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Alzheimer's Disease Detection Using Multimodal AI

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Abstract: *The project focuses on developing a robust Alzheimer's disease detection system using a multimodal AI approach. Given the devastating impact of Alzheimer's disease, early and accurate diagnosis is crucial. The proposed system leverages Convolutional Neural Networks (CNNs) with two distinct architectures, VGG16 and ResNet50, to analyze neuroimaging data. By utilizing these two models, the system aims to enhance detection accuracy and provide comprehensive classification reports. The VGG16 model, known for its simplicity and depth, excels in extracting high-level features, while ResNet50, with its residual connections, addresses the vanishing gradient problem, allowing for deeper network training. The combination of these models ensures a balanced approach, capturing both fine-grained and complex features of brain images. The project also includes a thorough literature survey of existing techniques, identifying gaps and challenges in current methodologies. The end goal is to create a system that can aid in the early diagnosis of Alzheimer's, providing a reliable tool for healthcare professionals.*

Keywords: *Alzheimer's Disease, MRI, CNN, VGG16, ResNet50*

1. INTRODUCTION

Alzheimer's disease is a progressive neurological disorder that causes memory loss, confusion, and changes in behavior. It affects brain cells, leading to their death and a decline in cognitive functions. The MRI images of the NonDemented MRI Brain, Very Mild Demented MRI Brain, Mild Demented MRI Brain, and Moderate Demented MRI Brain are shown in Fig.1 (a), (b), (c), (d).

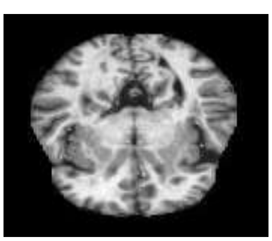

Fig.1(a).Non-Demented

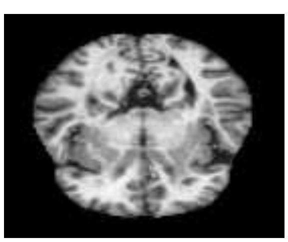

Fig.1(b).Very Mild Demented

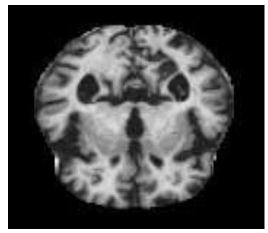

Fig. 1(c). Mild Demented

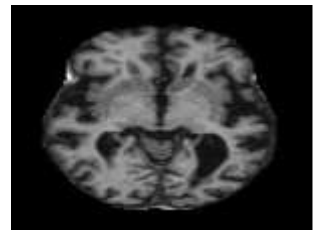

Fig. 1(d). Moderate Demented

In 2020, over 55 million people worldwide were living with dementia, a figure expected to nearly double every 20 years—reaching 78 million by 2030 and 139 million by 2050. The fastest-growing elderly populations are in China, India, and neighboring South Asian and Western Pacific regions. Diagnosing Alzheimer's disease (AD) through medical imaging has become a key focus of deep learning research, with convolutional neural networks (CNNs) playing a crucial role in detecting AD-related patterns in MRI scans. This study explores the performance of CNN models in MRI-based AD classification, emphasizing the impact of hyperparameter tuning on their effectiveness.

The CNN architecture is designed to optimize feature extraction from MRI images, exploring different convolutional layer configurations—categorized as converging, diverging, or equivalent—based on filter kernel size variations. This sequential design ensures progressive feature extraction, capturing both low-level patterns (e.g., edges) and high-level structures (e.g., brain regions associated with AD). A key feature of this architecture is its diverging receptive field, where increasing filter size and stride in deeper layers allows for capturing broader regions of interest while reducing redundancy. This enhances pattern recognition accuracy, mitigates overfitting, and improves generalization.

