**Journal of Information Systems Engineering and Management**
2025, 10(15s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

**Research Article**

# Early Diagnosis of Alzheimer's Disease using VGG 19 and RESNET 50

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**ARTICLE INFO**

Received: 30 Nov 2024

Revised: 25 Jan 2025

Accepted: 03 Feb 2025

**ABSTRACT**

Early diagnosis is crucial for Alzheimer's disease (AD), a neurodegenerative condition that affects language, memory, and cognitive function. Complicated language structures and lengthy conversations are difficult for current speech-to-text models to handle. Conventional methods have limitations in terms of accuracy and efficiency, such as analysing MFCC images using CNNs like VGG-16. To address these issues, the suggested system transforms speech into MFCC images and uses sophisticated pre-trained models such as VGG-19 and ResNet50 to analyse them. In order to boost performance, a hybrid model also incorporates these networks with a random classifier. In addition to addressing the drawbacks of speech-to-text systems, this approach minimizes preprocessing steps. The use of image-based analysis to provide quicker and more precise dementia classification helps to improve early detection and diagnosis of Alzheimer's disease.

**Keywords:** Alzheimer's disease, neurodegenerative

## I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that affects millions worldwide and is the primary cause of dementia in older adults. It affects cognitive abilities, memory, and the capacity to carry out everyday tasks. While late-onset Alzheimer's typically develops around age 65, early-onset Alzheimer's can appear as early as 30 to 60 years of age. Currently, there is no cure for AD; available treatments primarily manage symptoms but do not alter the disease's progression. Thus, early detection of AD is crucial, enabling timely interventions that may delay cognitive decline and improve patient outcomes.

Early symptoms of AD include memory impairment, but other cognitive challenges—such as difficulties with language, spatial awareness, reasoning, and judgment—are also common indicators.Advanced AD leads to severe complications like dehydration, malnutrition, and infections, which contribute to high mortality rates. Given the substantial healthcare burden posed by AD, early and accessible diagnosis is a significant area of research and innovation.

While effective, traditional diagnostic methods, including neuroimaging and cognitive assessments, are resource intensive and require specialized equipment. This has driven interest in developing non-invasive, cost-effective, accessible diagnostic alternatives. Machine learning (ML) and deep learning (DL) have shown promise in AD detection by analysing large, complex datasets to identify predictive biomarkers. Since audio analysis can identify subtle speech changes linked to cognitive decline, it has drawn interest as a potential diagnostic tool among emerging techniques.

MRI scans the brain in detail to discover anatomical alterations such as hippocampal atrophy, which may then be classified using deep learning algorithms. PET scans monitor brain metabolism and amyloid plaque buildup, and the generated images are used to train convolutional neural networks (CNNs) to detect Alzheimer 's specific patterns. CT scans produce 3D images of the brain to detect atrophy, which machine learning algorithms can use to highlight aberrant alterations symptomatic of Alzheimer's. SPECT monitors blood flow patterns, and machine learning models detect areas of diminished perfusion that are frequent in Alzheimer's patients. fMRI measures

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brain activity, and machine learning models assess shifts in neural activation during tasks to detect early indicators of cognitive deterioration in Alzheimer's.

Changes in vocal characteristics, such as pitch, intonation, pauses, and articulation, are often present in individuals with AD. According to recent research, ML algorithms are able to identify these vocal biomarkers and successfully differentiate between people who are healthy and those who are in the early stages of AD. In this study, we propose a deep learning approach leveraging audio data to enhance early AD detection, potentially increasing the scalability and accessibility of screening methods.

The proposed model uses raw audio recordings from participants, which are preprocessed and transformed into spectrograms—a visual representation of audio signals in the time-frequency domain. Spectrograms capture essential audio features, displaying signal frequency and amplitude over time. This representation allows the use of Convolutional Neural Networks (CNNs), which are adept at learning complex visual patterns, to extract subtle speech features relevant to AD.

