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Handwriting Analysis for Early Detection of Alzheimer's Using Machine Learning

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Abstract— Alzheimer's Disease (AD) is a progressive disorder that slowly affects memory, reasoning, and motor abilities. Detecting the condition early is crucial, but commonly used diagnostic procedures—such as brain scans and fluid analysis—are costly, invasive, and often unable to capture the earliest signs of decline. Handwriting, which relies on coordinated cognitive and motor processes, has emerged as a promising non-invasive indicator of early impairment. This study reviews current handwriting-based diagnostic approaches and examines how features such as pressure variation, stroke behavior, tremor patterns, and timing inconsistencies reveal subtle symptoms of AD. A comparison of traditional analytical methods and modern machine-learning techniques is presented, along with an evaluation of their strengths, limitations, and feature-extraction strategies. The review also identifies research gaps and suggests the integration of handwriting data with additional digital biomarkers to support more effective, scalable screening tools for early Alzheimer's detection.

I. INTRODUCTION

Alzheimer's Disease (AD) is a degenerative neurological condition that primarily affects older adults and is recognized as the most common source of dementia. Individuals with AD experience a gradual decline in memory, decision-making ability, behavior, and fine motor coordination, which eventually interferes with daily living. Reports from global health organizations, including the World Health Organization, predict a rapid increase in the number of people affected by AD in the coming decades, placing additional strain on medical systems and caregivers. Typical diagnostic procedures for AD include neuroimaging scans, cognitive assessments, and laboratory tests. Although these methods play a vital role in diagnosis, they are often expensive, time-consuming, and invasive, making them unsuitable for widespread early-stage screening.

These limitations have encouraged the search for alternative, accessible, and non-invasive assessment methods. One promising direction is the study of handwriting behavior. Writing requires simultaneous coordination of cognitive processing, visual perception, and motor control. Early deterioration in these functions can subtly influence a person's handwriting long before noticeable symptoms emerge. Researchers have observed variations in writing speed, spacing, pressure application, and stroke smoothness among individuals developing AD.

With the availability of digital writing devices such as smart pens and stylus-enabled tablets, these subtle variations can be captured with high precision. When combined with advancements in machine learning, handwriting data can be analyzed to differentiate between healthy individuals and those showing signs of early cognitive decline. This makes handwriting analysis a compelling candidate for accessible early detection of Alzheimer's Disease.

II. LITERATURE SURVEY

This section provides an overview of existing research related to handwriting analysis, machine learning applications, and neurodegenerative disease identification.

Belic et al. [1] reviewed how artificial intelligence techniques are used to support the diagnosis of Parkinson's Disease. While the work does not focus on Alzheimer's directly, the methods discussed—such as analyzing motor patterns and behavioral signals—can be adapted to handwriting-based Alzheimer's detection.

Scott, Carter, and Coiera [2] introduced a structured checklist to help clinicians evaluate machine-learning tools in healthcare. Their framework highlights essential considerations such as data quality, transparency, and clinical relevance. These principles are useful when assessing the reliability of handwriting-based diagnostic systems.

Precup et al. [3] explored fuzzy-logic models for interpreting myoelectric signals to control prosthetic hands. Their approach demonstrates how adaptive computational models can effectively interpret complex human-generated signals, offering insights applicable to handwriting data analysis for neurodegenerative disorders.

Vessio [4] emphasized the significance of dynamic handwriting features—including stroke velocity, pressure variation, and motion dynamics—in identifying neurological irregularities. This work supports the idea that analyzing writing movements can provide meaningful indicators of early cognitive decline.

De Stefano et al. [5] surveyed handwriting-based diagnostic methods for both Parkinson's and Alzheimer's. Their review covered a wide range of handwriting characteristics and outlined key challenges, such as variability in individual writing styles and the absence of standardized writing tasks.

Singh and Yadav [6] examined how various neurological conditions affect handwriting quality. They reported common changes such as tremors, spacing disturbances, and misalignment, which often appear before noticeable cognitive symptoms.

Impedovo et al. [7] proposed a structured handwriting assessment protocol specifically designed to identify early dementia indicators. The study demonstrated how machine-learning models can analyze writing patterns to distinguish healthy individuals from those experiencing cognitive decline.

Impedovo, Pirlo, and Vessio [8] investigated dynamic handwriting patterns to support early detection of Parkinson's Disease. Although focused on PD, their findings reinforce the value of analyzing fine motor behavior for earlyneurological screening. Cavallo et al. [9] used sensor-based motor assessment techniques to detect early motor irregularities. Their results indicate that subtle movement abnormalities—similar to those reflected in handwriting—can be identified before clinical symptoms arise. Myszczynska et al. [10] reviewed machine learning approaches for diagnosing multiple neurodegenerative diseases. Their analysis highlights the potential of AI to detect early behavioral abnormalities, supporting the use of handwriting as a digital biomarker.

