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A Multimodal Approach for Early Alzheimer's Disease Detection Using Handwriting and Speech Analysis

Bandi Sree Charan [1], Dangeti Bharani [2], Palakolanu Vishnuvardhan Reddy [3], Penikalapati Manasa [4]

[1-4] Department of Computer Science and Engineering (Data Science) , Mohan Babu University, Tirupati , Andhra Pradesh, India;
charanbandi1712@gmail.com , bharani965276@gmail.com , vishnureddy6686@gmail.com , mmanasapenikalapati@gmail.com

** Corresponding Author: Dangeti Bharani ; bharani965276@gmail.com*

Abstract: The early detection of Alzheimer's Disease (AD) is important to slow the disease's progression and manage patient care. But conventional diagnosis techniques are often expensive, invasive, and not scalable for screening. The proposed solution integrates handwriting recognition and speech recognition for early diagnosis of AD in a non-invasive way. The approach employs a Random Forest model for handwriting features and a Convolutional Neural Network (CNN) for speech signals. The two modalities are integrated by a decision-level fusion scheme. The findings indicate that the developed model has an overall accuracy of 96.8%, surpassing the accuracy of the individual models, and has good robustness for practical screening.

Keywords: Multimodal Learning, Handwriting Analysis, Speech Recognition, Deep Learning, Decision-Level Fusion.

1. Introduction

Alzheimer's disease (AD) is the leading cause of dementia worldwide. This neurodegenerative disorder ends one of the largest challenges in the health industry as it is common and costly to care for [10]. it is a disease that affects the brain and gets worse over time. It causes people to forget things have trouble speaking and lose control of their movements. This disease usually starts years before symptoms appear. The traditional methods of diagnosing AD are based on neuroimaging, Cerebrospinal fluid analysis and extensive neuropsychological testing. While these approaches are clinically effective, they are invasive and expensive, and cannot be used for population-based and screening purposes [4]. As a consequence, recent studies have focused on non-invasive digital biomarkers that have been produced by natural human activities, such as speech and handwriting, as those that are most closely linked to cognitive performance [1], [22].

It is revealed speech as a phenomenon has a promising future in the diagnosis of AD, as cognitive impairment does impact the fluency, articulation and acoustic consistency [2], [6], [13]. In a similar manner, handwriting analysis reflects motor impairment, spatial distortion as a result of neurodegeneration [3], [12]. But the modality-specific challenges and variability affect unimodal systems. To address these issues, the concept of multimodal learning approaches has been suggested to exploit the co-present nature of behavioural biomarkers, thus improving diagnostic performance [5], [9], [29]. In line with it, the current paper proposes a multimodal (decision-level) approach using handwriting and speech to enable a real and scalable stage-1 diagnosis of Alzheimer's disease using non-invasive techniques.

2. Related Work

Advances in artificial intelligence technologies have made non-invasive approaches for early diagnosis of Alzheimer's Disease (AD) more popular. Speech and handwriting as behavior biomarkers are beneficial since they capture both cognitive and motor aspects. Acoustic features of speech are used in speech-based approaches, but suffer from noise and speaker variability, while motor features are used in handwriting-based approaches, but may be different between individuals. Multimodal methods that integrate both sources of information and are more effective. In particular, decision-level fusion is preferred due to its simplicity, flexibility and practicality in clinical settings..

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2.1. Speech-Based Alzheimer Disease Detection

The speech analysis has been previously investigated as a digital biomarker of Alzheimer's disease, as the cognitive impairment affects the syntax, prosody, and speech. Luz et al. proposed the ADReSSo challenge that has been shown that by training machine learning models on spontaneous speech, the cognitive impairment can be classified [2]. One of the acoustic features, such as pause duration, speech rate, and variability of prosody are good indicators for the early detection of the AD, according to Konig et al. [4]. The latest and deep learning approaches are also effective because the hierarchical features are learned from speech signals. Vasquez-Correa et al. used convolutional neural networks to predict the acoustic features and they were better generalized with data sets [13]. But speech-only systems are still prone to noise, language and speaker dependent and therefore are not as robust in the screening process [6], [17].