With the aim to capture speech characteristics relevant to Alzheimer's disease (AD), the suggested approach converts patient raw audio recordings into MFCC (Mel-Frequency Cepstral Coefficients) images. Before proceeding with quantization, which replaces quiet parts by shifting zero amplitudes to near non-zero values, and normalization, which adjusts the audio values between -1 and 1, the method starts with digitizing and sampling the audio to produce discrete numerical representations. Highfrequency components are amplified by preemphasis filters, while spectral leakage can be reduced by framing and windowing, which split the signal into overlapping parts.

In order to extract MFCC, each audio frame is subjected to a Fourier Transform (FT), which transforms the time-domain signal into the frequency domain. The frequencies that the human ear is particularly sensitive to be highlighted by filtering the frequency spectrum with Mel scale filter banks. Perceptual loudness is captured by log-transforming the output, and the most pertinent speech elements are summarized by a Discrete Cosine Transform (DCT) to produce MFCCs. These coefficients are shown as two-dimensional (2D) pictures, with the x-axis representing time, the y-axis representing Mel frequency ranges, and the pixel intensity representing the MFCC values' magnitude.

By removing background noise, noise reduction techniques guarantee that only essential vocal characteristics are preserved. Pitch shifting and time stretching are examples of data augmentation techniques that are used to enrich datasets and improve model generalization. Convolutional Neural Networks (CNNs) use these MFCC images to find complex patterns associated with AD. Utilizing information from extensive image datasets, transfer learning with pre-trained CNNs allows for quicker training and improved accuracy on smaller audio datasets. Using features that have been extracted, the final classification layers classify inputs as either "Dementia" or "NonDementia."

This MFCC-based method offers a scalable solution for early AD detection and is economical by utilizing speech characteristics that are in line with human hearing. It opens the door for non-invasive, easily accessible, and prompt interventions by enabling remote monitoring and diagnosis with possible integration into mobile health platforms. This innovative approach has the potential to greatly advance Alzheimer's diagnosis, enhance patient outcomes, and significantly reduce the disease's burden on society.

## II. LITERATURE SURVEY

The study "Speech-Based Detection of

Alzheimer’s Disease: A Survey of AI Techniques, Datasets, and Challenges" provides a comprehensive examination of recent advancements in the use of AI in speech analysis for the diagnosis of Alzheimer’s disease. According to the paper, "Recent AI techniques for detecting Alzheimer’s disease through speech were surveyed, covering 85 studies from 2018 to 2023." Speech provides a useful, non-invasive diagnostic tool, it emphasizes, and datasets such as ADReSS "enable consistent comparison of models." BERT and other deep learning models are renowned for "achieving high accuracy." Among the difficulties are "data scarcity, privacy, and interpretability." "Improving multilingual capabilities, exploring multimodal approaches, and enhancing ASR systems" are some of the future research directions for AD detection.

By combining textual and audio data, "MultiModal Detection of Alzheimer’s Disease from Speech and Text" presents a deep learning-based technique for Alzheimer’s disease detection. While BERT-based and CNN components process textual transcripts, this multimodal model uses a CNNbased network to analyse audio segments. To categorize people as either healthy or AD-positive, the predictions from the two modalities are combined. The model performs 85.3% accurately with manual transcripts and 78.8% accurately with ASR-generated transcripts when tested on the Dementia Bank Pitt corpus. Obstacles include age and gender biases and ASR limitations that impact text-based model performance. Enhancing multimodal integration and investigating more reliable ASR methods for clinical application are suggested future directions.

The "Speech- and Language-Based Classification of Alzheimer's Disease: A Systematic Review" systematic review set out to identify the optimal methods and algorithms for language-based

Alzheimer's disease classification and detection. From January 2015 to May 2020, a thorough literature search was carried out, and articles that satisfied the inclusion requirements were reviewed. The review noted speech characteristics associated with the linguistic and acoustic footprint of Alzheimer's disease, identified the primary resources that can aid in the development of decision support systems for the disease, identified data models that can yield reliable results, and examined performance indicators documented in the literature.

