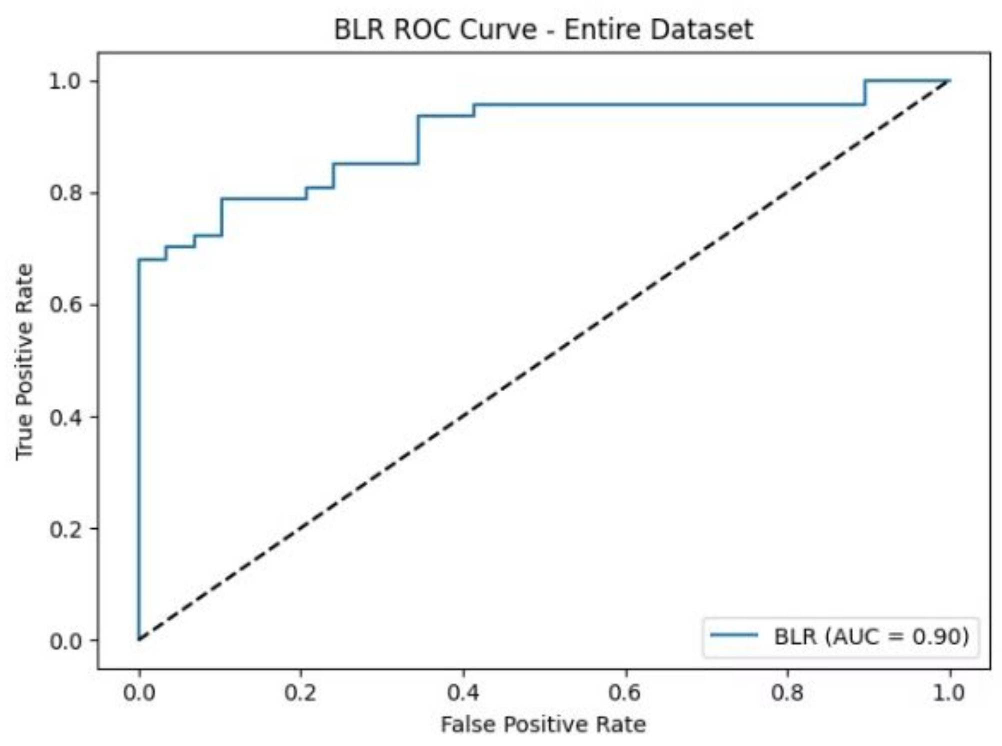


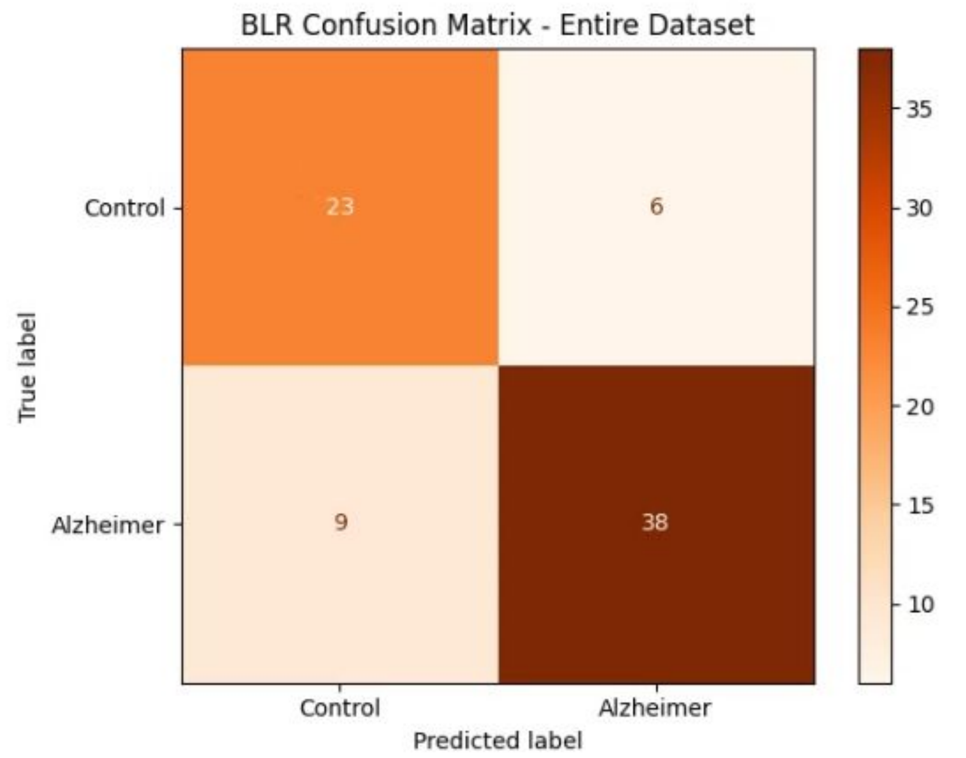
The MLP (Multi-Layer Perceptron) model demonstrated impressive capabilities in accurately identifying Alzheimer's disease from the EEG data.

