RESEARCH PAPER

Ml-Based Cognitve Health Evaluation And Care Platform

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ABSTRACT:

The Dementia app leverages advanced image processing and deep learning, particularly ResNet-101, to predict dementia progression through brain MRI scans. Dementia, a neurodegenerative disorder causing cognitive decline, requires early detection for effective management. The app extracts structural features from MRI scans, analyzing them to assess disease severity and monitor changes over time. By identifying patterns in brain scans, the app assigns a dementia risk score, aiding healthcare professionals in tracking symptom escalation. This predictive capability supports informed care decisions and intervention planning. Additionally, real-time assistance tools and long-term care planning enhance daily caregiving, reducing caregiver burden. Integrating image processing with predictive analytics, the app offers a data-driven, personalized approach to dementia care. It empowers healthcare providers and caregivers with actionable insights, enabling proactive management to potentially slow disease progression and improve patients' quality of life.

KEYWORDS: Dementia, Deep learning, Cognitive health, Predictive modelling, Convolutional neural networks (CNN), Recurrent neural networks (RNN), Early intervention.

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I . INTRODUCTION:

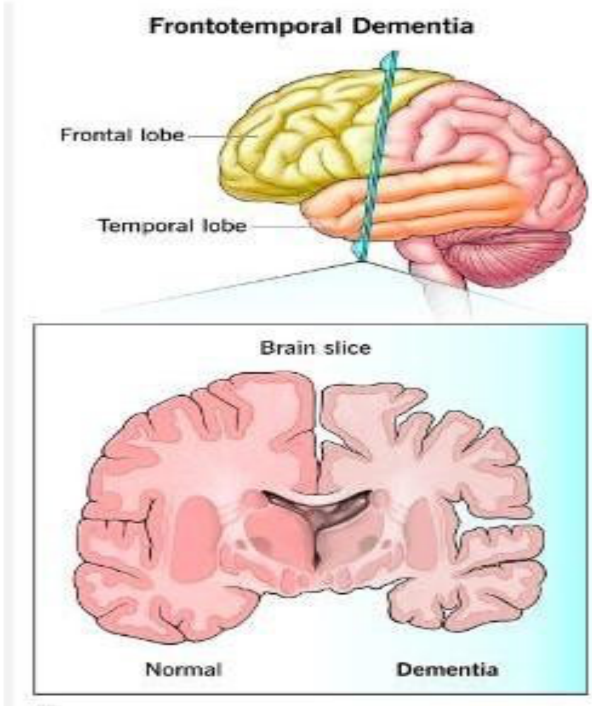
Dementia is a collective term for cognitive disorders that impair memory, thinking, and daily functioning. It results from brain damage and is not a normal part of aging. Alzheimer's disease is the most common form, accounting for 60-70% of cases, followed by vascular dementia, Lewy body dementia, and frontotemporal dementia. Early symptoms include mild memory loss and confusion, often

mistaken for aging. As dementia progresses, individuals experience communication difficulties, mood swings, personality changes, and impaired reasoning. In advanced stages, they require assistance with Alzheimer's disease stems from abnormal protein deposits disrupting cell function, vascular dementia results from reduced blood flow, and Lewy body dementia involves protein accumulations. Frontotemporal dementia affects specific brain regions. With 50 million cases worldwide and rising, dementia poses a major public health challenge, impacting families and healthcare systems. Caregivers play a crucial role but face emotional and physical strain. Assistive technologies, such as mobile apps, offer memory support, mood tracking, and communication tools. Machine learning aids in early detection by analyzing medical data, enabling personalized care plans and timely interventions to manage dementia effectively.

A. DEEP LEARNING:

Deep learning for image prediction using ResNet-101 involves employing a deep residual network architecture with 101 layers. ResNet-101 is a convolutional neural network (CNN) known for its ability to train very deep models without encountering vanishing gradient problems, thanks to its use of residual connections. These connections allow the model to skip certain layers, making training more efficient and helping it learn intricate features in images. In image prediction tasks, ResNet-101 is trained on large labeled datasets of images to recognize patterns and features. The network learns hierarchical representations of visual information, making it particularly effective for tasks like object detection, classification, and segmentation. By leveraging its depth, ResNet-101 can capture both low-level features (e.g., edges and textures) and high-level patterns (e.g., object shapes and complex structures), which are essential for accurate image prediction. During training, the model uses backpropagation and optimization techniques to adjust the weights of the layers. Once trained, the model can make predictions on new, unseen images, offering high accuracy and performance in image classification and prediction tasks. ResNet-101 is widely used in computer vision applications due to its robustness and effectiveness in handling complex image data.