Prasad et al. [11] specifically investigated handwriting features—both temporal and spatial—for Alzheimer's detection using machine- learning classifiers. Their models achieved strong classification performance, reinforcing handwriting's diagnostic value.Li et al. [12] introduced a hybrid deep-learning architecture that captures spatial and temporal handwriting variations. Their system produced accurate and clinically interpretable results, demonstrating the advantage of combining neural-network approaches with handwriting data.

Cilia et al. [13] proposed converting online handwriting recordings into synthetic images for analysis through deep-transfer learning. Their method maintained temporal and spatial details and achieved promising diagnostic accuracy.

Dao et al. [14] developed a model based on one-dimensional convolutional networks to analyze raw handwriting time-series signals. Their results show that these temporal patterns alone can effectivelydifferentiate early Alzheimer's samples.

Mitra and Rehman [15] evaluated a broad set of handwriting features using various machine-learning algorithms. Their emphasis on feature selection helped improve accuracy while reducing computational load.

Khan et al. [16] explored offline handwriting images using deep- learning methods, demonstrating that visual handwriting deterioration can serve as a useful diagnostic indicator even without temporal data.Subha et al. [17] introduced a hybrid handwriting-based detection system using Particle Swarm Optimization to improve classifier performance, showing enhanced accuracy in Alzheimer's prediction.

III. PROPOSED METHODOLOGY

This section allow us to understand the flow of operation of the system and what each block is responsible for.

1) Data Preparation

Handwriting images are collected, resized to 256×256, checked for RGB/grayscale, and normalized.

2) Augmentation

The training set is expanded using rotation, shifting, zoom, shear, brightness change, and flips.

3) Model Development

MobileNetV2 or a VGG-style CNN is selected based on image type, with BatchNorm and Dropout to improve performance.

4) Training & Evaluation

The model is trained with Adam and class weights, using callbacks; accuracy, loss, and classification metrics are computed to choose the best model.

5) Deployment & Prediction

The final model is deployed in a Flask app that processes uploads, generates Grad-CAM explanations, provides recommendations, and stores results in a database.

6) Regularization Techniques

Batch normalization and Dropout layers are added to improve generalization and reduce overfitting.

7) Model Training

The model is trained using the Adam optimizer with appropriate learning rates and class weights.

8) Performance Evaluation

Model performance is evaluated using accuracy, loss, precision, recall, F1-score, and confusion matrix.

9) Explainability Module

GRAD -CAM is used to visualize important regions of handwriting
influencing the model's prediction.

10) Deployment and Prediction

The final model is deployed in a Flask application to process uploads, generate predictions, and store results.

Overall, the proposed methodology ensures a structured and efficient pipeline, starting from data preprocessing to real-time deployment. Each stage is carefully designed to enhance model accuracy, robustness, and interpretability.

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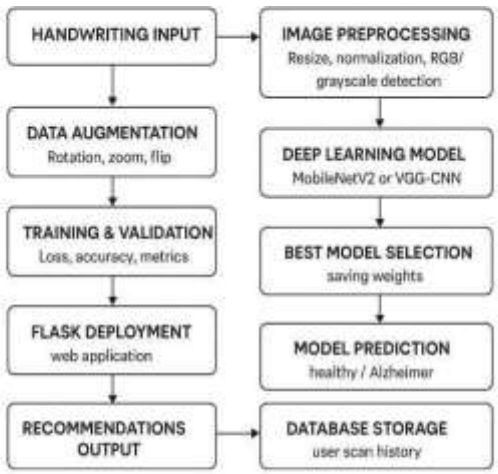

Fig-1

The figure 1 shows the workflow of the handwriting-based Alzheimer's detection system. Handwriting images are first given as input and preprocessed by resizing, normalization, and RGB/grayscale detection. Data augmentation techniques such as rotation, zoom, and flip are applied to improve learning. A deep learning model like MobileNetV2 or VGG-CNN is then trained and validated, after which the best model is selected and deployed using a Flask web application. The system predicts whether the handwriting is healthy or indicative of Alzheimer's, provides recommendations, and stores user scan results in a database for future reference

IV. RESULT AND ANALYSIS

The proposed handwriting-based Alzheimer's detection system demonstrates effective performance during training and evaluation. The classification accuracy increases consistently across training epochs, while the loss values decrease steadily, indicating stable convergence of the model. Performance evaluation using precision, recall, and F1-score shows that the model reliably distinguishes between Healthy and Alzheimer handwriting samples. The confusion matrix analysis confirms a high rate of correct classification with only a small number of misclassified instances.