The study "Exploiting Pre-Trained ASR Models for Alzheimer’s Disease Recognition Through Spontaneous Speech" investigates the use of pretrained ASR models in a simplified method for detecting Alzheimer’s disease (AD). The study integrates a simpler neural network for AD recognition, reducing model complexity by removing complex BERT classifiers and only keeping and modifying the lower layers of ASR models. This model does not require manual transcripts because it takes raw speech as input. Experiments on the NCMMSC Alzheimer's Disease Recognition Challenge dataset show that encoded linguistic information significantly improves accuracy, outperforming transcriptbased approaches.

A recent meta-analysis confirms the significant role lifestyle factors play in reducing the risk of Alzheimer's disease. The results highlight the protective benefits of exercise, nutrition, and mental activity. Notably, it has been demonstrated that the MIND diet, which combines the DASH and Mediterranean diets, can help prevent cognitive decline, underscoring the significance of taking preventative action. Furthermore, organized cognitive rehabilitation programs show promise for enhancing cognitive abilities in patients with Alzheimer's disease in its early stages. Promising results for cognitive health are provided by these interventions, which focus on particular abilities and techniques to improve everyday living and may slow the progression of disease.

## III.DATASET:

The dataset used in this project consists of 442 audio clips that were carefully categorized into two classes: dementia and non-dementia, and collected from a GitHub repository. Of these, 311 clips are classified as non-dementia samples, and 131 clips are classified as dementia samples. And 306 audio clips, comprising 185 dementia and 121 non-dementia speech recording samples, were taken from Dementia Bank.

The hybrid model developed for Alzheimer's diagnosis makes use of these audio clips, which are saved in.wav format, as its main input for training and assessment. In order ensure a successful training process, the dataset is carefully split with 10% set aside for testing and validation and 90% used for training. In order assure consistency when comparing model predictions, the datasets are organized to preserve the same kind of distribution.

The preprocessing pipeline involves converting audio clips into Mel-Frequency Cepstral Coefficients (MFCC) spectrogram images. These images are resized to a standardized input dimension of 224x224 pixels. Standardizing the input shape enhances uniformity across the dataset, allowing seamless integration with the model architecture. This resizing step also mitigates potential discrepancies arising from varying image sizes, contributing to improved model performance. By meticulously organizing and preprocessing the dataset, it is optimized for effective training and evaluation. These steps ensure the dataset is robust and well-suited for developing a reliable hybrid model. The carefully prepared data facilitates accurate Alzheimer's diagnosis by leveraging advanced machine learning techniques, demonstrating the potential of this approach in addressing a critical healthcare challenge. This partitioning technique preserves the integrity of the assessment process while ensuring that the model is exposed to a wide variety of samples. Audio recordings are transformed into MelFrequency Cepstral Coefficients (MFCC) spectrogram images as part of the preprocessing pipeline. A standardized input dimension of 224x224 pixels is used to resize these photos. By improving uniformity throughout the dataset, standardizing the input shape enables smooth integration with the model architecture. Additionally, by reducing possible disparities brought on by different image sizes, this resizing step enhances model performance.

## IV.METHODOLOGY:

The usage of audio datasets for Alzheimer's disease prediction has been examined by a number of researchers, who have transformed audio into MelFrequency Cepstral Coefficients (MFCC) images for analysis. By using the conversion of audio signals into visual representations, this method avoids the need for textual or CSV-based data extraction. System efficiency is increased by processing MFCC images more quickly using pre-trained deep learning models, as compared to textual formats that necessitate intricate and time-consuming NLP techniques. While allowing for robust classification, this approach preserves important speech characteristics. By using MFCC images, the suggested system maintains a high level of accuracy while addressing drawbacks in existing approaches, such as decision-making delays and the computational inefficiency of text-based processing.

### A. Conversion of Speech Signals to MFCC

Relevant features are extracted for analysis by transforming speech signals into Mel-Frequency Cepstral Coefficients (MFCC).