FIG 1.1 DEMENTIA VIEW



B. ARCHITECTURAL DESIGN

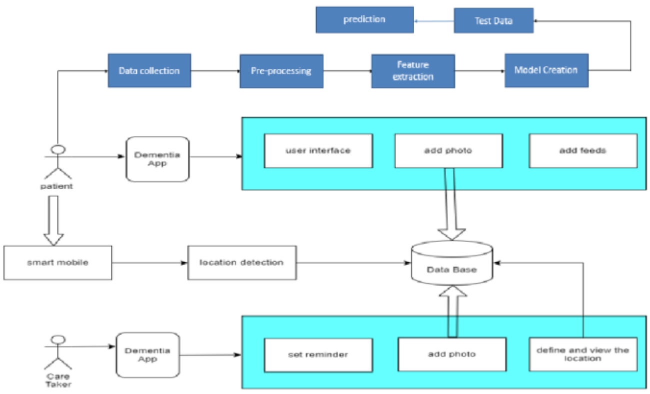


FIG 1.2 SYSTEM ARCHITECTURE

The proposed mobile application will have a scalable, reliable, and performant system architecture with three main layers: the presentation layer (user interface), the logic layer (core functionality), and the data layer (storage and retrieval of user data). React Native will be used for cross-platform compatibility, ensuring seamless experiences across devices. Secure cloud storage will manage data like patient memories and tracking info. The architecture will be modular, supporting future updates and feature integration. Security, data privacy, and interoperability will be prioritized to protect user data

II. LITRATURE SURVEY:

Joel Nyholm , Ahmad Nauman Ghazi , Sarah Nauman Ghazi, Johan Sanmartin Berglund, 2024 Nyholm et al. (2024) [1] explore the link between sleep disturbances and dementia risk in older adults using machine learning on the SNAC dataset. Their study highlights how specific sleep patterns can serve as early indicators of cognitive decline, emphasizing the need for timely intervention. Various machine learning models analyze sleep-related data to identify key predictors of dementia. However, the study notes that reliance on specific data features may limit the findings' applicability across diverse populations, requiring further validation. This research reinforces the role of machine learning in dementia prediction and management, contributing to technology-driven early detection and personalized care. Integrating these insights into our project will enhance the predictive analytics framework, ensuring robustness and broader applicability. By refining model generalizability, we can improve dementia risk assessment and intervention strategies, making early detection tools more effective for a wider audience. Yusuke Watanabe, Yuki Miyazaki, Masahiro Hata, 2024 [2] This study presents a deep learning model for detecting dementia and mild cognitive impairment (MCI) using resting-state EEG data from the Hospital O dataset. The model effectively classifies different dementia types while maintaining high balanced accuracy, highlighting its potential for early detection in clinical settings. The findings suggest that EEG data can enhance diagnostic precision by identifying distinct pathological features. However, the authors acknowledge a limitation: the model may not be fully optimized for diagnosing specific dementia types across diverse clinical environments. This underscores the need for further refinement and validation to improve its generalizability. Incorporating these insights, our project aims to develop a more robust predictive analytics framework. By addressing the identified challenges, we seek to enhance the reliability of dementia diagnosis and management, ensuring that the model performs effectively across different healthcare scenarios.

Hina Tufail, Abdul Ahad, Mustahsan Hammad Naqvi, 2024 [3] This study explores the classification of vascular dementia using deep learning on rs-fMRI data, demonstrating its potential as a highly accurate and non-invasive diagnostic tool. The research identifies specific imaging biomarkers, improving diagnostic precision and understanding of neural mechanisms. The findings highlight deep learning's role in early detection and clinical intervention while reducing reliance on invasive procedures. However, further validation across diverse populations is needed. Integrating these insights into our project will enhance predictive analytics for better dementia diagnosis and management.