This project employs Google's Inception V3 (GoogLeNet), known for its computational efficiency and strong classification performance. Multiple experiments evaluate its effectiveness in AD prediction, analyzing factors like memory consumption, parameter count, runtime efficiency, classification error, and generalization error. The study also examines the influence of hyperparameter tuning, network depth, and dataset size on performance. By systematically adjusting learning rates, filter sizes, and layer counts, the research aims to identify the most effective configurations for improving generalization across unseen MRI data, enhancing early AD detection

2. LITERATURE SURVEY:

TITLE: Cognitive Decline Detection for Alzheimer's Disease Patients Through an Activity of Daily Living (ADL)

YEAR:2022

AUTHORS: G. Palacios-Navarro, J. Buele, S. Gimeno Jarque, A. Bronchal García

DESCRIPTION: There are conventional screening instruments for the detection of cognitive impairment, but they have a reduced ecological validity and the information they present could be biased. This study aimed at evaluating the effectiveness and usefulness of a task based on an activity of daily living (ADL) for the detection of cognitive impairment for an Alzheimer's disease (AD) population. Twenty-four participants were included in the study. The AD group (ADG) included twelve older adults (12 female) with AD (81.75±7.8 years). The Healthy group (HG) included twelve older adults (5 males, 77.7 ± 6.4 years). Both groups received an ADL-based intervention at two-time frames separated by 3 weeks. Cognitive functions were assessed before the interventions by using the MEC-35. The test-retest method was used to evaluate the reliability of the task, as well as the Intraclass Correlation Coefficient (ICC). The analysis of the test-retest reliability of the scores in the task indicated excellent clinical relevance for both groups. The hypothesis of equality of the means of the scores in the two applications of the task was accepted for both the ADG and HG, respectively. The task also showed a significantly high degree of association with the MEC-35 test (rho = 0.710, p = 0.010) for the ADG. Our results showed that it is possible to use an ADL-based task to assess everyday memory intended for cognitive impairment detection. In the same way, the task could be used to promote cognitive function and prevent dementia.

TITLE: Alzheimer's Disease Diagnosis via Intuitionistic Fuzzy Random Vector Functional Link Network

YEAR:2022

AUTHORS: A. K. Malik, M. A. Ganaie, M. Tanveer, P. N. Suganthan, Alzheimer's Disease Neuroimaging Initiative

DESCRIPTION: Alzheimer's disease (AD) is a progressive neurodegenerative disorder that leads to memory loss, cognitive decline, and irreversible atrophy in the cerebral cortex. Early diagnosis and timely intervention are crucial in slowing disease progression and reducing neuronal damage. Brain imaging techniques, particularly magnetic resonance imaging (MRI), have been widely utilized for AD diagnosis. To enhance diagnostic accuracy, we propose a novel Intuitionistic Fuzzy Random Vector Functional Link Network (IFRVFL).

Unlike traditional models such as Random Vector Functional Link (RVFL) networks, Extreme Learning Machines (ELM), and Kernel Ridge Regression (KRR), which use uniform weighting in classification, IFRVFL employs a fuzzy-weighted approach. Conventional models assume that all data samples contribute equally, but real-world datasets often contain noise and outliers, leading to poor generalization. IFRVFL addresses this issue by assigning each sample an Intuitionistic Fuzzy Number (IFN), based on its membership and non-membership scores. The membership score reflects a sample's proximity to its class centroid, while the non-membership score incorporates both centroid distance and neighborhood influence. This approach effectively reduces the impact of outliers, improving model robustness.

Experimental results demonstrate that IFRVFL excels in distinguishing mild cognitive impairment (MCI) from AD cases. Its strong performance on benchmark datasets highlights its potential for clinical application, making it a promising tool for early AD detection.

TITLE: Identifying Combinatorial Significance for Classification of Alzheimer's Disease Proteomics Expression with Logical Analysis of Data

YEAR:2021

AUTHORS: Sunung Kim, Sangkyun Noh, Hong Seo Ryoo

DESCRIPTION: In this paper, we develop a clinical Alzheimer's Disease pattern as a combination of protein expression quantity using logical analysis of data on ROSMAP brain samples [1]. As a result, 14 transcripts are selected as support markers and compose interpretable patterns. These patterns show far more statistical significance than any individual transcripts. In addition, patterns also indicate novel combinations of transcripts that have little relation to the STRING network. Our result demonstrates a possible novel approach to analysing interconnected transcripts, expecting a full pathology of Alzheimer's Disease.