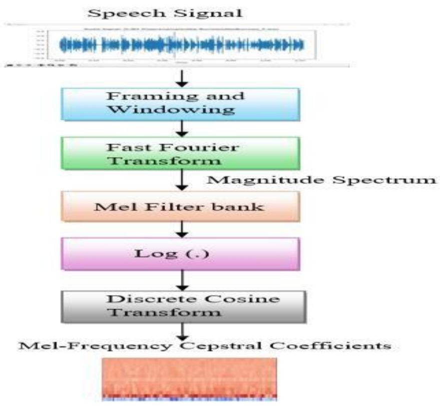


Fig: Generation of MFCC from Audio Dataset

The initial step is to convert the speech signal from the time domain to the frequency domain using the Fast Fourier Transform (FFT). A Hamming window, typically with a hop length of 1024 samples and a window size of 2048 samples at a sampling rate of 44.1 khrs, is used to segment the signal into overlapping frames. In order to map the frequency axis to the Mel scale, which corresponds with human auditory perception, the power spectrum is calculated and Mel filter banks are used. The lower frequencies that humans are more sensitive to are highlighted by this mapping.

After compressing the dynamic range using the logarithmic transformation, the MFCCs are obtained using the Discrete Cosine Transform (DCT) as shown in the figure. A concise and informative representation of the short-term power spectrum of speech, MFCCs capture both temporal and spectral features that are essential for audio classification tasks. Deep learning models can process the MFCC images that are produced using these coefficients.

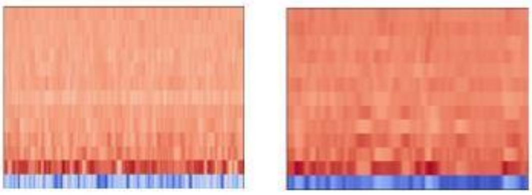

Fig: MFCC images

### B. Disease Classification Using VGG19

The proposed approach uses Mel-Frequency Cepstral Coefficients (MFCC) images obtained from speech signals to classify Alzheimer's Disease (AD) and Cognitive Normal (CN) states using the VGG19 pre-trained deep learning model. Before being transformed into images, the speech signals are first processed using the Fast Fourier Transform (FFT), Mel filter banks, and Hamming windows to create MFCCs. The 224×224×3 resizing of these images complies with VGG19's input specifications, allowing the model to efficiently analyse and categorize the illness. Image augmentation techniques like rotation, translation, zoom, and flipping are used to improve the generalization of the model and increase data variability in order to overcome the problem of small dataset sizes.

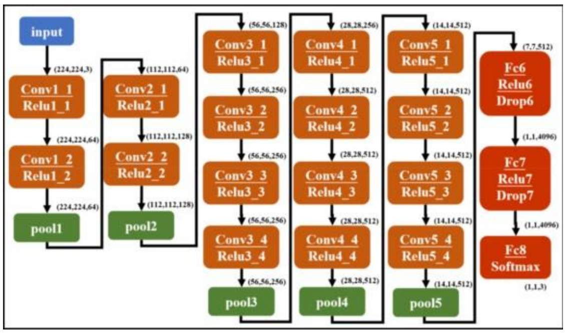


Fig: VGG19 Architecture

The VGG19 architecture consists of three fully connected layers, including a softmax output layer for classification, 16 convolutional layers with ReLU activation, and max-pooling layers for feature extraction as shown in the figure. Robust disease identification is achieved by the model's ability to extract intricate spatial and temporal patterns from the MFCC images thanks to its hierarchical design. In order to improve data quality and mitigate problems brought on by external voice modulations, preprocessing techniques are used to denoise the MFCC images. The system combines data augmentation, preprocessing, and the advanced feature extraction capabilities of VGG19 to achieve reliable and accurate Alzheimer's disease classification. This helps with early detection and diagnosis of the disease.