Maria K. A. S. Alzubaidi, Abir M. Al-Khalidi, Hossam A. Gaber [4] This review analyzes various machine learning approaches for dementia diagnosis and prediction, highlighting advancements that enhance diagnostic accuracy. It discusses the integration of clinical, imaging, and genetic data, stressing the importance of combining these data types for more robust and interpretable predictive models. While machine learning shows promise in transforming dementia care, the effective fusion of multimodal data remains a significant challenge. The authors suggest that addressing this challenge through improved data integration methods could lead to more accurate dementia prediction systems. By incorporating these insights into our project, we aim to develop a predictive analytics framework that leverages diverse data and improves decision-making in dementia management. Sara Dhakala , Sami Azama , Khan Md. Hasibb , Asif Karima , Mirjam Jonkmana, ASM Farhan Al Haquec, 2023 [5] In their 2023 study, the authors examine machine learning techniques for predicting dementia using the OASIS dataset, achieving high accuracy through models like decision trees, support vector machines, and neural networks. This approach facilitates early detection and timely interventions for cognitive decline. The findings demonstrate the potential of machine learning in enhancing dementia care. However, the authors note that these models, developed in controlled settings, may face challenges when applied in diverse clinical environments. This underscores the need for further validation and adaptation to ensure their practical use. By incorporating these insights, our project aims to create a predictive analytics framework that is effective in real-world dementia management scenarios. Janice M. Ranson, Magda Bucholc , Donald Lyall, Danielle Newby, 2023 [6] This study explores the use of machine learning and AI in dementia research, utilizing the MAGMA dataset to predict dementia risk and improve patient outcomes. The authors demonstrate that advanced algorithms can accurately predict dementia by analyzing various data features, including cognitive assessments, behavioral metrics, and demographic information. The findings highlight the potential of machine learning and AI to create predictive models that enable early intervention and personalized care for individuals at risk of dementia. However, the authors caution that the accuracy of these predictions depends on the quality and comprehensiveness of the data used. Incomplete or biased datasets may lead to unreliable predictions, emphasizing the need for high-quality data collection and management. Incorporating these insights, our project aims to develop a reliable predictive analytics framework, ensuring that dementia models are built on robust data and can effectively support dementia management strategies.

III. PROPOSED SYSTEM:

The proposed system is an innovative dementia prediction and monitoring application that leverages brain MRI scans and advanced deep learning techniques to assess and track the progression of dementia. By processing brain MRI images, the system identifies critical patterns and abnormalities indicative of early-stage dementia or Alzheimer's disease. The app extracts relevant features from these scans using sophisticated image processing methods and analyzes them with the ResNet-101 deep learning algorithm. This model helps predict dementia severity and anticipate potential symptom escalation, providing healthcare professionals and caregivers with valuable insights into the patient’s cognitive health. The app’s predictive capabilities facilitate timely interventions and personalized care plans, enabling users to track the progression of dementia by monitoring changes in memory, mood, and behavior over time. This longitudinal data allows for better-targeted treatment adjustments and improved patient care. Additionally, the app offers real-time support for caregivers, helping them manage daily activities effectively and reduce their burden. By integrating advanced technology with caregiving practices, the app aims to enhance the quality of life for dementia patients and enable proactive, data-driven interventions for better outcomes.

A. DATA COLLECTION:

The data collection process for dementia prediction from Kaggle open-source datasets plays a pivotal role in building and refining machine learning models for diagnosing dementia and Alzheimer’s disease. It involves gathering diverse brain MRI scans and associated metadata to create robust, accurate predictive models. Datasets like the OASIS Alzheimer’s Detection Dataset and Best Alzheimer MRI Dataset feature MRI images labeled with varying degrees of dementia severity, such as "Non-Demented," "Mild Demented," and "Moderate Demented." This classification allows researchers to train models to differentiate between healthy and diseased states and recognize the progression of the disease. Some datasets also incorporate longitudinal data, tracking changes in brain scans over time, which is critical for understanding the disease’s progression and building models that can predict future outcomes. This time-sensitive data offers deeper insights, particularly for early-stage detection and monitoring the effectiveness of potential interventions. With labeled cognitive state information, these datasets are ideal for supervised learning algorithms, enabling the creation of dementia detection systems that can classify MRI images with high precision. By using such open-source resources, developers and researchers can accelerate the development of predictive tools that will ultimately support healthcare providers in diagnosing and managing dementia more effectively.

