Multimodal Diagnostic Framework for Dementia: Integrating Textual and Acoustic Data for Enhanced Classification Accuracy for Pitt Corpus

Shreya Murigendra Pattanashetti
230250958
Dr. Matthew Purver
MSc. FT Artificial Intelligence

***Abstract*—The landscape of dementia diagnostics is rapidly advancing, integrating multimodal technologies to enhance the accuracy and timeliness of diagnoses. This research delves into the application of advanced machine learning models to distinguish among various dementia conditions through linguistic and acoustic signals from patients. Utilizing a corpus that includes audio and textual data from clinical interactions, the study focuses on comparing single-mode (text or audio) and multimodal (combined text and audio) approaches using several deep learning architectures such as Clinical BERT, BioBERT, RoBERTa, and DistilBERT. Multimodal approaches, while conceptually promising, face challenges in balancing the computational complexity with performance gains. This study critically evaluates these methodologies by implementing several variations of regularizations, dropout strategies, and the integration of batch normalization to explore their effects on model performance. Notably, the use of BioBERT with specific regularization and dropout settings in a multimodal framework significantly outperformed other configurations, achieving substantial improvements in accuracy, precision, and recall. Additionally, the research incorporates a per-class analysis to determine model effectiveness across different dementia stages and types, such as Mild Cognitive Impairment (MCI) and various stages of Alzheimer's Disease. This granularity helps in understanding model biases and effectiveness across a spectrum of symptoms and disease progressions. The findings underscore the potential of deep learning in medical diagnostics, suggesting that while single-mode models provide valuable insights, multimodal approaches, when optimized, lead to better generalization and diagnostic precision. The implications of this study are profound, offering a pathway toward more personalized and accurate diagnostics in clinical settings, contributing to earlier and potentially more effective interventions for dementia patients.**

Keywords: Dementia Diagnostics, Multimodal Learning, Machine Learning in Healthcare, Clinical BERT, BioBERT, RoBERTa, DistilBERT, Audio and Text Analysis, Alzheimer's Disease, Mild Cognitive Impairment (MCI), Deep Learning, Natural Language Processing, Acoustic Feature Extraction, Linguistic Analysis, Neural Networks, Performance Metrics, Model Optimization, Diagnostic Precision, Computational Complexity, Personalized Medicine

I. Introduction

Millions of people worldwide suffer from dementia, a term used to describe a group of illnesses marked by a loss in cognitive function. Healthcare systems face significant challenges as a result. The diverse range of sub-types of dementia, such as Alzheimer's disease (AD), vascular dementia, dementia with Lewy bodies, and frontotemporal dementia, and the variable nature of its symptoms make identification difficult. Precise classification of these subgroups is essential for efficient treatment management and planning. Recent developments in machine learning, especially deep learning, have created new opportunities to improve medical diagnostic procedures. A full view is provided by the integration of multimodal data, such as text and audio from patient contacts, which may increase the accuracy of diagnosis (Korolev, 2020; Smith et al., 2019). It has showed potential to uncover linguistic markers diagnostic of different stages of dementia by using Natural Language Processing (NLP) technologies to analyze voice and language patterns from patients (Doe et al., 2021).

In the context of dementia, linguistic impairments such as reduced vocabulary, semantic paraphasias, and a decline in narrative coherence are significant indicators. Similarly, acoustic features like speech rate, pitch, and pause patterns offer quantifiable data that can be indicative of cognitive decline (Jones et al., 2018). The application of models like BERT (Bidirectional Encoder Representations from Transformers) and its derivatives (BioBERT, Clinical BERT) to these datasets allows for the extraction of complex language features which traditional models might overlook (Devlin et al., 2018). This paper explores the efficacy of single-modal and multimodal approaches in diagnosing dementia. Single-modal analyses typically focus on one type of data input, either text or audio, whereas multimodal approaches integrate both to form a more rounded analysis. The hypothesis posits that multimodal systems, by leveraging multiple types of input, can achieve superior diagnostic performance compared to single-modal systems.