### C. Disease Classification Using ResNet50

The suggested approach employs the ResNet50 deep learning model to classify Alzheimer's Disease (AD) and Cognitive Normal (CN) states using MelFrequency Cepstral Coefficients (MFCC) images derived from speech signals. First, the speech signals are converted into MFCC images by applying methods like logarithmic scaling, Mel filter banks, and Fast Fourier Transform (FFT). For using them for disease classification, these images are resized to

224×224×3 dimensions in order to satisfy

ResNet50's input requirements.

Data augmentation methods such as flipping, translation, zooming, and rotation are used to boost variability and strengthen the model's resilience in order to overcome the limitations of small datasets.

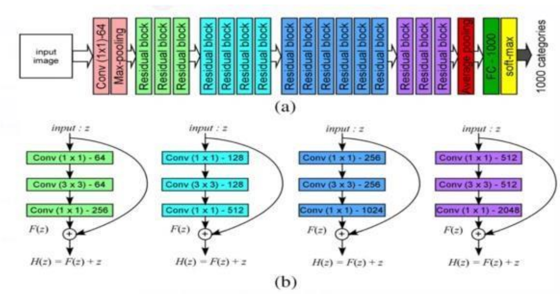


Fig: (a) Architecture of ResNet50 model (b) Residual block

Through the use of residual connections, ResNet50's 50-layer deep architecture mitigates the vanishing gradient issue and improves feature learning by enabling information to bypass specific layers. While global average pooling layer reduces the number of trainable parameters and prevents against overfitting, ResNet50's convolutional layers and residual blocks efficiently extract hierarchical spatial and temporal features from the MFCC images. The last fully connected layer divides the images into AD and CN groups based on a softmax activation function. ResNet50's capacity to extract fine-grained features through data augmentation and preprocessing makes disease classification precise and efficient.

### C. Disease Classification Using VGG19 and RESNET50 Hybrid model

By combining VGG19 and ResNet50, the hybrid model for Alzheimer's disease early identification enhances feature extraction and classification performance by leveraging the advantages of both architectures. ResNet50's residual connections allow for deeper learning without vanishing gradient problems, while VGG19's deep convolutional layers are capable at capturing fine-grained features. The model gains from both shallow and deep feature extraction when these two architectures are implemented together, giving it a more thorough comprehension of the data as shown in the figure.

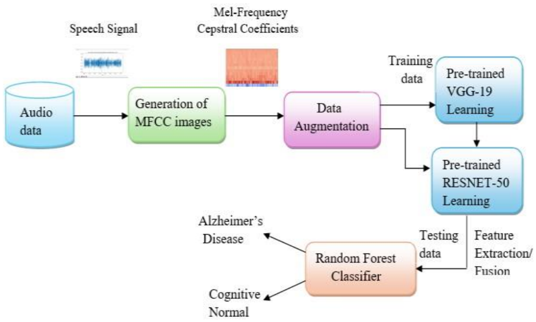


Fig: Overall Architecture of Proposed SystemAdvanced training methods are used in the hybrid approach to maximize performance. To ensure effective and efficient training, these include batch normalization, dropout, data augmentation, and dynamic learning rate adjustment via ReduceLROnPlateau. By stopping training when validation performance no longer improves, EarlyStopping prevents overfitting, improves generalization, and eliminates undesirable computation.

This hybrid model performs better than standalone architectures such as ResNet50 or VGG19. Deeper networks may be difficult for VGG19 to handle on its own because of vanishing gradient issues, particularly in complicated datasets like audio data transformed into MFCC spectrograms. Even though ResNet50 can handle deeper features, it still gains from VGG19's additional shallow feature extraction. Accuracy is also increased when these architectures work together to improve the model's capacity to capture a wide variety of the features.

Furthermore, the hybrid model uses scikit-learn to implement classic machine learning algorithms like Random Forest in order to improve classification performance even more. Alzheimer's disease can be diagnosed from audio data more accurately and with less overfitting when deep learning and conventional machine learning techniques are combined.