B. PRE-PROCESSING:

Pre-processing the dementia prediction dataset involves multiple steps to prepare the data for machine learning model training. First, data cleaning addresses any missing values or artifacts in the dataset, which could be removed or imputed to maintain consistency. MRI scans are often noisy or contain artifacts, so techniques like Gaussian blurring or median filtering are applied to smooth the images and eliminate such issues. Next, data normalization and standardization are crucial to ensure the pixel intensity values of MRI images are scaled uniformly, typically within the range of 0-1 or -1 to 1, which helps improve model performance. Image augmentation, including rotation, scaling, and flipping, increases the dataset's diversity, allowing the model to generalize better. Resizing the images to a consistent size ensures compatibility with deep learning models, which require fixed-size inputs. Additionally, label encoding is used to convert categorical labels, like "Non-Demented" or "Mild Demented," into numerical values, making them suitable for machine learning algorithms. Finally, the dataset is split into training, validation, and test sets, which allows for unbiased performance evaluation and prevents overfitting. These pre-processing steps ensure the dataset is clean, consistent, and ready for accurate and efficient dementia prediction.

C. FEATURE EXTRACTION:

Feature extraction in the context of dementia prediction using brain MRI scans involves transforming raw image data into meaningful, structured information that can be used by machine learning models for analysis. This process focuses on identifying key characteristics or patterns in the MRI scans that are indicative of brain abnormalities associated with dementia, such as atrophy or changes in brain structurre

Common feature extraction techniques include analyzing texture features, such as contrast, entropy, and homogeneity, which provide insights into the variation of pixel intensities and help detect abnormal patterns in the brain. Additionally, shape and morphological features are extracted to capture the size, shape, and structural changes of specific brain regions, like the hippocampus, which is critical in diagnosing Alzheimer's disease. Advanced deep learning techniques, particularly Convolutional Neural Networks (CNNs), are also employed to automatically learn and extract complex features from MRI images without manual intervention. These deep features often capture subtle changes in brain structures, which are essential for detecting early signs of dementia. Effective feature extraction improves the accuracy and reliability of dementia prediction models, enabling early detection and better disease progression monitoring.

D. MODEL CREATION USING RESNET 101:

The proposed system for dementia prediction uses ResNet-101, a deep learning model, to analyze brain MRI scans and predict the progression and severity of dementia. First, the system preprocesses the MRI images, including resizing, normalization, and data augmentation to enhance the model's ability to generalize. These images are then passed through the ResNet-101 architecture, a deep convolutional neural network known for its ability to learn complex features without the risk of vanishing gradients. ResNet-101's residual blocks allow the model to effectively extract high-level features from the MRI scans, such as changes in brain structure that indicate the presence and stage of dementia. The extracted features are used to train the model on labeled data, where each MRI scan is associated with a cognitive condition (e.g., non-demented, mild, moderate, or severe dementia). The model is then evaluated on a separate validation set to assess its predictive accuracy. Once trained, the model can predict the severity of dementia for new MRI scans, providing healthcare professionals with a dementia risk score or stage. This system not only helps predict the progression of dementia but also assists in planning personalized care, offering real-time support and long-term insights to improve the quality of care for patients. The use of ResNet-101 ensures a highly accurate and efficient approach to dementia detection based on brain imaging.

E. PREDICTION:

The model creation using ResNet-101 for dementia prediction involves leveraging the power of the deep learning architecture to analyze brain MRI scans. ResNet-101, with its 101 layers and residual connections, efficiently extracts relevant features from the images, such as brain structure abnormalities, to detect early signs of dementia. The preprocessing step includes resizing and normalizing the MRI images, followed by data augmentation to improve the model's robustness. The model is then trained on labeled MRI datasets, where it learns to classify dementia severity levels based on extracted features. After training, the model is evaluated on a test set to assess its prediction accuracy. Once validated, the model can predict the stage of dementia in new MRI scans, providing healthcare professionals with valuable insights for personalized care planning and early intervention.

F. REGISTRATION OF USER AND CAREGIVER:

For the system to be personalized and secure, it includes a user registration feature. Patients and caregivers can create accounts on the Android application, which requires collecting relevant information such as name, age, medical history, and caregiver details. This registration process ensures that the system can track individual patients, store their data securely, and provide tailored care. The caregiver also registers, enabling them to access the patient's data and receive real-time alerts, providing them with the necessary tools for managing the patient's well-being. The registration system ensures the privacy of sensitive data while allowing caregivers to have control over the patient's care.

G. PREDICTION

A key feature of the app is live location tracking, which helps ensure the safety of dementia patients who may wander or lose their way. Caregivers can monitor the patient's real-time location via GPS, receiving instant notifications if the patient strays from a predefined safe zone. This feature is critical in preventing accidents or harmful situations, providing caregivers with peace of mind knowing they can act quickly in case of an emergency. Additionally, caregivers can check the patient's movement history, ensuring that any irregular activity patterns are detected early.