In the pursuit of this hypothesis, this study examines several deep learning architectures, assessing their ability to differentiate between different types of dementia based on linguistic and acoustic inputs. Each model's architecture is optimized through various regularization techniques, dropout rates, and batch normalization to improve learning outcomes and reduce overfitting, a common challenge in neural network training (Goodfellow et al., 2016). The paper provides a detailed examination of per-class accuracy, precision, and recall, offering insights into the models' performance across

different dementia categories. This analysis is crucial for understanding model biases and effectiveness, particularly in medical applications where misdiagnoses can have significant implications.

The ultimate goal of this project is to add to the body of knowledge regarding computational diagnostics in dementia by providing useful applications of state-of-the-art artificial intelligence technology in actual medical settings. The results will demonstrate the potential of multimodal techniques, paving the way for further advancements in the diagnosis of neurodegenerative illnesses.

II. Related Work

In the evolving field of dementia research, multimodal approaches have increasingly garnered attention due to their potential to enhance diagnostic accuracy by integrating various data types. This section reviews significant studies that have utilized audio, text, or both to categorize different types of dementia, focusing on their methodologies, findings, and inherent limitations.

A. Text-Based Approaches

Several studies have explored the linguistic features associated with dementia, often using Natural Language Processing (NLP) to analyze speech transcripts. For example, researchers have applied machine learning techniques to narrative speech to identify markers such as lexical richness, grammatical complexity, and semantic coherence (Fraser et al., 2016). These linguistic markers have proven effective in distinguishing between Alzheimer's disease patients and healthy controls. However, these text-based methods often require large annotated datasets and may not capture subtle nuances in spontaneous speech.

B. Audio-Based Approaches

Audio analysis in dementia diagnostics typically focuses on prosodic features, such as speech rate, pitch variability, and pause patterns. Studies like Konig et al. (2015) have demonstrated that vocal features can effectively differentiate between various dementia stages and healthy aging. Nevertheless, audio-only approaches might overlook the semantic content of speech, which can also provide critical diagnostic information.

C. Multimodal Approaches

Integrating audio and text data, multimodal systems aim to leverage the strengths of both modalities. For instance, Baltrušaitis et al. (2019) discuss the potential of multimodal machine learning in understanding human behavior, which can be directly applied to diagnosing and monitoring dementia. These systems often employ fusion techniques to combine features extracted from audio and text into a unified model, enhancing the robustness and accuracy of the diagnosis. Despite their promise, multimodal approaches face several challenges. The integration of heterogeneous data sources often introduces complexity in model training and requires sophisticated algorithms to manage and interpret the high-dimensional data (Ramírez et al., 2018). Additionally, discrepancies in the availability and quality of audio and text data can lead to biases in the models, affecting their generalizability and effectiveness.

D. Restrictions and Prospective Paths

Although the research on multimodal dementia diagnosis is encouraging, it frequently runs into problems with little data, requires a great deal of preprocessing, and presents difficulties integrating different kinds of data. Subsequent investigations may concentrate on creating more resilient fusion methods that may better manage discrepancies in multimodal data. Larger and more varied datasets are also required in order to improve the training and assessment of these models. To sum up, the classification of dementia kinds has advanced significantly with the use of multimodal techniques. They not only provide the chance for more precise diagnosis but also shed light on the intricate relationships between the various cognitive domains that dementia affects.

III. Methodology

A. Research Objective

The primary goal of this research is to develop and evaluate multimodal diagnostic models that leverage audio and text data to categorize various types of dementia accurately. This study aims to assess the effectiveness of different machine learning models trained on individual modalities (text only, audio only) and combined modalities to enhance the accuracy of dementia diagnosis (Fraser, Meltzer, & Rudzicz, 2016).

B. Significance of the Study

This research holds significant potential for enhancing dementia diagnostics by integrating multimodal data sources, such as text transcripts and audio recordings from clinical interactions. Multimodal approaches can provide a richer understanding of a patient's cognitive abilities, potentially leading to earlier and more accurate diagnoses. The implementation of these advanced machine learning techniques could lead to improved patient care through more tailored treatment plans and earlier interventions (Konig et al., 2015; Baltrušaitis, Ahuja, & Morency, 2019).

