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Research Article

Multimodal Approach in Prediction of Alzheimer's Disease Using Voice, Transcript Dataset

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ABSTRACT

Introduction Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by cognitive decline , memory impairment and impact on language abilities. Early and accurate prediction of AD is critical for effective intervention and management. This study proposes a multimodal approach that integrates heterogeneous data sources—including voice recordings, transcribed speech, textual metadata, and neuroimaging—to enhance prediction accuracy

Objectives: The primary objective of this study is to develop and evaluate a multimodal machine learning framework that combines acoustic features from voice recordings and linguistic features from speech transcripts to improve the accuracy and reliability of early Alzheimer's disease prediction. By utilizing both speech and textual data, the approach aims to capture subtle cognitive and behavioral patterns that may not be evident through a single modality, ultimately contributing to earlier, non-invasive, and scalable diagnostic tools..

Methods: This study proposes a multimodal approach that integrates heterogeneous data sources—including voice recordings, transcribed speech, textual metadata, and neuroimaging—to enhance prediction accuracy. By leveraging the complementary strengths of each modality, the system captures both linguistic and paralinguistic features from speech, semantic and syntactic cues from transcripts, and structural biomarkers from MRI scans.

Results: Experimental results on benchmark datasets demonstrate that the multimodal fusion approach significantly outperforms unimodal baselines, offering a more robust and holistic understanding of AD-related indicators.both train ans test accuracy are almost same. Both the dataset have good accuracy more than 70% accuracy is achieved. This approach underscores the potential of multimodal machine learning in advancing non-invasive, early-stage Alzheimer's diagnosis.

Conclusions: This study demonstrates the effectiveness of a multimodal approach that integrates both voice and transcript data for the prediction of Alzheimer's disease. By leveraging linguistic features from transcripts alongside acoustic features from voice recordings, the model achieves a more comprehensive understanding of cognitive decline indicators. The fusion of these modalities not only improves prediction accuracy but also provides a non-invasive, cost-effective alternative for early detection. Future work may focus on expanding datasets, incorporating other modalities (e.g., facial expressions or brain imaging), and enhancing real-time clinical applicability to support early intervention and better patient outcomes.

Keywords: lorem ipsum.

INTRODUCTION

Alzheimer's disease (AD) is one of the most prevalent forms of dementia, affecting millions of individuals worldwide. It is characterized by progressive cognitive decline, memory loss, and behavioral changes, often leading to severe impairment in daily functioning. Early diagnosis plays a crucial role in slowing the progression of the disease and improving the quality of life for patients and caregivers. However, traditional diagnostic methods—such as clinical assessments and neuroimaging—are often time-consuming, costly, and may not detect subtle early-stage

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symptoms.In recent years, artificial intelligence (AI) and machine learning (ML) have shown promise in medical diagnosis, particularly in the detection of neurological disorders. With the increasing availability of diverse data types—such as voice recordings, transcripts of patient speech, clinical notes, and brain imaging—multimodal approaches have emerged as a powerful strategy for improving prediction performance. Each modality offers unique insights: voice data captures acoustic and prosodic features, transcripts reveal linguistic and semantic patterns, textual data provides contextual information, and neuroimaging uncovers structural brain abnormalities associated with AD.This research aims to develop a multimodal machine learning framework that integrates voice, transcript, textual, and image data to predict Alzheimer's disease more accurately and efficiently. By combining features across these modalities, the proposed model seeks to enhance diagnostic precision and support early intervention strategies. The fusion of heterogeneous data sources is expected to uncover subtle markers of cognitive decline that may be missed when relying on a single modality, thus offering a comprehensive and robust solution for AD prediction.

LITERATURE SURVEY

VOICE DATASET

A benchmark dataset of spontaneous speech that has been acoustically pre-processed and balanced in terms of age and gender will be made accessible as part of the ADReSSo-2021 challenge. This will provide a common task that will allow various techniques to AD recognition in spontaneous speech to be compared. The ADReSS Challenge dataset was carefully chosen to reduce common biases that are frequently disregarded in assessments of AD detection techniques. These biases include imbalances in gender and age, variations in audio quality, and repeated instances of speech from the same participant—all of which are common in longitudinal datasets. [1] have extracted Spectogram feature and identify AD using Linear SVC, Logisitic Regression CV. A reliable measure of an AD patient's cognitive condition is speech anal vision. This enables the identification of initial symptoms years prior to the establishment of a likely clinical diagnosis. Feature extraction techniques and classification methods used for that [5]. [2] develop ML models to detect AD from speech using picture description data of the demographically matched ADReSS Challenge speech dataset. Predict the AD with deep learning [18]. The automation of the interview process is currently a very interesting unexplored field for its application [3] the level of growth in speech and natural language processing interactions, which serves as a foundation for long-term health tracking and cognitive evaluation[6]. The classification and correlation results provide evidence of the potential utility of voice and speech for the diagnosis and evaluation of Parkinson's disease.[20] GPT-3 based text embedding is a viable approach for AD assessment directly from speech and has the potential to improve early diagnosis of dementia [7] the transfer learning method in this study improves AD prediction, reduces the need for feature engineering [10] The models use a sequence o f acoustic features and covariates (age, gender, education) to make the predictions.[19]. In order to reduce common biases that are frequently ignored in assessments of AD detection techniques, such as imbalances in sex, age, and educational attainment, audio quality changes, and repeated speech from the same person, the ADReSS-M challenge offered a statistically balanced data set.[23] and [15] the potential of a brief and cost-effective SS protocol in distinguishing between different degrees of cognitive impairment and forecasting performance in cognitive domains commonly affected within the AD spectrum. The pervasiveness of textual information and its wide range of uses, including sentiment analysis, document classification, and recommendation systems, was emphasized by [39].