H. SHOW WATER REMINDER:

Hydration is an essential aspect of patient care, especially for dementia patients who may forget to drink enough water. The app includes a feature that sends reminders to the patient and caregiver at regular intervals to ensure t he patient is staying hydrated. These reminders can be customized based on the patient's preferences or specific medical needs. By reminding the patient to drink water, the app helps improve their overall health and prevents dehydration-related complications, which is common in patients with cognitive decline.

I. FEED VIDEO AND FAMILY TREE:

To enhance emotional well-being, the app includes a feature to display personalized videos and a family tree for dementia patients. Videos may contain motivational messages, reminders, or simple, comforting content that can help keep the patient engaged and reduce feelings of loneliness. The family tree feature provides a visual representation of the patient's family members, helping the patient recognize loved ones and fostering a sense of connection. These features aim to improve the patient's emotional state, enhance cognitive engagement, and provide comfort ,creating a more supportive and holistic care environment.

IV . RESULT AND DISCUSSION:

The results of the study indicate that the proposed system, leveraging advanced deep learning algorithms like ResNet-101, demonstrates strong performance in predicting and monitoring the progression of dementia using brain MRI scans. The system's ability to accurately identify early-stage dementia and Alzheimer's disease through image processing showcases its potential as a powerful diagnostic tool. Furthermore, its real-time monitoring capabilities allow caregivers to track changes in cognitive health, facilitating timely interventions and personalized care plans. The discussion highlights the system's effectiveness in enhancing dementia care by offering not only predictive insights but also providing a comprehensive view of the patient's condition over time. While the system shows great promise, further validation in diverse clinical settings is necessary to refine its accuracy and ensure broader applicability. Moreover, user feedback suggests that the integration of additional features such as mood tracking and behavior analysis could enhance the overall care experience. In ResNet-101, the core innovation is the residual block structure, which introduces the concept of skip connections(also known as identity mapping) to alleviate the vanishing gradient problem and make deep networks more trainable. The state update formula in the context of ResNet-101 primarily refers to the update rule for the activations of each layer in the network, where residual connections play a crucial role in enabling easier flow of gradients during backpropagation. The general state update formula for the residual block in ResNet can be described as:

$$\boldsymbol{y} = \boldsymbol{\mathcal{F}}(\boldsymbol{x}, \{\boldsymbol{W}_i\}) + \boldsymbol{x}$$

Where:

- **y** is the output of the residual block.
- $\boldsymbol{\mathcal{F}}(\mathbf{x}, \{W_i\})$ is the learned transformation of the input **x** by the weights W_i, typically a series of convolutional layers followed by batch normalization and activation functions like ReLU.
- **x** is the input to the block (i.e., the previous layer's output).
- W_i refers to the weights of the convolutional layers in the residual block.

This formula signifies that the output Y of a residual block is the sum of the transformed input F(x,Wi**}**) and the original input x itself. The skip connection allows the identity of the input x to be directly passed to the output, providing an unimpeded flow of gradients during backpropagation, thus avoiding gradient vanishing and improving the learning of deeper layers. In terms of optimization, this means that during training, the update rule for weights using gradient descent will update the weights in the residual block by minimizing the loss function, while the skip connection ensures that the input X contributes directly to the output y, making the learning process more stable and efficient.

A. OUTPUT LAYER:

The output layer in a ResNet-101 architecture is the final layer that produces the model's prediction, typically a classification score or regression value, depending on the type of task (e.g., object classification, disease prediction). In a classification task, the output layer typically consists of a fully connected (dense) layer followed by a soft max activation function for multi-class classification or sigmoid activation for binary classification .For a classification task, the output layer can be represented as:

$$\mathbf{y}_{\mathbf{output}} = \mathbf{Softmax}(\mathbf{W}_{\mathbf{out}} \cdot \mathbf{h}_{\mathbf{final}} + \mathbf{b}_{\mathbf{out}})$$

Where:

- $\mathbf{y}_{output}$ represents the predicted class probabilities for each class.
- W_{out} and b_{out} are the weights and bias of the output layer.
- $\mathbf{h}_{final}$ is the output from the last convolutional block or fully connected layer before the output layer.
- The Softmax function is applied to convert the output into a probability distribution over the class labels.