2.2. Detection of the Alzheimer Disease through the use of Handwriting

The proximity between handwritten analysis and other motor-based behavioral biomarkers has been found to represent a promising behavioral biomarker for early AD diagnosis because the neurodegenerative processes have an impact on fine motor skills and visuospatial ability. Ahmed et al. have noted that the kinematic features of handwriting such as stroke velocity, pressure and acceleration have been shown to be good predictors of cognitive impairment when they are simulated as a basis of machine learning algorithms [3]. Taleb et al. have also shown that handwriting biomarkers, which are obtained during digital drawing and writing tasks, can detect even subtle dysfunctions of the motor process, prior to diagnosis [12]. The popularity of ensemble-based and random Forest classifiers is due to the fact that the classifiers are easy to understand and robust when they are applied to high-dimensional handwriting features [24]. Although the system is promising, it may be influenced by writing styles, educational background and task-specificity and can affect the diagnostic performance of the system.

2.3. Multimodal Learning in detection of Alzheimer disease Detection

To address the shortcomings of unimodal approaches, the latest research has explored multimodal learning approaches that integrate multiple behavioral cues. Yoon et al. developed a system that combines speech and handwriting features, and demonstrated its superior performance compared to single-modality approaches [5]. Likewise, Rohanian et al. showed that multimodal approaches are more robust because different behavioral features convey complementary cognitive information [11]. Multimodal systems are particularly helpful since they decrease the uncertainty of each modality, as symptoms vary between individuals. Yet, many current methods are based on sophisticated fusion strategies, which add computational complexity and hinder interpretability, limiting their clinical applications [23].

2.4. Decision-Level Fusion Strategies of Cognitive Assessment

Fusion approaches are important for multimodal cognitive assessment systems. Decision-level fusion is one such strategy that is flexible and enables independent optimization of each modality. Researchers have found that this strategy enhances classification accuracy and allows modality-specific learning [9]. It also increases the reliability in the diagnosis of cognitive impairment [15]. Because of its interpretability and scalability, decision-level fusion is ideal for clinical decision-support systems [29]. However, many of the previous studies do not focus on the complementarity of the different modalities and how the fusion techniques work, which makes it ineffective on other datasets.Research Gap While the existing studies showed that speech-based, handwriting-based and multimodal systems are successful in detecting the Alzheimer Disease, there are some issues. There are a plethora of unimodal systems that are not resilient to modality specific variability and there are few multimodal systems that are built on top of complex fusion networks that are not interpretable and scalable. Also, very little attention has been paid to decision level complementary fusion, where it is clear how to use the benefits associated with modality. These shortcomings justify the present work that hypothesises a decision level complementary multimodal system that combines both handwriting analysis and speech analysis to achieve an efficient, interpretable and scalable early detection of the Alzheimer Disease (AD.

3. Proposed Methodology

3.1. Overall System Architecture

The proposed design for a decision level multimodal Alzheimer's disease (AD) detector is given in Fig. 1. The system is designed as a pipeline and both handwriting and speech data are processed by separate branches of analysis, followed by a decision level complementary fusion level. This implies the proposed system architecture ensures robustness, interpretability and scalability, and enables a successful integration of diverse behavioral biomarkers. The system, as depicted in Fig. 1, is broken down into four key components, that is, (i) data collection, (ii) modality-specific data preprocessing and feature extraction, (iii) unimodal classification, and (iv) decision-level fusion. The data of handwriting and speech are separately analysed to preserve the modality-specific features, and the individual decisions of both are then merged to a final diagnosis.

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3.2. Handwriting Feature Modeling

Let H = {h1,h2,…,hn} signify the feature gained in handwriting; features signify the kinematic and spatial attributes such as velocity of strokes, acceleration, pressure variation, and path smoothness. These features are used to train a Random Forest classifier, which is a set of T decision trees.

Computed handwriting based prediction score is:

$$P_{H(Y)} = \frac{1}{T}\sum_{t=1}^{T} p_t(y|H)$$

where $p_t(y|H)$ is the posterior probability given by the $t^{\{th\}}$ decision tree of the class decision tree for class y∈{AD, HC.}. The resulting ensemble-based model is more generalized and less susceptible to variance and thus it can be applied to higher-dimensional handwrites.