TITLE: Genetic Basis of Alzheimer's Disease and Its Possible Treatments Based on Big Data

YEAR:2020

AUTHORS:ChenyuZhang

DESCRIPTION: This article is about the genetic basis which causes Alzheimer's disease, and big data which is related to Alzheimer's disease, focusing on which gene and how it can cause Alzheimer's disease and the ways to use big data to try to figure out the treatments for Alzheimer's disease. In addition, the article adopts the general idea about how to use big data to help researchers figure out a better way the treat Alzheimer's disease. The present study shows that the more APOE ε4 exists, the more possibility of getting Alzheimer's disease. The main contribution of the paper is focusing on the genetic basis of Alzheimer's disease as well as giving a general idea of how to use big data to help find the treatment for Alzheimer's disease.

TITLE: Early Prediction of Alzheimer's Disease Dementia Based on Baseline Hippocampal MRI and 1-Year Follow-Up Cognitive Measures Using Deep Recurrent Neural Networks

YEAR:2019

AUTHORS: Hongming Li, Yong Fan

DESCRIPTION: Multi-modal biological, imaging, and neuropsychological markers have demonstrated promising performance for distinguishing Alzheimer's disease (AD) patients from cognitively normal elders. However, it remains difficult to early predict when and which mild cognitive impairment (MCI) individuals will convert to AD dementia. Informed by pattern classification studies which have

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demonstrated that pattern classifiers built on longitudinal data could achieve better classification performance than those built on cross-sectional data, we develop a deep learning model based on recurrent neural networks (RNNs) to learn informative representation and temporal dynamics of longitudinal cognitive measures of individual subjects and combine them with baseline hippocampal MRI for building a prognostic model of AD dementia progression. Experimental results on a large cohort of MCI subjects have demonstrated that the deep learning model could learn informative measures from longitudinal data for characterizing the progression of MCI subjects to AD dementia, and the prognostic model could early predict AD progression with high accuracy.

TITLE: Early Prediction of Alzheimer's Disease Dementia Based On Baseline Hippocampal MRI and 1-Year Follow-Up Cognitive Measures Using Deep Recurrent Neural Networks

YEAR: 2019

AUTHORS: Hongming Li,Yong Fan,

DESCRIPTION: Multi-modal biological, imaging, and neuropsychological markers have demonstrated promising performance for distinguishing Alzheimer's disease (AD) patients from cognitively normal elders. However, it remains difficult to early predict when and which mild cognitive impairment (MCI) individuals will convert to AD dementia. Building on pattern classification research, which has shown that models trained on longitudinal data outperform those based on cross-sectional data, we propose a deep learning approach utilizing recurrent neural networks (RNNs). This model captures informative representations and temporal dynamics of longitudinal cognitive measures in individual subjects and integrates them with baseline hippocampal MRI data to develop a prognostic model for Alzheimer's disease (AD) dementia progression. Experimental results from a large cohort of individuals with mild cognitive impairment (MCI) demonstrate that our deep learning framework effectively extracts meaningful features from longitudinal data, enabling the accurate characterization of MCI progression to AD dementia. Moreover, the proposed prognostic model achieves high accuracy in the early prediction of AD progression.

EXISTING SYSTEM:

Alzheimer's disease detection relies on neuroimaging techniques like MRI and PET scans with machine learning. MRI captures structural atrophy, while PET detects metabolic changes and protein deposits. However, machine learning models face challenges such as overfitting, high dimensionality, and demographic biases due to limited datasets. Single-modal approaches often detect changes late and may misinterpret age-related variations. Multimodal integration addresses these issues by combining MRI and PET data, enhancing diagnostic accuracy. Fusion at data, feature, or decision levels creates robust models for early detection, improving sensitivity and specificity. This approach enables earlier intervention, potentially enhancing treatment efficacy.

DRAWBACKS OF EXISTING SYSTEM:

Many existing models rely on single-modal data, limiting their ability to capture all aspects of Alzheimer's disease. Additionally, some models struggle with overfitting due to limited training data, reducing their effectiveness in real-world applications. While multimodal approaches offer promising improvements, they often come with high computational complexity, making them less accessible for widespread clinical use.