The output layer in ResNet-101 plays a crucial role in generating the final prediction by processing the learned features from the preceding layers. In multi-class classification tasks, the softmax activation function is used to normalize the output values between 0 and 1, ensuring that the sum of all class probabilities equals 1, thereby representing the likelihood of each class. For binary classification, a sigmoid activation function is often preferred, as it outputs a probability score between 0 and 1 for each sample. Before reaching the output layer, the extracted features from the final residual block are passed through a fully connected (dense) layer, which maps them into the desired output size, typically corresponding to the number of target classes in classification tasks or a single value in regression tasks. During training, the model optimizes its predictions using a **loss** function, such as cross-entropy loss for classification, which measures the difference between predicted and actual labels.

B. HIDDEN LAYER:

The hidden layers in ResNet-101 play a critical role in feature extraction and transformation, enabling deep learning models to learn complex patterns from input data. ResNet-101 consists of multiple hidden layers organized into residual blocks, which help mitigate the vanishing gradient problem through skip connections (shortcut connections)**.** These connections allow gradients to flow directly to earlier layers, ensuring effective learning even in deep networks. Each hidden layer applies a series of convolutional operations, followed by batch normalization and ReLU activation, which introduce non-linearity to improve feature learning. The network's depth, with 101 layers, enables it to capture intricate details and hierarchical patterns in images, making it highly effective for tasks like image classification, object detection, and medical imaging. Each residual block follows the transformation:

$$\mathbf{H}(\mathbf{x}) = \mathbf{F}(\mathbf{x}) + \mathbf{x}$$

Where:

- $\mathbf{H}(x)$ is the output of the residual block.
- $\mathbf{F}(x)$ represents the transformation applied through convolutional layers and activation functions.
- x is the original input (skip connection).

Each hidden layer consists of a convolution operation, which extracts features, followed by batch normalization, which stabilizes learning, and a ReLU activation function, which introduces non-linearity to improve learning efficiency. The depth of ResNet-101 is achieved by stacking these residual blocks, allowing it to learn complex patterns without degradation in performance.

The input layer in ResNet-101 is responsible for receiving the raw image data and preparing it for feature extraction. It processes the input using an initial convolutional layer followed by batch normalization and activation.

$$\mathbf{X}' = \mathbf{ReLU}(\mathbf{BatchNorm}(\mathbf{Conv}(\mathbf{X}, \mathbf{W}) + \mathbf{b}))$$

Where:

- **X** is the input image.
- W represents the convolutional filter weights.
- b is the bias term.
- Conv applies a 7×7 convolution operation with 64 filters to extract basic image features.
- BatchNorm normalizes the activations for stable learning.
- ReLU introduces non-linearity for effective feature learning.

After this transformation, the processed image is passed through a max pooling layer to reduce dimensionality while preserving important spatial information, preparing it for deeper residual blocks.

F. ACCURACY:

Accuracy is one of the most commonly used metrics to evaluate the performance of a classification model. It measures the proportion of correct predictions made by the model out of the total predictions. Accuracy provides a straightforward way to understand how often the model is right in its predictions, whether predicting positive or negative outcomes. Mathematically, it is defined as the ratio of the sum of True Positives (TP) and True Negatives (TN) to the total number of instances, which includes True Positives, True Negatives, False Positives (FP), and False Negatives (FN).

Accuracy = (TP + TN) ÷ (TP + TN + FP + FN)

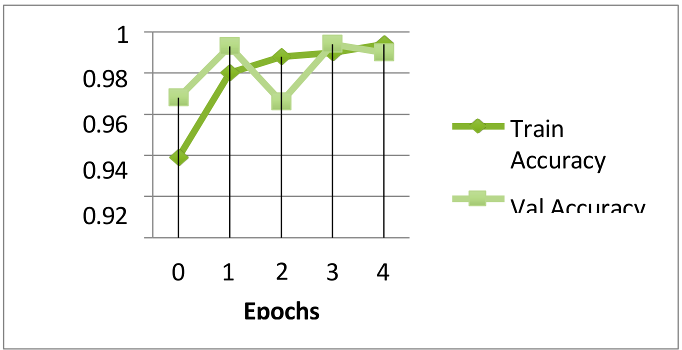


Fig 4.1 ACCURACY GRAPH

Accuracy is particularly effective when the costs of misclassifying positive and negative cases are similar, and the dataset is balanced. However, when the dataset is skewed, or the cost of misclassification varies significantly, other metrics such as Precision, Recall, or F1Score may be more appropriate. In real-world applications, it is often combined with other metrics to provide a more comprehensive evaluation of the model's performance. Accuracy is widely used across various domains, including medical diagnosis, spam detection, and image classification, to provide a high-level understanding of model performance. Despite its simplicity, its reliability depends heavily on the dataset's distribution and the specific application context.