True Positives	47	Alzheimer's cases correctly identified
True Negatives	18	Control cases correctly classified
False Positives	11	Controls misclassified as Alzheimer's
False Negatives	0	Alzheimer's misclassified as Control

With an impressive accuracy of **85.37%**, the MLP model demonstrated a remarkable ability to detect Alzheimer's disease from the EEG data. This breakthrough paves the way for earlier, more affordable screening - a crucial step in combating this silent epidemic.

Results—Bayesian Logistic Regression (BLR)





The BLR (Bayesian Logistic Regression) model demonstrated impressive capabilities in confirming diagnoses from the EEG data. Let's dive into the key performance metrics:

True Positives	38	Alzheimer's cases correctly identified
True Negatives	23	Control cases correctly classified
False Positives	6	Controls misclassified as Alzheimer's
False Negatives	9	Alzheimer's misclassified as Control

With an impressive accuracy of **82.92%**, the BLR model demonstrates a more balanced performance by reducing false positives but with a trade-off for sensitivity, suggesting that the BLR model offers a more conservative approach for confirming diagnoses.

Results Analysis

- The Receiver Operating Characteristic (ROC) curves and AUC scores provide a comprehensive evaluation of the models' ability to distinguish between Alzheimer's and control groups. The MLP model achieved an AUC of 0.81, indicating good discriminatory performance, while the BLR model achieved a higher AUC of 0.90, suggesting stronger overall classification capability. The higher AUC score for the BLR model reflects its ability to reduce false positives, making it more precise in correctly identifying control cases. However, in the context of Alzheimer's detection, recall is often the most critical metric, as missing a true Alzheimer's case (false negative) could delay intervention and treatment.
- The recall (sensitivity) metric highlights this distinction. The MLP model achieved 100% recall, successfully identifying all Alzheimer's cases, ensuring no potential patients were overlooked. In contrast, the BLR model, with a recall of 80.85%, missed some true Alzheimer's cases. Although the MLP model generates more false positives (81.03% precision compared to BLR’s 86.36%), the consequence of a false positive—further diagnostic testing—is far less severe than missing an actual case, which could result in delayed medical intervention. Despite the BLR model's higher precision, the MLP model’s ability to detect all potential cases makes it a valuable tool for screening purposes.
- The F1-score, which provides a balance between precision and recall, further illustrates these differences. The MLP model achieved an F1-score of 89.49%, surpassing the BLR model's score of 83.50%, indicating its stronger performance when considering both detection accuracy and false positive reduction. The BLR model presents a conservative approach with fewer false positives, while the MLP model’s superior recall and balanced F1-score indicate its effectiveness in capturing potential Alzheimer's cases without missing critical diagnoses.

Conclusion

The results of this study support the hypothesis that EEG data, when analyzed using machine learning models, can effectively detect early-stage Alzheimer's disease. The first part of the hypothesis was validated, as the machine learning models successfully distinguished between Alzheimer's and control groups with high accuracy. Specifically, the Multi-Layer Perceptron (MLP) model achieved 100% recall, ensuring that no Alzheimer's cases were missed, while the Bayesian Logistic Regression (BLR) model demonstrated higher precision, effectively minimizing false positives. This confirms that EEG signals contain critical biomarkers that can be leveraged for Alzheimer's detection. The inclusion of deep learning-based Transformer features further enhanced the models' performance by capturing complex temporal dependencies that traditional methods might overlook.

The second part of the hypothesis, which suggested that feature-based analysis of EEG data could provide meaningful insights into cognitive decline, was also supported by the results. Statistically significant features such as **Theta Ratio, Hjorth Mobility, and Shannon Entropy** exhibited clear distinctions between Alzheimer's and control groups, reinforcing their potential as reliable biomarkers. The analysis revealed that Alzheimer’s patients exhibited significant deviations in Theta activity and signal complexity compared to healthy individuals, providing critical insights into the progression of cognitive impairment. These findings affirm that EEG-based feature extraction, combined with machine learning, offers a robust approach to early Alzheimer's detection.

The research question was answered, demonstrating that EEG-based machine learning models can serve as an effective tool for early Alzheimer's diagnosis, with the MLP model proving most suitable for applications where early detection is prioritized. The results are significant in the field of neurodegenerative disease research, as they provide a non-invasive, affordable, and scalable solution for monitoring cognitive decline. This work has potential applications in clinical and home-based monitoring systems, allowing for timely intervention and improved patient outcomes. Additionally, the feature importance analysis can inform future research efforts in identifying new EEG biomarkers for Alzheimer's and related conditions, potentially leading to the development of more targeted diagnostic and therapeutic approaches.

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