PROPOSED SYSTEM:

This research focuses on developing an advanced multimodal artificial intelligence system for Alzheimer's disease detection by integrating multiple neuroimaging modalities. The approach leverages two powerful convolutional neural network architectures—VGG16 and ResNet50—each contributing unique advantages in brain imaging analysis. VGG16, with its deep sequential structure, excels at capturing fine structural details within MRI and PET scans, identifying early neurodegenerative changes. ResNet50, on the other hand, employs residual connections to mitigate the vanishing gradient problem, enabling deeper networks to learn complex patterns across imaging modalities.

The system's multimodal design enhances diagnostic accuracy by integrating MRI scans, which detect structural brain changes, with PET scans, which provide insights into metabolic and functional alterations. This comprehensive approach enables the detection of subtle disease markers and correlations that may go unnoticed in single-modality analysis. By combining these complementary data sources, the model offers a more holistic neurological assessment. Additionally, it generates detailed classification reports that not only provide diagnostic predictions but also offer transparent insights into its decision-making process, aiding clinicians in their assessments.

This multimodal AI framework represents a significant advancement in early Alzheimer's detection. By identifying disease indicators before severe symptoms emerge, the system could facilitate early intervention, potentially slowing disease progression and improving patient outcomes. This research addresses key limitations of existing diagnostic methods while leveraging state-of-the-art deep learning techniques to enhance detection accuracy, reliability, and clinical applicability.

BLOCK DIAGRAM:

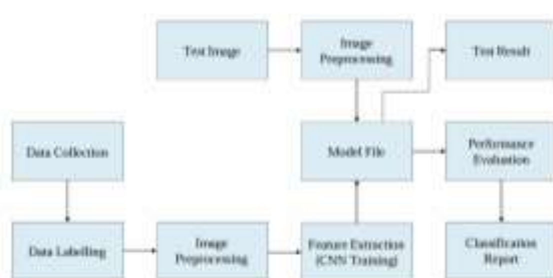

Fig. 2. Block diagram for Alzheimer's Disease Detection using Multimodal AI

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BLOCK DIAGRAM DESCRIPTION:

The process begins with **data collection**, followed by **data labeling** to assign appropriate categories. The labeled data undergoes **image preprocessing** to enhance quality and remove noise. Next, **feature extraction** is performed using **CNN (Convolutional Neural Network) training**, generating a **model file**. A **test image** is then preprocessed and passed into the trained model for classification, producing a **test result**. The model's performance is assessed through **performance evaluation**, leading to a **classification report** summarizing its accuracy and effectiveness. This structured approach ensures a robust image classification system with optimized detection and analysis capabilities.

ADVANTAGES OF PROPOSED SYSTEM:

The proposed system offers several advantages in Alzheimer's disease detection by integrating multimodal AI techniques. By combining VGG16 and ResNet50, it effectively captures detailed structural features from MRI scans while leveraging residual connections to analyze deeper patterns in PET scans, enhancing diagnostic accuracy and robustness. This multimodal approach provides a more comprehensive assessment of the brain's condition, reducing the limitations of single-modal models. Additionally, the system generates a classification report, offering clinicians valuable insights into model predictions, and improving interpretability. With its early detection capabilities, the system facilitates timely intervention, potentially improving patient outcomes and advancing Alzheimer's research.

SYSTEM IMPLEMENTATION:

MODULE 1: Data Collection and Preprocessing

Collecting neuroimaging data (MRI and PET scans) from reliable sources.

Preprocessing MRI brain images is essential for improving the performance of deep learning models, ensuring consistent input data, reducing overfitting, and enhancing accuracy. The key preprocessing steps include **normalization, augmentation, and resizing**. These steps prepare MRI scans for feature extraction and classification using **CNN architectures like VGG16 and ResNet50**.

1. Normalization

Normalization adjusts pixel values to a standard range, making learning more efficient and stable. MRI scans may have varying intensities due to differences in **scanners, acquisition settings, and patient conditions.** CNN models (VGG16, ResNet50) require **standardized pixel distributions** to perform efficiently. Normalization prevents **vanishing or exploding gradients**, leading to better model convergence.

2. Data Augmentation

Augmentation artificially increases the diversity of MRI images, helping CNN models generalize better.. **Medical datasets are often** leading to overfitting. MRI scans may have **slight variations in position, contrast, and brightness** based on scanning conditions. Augmentation introduces variations to help the model learn more robust features.

