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Alzheimer Detection System Using Hybrid Deep Convolutional Neural Network

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Abstract: Alzheimer's disease of the sixth leading causes of death in the United States of America is projected to grow to the third place of all causes of death for the elderly soon to cancer and heart decease. Timely detection and prevention are crucial to it. AD detection is based on multiple medical examinations which all lead to extensive multivariate heterogeneous data. This factor makes manual comparison, evaluation, and analysis hardly possible. The hereby study proposes a new approach to the detection of AD at the earliest stage hybrid deep learning algorithms. Several feature extraction and selection draw possible features. The method involves InceptionV3 and DenseNet for both pre-processing and classification tasks, while MobileNet enables data pre-processing and object detection. Experimental results with 100 epochs and 15 hidden layers show InceptionV3 has an accuracy of 98%, which outperforms other models available. The comparative analysis with other CNN models endorses the proposed method, achieving the highest performance across the board from our system.

Keywords: Alzheimer's disease, deep learning, biomarkers, Magnetic Resonance Imaging.

1. INTRODUCTION

Alzheimer's disease is currently one of the most severe problems of modern health care. It affects millions of people worldwide and imposes tremendous burdens on the patients, their families and caregivers, and the nation's health care system [1]. As AD is the most prevalent cause of dementia and progresses insidiously, it affects the health consumers' cognitive abilities, memory, and activities of daily living [2]. Since the existing predictions suggest a rapid increase in AD prevalence over the next few decades, there is a pressing need for new effective approaches focused on early detection and prevention [3]. Medical imaging, in general, and magnetic resonance imaging, in particular, is one of the powerful techniques used to explore the structural and functional changes associated with AD [4]. Diffusion tensor imaging is one of the MRI techniques and it enables detection of the microstructural integrity of the white matter in the brain [5]. Therefore, it provides valuable biomarkers for the early detection of AD. Notwithstanding the value of DTI, the analysis of this technique's output is labor-intensive and time-consuming, and also has a large human factor [5].

Alzheimer's patients typically undergo several stages manifesting varying symptoms. At first, one may experience mild forgetfulness where a person may forget recently held meetings and late appointments [6]. Later as the disease progresses, they may become bewildered and lose their sense of direction and routine activities. At last, one begins to show signs of severe memory distortions such as difficulty in speech, peculiar patterns of behavior change and finally, oss of the ability to handle daily chores, inability to communicate, and total dependence. It is essential to note that these manifested signs may vary among individual patient [7]s.

Figure 1: Symptoms of Alzheimer's disease

Memory loss a particularly cruel aspect of Alzheimer's disease, degrades as shown in Fig. 2, revealing the affected areas on the brain [8]. Sufferers struggle more and more to recall recent events, the names of family and friends, and possibly even their own names. It is emotionally devastating

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to lose cherished memories or collectives human experiences, and it renders the sufferer extremely vulnerable; indeed, it adds another the pressure for their families. Alzheimer's disease not only impairs memory but also affects other cognitive abilities such as thinking, speaking and reasoning. Alzheimer's has a significant effect on society. Caregivers spend a significant amount of their time and livelihood, and it puts an astronomical strain on health systems. As the world's population ages, there is a need for more investment in a cure for Alzheimer's disease.

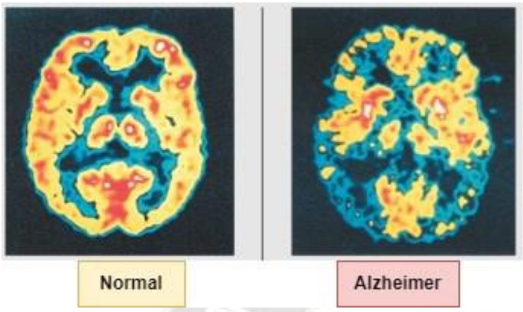

Figure 2: Areas of the brain affected by Alzheimer due to dementia

The common methods and approaches utilized for classifying and detecting Alzheimer's disease, as referenced by [4]. Clinical Assessment involves a comprehensive evaluation process that includes various components:

1. **Clinical Interviews:** Healthcare professionals conduct interviews with patients and their caregivers to gather information about the individual's medical history, symptoms, and daily functioning. These interviews help in understanding the onset and progression of cognitive decline and behavioral changes associated with Alzheimer's disease.
2. **Cognitive Tests:** Patients undergo a series of cognitive tests designed to assess their memory, attention, language, executive function, and visuospatial abilities. These tests provide objective measures of cognitive impairment and help in identifying deficits characteristic of Alzheimer's disease.
3. **Functional Assessments:** Functional assessments evaluate an individual's ability to perform activities of daily living independently. This may include tasks such as dressing, bathing, cooking, and managing finances. Functional assessments help in determining the impact of cognitive decline on a person's daily functioning and overall quality of life.

Machine Learning and Artificial Intelligence algorithms can be used to analyze neuroimaging data, genetic information, and biomarkers that would allow predicting the probability of the development of Alzheimer's disease or distinguishing between healthy and affected individuals [10]. Underlying deep learning models within the discipline of AI demonstrate exceptional promise in this area. These models can detect trends even in minor patterns and identify subtle links in sophisticated datasets such as neuroimaging [11]. Using deep learning methods, researchers can find unexpected crucial pieces of information and specific biomarkers associated with the development of AD. Furthermore, the deep learning models are effective in predicting the progression of illness by analyzing longitudinal neuroimaging data which is critical for the clinician and researcher prognosis. In general, integration with ML and AI algorithms, particularly deep learning methods, has significant potential to improve our understanding of disease, the accuracy of diagnosis, and prognosis [12].