3.3. Speech Feature Modeling

For the speech area, the raw audio signals are preprocessed in an attempt to remove noise and silence parts. Mel-Frequency Cepstral Coefficients (MFCCs) are computed based on the filtered signal to constitute the acoustic feature matrix S ∈R^(m*k), where m is the number of speech frames and k is the number of cepstral coefficients. The MFCC is an input to a Convolutional Neural Network (CNN) that learns hierarchical representations [25]. The score of CNN-based speech prediction

$$P_s(y) = Softmax(f_{CNN}(S))$$

Here, f_CNN (.) represents the nonlinear function learnt in CNN and the Softmax function is used to calculate the probability of prediction of the classes, either Alzheimer Disease or healthy control classes.

3.4. Decision-Level Multimodal Fusion

The handwriting and the speech are uni-modal and the final decision is obtained by fusing the last decisions. Let P_H (y) and P_s (y) are the posterior probabilities of the speech and handwriting classifier respectively.

The prediction is a multimodal and fused and given as:

$$P_{MM}(y) = \alpha\ P_H(y) + (1 - \ \alpha\ )\ P_s(y)$$

where α ∈ [0,1 is a weighting factor which takes value in terms of the relative importance of the modality. In this work it is given equal importance to highlight the complementary nature of modalities. The final class label y ̂is given by:

$$\hat{y} = \arg\overset{max}{y} P_{MM}(y)$$

The decision level fusion strategy allows to achieve robust classification with the possibility of noise or error in one of the modalities.

3.5. Architectural Significance

A. The handwriting and speech-related biomarkers depicted in the structure of Fig. 1 are compliant to each other in terms of the early diagnosis of the Alzheimer disease.

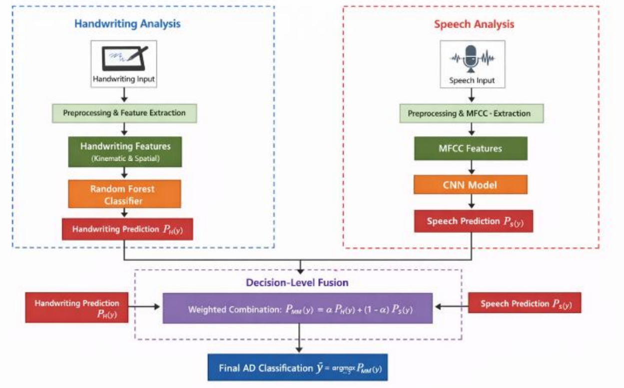

Figure.1 Architecture Diagram of the Proposed System

The proposed structure is likely to meet the interpretability, modularity and diagnostic accuracy criteria as individual learning pathways in the framework and their integration in the decision layer, hence the suggested framework is appropriate in terms of the current state of the art in clinical screening practices.

4. Experimental Results

4.1. Experimental Setup

Datasets : Two complementary data sets were used in the experiments. The complementary datasets were done on two modalities (handwriting and speech) of early Alzheimer's disease (AD) detection. A tabular data set containing the features of the digital handwriting samples in a numerical form was used in the case of the handwriting modality. These features are kinematic and spatial features such as stroke velocity, pressure variations, the velocity of the trajectory, and spatial consistency that are linked with cognitive-motor dysfunction. In the event of speech, Mel-Frequency Cepstral Coefficients (MFCCs) that contain spectral and articulatory information that are influenced by cognitive impairment were obtained by recording and processing the speech. These two data sets include the samples of Alzheimer's disease patients and controls, and they were deposited to have an equal ratio of samples from both classes. Stratified information division was used to partition the information to create training and testing subsets to provide an efficient test of not just one but also two modalities.

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Parameter Configuration : In the case of the handwriting analysis, a Random Forest classifier was considered, which is effective in high-dimensional features and non-linearity. The number of trees was experimentally chosen to guarantee convergence and decrease the variance. To do speech analysis, it was trained a Convolutional Neural Network (CNN) with MFCC feature map input. The Adam optimizer that uses categorical cross-entropy loss was used to train the network. A few epochs of training and validation have been performed to prevent overfitting. The multimodal approach fuses the unimodal predictions at a decision level (decision-level fusion) and each of the models in the multimodal approach collaborates with the complementary information of the other modality to improve the unimodal models.