G. PRECISION:

Precision is a performance metric used to evaluate the accuracy of a model's positive predictions. It quantifies how many of the instances predicted as positive by the model are actually true positives. Precision is particularly important in applications where false positives carry a significant cost, such as medical diagnoses or fraud detection. A higher precision indicates that the model is making fewer false positive errors, which is critical when the accuracy of positive predictions is paramount.

Precision = TP ÷ (TP + FP)

Where:

- TP (True Positives): The number of correctly predicted positive instances.
- FP (False Positives): The number of instances incorrectly predicted as positive.

Precision focuses solely on the model’s performance in predicting positive outcomes and ignores how well it identifies negatives. For example, in a cancer detection system ,high precision ensures that if the model predicts a patient has cancer, it is highly likely to be correct, minimizing unnecessary stress or treatment for false positives. However, precision must be balanced with **recall**, as a model optimized for precision alone might become overly conservative, predicting fewer positives to avoid false positives. This trade-off is often addressed using metrics like the F1Score, which considers both precision and recall. Precision is critical in domains where the cost of false positives is high, making it a key metric for ensuring reliable and meaningful predictions in these scenarios.

H. RECALL:

Recall**,** also known as sensitivity or true positive rate, is a metric used to measure a model's ability to identify all relevant positive instances in a dataset. It reflects how well the model captures the actual positive cases, making it particularly crucial in scenarios where missing a positive instance (false negative) has serious consequences, such as in medical diagnoses or fraud detection. Recall evaluates the proportion of actual positives that the model successfully identified. For instance, in a cancer screening system, a high recall ensures that most, if not all, cancer cases are detected, reducing the chances of leaving patients untreated due to missed diagnoses. However, achieving high recall might come at the cost of increasing false positives, which impacts precision. Recall is particularly vital in applications where failing to detect positives has a higher cost than occasionally misclassifying negatives. For example, in identifying rare diseases, it is more critical to ensure no cases are missed than to minimize unnecessary further testing caused by false positives. In summary, recall focuses on minimizing false negatives, ensuring comprehensive detection of positives. However, it should be balanced with precision, as emphasizing recall alone can lead to a higher number of false

- positives, impacting overall model reliability.
- positives, impacting overall model reliability.

Recall = TP ÷ (TP + FN)

Where:

- TP (True Positives): The number of positiveinstances correctly identified by the model.
- FN (False Negatives): The number of positive instances incorrectly classified as negative.

I. F1 SCORE:

F1 Score is a metric that combines precision and recall into a single measure, providing a balanced assessment of a model’s performance, particularly when dealing with imbalanced datasets. It is the harmonic mean of precision and recall, ensuring that both metrics are given equal weight. The F1 Score is useful in scenarios where improving one metric often results in compromising the other. Unlike the arithmetic mean, the harmonic mean used in the F1 Score penalizes extreme values, ensuring that a high score is only achieved when both precision and recall are relatively high.

F1 = 2 × (Precision × Recall) ÷ (Precision + Recall)

Where:

- Precision measures the proportion of correctly predicted positives out of all predicted positives.
- Recall measures the proportion of correctly predicted positives out of all actual positives.

For instance, if a model has high precision but low recall, or vice versa, the F1 Score will reflect this imbalance by being closer to the lower value. The F1 Score is particularly relevant in domains like medical diagnosis, fraud detection, or spam classification, where both false positives and false negatives carry significant consequences. A high F1 Score indicates that the model is effectively balancing precision and recall, making it a robust measure for evaluating models in such critical applications. In summary, the F1 Score provides a comprehensive measure of a model's accuracy by harmonizing precision and recall. It is indispensable in assessing models where achieving a balance between correctly identifying positives and minimizing errors is critical.