## V.RESULTS:

This project uses Google Colaboratory and publicly available datasets to detect Alzheimer's disease. It uses GPUs to process speech signals that are labelled "AD" (Alzheimer's Disease) and "CN" (Cognitively Normal). In order to simulate human auditory perception, Mel-Frequency Cepstral Coefficients (MFCC) features are utilized to depict the short-term power spectrum of audio signals. Audio preprocessing, MFCC computation with Librosa, and MFCC visualization for AD and CN samples are all steps in the process, which highlights the variations in speech patterns between the two classes. In order to increase dataset diversity and model generalization, data augmentation techniques like time stretching, pitch shifting, adding noise, time shifting, dynamic range compression, and volume scaling have been utilized. A varied training set is produced by these augmentations, increasing robustness and decreasing overfitting.

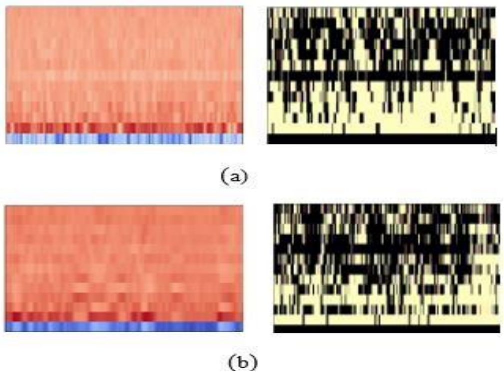


Fig: MFCC and Augmented images (a) AD class label (b) CN

class label

The VGG19 model achieves a test accuracy of approximately **82.18%**, demonstrating its effectiveness in classifying MFCC images of dementia and non-dementia patients. The model is trained using MFCC features derived from audio data, leveraging the deep feature extraction capabilities of VGG19 to distinguish between the two classes accurately.

To illustrate the training process, the following fig shows the loss and accuracy metrics across a few iterations during the training phase of VGG19. This visualization highlights the convergence of the model and its improvement over the epochs.

```
Epoch 1/10
33/33 [==============================] - ETA: 0s - loss: 1.2983 - auc: 0.7974
Epoch 1: val_auc improved from -inf to 0.76418, saving model to ./best_weights.hdf5
33/33 [==============================] - 1104s 34s/step - loss: 1.2983 - auc: 0.7974 - val_loss: 1.3682 - val_auc: 0.7642
Epoch 2/10
33/33 [==============================] - ETA: 0s - loss: 1.1348 - auc: 0.8188
Epoch 2: val_auc did not improve from 0.76418
33/33 [==============================] - 64s 2s/step - loss: 1.1348 - auc: 0.8188 - val_loss: 1.2924 - val_auc: 0.6692
Epoch 3/10
33/33 [==============================] - ETA: 0s - loss: 1.0221 - auc: 0.8366
Epoch 3: val_auc improved from 0.76418 to 0.82187, saving model to ./best_weights.hdf5
33/33 [==============================] - 66s 2s/step - loss: 1.0221 - auc: 0.8366 - val_loss: 0.9789 - val_auc: 0.8219
Epoch 4/10
33/33 [==============================] - ETA: 0s - loss: 0.9666 - auc: 0.8475
Epoch 4: val_auc did not improve from 0.82187
33/33 [==============================] - 63s 2s/step - loss: 0.9666 - auc: 0.8475 - val_loss: 1.1313 - val_auc: 0.7401
Epoch 5/10
33/33 [==============================] - ETA: 0s - loss: 0.9172 - auc: 0.8571
Epoch 5: val_auc did not improve from 0.82187
33/33 [==============================] - 62s 2s/step - loss: 0.9172 - auc: 0.8571 - val_loss: 1.0364 - val_auc: 0.7927
Epoch 6/10
33/33 [==============================] - ETA: 0s - loss: 0.8700 - auc: 0.8677
Epoch 6: val_auc did not improve from 0.82187
33/33 [==============================] - 61s 2s/step - loss: 0.8700 - auc: 0.8677 - val_loss: 1.0466 - val_auc: 0.7824
Epoch 7/10
33/33 [==============================] - ETA: 0s - loss: 0.8637 - auc: 0.8683
Epoch 7: val_auc did not improve from 0.82187
33/33 [==============================] - 64s 2s/step - loss: 0.8637 - auc: 0.8683 - val_loss: 0.9998 - val_auc: 0.8099
Epoch 8/10
33/33 [==============================] - ETA: 0s - loss: 0.8370 - auc: 0.8745
Epoch 8: val_auc did not improve from 0.82187
33/33 [==============================] - 61s 2s/step - loss: 0.8370 - auc: 0.8745 - val_loss: 1.0478 - val_auc: 0.7870
Epoch 9/10
33/33 [==============================] - ETA: 0s - loss: 0.7985 - auc: 0.8834
Epoch 9: val_auc did not improve from 0.82187
33/33 [==============================] - 62s 2s/step - loss: 0.7985 - auc: 0.8834 - val_loss: 1.0701 - val_auc: 0.7976
Epoch 10/10
33/33 [==============================] - ETA: 0s - loss: 0.8188 - auc: 0.8817
Epoch 10: val_auc did not improve from 0.82187
33/33 [==============================] - 63s 2s/step - loss: 0.8188 - auc: 0.8817 - val_loss: 1.0020 - val_auc: 0.8147
```