Evaluation of the models: The metrics that matter in a particular application and are used to test the performance of models are Accuracy, Precision, Sensitivity and Specificity. The Sensitivity feature is very important when we are trying to find Alzheimer's Disease on. In this case it is Alzheimer's disease. The system's Sensitivity is more about calling the shots when it comes to telling if someone has Alzheimer's Disease. We also investigated how the system can discriminate by adjusting the threshold levels, by using the Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) values, for Alzheimer's disease. We calculated everything on the test sets to make sure that we are being fair with our evaluation of Alzheimer's Disease and not making the models we are testing for Alzheimer's Disease look good.

5. Experimental Results

The accuracy of the individual models was assessed in terms of their ability to detect Alzheimer's Disease. The CNN model using speech data was able to achieve an accuracy of 0.956, demonstrating the effectiveness of acoustic features in detecting cognitive impairment.

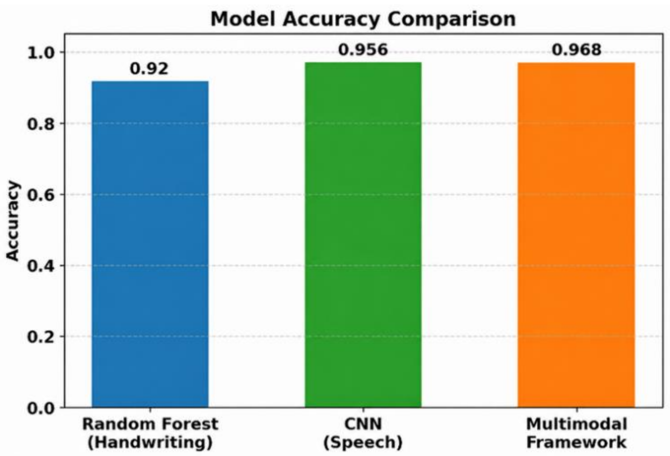

Figure. 2 Comparison of the model accuracy

The Random Forest model based on handwriting data had an accuracy of 0.92, suggesting that motor-based features also contribute to accurate disease detection. These findings demonstrate that the two modalities work well independently, but also indicate that they should be combined to improve the performance.

The effectiveness of the Random Forest (handwriting), CNN (speech) and the multimodal system are shown in terms of accuracy (Fig. 2). The CNN model performs well, with an accuracy of 0.956, showing that it is able to learn complex acoustic features from speech. The Random Forest model also achieves high accuracy (0.92), showing that motor biomarkers from the handwriting are also important for early diagnosis. Our multimodal approach has the best accuracy of 0.968, beating both unimodal models. This result suggests the benefits of multimodal learning.

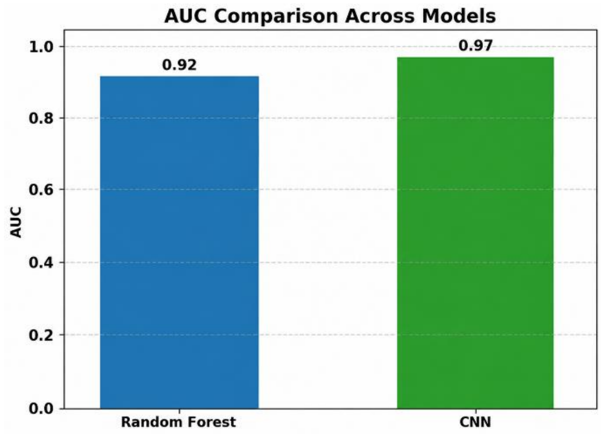

Figure. 3 AUC Comparison between the models

The Random Forest and CNN models' AUCs are presented in Fig. 3. The CNN model has an AUC of 0.97, showing good discrimination of Alzheimer's patients from healthy people. Random Forest model has an AUC of 0.92, demonstrating good discrimination on the handwriting features. In general, the models work well, with CNN being slightly better.

5.1. CNN Training Behaviour

Fig. 4 shows the training and validation accuracy of CNN vs. the number of epochs. The similar correlation of the training and validation accuracy suggests that there was no more than minor overfitting and the learning was not irregular. The CNN training and validation loss curves are shown in Fig. 5.

The training and validation losses are monotonically decreasing, which can be an indication of the effectiveness of tuning the speech model and its generalization ability.