3. Image Resizing

Since CNN models require **fixed input sizes**, MRI images must be resized without losing important structural details.

MRI scans come in different resolutions (e.g., **512×512**, **256×256**, or even **1024×1024**), but **VGG16 and ResNet50 require 224×224** input sizes. Ensures compatibility with **pretrained CNN architectures**. Reduces memory usage, making training feasible on **GPUs**.

Fig. 3(a). Data collection

Fig. 3(b). Data Preprocessing

MODULE 2: Model Implementation of VGG-16 and ResNet50

The VGG16 model is employed to extract high-level features such as edges, shapes, and textures from preprocessed MRI and PET images, aiding in the identification of Alzheimer's disease markers. With its 16-layer deep architecture, VGG16 processes brain scans hierarchically, capturing both low- and high-level features through sequential convolutional and max-pooling layers. During training, it learns to detect subtle visual patterns associated with Alzheimer's pathology. The model's performance is assessed using key evaluation metrics, including accuracy, precision, recall, and F1-score. Once trained, the final model is saved in a .h5 format for future analysis and deployment.

ResNet50, a more advanced 50-layer architecture, is integrated to capture deeper and more complex neuroimaging patterns. Its unique residual connections enhance learning efficiency, addressing the vanishing gradient problem in deep networks. This makes ResNet50 highly effective in detecting intricate details linked to Alzheimer's disease progression. The trained model undergoes rigorous testing using standardized performance metrics before being saved for deployment. Additionally, the system integrates high-level features from VGG16 with deep, complex representations from ResNet50, allowing for comparative analysis of accuracy, processing efficiency, and feature extraction. This evaluation determines the most effective model for Alzheimer's detection, ensuring a robust and accurate diagnostic system.

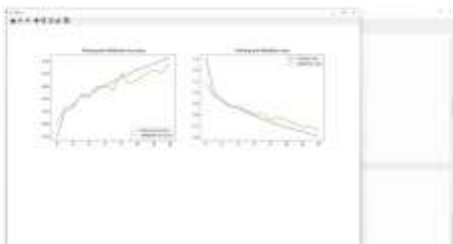

Fig. 4(a). Graph of VGG-16 accuracy level

Fig. 4(b). Confusion Matrix of VGG-16

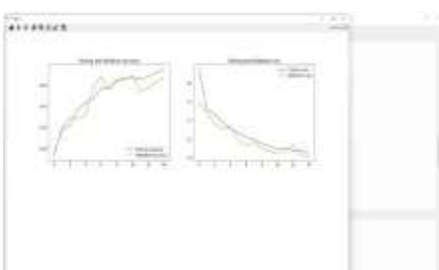

Fig. 5(a). Graph of ResNet50 accuracy level

Fig. 5(b). Confusion Matrix of ResNet50

MODULE 3: MODEL FUSION

A crucial step in enhancing Alzheimer's disease classification involves leveraging the strengths of both VGG16 and ResNet50 to classify neuroimaging data into categories such as Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. VGG16 excels at capturing high-level spatial features like texture and structure, while ResNet50 extracts deeper and more complex representations through its residual connections. The fusion process begins by extracting feature maps from both models after their final convolutional layers. These feature vectors are then concatenated or merged using techniques such as element-wise addition, max pooling, or fully connected layers. To refine the combined feature set, dimensionality reduction methods like Principal Component Analysis (PCA) or feature selection techniques are applied to retain the most relevant patterns for classification. By integrating both shallow and deep feature information, the system ensures not only high accuracy but also improved interpretability. The trained models, saved in **.h5** format, are stored for future validation on unseen data. Additionally, attention mechanisms can be incorporated to assign different weights to feature components, enabling the model to prioritize crucial patterns and further enhance diagnostic precision.