TRANSCRIPT DATASET

Dementia Bank is a collaborative and specialized database that is part of the TalkBank project, which is overseen by Brian MacWhinney at Carnegie Mellon University. Data is available in multiple languages, including English, within the database. Additionally, there are a ton of text and audio file corpora available. For cooperative members, through a password-protected system the DementiaBank dataset is accessible. The project supervisor politely and succinctly requested authorization from TalkBank, stressing the importance of handling data in an ethical and responsible manner. The Pitt corpus has the most data that has been gathered of any of them. The Pitt Corpus was selected for the study. The Pitt corpus has two different text scripts. One is labeled "Control" and is intended for healthy individuals, while the other is labeled "Dementia" and is intended for dementia patients. In this instance, The format of the script is primarily question-and-answer. The transcribed voice data kept in CHA (CHAT) files served as the research's data source. These files are frequently used for spoken language transcription in linguistic and phonetic research. CHA files are appropriate for our study since they provide linguistic annotations and information.[11] used

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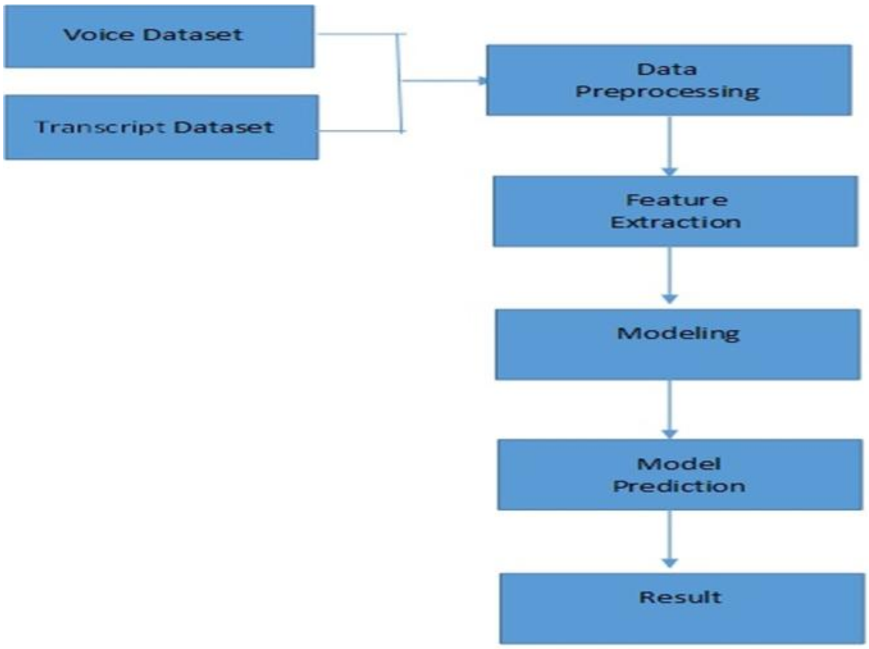
pre-trained language models can improve AD prediction. This eliminates the need for expert-defined characteristics and addresses the issue of insufficiently large datasets.[8] the proposed combination of ADR audio and textual features is capable of successfully modelling temporal aspects of the data with the help of CNN, designed a hybrid model with CNN & Bidirectional LSTM by [36] and prove the applicability of deep neural networks with two embedding techniques to classify AD patients. the feasibility of using the AI-powered end-to-end model for early AD diagnosis and severity prediction directly based on voice, showing its potential for screening Alzheimer's disease in a community setting used machine learning technique by [7]. [16] studied leverages the interpretation provided by decision tree-based methods and ANNs for analysing different sets of acoustic features for the assessment of AD. In order to precisely diagnose Alzheimer's disease, speech signals can be a valuable diagnostic tool as well as a trustworthy biomarker.[32] applied DL-based speech and language techniques to support the dementia diagnostic process. It also offers an understanding of the advancements made in this field thus far and highlights some challenges that still need to be addressed by [8].