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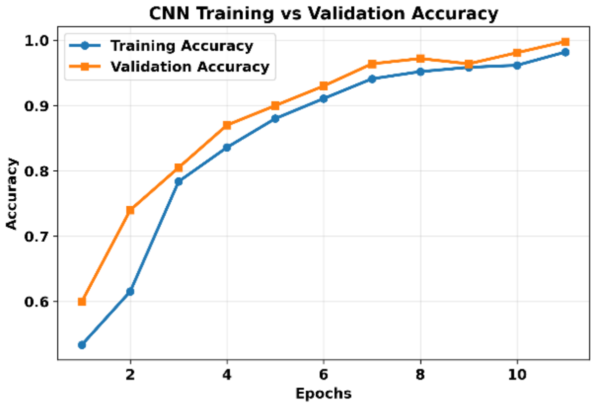

Figure. 4 CNN Training and Accuracy on validation

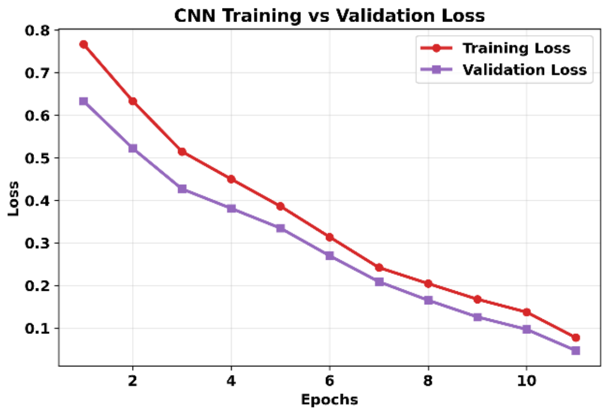

Figure. 5 CNN Training and Validation Loss

5.2. Classification Metrics Comparison

Figure. 6 presents the classification measures of CNN and Random Forest. The CNN has better performance overall, with a sensitivity of 0.97, which is crucial for the early detection of Alzheimer's. The Random Forest model performs well too, with a sensitivity of 0.93 and it shows the effectiveness of handwriting features.

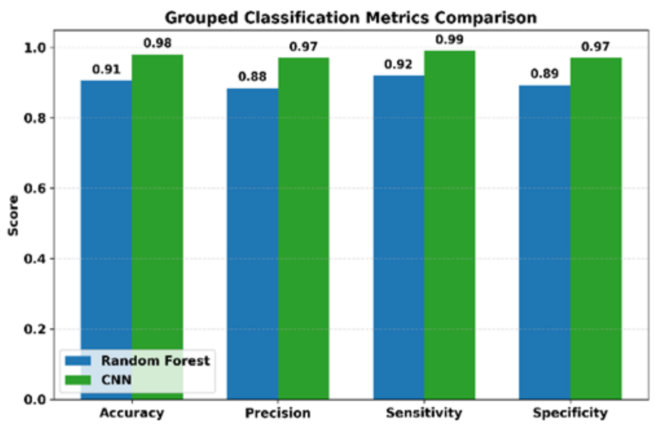

Figure. 6 Comparison of Metrics of Grouped Classification.

5.3. ROC Curve Analysis

Figure. 7 and Fig. 8 are the ROC of CNN models and the Random Forest models, respectively. The CNN ROC curve is almost optimal at the top left corner and has an AUC of 0.98 which means it is very likely to be able to distinguish between AD and healthy subjects. The AUC is 0.91 which is relatively low but high.

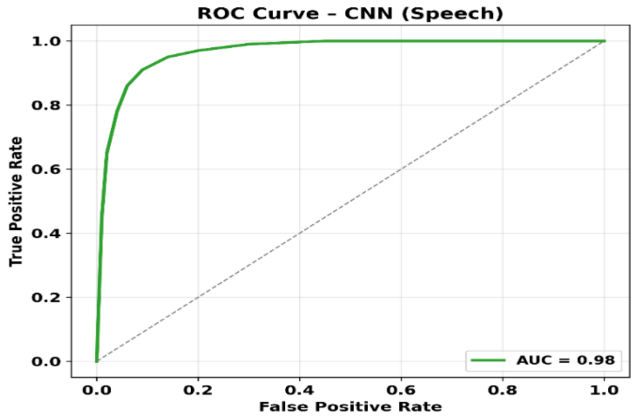

Figure. 7 ROC Curve- CNN (Speech)