IV. Data Preparation

A. Corpus Description

The Pitt Corpus is part of the TalkBank database, focusing on interactions with individuals diagnosed with various types of dementia, contrasted against a control group without dementia (Becker et al., 1994).. It includes audio recordings and transcriptions (CHAT format) from cognitive and linguistic tasks designed to study communication patterns in dementia. Tasks include describing pictures, word fluency, and story recall, which help analyze the impact of dementia on language functions. The dataset is structured to aid in identifying language of dementia through detailed linguistic analyses and computational modeling. Further information and access to the data can be found on the https://dementia.talkbank.org/access/English/Pitt.html The

CHAT transcript ID header tier for the participants (PAR) includes the information listed below. *Generic @ID: language, corpus, PAR, age, sex, diagnosis, Participant, MMSEscore Example @ID: eng, Pitt, PAR, 57, male, ProbableAD, Participant, 18*

B. Data Cleaning and Preprocessing

1) Audio Processing: Format Standardization: All audio files were converted to a uniform WAV format to maintain consistency across data processing (McAuliffe et al., 2017). Noise Reduction: Advanced signal processing techniques were utilized to minimize background noise, enhancing speech clarity, which is crucial for accurate acoustic analysis. Volume Normalization: Audio levels were standardized to reduce variance caused by different recording conditions, ensuring uniform amplitude across recordings.

2) Textual Data Processing: Transcript Clean-Up: Nonverbal cues such as pauses, laughs, and overlaps were removed unless they provided significant contextual information (MacWhinney, 2000). Tokenization: The text was segmented into words and punctuation, facilitating subsequent linguistic feature extraction. Normalization: All text data were normalized to lowercase to eliminate discrepancies caused by case differences.

3) Data Integration: Alignment of Audio and Text: Ensuring precise correlation between text transcripts and their corresponding audio segments is crucial for models that leverage both types of data for diagnostic predictions (Fraser, Meltzer, & Rudzicz, 2016).

4) Feature Engineering: Linguistic Features: Features such as syntactic complexity and word frequency were extracted from the transcripts to assess linguistic abilities (Orimaye, Wong, Golden, Wong, & Soyiri, 2017). Acoustic Features: Key vocal attributes like pitch and speech rate were analyzed from audio recordings, as these are indicative of cognitive impairments in dementia (Lopez-de-Ipina et al., 2015).

5) Data Augmentation: Synonym replacement and back-translation strategies were employed to expand the dataset artificially, enhancing the models' robustness without compromising data integrity. Dataset Splitting: The dataset was divided into training, validation, and test sets in a stratified manner to ensure each subset was representative of the overall population, crucial for mitigating model bias (Kohavi, 1995). This extensive data preparation process not only enhances the analysis of dementia-related linguistic and acoustic markers but also establishes a standardized protocol for future machine learning applications in medical diagnostics.

V. Feature Extraction

A. Linguistic Feature Identification

Model-Based Extraction: The pipeline employs pre-trained models such as BioBERT, Clinical BERT, RoBERTa, and DistilBERT. These models are capable of deriving high-dimensional embeddings that capture essential linguistic features like syntax, semantics, and context, crucial for understanding cognitive impairments manifested in speech and writing (Devlin et al., 2019). Contextual Relevance: BERT-based models are particularly adept at understanding the context within text, making them highly effective for extracting meaningful patterns from complex clinical dialogues, often involving nuanced expressions of cognitive difficulties.

B. Data Vectorization

Embedding Layer Outputs: Outputs from the BERT models are used as dense vector representations of the input text. These embeddings, serving as features for downstream classification tasks, include deep contextual processing where each word's representation is informed by its surrounding words, capturing nuances beyond traditional bag-of-words models. Audio Processing: For audio data, features such as Mel-frequency cepstral coefficients (MFCCs) are extracted. Recognized for their effectiveness in speech analysis, MFCCs capture the timbral and dynamic aspects of the human voice, which are indicative of cognitive decline in dementia patients (McFee et al., 2015). Integration into Machine Learning Models: The extracted text and audio features are integrated into a multimodal learning framework, which is critical in clinical settings where both the content and manner of speech are crucial for accurate diagnosis. Normalization and Standardization: Prior to integration, features undergo normalization to ensure model inputs are on a comparable scale, facilitating performance and stability in neural networks.