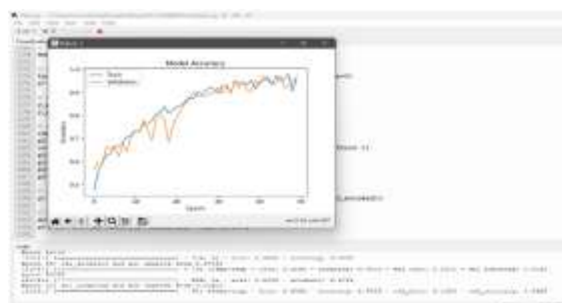

Fig. 6(a). Model accuracy level for fusion of VGG-16 and ResNet50

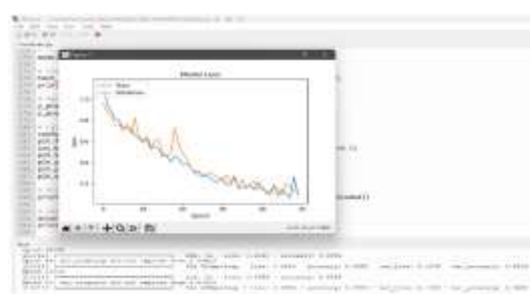

Fig. 6(b). Model Loss level for fusion of VGG-16 and ResNet50

MODULE 4: EVALUATION AND CLASSIFICATION

Evaluation: Assessing the performance of the Alzheimer's disease classification model is essential to ensure its reliability for clinical applications. This phase involves analyzing key evaluation metrics such as accuracy, precision, recall, and F1-

score to determine the model's effectiveness in differentiating between various stages of Alzheimer's disease. A crucial tool in this assessment is the confusion matrix, which provides a detailed breakdown of the model's predictions by displaying correctly classified instances (true positives and true negatives) and misclassified cases (false positives and false negatives). By examining the confusion matrix, researchers can identify potential challenges, such as distinguishing between mild cognitive impairment and early-stage Alzheimer's, which is critical for timely diagnosis and intervention.

Classification: The classification report provides a detailed evaluation of the model's performance across different stages of Alzheimer's disease by presenting precision, recall, and F1-score for each class. High precision indicates fewer false positives, while high recall ensures that most positive cases are correctly identified. The F1-score balances these metrics, offering a comprehensive assessment, particularly for imbalanced datasets. In the final classification phase, the trained and validated model is used to classify new neuroimaging data based on extracted and fused feature representations from VGG16 and ResNet50. The system assigns labels corresponding to different Alzheimer's disease stages, and by incorporating attention mechanisms or ensemble learning techniques, the classification process is further refined, improving overall accuracy and reliability. Evaluation results are then analyzed to identify potential areas for enhancement, ensuring the model's clinical applicability and robustness in real-world scenarios.

Fig. 7(a). Image selection for classifiaction

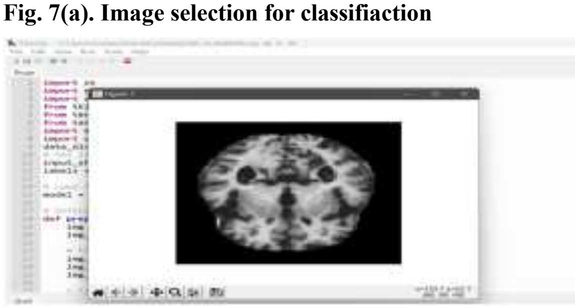

Fig. 7(b). Image of Mild Demented MRI Brain image

Fig. 7(c). Predicted class as Mild Demented

Fig. 7(d). Accuracy Level of 97%

CONCLUSION AND FUTURE WORK:

This experiment leveraged deep learning techniques, specifically Convolutional Neural Networks (CNNs), to classify Alzheimer's Disease (AD) and Mild Cognitive Impairment (MCI) patients from healthy individuals. The study employed the Google Net architecture, achieving an impressive 98% accuracy using the TensorFlow and Keras framework. CNNs were selected for their lightweight architecture, high performance, and ability to extract spatial features from brain scan images, demonstrating superior efficiency compared to traditional neural networks. The model effectively classified different stages of Alzheimer's, including Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented, highlighting the potential of deep learning in medical diagnosis. Future research aims to enhance model reliability by expanding the dataset with real-world clinical data from hospitals, ensuring better generalizability. Beyond increasing dataset size, incorporating additional biomarkers—beyond grey matter, white matter, and cerebrospinal fluid (CSF)—could further refine detection capabilities. Evaluating the model on larger and more diverse datasets will validate its robustness across different populations, ultimately advancing its clinical applicability.

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