Fig: Few Iterations of VGG19

The ResNet50 model successfully distinguishes between MFCC images of patients with dementia and those without, achieving a test accuracy of 83.56%. ResNet50 is well-suited for Alzheimer's disease detection using MFCC features extracted from speech signals because it leverages its deep residual architecture to demonstrate reliable feature extraction and effective learning. Visualizations of the training iterations demonstrate the model's ability to discriminate between the two classes, with consistent gains in accuracy and loss convergence across epochs.

```
Epoch 5/10
3/3 [==============================] - 2s 680ms/step - loss: 0.4255 - accuracy: 0.8356
Epoch 6/10
3/3 [==============================] - 2s 412ms/step - loss: 0.4219 - accuracy: 0.8356
Epoch 7/10
3/3 [==============================] - 2s 645ms/step - loss: 0.4092 - accuracy: 0.8356
Epoch 8/10
3/3 [==============================] - 2s 409ms/step - loss: 0.3927 - accuracy: 0.8356
Epoch 9/10
3/3 [==============================] - 2s 689ms/step - loss: 0.3933 - accuracy: 0.8356
Epoch 10/10
3/3 [==============================] - 2s 410ms/step - loss: 0.3557 - accuracy: 0.8356
```

Fig: Few Iterations of RESNET50

The hybrid model outperforms both VGG19 and ResNet50 in medical image analysis binary classification tasks, achieving the highest test accuracy of 88.34% in MFCC image classification as shown in the fig. The hybrid model is the most accurate and reliable method for differentiating between dementia and non-dementia cases using MFCC features made from speech signals, as evidenced by its superior performance, which shows how well it leverages the combined strengths of the VGG19 and ResNet50 architectures.


Fig: Hybrid model iterations

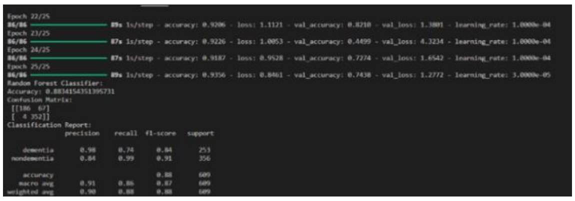


Fig: Overall Report Result of Hybrid Model

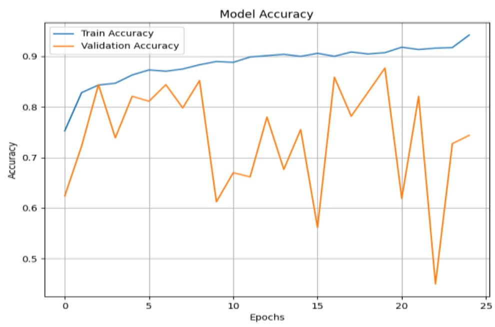


Fig: Results of Hybrid model for Predicting Alzheimer's Disease

The confusion matrix is a crucial tool for evaluating a classification model's performance. It presents the following values as shown in the fig.