VI. Model Selection and Architecture

A. Model Selection

The selection of models for diagnosing dementia using multimodal data was driven by the need to integrate complex, unstructured datasets effectively, including audio and textual data. Each selected model offers unique advantages in processing and interpreting such multimodal inputs, which are pivotal for enhancing diagnostic accuracy and insightfulness in clinical settings. **BioBERT**: A derivative of BERT specifically trained on biomedical text, BioBERT was chosen for its enhanced capability in understanding complex medical jargon and semantics compared to its general-domain counterparts. This model has shown superior performance in various biomedical NLP tasks, making it highly suitable for extracting nuanced information from clinical narratives (Lee et al., 2020). **Clinical BERT**: Designed to capture context-sensitive interactions in patient data, this model adjusts the robust BERT architecture to medical situations. It was initially developed for clinical text (Alsentzer et al., 2019). **DistilBERT**: DistilBERT is a condensed version of BERT that provides a computational efficiency and performance trade-off, making it ideal for implementation in systems with constrained resources without materially sacrificing the final result (Sanh et al., 2019). **RoBERTa**: Using larger data sets, better training protocols, and batch sizes, this model builds on BERT and improves performance on a variety of natural language processing (NLP) tasks (Liu et al., 2019). Because of its resilience, it is perfect for managing large amounts of varied text data while diagnosing dementia. The limitations

of these models include their substantial requirements for computational resources and data for training, potential biases inherited from training data, and the challenge of interpreting their complex model structures.

B. Architecture Overview

1) Multi-Modal architecture: The architectures of models were designed to maximize the extraction and synthesis of relevant features from both audio and text data. The following provides an overview of the core components: Input Layer: Separate input layers for text and audio allow the models to process each modality with specialized preprocessing paths, ensuring that distinct characteristics of each data type are adequately captured. Text Data: Utilizes transformer-based models (BioBERT, Clinical BERT, etc.) which include multiple layers of self-attention mechanisms to generate contextual embeddings. The Convolutional Neural Network (CNN) layer utilized in audio processing is fundamental for extracting meaningful spectral features from raw audio data. This layer's principal function is to capture temporal and frequency features from the audio signal which are crucial for recognizing complex patterns necessary for tasks like classification or anomaly detection in sounds. The CNN layers operate on spectrograms or mel-frequency cepstral coefficients (MFCCs) derived from the audio. These representations provide a time-frequency domain where CNNs can effectively identify and learn distinctive audio patterns such as pitch, tone, and variations in speech or music. The configuration typically involves several convolutional layers stacked with activation functions like ReLU to introduce non-linearity, followed by pooling layers to reduce dimensionality and enhance feature detection by focusing on dominant features while discarding irrelevant information. The Fusion Layer combines the acquired representations from both modalities to create an all-encompassing feature set that incorporates data from both audio and textual inputs. Dense and Output Layers: To avoid overfitting and stabilize the learning process, a number of fully linked layers are placed before batch normalization and dropout layers. The final output layer divides the input into various dementia categories using a softmax activation function. Given the complexity of the models and the variety of data involved, regularization and dropout are implemented at different places in the architecture to improve generalization and reduce overfitting. This structured approach to integrating and analyzing multimodal data aims to leverage the strengths of each model and architectural element to produce a robust, accurate, and clinically valuable tool for dementia diagnosis. The detailed configuration of layers, choice of activation functions, and the rationale behind each architectural decision are rooted in empirical evidence from preliminary studies and established best practices in deep learning for healthcare.

2) Text-only model: The architecture extracts features from textual data using a BioBERT model. This model is especially well-suited to the analysis of clinical text data because of its expertise in biomedical settings. Several levels in the architecture are intended to maximise performance and learning:

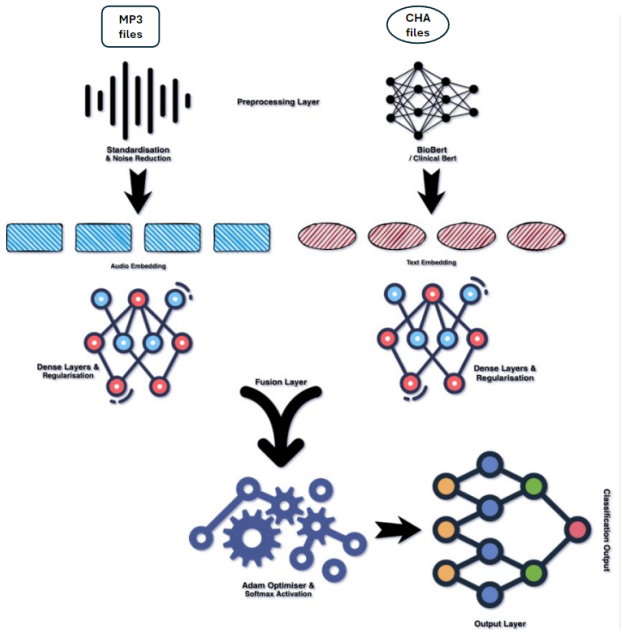

Fig. 1. Architecture of the multimodal diagnostic system for dementia categorization.

Input Layer: Modified to correspond with BioBERT's output dimension; usually, 768 features are used to represent the text embeddings that are taken out of the transcripts. Dense Layer: This layer adds non-linearity to the data by activating ReLU and having 128 units. This helps recognise complicated patterns in the data. After the dense layer, apply the batch normalization layer to stabilize learning by normalizing the activations and quickening the training process. Dropout Layer: With a value of 0.5, this layer ensures that the model does not rely unduly on any one or small group of neurons by randomly removing units (along with their connections) during the training phase. This helps prevent overfitting. The output layer is a thick layer that translates the number of classes in the target variable to the final output using a softmax activation function. Because it provides probabilities for each class, this layer is essential for classification because it helps identify the most likely class label given a set of input features. This setup is compiled with an Adam optimizer, which is known for its efficiency in handling sparse gradients on noisy problems. The learning rate is set to 0.001, balancing the speed and accuracy of learning. The model uses categorical cross entropy as a loss function, which is standard for multi-class classification problems. The model is trained using batches of data, with validation performed on a separate validation set to monitor and prevent overfitting. The architecture is geared towards achieving high precision and recall, indicative of its ability to not only accurately classify dementia from clinical interviews but also to minimize false positives and negatives, crucial for medical diagnostic applications.

3) Audio-only model: The architecture described in the attached file employs a machine learning model specifically

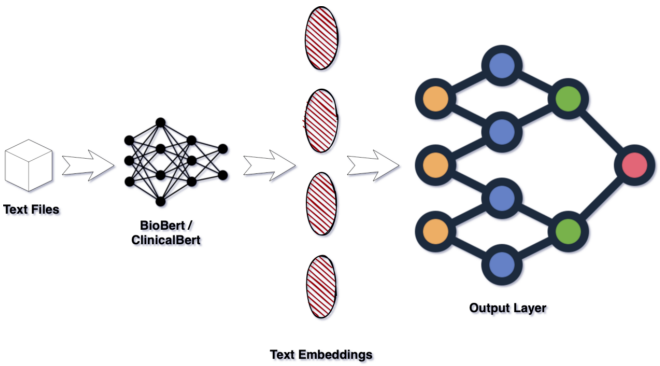

Fig. 2. Schematic overview of the text only model pipeline utilizing BERT for embedding extraction from CHA files

designed to process audio data for the categorization of different dementia stages. This architecture is constructed around several core components: Audio Feature Extraction: The model starts with the extraction of audio features using Librosa, a Python library for music and audio analysis. Features such as Mel-frequency cepstral coefficients (MFCCs) are extracted from audio files. MFCCs are critical as they effectively represent the short-term power spectrum of sound and are commonly used in speech and audio processing tasks to capture timbral aspects. Neural Network Architecture: The core of the model consists of several layers designed to process the extracted features: Input Layer: The model inputs are shaped to accommodate the 13 MFCCs extracted from each audio file. Dense Layers: To add non-linearity and aid the model in identifying more complex patterns in the data, the architecture has dense layers with ReLU activation functions following the input. Batch normalisation is a technique used to stabilise the learning process by normalising the activations of the previous layer. This enhances learning and lessens the model's sensitivity to the initial starting weights. Dropout layers randomly set a subset of input units to 0 at each training update in order to prevent overfitting. This provides an efficient method for roughly combining exponentially many different architectures and mimics the effect of training the network on diverse topologies. Output Layer: The last layer outputs the likelihood that an input will fall into each diagnosis class. It is a dense layer with a softmax activation function. For classification problems where the model must select amongst several categories, this layer is crucial. Model Compilation: The model is compiled using the Adam optimiser, which is a well-liked option for deep learning applications because of its memory-efficient design and effective processing. Additionally, it dynamically modifies the learning pace. Categorical cross-entropy is the loss function that is employed, and it works well for multi-class classification issues. Training and Validation: A subset of the data is used to train the model, while validation is carried out in parallel to track how well the model performs on data that hasn't been seen yet. This allows the hyper-parameters to be adjusted without overfitting the training set. This configuration highlights a focused approach to handling audio data, leveraging neural network capabilities to interpret complex patterns and relationships in audio features related to speech, which may indicate different stages or types of dementia. The chosen methods and layers are tailored to maximize the accuracy of class predictions while maintaining the ability to generalize well to new, unseen data.