To enhance interpretability, Grad-CAM visualizations are employed to identify the regions of handwriting that influence the model's decisions. The generated heatmaps highlight meaningful features such as stroke irregularities and spatial distortions, validating that the model focuses on relevant handwriting patterns. Furthermore, the Flask-based web application successfully processes user uploads, generates predictions along with confidence scores, produces Grad-CAM explanations, and stores results in the database without performance degradation. These results indicate that the proposed system is reliable, interpretable, and suitable for practical early screening applications

1. .Model Performance

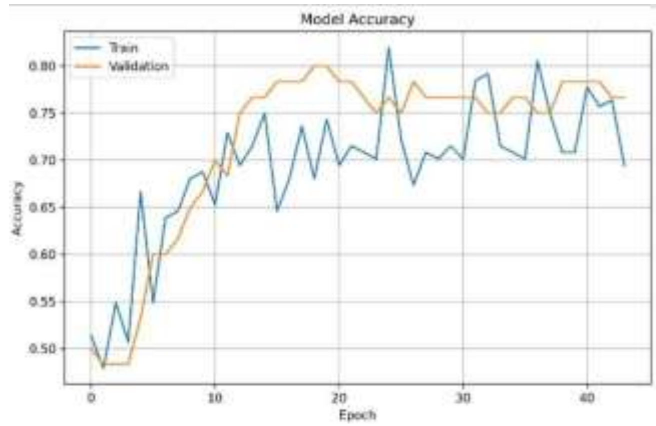

Fig-2

The figure 2 shows the variation of training and validation accuracy across epochs. Training accuracy increases gradually with minor fluctuations, indicating continuous learning of handwriting features. Validation accuracy also improves steadily and stabilizes after initial epochs, remaining close to training accuracy. This behavior suggests good generalization of the model with minimal overfitting and stable performance during training.

2. Confusion matrix

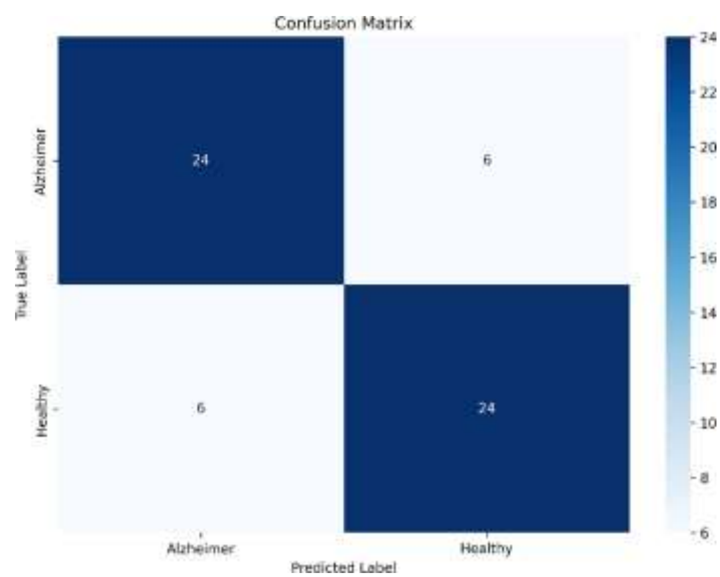

Fig-3

The Figure 3 shows how well the model classified handwriting samples into the Healthy and Alzheimer's classes. The diagonal elements represent correctly classified samples, while the off- diagonal elements show misclassifications. A higher number of correct predictions along the diagonal indicates that the model is performing accurately, while fewer misclassifications demonstrate its reliability in distinguishing between Healthy and Alzheimer's handwriting. This matrix provides a detailed view of the model's performance beyond overall accuracy, highlighting strengths and potential areas for improvement.

3. Classification Report

	precision	recall	f1-score	support
Alzheimer	0.8000	0.8000	0.8000	30
Healthy	0.8000	0.8000	0.8000	30
accuracy			0.8000	60
macro avg	0.8000	0.8000	0.8000	60
weighted avg	0.8000	0.8000	0.8000	60

Fig-4

The Figure 4 provides detailed performance metrics for the model, including precision, recall, F1-score, and support for each class (Healthy and Alzheimer's). Precision shows how many of the predicted samples for a class are actually correct, while recall shows how many actual samples were correctly identified. The F1- score balances precision and recall to give a single measure of accuracy, and support indicates the number of samples per class. Together, these metrics give a comprehensive view of the model's effectiveness in classifying handwriting samples and highlight how well it performs across both classification.

