Explainable AI-Driven Clinical Support System for Early Alzheimer's Detection Using Handwriting Biomarkers.

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Abstract - *Early detection of Alzheimer's disease (AD) is critical for improving patient outcomes, yet traditional diagnostic methods are often invasive and costly. This paper proposes an intelligent clinical decision support system (CDSS) that leverages machine learning and Explainable Artificial Intelligence (XAI) to detect early signs of AD through handwriting-based biomarkers. Utilizing the DARWIN dataset, the system processes high-dimensional kinematic signals to identify subtle cognitive and motor impairments. We implemented optimized classification models, including XG Boost and Random Forest, to distinguish between healthy individuals and AD patients. To address the black-box nature of these models, SHAP (Shapley Additive explanations) was integrated to provide clinicians with transparent, feature-level insights into each diagnosis. The result demonstrates high predictive accuracy and suggests that incorporating transparency into AI-driven diagnostics can significantly enhance clinical trust and facilitate early medical intervention.*

Key Words: alzheimer 's disease, Explainable AI (XAI), SHAP, Machine Learning, Clinical Decision Support Systems, Handwriting Analysis, DARWIN Dataset.

1. INTRODUCTION

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder that represents a significant global health challenge [1],[11], affecting millions of individuals and their families. Early diagnosis is paramount, as it allows for timely therapeutic intervention that can slow cognitive decline and improve the quality of life. Traditional diagnostic procedures, such as Magnetic Resonance Imaging (MRI) and cerebrospinal fluid analysis, while effective, are often expensive, invasive, and inaccessible in many clinical settings [6]. Consequently, there is a growing need for non-invasive, cost-effective, and reliable screening tools.

Recent research has identified handwriting as a potent functional biomarker for early cognitive impairment [9], [15]. Subtle changes in handwriting kinematics such as pen pressure, stroke velocity, and pauses can reflect underlying neurological shifts long before clinical symptoms become overt. While Machine Learning (ML) models have demonstrated high efficacy in detecting these patterns using datasets like DARWIN, their adoption in clinical practice is hindered by the black-box nature of advanced algorithms. Clinicians require not only a prediction but also an understandable rationale behind it to ensure patient safety and ethical accountability.

This study addresses these challenges by developing an intelligent web-based clinical decision support system. The proposed framework integrates optimized ML classifiers with Explainable Artificial Intelligence (XAI) techniques, specifically SHAP (Shapley Additive explanations). By providing transparent visualizations of how specific handwriting features contribute to a diagnosis, this system aims to bridge the gap between complex computational models and practical clinical application, fostering trust in AI-driven diagnostic tools.

Contributions to this work include:

1) Integration of Machine Learning and Explainable AI (SHAP) for Alzheimer's detection.
2) Use of handwriting biomarkers as a non-invasive diagnostic approach.
3) Development of a web-based clinical decision support system.
4) Providing interpretable predictions to enhance clinical trust and support medical decision-making.

2. RELATED WORK

Previous research has extensively explored the use of digital handwriting as a diagnostic tool for neurological disorders. Several studies have utilized the DARWIN dataset to train classifiers like Support Vector Machines (SVM) and Random Forests, achieving impressive accuracy levels [5], [7], [12]. However, most existing works focus primarily on predictive performance without addressing the interpretability of the results.

Recent trends in medical AI emphasize the importance of Explainable AI (XAI) to ensure clinical accountability. While some researchers have begun applying local explanations methods to medical imaging, their application in handwriting-based Alzheimer's detection remains limited [2], [13]. Our work contributes to this field by not only achieving high diagnostic accuracy but also providing a transparent framework that ranks and visualizes the influence of kinematic handwriting features on each individual prediction.

3. METHODOLOGY

The proposed methodology follows a structured pipeline designed to transform raw kinematic handwriting data into interpretable diagnostic insights. The process is divided into data acquisition, feature engineering, model development, and the integration of explainability layers.