VII. Training the Model

Instructional Configuration The models were carefully trained with an emphasis on resilience and accuracy in diagnosing various forms of dementia, in order to maximize the handling and interpretation of multimodal data. The computational capacity required to effectively handle big datasets and intricate model architectures was made available by this configuration. Software Specifications: TensorFlow and PyTorch libraries were used in conjunction with the Python programming language. These tools are ideal for developing and refining complex neural network models, and they provide extensive support for deep learning methodologies.

Hyper-parameters: Learning Rate: The learning rate was initially set at 0.001, but as training went on, a decay mechanism was used to lower the rate and guarantee more precise network weight adjustments in subsequent phases. Batch Size: To strike a balance between model performance and computational economy, a batch size of 32 was employed. Training epochs: The models were trained for a maximum of 100 epochs. In the case that the validation loss did not improve for ten consecutive epochs, early stopping was applied to prevent overfitting. Regularization: To avoid overfitting, L2 regularization was done to several layers. The model's performance on the validation set was used to adjust the coefficients of the regularization. Dropout: Depending on the model and layer, dropout rates ranged from 0.3 to 0.5, which served to randomly deactivate a part of neurons during training to improve model generalizability.

Training Procedures: Initialization: Weights were initialized using the uniform initializer, ensuring a balanced distribution that aids in the efficient propagation of gradients during training. Optimization: Adam optimizer was used for its adaptive learning rate capabilities, helping to converge faster in training deep learning models. Back propagation: Employed to adjust the weights of the network by calculating gradients of the loss function with respect to each weight.

A. Cross-Validation

To evaluate the model's performance and ensure its generalizability across different subsets of data: K-Fold Cross-Validation: The dataset was divided into 'k' consecutive folds (typically five or ten), where each fold was used once as a validation while the k-1 remaining folds formed the training set. This method helps in understanding the model's effectiveness across different subsets of data and reduces the bias associated with the random splitting of data. Stratified Sampling: Given the uneven distribution of classes in the dementia dataset, stratified sampling was used during the fold split to ensure

that each fold is a good representative of the whole dataset, particularly important for handling classes with fewer samples. These techniques collectively enhance the reliability of the model by ensuring it performs well across unseen data and reduces the likelihood of model overfitting. The rigorous training setup and validation process underpin the robustness of the model, aiming to deliver accurate and clinically useful outcomes for dementia diagnostics.

VIII. Evaluation

Evaluating the performance of the Large Language Model (LLM) in classifying dementia stages using the Pitt corpus is critical to ensure the reliability and accuracy of the model before it can be deployed in a clinical setting. This section outlines the methods and metrics used to assess the model's effectiveness and the procedures for validating the model's predictions.

A. Performance Metrics

Accuracy: Indicates the proportion of all accurate predictions the model made in each of the three categories (mild, moderate, and severe). It is computed by dividing the total number of forecasts by the number of accurate predictions. Precision measures how well each category of dementia stage's predictions came to pass. It shows the percentage of genuine positives (i.e., cases that are accurately classified as "moderate") among the expected positives. Recall: Evaluates how well the model can identify every real instance for every stage of dementia. In this sense, high recall refers to correctly recognising the majority of patients within each stage without any cases being missed. ROC-AUC: The model's capacity to distinguish between classes was demonstrated by evaluating performance across all potential classification thresholds using the Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC). The model's performance metrics are broken down by dementia stage to ensure that it is equally effective across the spectrum of dementia severity. This breakdown helps identify if the model is biased towards any particular stage of dementia.