METHODS

Recently, machine learning has advanced significantly in several application areas, which has effectively increased demand for it among ML learners (Feurer et al. Furthermore, a robust machine learning system should address the core issues by identifying which ML algorithm to use on a dataset, how to perform preprocessing, and how to adjust its hyperparameters.In this work, we provide a hybrid method for classifying AD as a diagnostic tool. The suggested model classifies data into healthy and nonhealthy patients with AD after learning the data using an ML algorithm. Pytorch, an experimental environment that uses Python libraries, was what we used. The Pytorch platform offers developers a clear framework for processing, creating, and evaluating their models. Python is a higher-level, interpreted programming language featuring dynamic semantics.



[Fig :-1]

Pipelines involve a linear sequence of data transformations and are coupled in a way that yields a model that can be further analyzed and utilized. The intention was to ensure that each pipeline step was followed. Furthermore, it was restricted to the datasets—such as the test and train datasets—that were available for the evaluation. The proposed architecture has a five-level sequential concept. Each level's sub-levels are maintained in a sequential order.The working program of the model used is as above Data preprocessing was the first step, which included pre-processing both voice and transcript data. This included the procedures of data collection, data visualization, feature extraction, feature selection, and data transformation.The data was handled more simply in this initial step. The technique

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handles missing data, removes current outliers, normalizes to a specific range, and chooses features based on their ability to influence. Additionally, the data visualization helps us see the raw data on a broader scale by displaying the distribution, correlation, and skewness of the data. The second stage uses clean data, which is the output of the previous level, as its input. Data segregation, which required dividing the dataset into train and test data, made up the second stage.There is an 80:20 ratio between the train and test data. The third level then uses the split data to form the model. The third stage had four sub-levels: model training, model assessment, cross-validation, and hyperparameter adjustment through model validation. This covers the actual process of machine learning, which involves developing several ML classifiers, evaluating the model according to the accuracy it generates, doing cross-validation, and adjusting parameters to improve accuracy.To construct the model and evaluate it, a range of machine learning techniques for data classification and learning were used. The model developed in the third stage is evaluated at the model prediction level, which follows. Based on the model's prediction on the test set, it divides the group into AD and non-AD patients. By visually representing the model's performance, the fifth stage, also known as the performance evaluation level, provided insights into the model. The five-level workflow design of the pipeline was maintained by sequential adherence to the order.

RESULTS

AUDIO DATASET

Best CV Accuracy: 61.33%

Test Accuracy: 60.61%

Classification Report:

	precision	recall	f1-score	support
0	0.60	0.71	0.65	17
1	0.62	0.50	0.55	16
accuracy			0.61	33
macro avg	0.61	0.60	0.60	33
weighted avg	0.61	0.61	0.60	33

The best CV accruacy of audio dataset is 61.33% . This is the highest cross-validation accuracy of my model achieved during training and validation. Cross-validation helps estimate how well model will perform on data. Test Accuracy: 60.61%.When tested the model on completely data it achieved 60.61% accuracy which is very close to the CV accuracy.

TANSCRIPT DATASET

Accuracy:73%

Test accuracy: 72.73%

Classification Report:

	precision	recall	f1-score	support
0	0.75	0.60	0.67	10
1	0.71	0.83	0.77	12
accuracy			0.73	22
macro avg	0.73	0.72	0.72	22
weighted avg	0.73	0.73	0.72	22

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This is validation accuracy meaning that during model evaluation the model correctly predicted about 73% of the samples. Test Accuracy: 72.73% On test set, the model predicted correctly about 73% of the samples. It is Important that the training and test accuracy are very close, meaning no overfitting or underfitting the model generalizes well!

DISCUSSION

The classification accuracies of all machine learning techniques used on both speech and transcript datasets have been reported in the Model Prediction for an objective comparison. Among them, cross validation performs better than the other classifiers, indicating that our suggested method works better for AD detection. Compared to alternative methods, our model's accuracy, recall, and specificity are noticeably superior. Given that we are suggesting a hybrid approach, it is clear that our strategy works well in identifying, performing an enhanced diagnostic, and categorizing both healthy and AD-afflicted patients. There are five layers of density. Our approach performs well, with an accuracy of more than 70%.computer-based techniques for diagnostics, some data is available. As a result, we used random selection in the models we developed to maintain the train-test ratio. Our efforts are yielding encouraging results. The imputation of missing values during the data preprocessing step greatly increased the diagnostic accuracy of the AD prevalence in both of our datasets. When we contrasted the outcomes with those of a missing value non-imputation approach This is because of our model's great sensitivity, which produced far better results than earlier techniques used by other researchers. We were able to predict the right classification of patients as healthy or unwell with the highest test accuracy possible. The advanced diagnostic performance of the AD test is largely attributed to a small number of variables from the longitudinal collection of voice recordings. As a result, the analytical procedure shouldn't ignore this set of characteristics.

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