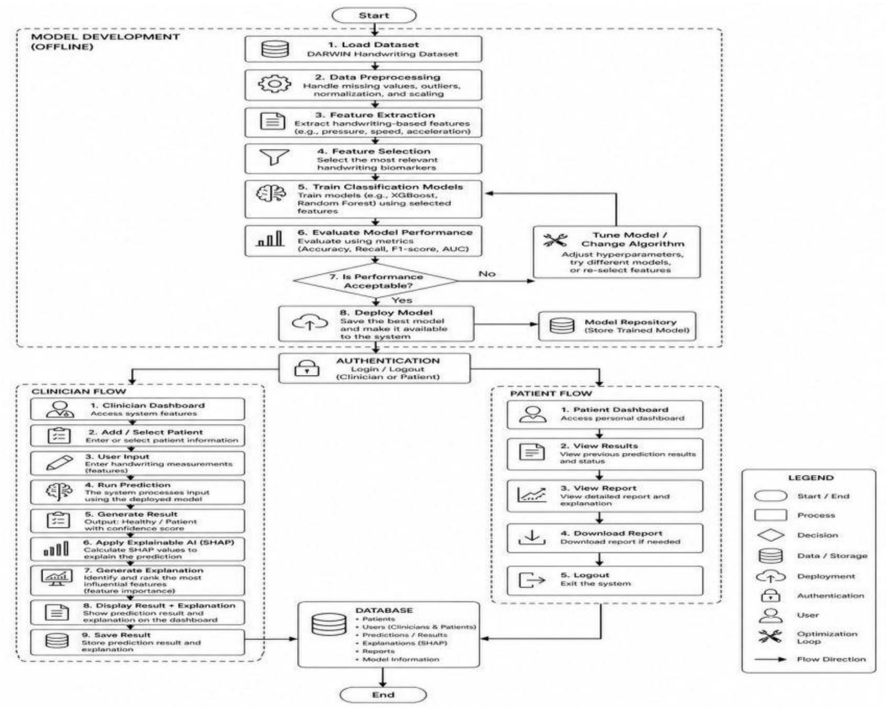

Fig - 1: Overall System Architecture Illustrating the Offline Model Development Phase and The Online Real-Time Prediction and Explanation Workflow.

3.1 Data Source and preprocessing

The system utilizes the DARWIN dataset, which contains 13,000 handwriting features collected from 167 participants (healthy and Alzheimer's patients) [3]. To ensure computational efficiency, we performed data cleaning and normalization. High-dimensional kinematic features, such as velocity, pressure, and stroke duration, were standardized to improve the convergence of the machine learning algorithms.

3.2 Feature Selection

Given the high dimensionality of the dataset, feature selection was performed to identify the most significant biomarkers. We focused on features that capture motor-cognitive coordination, such as 'Pen Pressure', 'Total Time', and 'Writing Velocity'. This reduction not only enhances model performance but also aligns with clinical requirements for focusing on the most relevant medical indicators.

3.3 Classification models

We implemented and compared several supervised learning algorithms to determine the most effective classifier for AD detection. These include:

1) Random Forest (RF)[10]: Utilized for its robustness and ability to handle non-linear relationships.
2) XGBoost [11]: Employed for its high performance and efficiency in handling tabular data through gradient boosting.
3) Logistic Regression: Used as a baseline model for comparative analysis.

3.4 Explain ability with SHAP

To bridge the gap between AI and clinical trust, we integrated SHAP (Shapley Additive explanations). SHAP provides a mathematical framework to explain individual predictions by calculating the contribution of each feature [16]. The system generates summary plots and force plots, allowing clinicians to see exactly which handwriting patterns (e.g., decreased pressure or increased pauses) led to a specific 'Patient' or 'Healthy' classification.

4. RESULTS AND DISCUSSION

The performance of the proposed diagnostic system was evaluated using the DARWIN dataset. The model demonstrated significant predictive capability, as detailed in the following subsections.

4.1 Feature Importance Analysis

The model identified the most discriminative handwriting biomarkers from total 450 features. Based on the importance scores, the top five features were:

1) total_time23 (Importance: 0.0567).
2) paper_time23 (Importance: 0.0299).
3) total_time17 (Importance: 0.0273).
4) air_time15 (Importance: 0.0261).
5) air_time23 (Importance: 0.0249).

These results, derived from the automated feature selection process, highlight that temporal handwriting dynamics specifically total duration and air movement are primary indicators for early Alzheimer's detection.

4.2 Classification Performance

The overall accuracy of the final model reached 71%. The detailed performance metrics, including precision, recall, and F1-score for both healthy and patient classes, are summarized in Table I.

Table 1- Performance Metrics Evaluation.

Metric	Class: Healthy	Class: Patient
Precision	0.88	0.67
Recall	0.50	0.89
F1-Score	0.64	0.76
Accuracy	71%	

The high recall for the 'Patient' class (0.89) is particularly important in clinical settings, as it indicates the model's ability to correctly identify the majority of individuals with early signs of the disease, minimizing false negatives.

Our accuracy results are consistent with recent finding in the field [5], [9], while providing superior interpretability.

5. CONCLUSIONS

This study presented an intelligent, explainable clinical decision support system for the early detection of Alzheimer's disease using handwriting biomarkers. By integrating machine learning with SHAP-based explanations, the system achieves a balance between predictive accuracy and clinical transparency. Our findings emphasize that digital handwriting kinematics offer a non-invasive and cost-effective screening tool. Future work will focus on integrating deep learning models and smart pen technologies to further refine diagnostic precision in real-world clinical environments.

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