The project resulted in a functional deep-learning system capable of identifying Alzheimer's indications from handwriting samples with strong accuracy. The trained model successfully distinguished between Healthy and Alzheimer categories, supported by clear evaluation metrics and meaningful Grad-CAM visual explanations. The deployment through a Flask web application enabled users to upload images, receive instant predictions, and view confidence scores and heatmaps. Overall, the system demonstrated that handwriting analysis, combined with modern AI techniques, can serve as a practical early- screening tool for cognitive impairment. The results highlight the potential of non-invasive, low-cost handwriting-based screening methods for assisting early Alzheimer's detection. Such a system can be easily used in clinical, educational, or home settings without the need for specialized equipment. The interpretability provided by Grad- CAM increases trust by showing which handwriting regions influenced the decision. With further validation on larger and more diverse datasets, the system could evolve into a reliable decision- support tool for healthcare professionals.

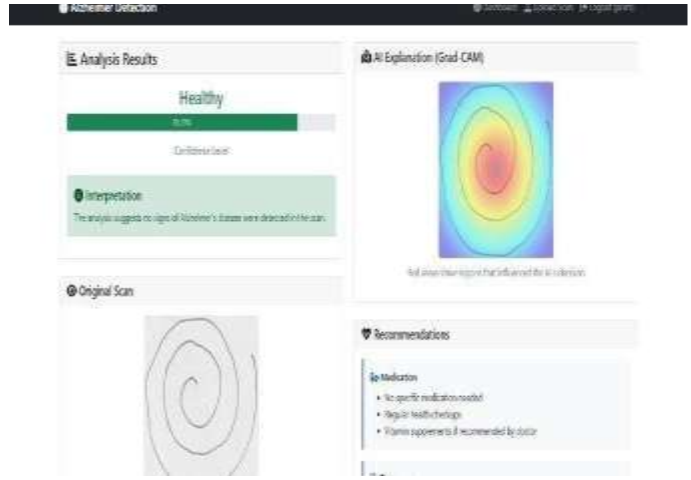

Fig-5

The figure 5 shows a healthy prediction with a high confidence score, indicating that no significant signs of Alzheimer's disease are detected in the uploaded handwriting sample. The interpretation section confirms the absence of abnormal handwriting patterns. The Grad-CAM heatmap highlights normal and evenly distributed regions, suggesting stable stroke formation. The original scan is displayed for reference, and basic recommendations are provided, mainly advising routine health monitoring.

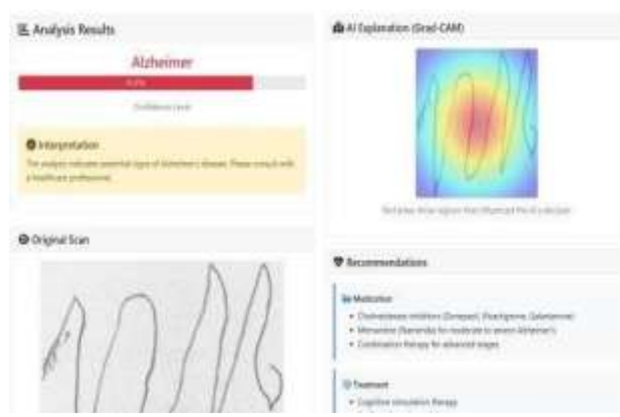

Fig-6

The Figure 6 presents an Alzeihmer prediction with a strong confidence level, indicating potential cognitive impairment. The interpretation section advises consulting a healthcare professional for further evaluation. The Grad-CAM visualization highlights irregular and distorted stroke regions that influenced the model's decision. Along with the original handwriting scan, the system provides medical and treatment-related recommendations, demonstrating the practical usefulness of the application in supporting early screening and awareness.

V. CONCLUSION

The proposed handwriting-based Alzheimer's detection system successfully identified differences between Healthy and Alzheimer-affected handwriting using deep learning. The model achieved strong accuracy, reliable classification metrics, and meaningful Grad-CAM visualizations, confirming that it learned relevant handwriting patterns. The Flask-based interface further demonstrated smooth real-time prediction, making the system suitable as an early screening support tool. Future enhancements can include expanding the dataset with more diverse handwriting samples to improve robustness and generalization. Integrating multimodal data such as speech, drawing tasks, or cognitive test scores can further increase diagnostic accuracy and clinical usefulness.

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