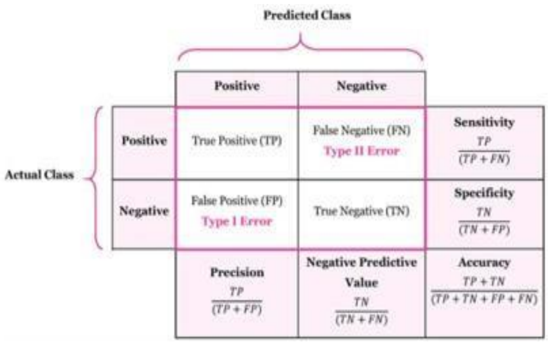


Fig: Confusion Matrix

In Alzheimer's Disease detection, the confusion matrix helps evaluate how well the model identifies dementia (positive class) and non-dementia (negative class), guiding further improvements as shown in the fig.

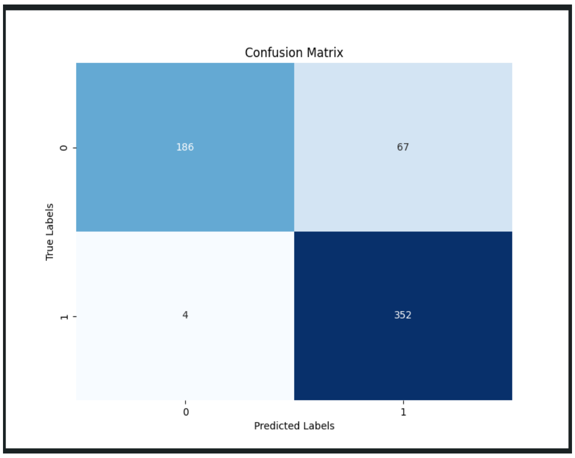


Fig: Confusion Matrix of Hybrid Model

The accuracy comparison of VGG19, ResNet50, and the hybrid model shows that the hybrid model outperforms both individual models, demonstrating the combined strengths of feature extraction and residual learning as shown in the fig.

| Model | Accuracy |
|---|---|
| VGG19 | 82.18% |
| RESNET50 | 83.56% |
| HYBRID MODEL | 88.34% |

Fig: Comparison Table

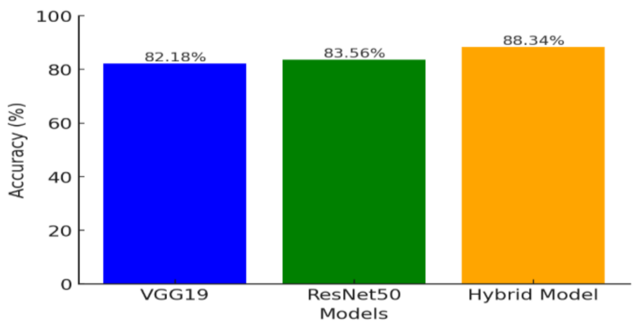


Fig: Comparison of trained models with their Accuracy

## VI.CONCLUSION:

In this paper, we propose a hybrid model for Alzheimer's disease diagnosis utilizing audioderived MFCC spectral images that combines the feature extraction powers of VGG19 and ResNet50 with a Random Forest classifier. The accuracy of the two models, VGG19 and ResNet50, was 82.18% and 83.56%, respectively. But with an accuracy of 88.34%, the hybrid model outperformed the others, demonstrating the advantages of integrating ensemble classifiers with deep learning architectures to improve diagnostic accuracy.

This research highlights how hybrid models, which offer better performance and resilience than standalone methods, can handle complicated medical information. The suggested model addresses the challenges of early Alzheimer's diagnosis by utilizing the complimentary advantages of feature extraction and ensemble approaches. Future research should examine improving this hybrid technique, adding other data modalities, and testing on larger data sets in order to increase generalizability even more. These developments may result in useful and accurate tools for diagnosis for use in medical facilities.

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