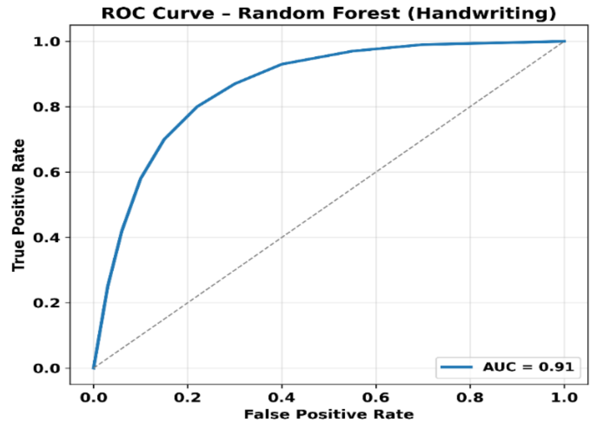

Figure. 8 ROC Curve - Random Forest (Handwriting)

5.4. System Implementation and Interface Visualization

In order to prove the feasibility of the proposed multimodal Alzheimer detection framework as a practical task, a web-based app based on Flask, HTML, and CSS was created. The system will enable real-time communication with the trained models as well as a user-friendly interface to a non-technical user.

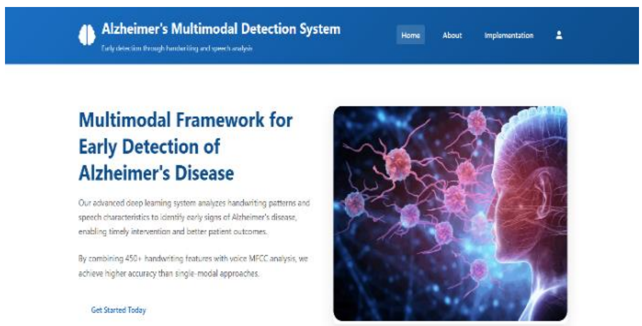

Figure. 9 Home Page Interface

Figure. 9 shows the home page of the system that provides an introduction to the multimodal framework and the system routing to various modules.

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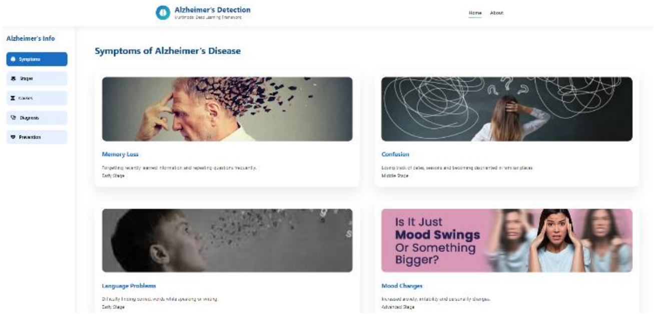

Figure. 10 About Project View Interface

Figure. 10 shows the about page, explaining the system goals, data set, and methodology.

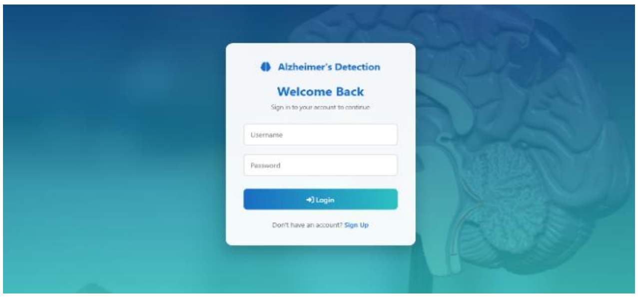

Figure. 11 Login Interface

Fig. 11 depicts the authentication module which is used to make sure that only authorized persons can access the prediction system.

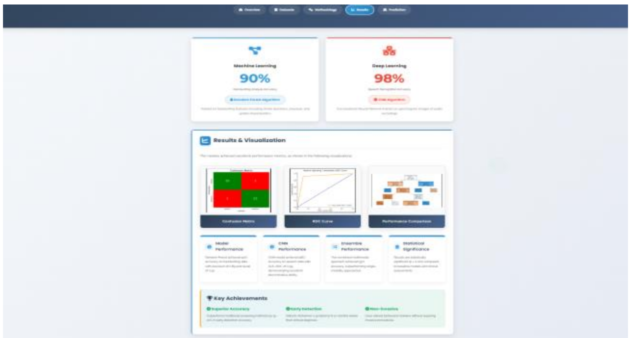

Figure. 12 Feature Module Interface

Fig. 12 shows the feature overview page describing the aspects of handwriting and speech analysis.