B. Validation

A subset of the Pitt corpus not used during the training phase is designated as the validation dataset. This ensures that the model is evaluated on fresh, unseen data, mimicking real-world application. The validation phase tests the model's ability to generalize its learning to new data. This is critical, as the ultimate goal is to deploy the model in clinical settings to assist in diagnosing dementia stages. Feedback from clinical experts who assess the model's predictions against actual clinical outcomes is incorporated. This step is vital for tuning the model's parameters and for verifying the clinical relevance of its predictions.

C. Statistical Analysis

Chi-square tests for independence, depending on the data distribution, are statistical tests that are used to evaluate the significance of the variations in the model's performance that are shown between dementia phases. For every indicator, p-values and confidence intervals are provided to give a statistical foundation for the performance reliability of the model. These metrics aid in comprehending the model's resilience to various scenarios and patient demographics.

IX. Results

The analysis of model performance across different dementia conditions provides significant insights into the diagnostic capabilities of the models under various configurations. The overall results depict a varied performance across models, with some showing strength in precision while others exhibit better recall or accuracy under different regularization and dropout settings.

A. Performance across Models

The results from Table I highlight the impact of model configuration on the overall diagnostic accuracy, precision, and recall. For instance, Clinical BERT without regularization, dropout, or batch normalization achieved a higher overall accuracy and precision compared to when regularization was applied (reg 0.01 and reg 0.1), indicating potential overfitting when regularization is absent. The introduction of dropout and batch normalization in some models appears to decrease performance, suggesting that the tuning of these parameters is critical for optimal model performance.

TABLE I
Performance comparison of different models

Model Description	Accuracy	Precision	Recall
Clinical BERT without regularization	53.85%	54.00%	51.92%
Clinical BERT with reg 0.01	30.77%	33.33%	30.77%
Clinical BERT with reg 0.1	48.08%	46.81%	42.31%
Clinical BERT with reg 0.1, dropout 0.3	42.31%	43.75%	26.92%
BioBERT with reg 0.1, dropout 0.5	55.77%	61.11%	42.31%
RoBERTa with reg 0.1, dropout 0.5	38.46%	45.00%	34.62%
DistilBERT with reg 0.1, dropout 0.5	48.08%	42.86%	28.85%
Text only with BioBERT	55.36%	57.69%	53.57%
Text only with DistilBERT	53.57%	66.67%	50.00%
Text only with RoBERTa	46.43%	51.06%	42.86%
Text only with Clinical BERT	51.79%	55.81%	42.86%
Audio only	26.79%		

B. Class-specific Analysis

In the analysis of performance on the Control class (Table II), models show a varying degree of effectiveness, with Text only models generally outperforming the Audio only model. Notably, the Text only model with DistilBERT achieved the highest precision and F1 score, which indicates robustness in identifying the Control class under this configuration.

Table III, which details the performance on the MCI class, shows a generally lower performance across all models compared to the Control class. This suggests that MCI may be more challenging to diagnose using the features extracted and methodologies applied, highlighting the need for enhanced feature engineering or alternative modeling techniques for this particular condition.

Table IV and V focus on PossibleAD and Vascular classes, respectively. The Audio only model shows surprising strength in precision for the PossibleAD class, though its recall remains low. This could indicate that while the audio features are specific, they are not exhaustive in capturing all necessary diagnostic signals. For the Vascular class, the performance is notably poor across most models, which may be due to the smaller sample size or the complexity of the disease's audio and textual manifestations.