J. LOSS:

The loss function plays a crucial role in optimizing deep learning models for image processing by measuring the discrepancy between predicted and actual labels. It guides the model in adjusting its parameters to minimize errors and improve accuracy. For classification tasks, categorical cross-entropy is commonly used, ensuring that the predicted probability distribution closely matches the true labels. In binary classification, binary cross-entropy loss effectively penalizes incorrect predictions, helping the model differentiate between two classes. By continuously updating the model weights through backpropagation, the loss function enables the network to learn meaningful patterns from the image data, leading to more precise and reliable classifications.For image classification tasks, categorical cross-entropy loss is commonly used to measure then

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

Where:

- N is the total number of classes.
- y_i is the true label (1 for the correct class, 0 otherwise).
- $\hat{y}_i$ is the predicted probability for class i.

difference between predicted and actual class probabilities. It is defined as:

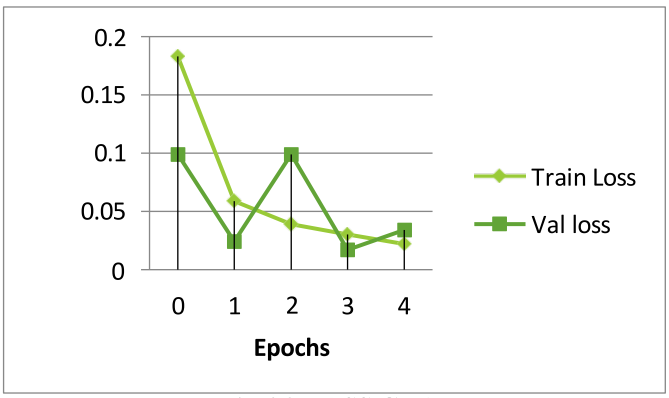


Fig 4.2 LOSS GRAPH

K. CONFUSION MATRIX:

The confusion matrix is a performance evaluation tool for classification models, providing a detailed breakdown of the model's predictions versus actual labels. It consists of four key components: True Positives (TP), where the model correctly predicts a positive class; True Negatives (TN), where it correctly predicts a negative class; False Positives (FP), where it incorrectly predicts a positive class; and False Negatives (FN), where it incorrectly predicts a negative class.

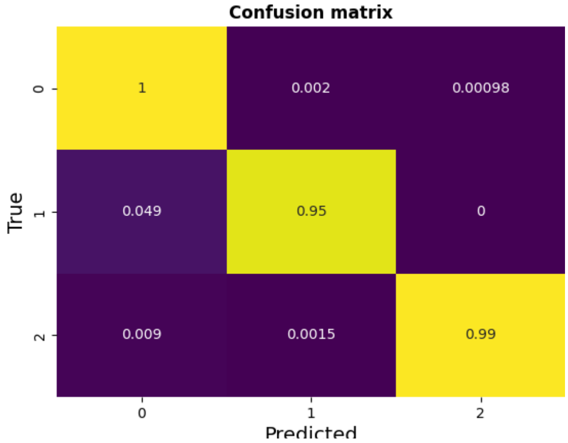


Fig 4.3 CONFUSION MATRIX

These values help derive important metrics like accuracy, precision, recall, and F1-score, which assess the model's effectiveness. A well-balanced confusion matrix indicates strong classification performance, while imbalances highlight areas for improvement, such as reducing false positives or false negatives. a confusion matrix used to evaluate the performance of a classification model. The matrix is normalized, with values representing proportions rather than absolute counts. The rows correspond to the true class labels (0, 1, and 2), while the columns correspond to the predicted class labels. The diagonal elements, which are close to 1 (100%) for each class, indicate high classification accuracy, meaning the model correctly predicts the majority of instances. Off-diagonal elements represent misclassifications, where the model predicts a different class than the true label. For instance, class 1 has a 95% correct prediction rate, but 4.9% of class 1 instances are misclassified as class 0. The color intensity highlights the values, with bright yellow dicating high accuracy and dark purple representing lower values. Overall, the model demonstrates strong classification performance, with minimal misclassifications.

V. CONCLUSION:

In conclusion, the proposed dementia prediction and monitoring application demonstrates significant potential in improving early detection, monitoring, and management of dementia. By leveraging brain MRI scans and deep learning models like ResNet-101, it offers a reliable tool for healthcare professionals and caregivers to track cognitive health and personalize care plans. However, further validation across diverse clinical settings is necessary to confirm its real-world effectiveness. Future work will focus on refining the system's capabilities, such as integrating additional biomarkers and enhancing its adaptability to different types of dementia. Future iterations will also explore the inclusion of real-time symptom tracking, advanced user feedback mechanisms, and increased integration with other health monitoring tools to provide a more comprehensive and robust solution for dementia care.

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