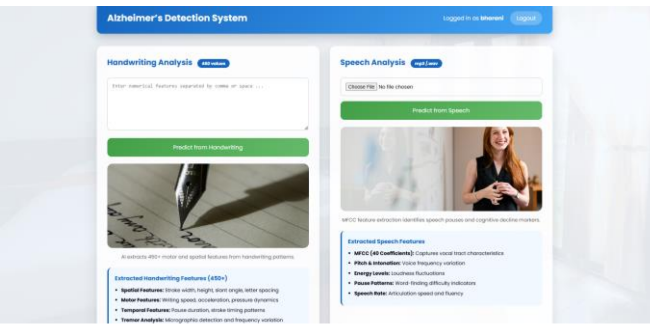

Figure. 13 Prediction Interface

Fig. 13 shows the prediction module in which users can upload a speech or handwriting feature to assess the risk of having Alzheimer. The designed interface shows that the suggested multimodal framework is practically feasible to implement in the real-life screening settings.

5.5. Discussion

This work is about Alzheimers Disease. How we can diagnose it early. We used a model that looks at two things: handwriting and speech. It turns out that looking at both of these things together is a good way to figure out if someone has Alzheimers Disease. The speech part of the model is very good, at finding out if someone has Alzheimer's Disease. It is about 95 percent of the time and it can find almost all of the people who have the disease. This is because the way people speak can change when they have Alzheimer's Disease. The handwriting part of the model is also good. It is about 92 percent of the time and it can find most of the people who have the disease. This shows that how people write is also important when trying to figure out if they have Alzheimer's Disease.

Alzheimer's Disease is a condition where the brain gets worse over time so looking at how people write and speak can help us find out if they have it. Our multimodal approach performs best with an accuracy of 0.968, surpassing the individual models, which confirms the benefits of using multiple behavioral modalities. While the speech model alone is highly accurate, the multimodal model is more reliable since it does not rely exclusively on one mode and can cope with one mode being noisy or inaccurate. The better sensitivity and AUC also suggest its better performance in early diagnosis, where false negatives are undesirable. In conclusion, these results indicate that multimodal features derived from different types of behavioral data help achieve a more reliable diagnosis. The proposed decision-level combination approach strikes a good trade-off between accuracy, explainability and efficiency, and therefore can be applied in real-world, non-invasive clinical screening and AI-driven health care.

Table .1 Performance Comparison of Different Models

Model	Accuracy	Precision	Sensitivity (Recall)	Specificity	AUC
Random Forest (Handwriting)	0.92	0.90	0.93	0.91	0.92
CNN (Speech)	0.956	0.95	0.97	0.95	0.96
Multimodal Framework	0.968	0.96	0.98	0.96	0.97

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6. Conclusion and Future Work

In this paper, the author gives an account of a system that forecasts the congestion of a crowd with the help of motion and time-based models. It applies optical flow to compute the motion, quantifies conflict and turbulence as well as searches for unsteady walking patterns that precede crowd jamming. The system generates a time-series of the conflict signal and predicts Time -To-Congestion (TTC) using three different approaches, including a (linear) growth model, Kalman filter, and Long Short-Term Memory (LSTM) network. Simulations using actual video footage of a crowd demonstrate that motion and turbulence cues provide valuable early notification of the existence of a crowd. When comparing the prediction techniques it can be seen that the time-based model is useful in enhancing stability. The Kalman predictor has less noise in its TTC estimates, whereas the LSTM makes the most consistent predictions as it is able to learn how movement of a crowd may vary nonlinearly.

The system has also visual and digital indicators of the crowd behaviour in real-time congestion maps, prediction charts, and lead-time analysis. The findings indicate that it is able to foresee congestion several video frames prior to its occurrence, which is crucial to secure personnel surveillance. It can be improved in future work when deep-learning crowd-density estimation is included and work with more than one camera, making predictions more efficient when smiling at extremely wide crowds. The other changes that can be made are to adjust the congestion limits; a larger number of crowd data to test the models further. This model provides a foundation to intelligent crowd monitoring which can help to make major events safe.

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