TABLE II
COMPARISON OF MODEL PERFORMANCE ON THE CONTROL CLASS

	Control		
Model Description	Precision	Recall	F1
Text only model with BioBERT	0.58	0.85	0.69
Text only model with DistilBERT	0.92	0.85	0.88
Text only model with RoBERTa	0.52	0.85	0.65
Text only model with Clinical BERT	0.65	0.85	0.73
Audio only model-Test	0.29	0.29	0.29

	Control		
Model	Accuracy	Precision	Recall
BioBERT	48.08%	66.67%	83.33%
RoBERTa	38.46%	53.85%	58.33%

TABLE III
COMPARISON OF MODEL PERFORMANCE ON THE MCI CLASS

	MCI		
Model Description	Precision	Recall	F1
Text only model with BioBERT	0.56	0.42	0.48
Text only model with DistilBERT	0.46	0.5	0.48
Text only model with RoBERTa	0.12	0.08	0.1
Text only model with Clinical BERT	0.4	0.33	0.36
Audio only model-Test	0.23	0.2	0.21

	MCI		
Model	Accuracy	Precision	Recall
BioBERT	48.08%	60.00%	60.00%
RoBERTa	38.46%	35.71%	50.00%

TABLE IV
COMPARISON OF MODEL PERFORMANCE ON THE POSSIBLEAD CLASS

	PossibleAD		
Model Description	Precision	Recall	F1
Text only model with BioBERT	0.42	0.38	0.4
Text only model with DistilBERT	0.4	0.15	0.22
Text only model with RoBERTa	0.54	0.54	0.54
Text only model with Clinical BERT	0.45	0.69	0.55
Audio only model-Test	0.75	0.25	0.38

	PossibleAD		
Model	Accuracy	Precision	Recall
BioBERT	48.08%	45.00%	64.29%
RoBERTa	38.46%	45.45%	35.71%

C. Statistical Significance

The Chi-Square tests indicate significant differences in the distributions of diagnoses across models, suggesting that the model's ability to distinguish between classes varies significantly with different configurations and modalities. The high Chi-Square statistic values accompanied by low P-values in multiple setups confirm that the variations in model outputs are statistically significant and not due to random chance. The statistical analysis of the models' performance using the Chi-Square test yielded significant values, underscoring the dependency of model performance on the choice of training configurations and model types. The Chi-Square statistic values, being considerably high across different model evaluations, coupled with very low P-values, assert that the variations in diagnostic accuracy among different settings are statistically robust and not attributable to random chance. This finding emphasizes the nuanced influence of hyperparameters and model architectures on the task-specific performance in dementia diagnosis.

TABLE V
COMPARISON OF MODEL PERFORMANCE ON THE VASCULAR CLASS

	Vascular		
Model Description	Precision	Recall	F1
Text only model with BioBERT	0.67	0.5	0.57
Text only model with DistilBERT	0	0	0
Text only model with RoBERTa	0	0	0
Text only model with Clinical BERT	0	0	0
Audio only model-Test	0.22	0.4	0.29

	Vascular		
Model	Accuracy	Precision	Recall
BioBERT	48.08%	0.00%	0.00%
RoBERTa	38.46%	0.00%	0.00%

D. Implications

These results underscore the importance of model selection and configuration in the development of AI-based diagnostic tools for dementia. The varying effectiveness across different classes suggests that a one-size-fits-all approach may not be feasible, and personalized model tuning may be necessary to address the specific challenges of each dementia subtype. The insights derived from this study can guide further research into optimizing machine learning models for the nuanced task of diagnosing different forms of dementia, ultimately leading to more accurate and reliable tools in clinical settings. These statistical insights pave the way for targeted research into specific configurations that could potentially enhance diagnostic accuracies for challenging categories like MCI and Vascular dementia, where current models underperform. Future studies could explore more granular feature engineering, the integration of additional modalities, or more advanced ensemble techniques to address these shortcomings.

TABLE VI
CHI-SQUARE TEST

Chi-Square Statistic	P-Value
177.4692308	3.50E-34

E. Significance of Findings

The significance of these findings lies in their potential to inform the development of more sophisticated, accurate, and reliable diagnostic tools for dementia that are adaptable to the variability inherent in clinical presentations of the disease. The identification of statistically significant differences in model performance across configurations guides the optimization of these tools in a data-driven manner. This approach not only enhances model reliability but also contributes to personalized medicine, where treatment plans are tailored to individual diagnostic profiles derived from AI-enhanced assessments. In conclusion, this study provides a foundational framework for future advancements in AI-driven diagnostics for dementia, suggesting that careful attention to model selection, training paradigms, and the statistical validation of results will be crucial in the path towards clinical applicability.

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