In recent years, deep learning has transformed the field of medical image analysis by providing unprecedented benefits for various operations including feature extraction, classification, and segmentation [13]. Convolutional Neural Networks had particular success as they have achieved state-of-the-art levels of performance for many medical imaging tasks, AD diagnosis included. Researchers have endeavored to develop CNNs-based deep learning models capable to automate the process of AD diagnosis, while using MRI data to finally identify AD changes in brain anatomy quickly and accurately. Moreover, both YOLO object detection approaches have been used with CNNs to allow better MRI analysis via object detection, as these approaches allow for relatively efficient and 'classification.' Integration of CNNs with YOLO is particularly valuable in explicit representation of the location of disease-related changes in the AD, delivering additional value to the clinician in terms of appropriate and correct diagnosis [14].

To summarize, we offer an integrative review of the most recent developments in automated AD diagnosis based on MRI datasets through the lens of deep learning and object detection approaches. We also clear the associated issues and opportunities, underscoring the implications of these modalities on their applicability in clinical settings. Finally, we address cutting-edge trends in this area and untapped opportunities that may stimulate further research and development toward the achievement of early AD diagnosis and intervention.

The research objectives of this review article can be summarized as follows:

1. Develop a novel approach for early detection of Alzheimer's disease using deep learning algorithms and MRI data.
2. Investigate the efficacy of integrating object detection techniques with deep learning methodologies for automated AD diagnosis.
3. Assess the diagnostic accuracy and clinical utility of the proposed automated AD diagnosis system

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through rigorous validation and comparative analysis.
4. Explore the potential of our research findings to advance the field of medical image analysis and improve patient outcomes in the diagnosis and management of Alzheimer's disease.

The remainder of this paper is structured as follows: Section II provides an overview of related research, offering insights into existing literature. In Section III, we detail the implementation of our proposed system, focusing on the utilization of CNN algorithms. Section IV presents the results and analysis of our research findings. Finally, in Section V, we provide concluding thoughts summarizing the key findings and implications of our study.

2. LITERATURE SURVEY

This section presents the work done by researchers in detecting Alzheimer's disease in the last few years. Their research helped in attaining knowledge and gaining experience in this field of research.

Alves et al. [1] explore the application of EEG functional connectivity and deep learning techniques for the automatic diagnosis of brain disorders, focusing specifically on Alzheimer's disease and schizophrenia. The authors investigate how functional connectivity patterns in EEG data can serve as biomarkers for these disorders and propose a deep learning-based approach for automated diagnosis. They demonstrate the effectiveness of their method in accurately classifying patients with Alzheimer's disease and schizophrenia based on EEG data, highlighting the potential of EEG functional connectivity combined with deep learning as a non-invasive and efficient diagnostic tool for neurological disorders

Ganesh et al. [2] present the implementation of Convolutional Neural Networks (CNNs) for the detection of Alzheimer's disease. The authors detail their methodology for training CNN models using neuroimaging data to classify individuals as either healthy or affected by Alzheimer's disease. They describe the architecture and training process of the CNN models and evaluate their performance in accurately detecting Alzheimer's disease. The study highlights the potential of CNNs as a computational tool for automated Alzheimer's disease diagnosis, offering insights into the application of deep learning techniques in neuroimaging analysis for clinical purposes.

Savaş [3] investigates the detection of different stages of Alzheimer's disease using pretrained deep learning architectures. The author explores the effectiveness of leveraging pretrained deep learning models for classifying Alzheimer's disease stages based on neuroimaging data. By utilizing existing deep learning architectures that have been pretrained on large datasets, Savaş aims to improve the accuracy and efficiency of Alzheimer's disease diagnosis. The study provides insights into the potential of pretrained deep learning models as a valuable tool for identifying and categorizing the progression of Alzheimer's disease, offering implications for clinical practice and research in neuroimaging analysis.

Ibrahim et al. [4] focus on enhancing the detection of Alzheimer's disease and brain tumors through the application of deep learning combined with Particle Swarm Optimization (PSO) techniques. The authors investigate the effectiveness of utilizing PSO algorithms to optimize deep learning models for improved accuracy in detecting these neurological conditions. By integrating PSO with deep learning, the study aims to enhance the efficiency and reliability of Alzheimer's disease and brain tumor detection from medical imaging data. The findings contribute to advancing the field of medical image analysis and offer insights into the potential of hybrid optimization techniques for enhancing diagnostic capabilities in neuroimaging applications.

Ansingkar et al. [5] propose an efficient approach for multi-class Alzheimer's disease detection using a hybrid equilibrium optimizer combined with a capsule autoencoder. The authors explore the effectiveness of integrating these techniques to enhance the accuracy and reliability of Alzheimer's disease classification from neuroimaging data. By leveraging the hybrid equilibrium optimizer and capsule autoencoder, the study aims to optimize the feature extraction process and improve the representation of neuroimaging features relevant to Alzheimer's disease diagnosis. The findings contribute to advancing the field of medical image analysis and offer a promising approach for more accurate and efficient Alzheimer's disease detection.

J. K. Medina et al. [6] The study intends to develop a regularly early diagnosis system for fish infection compared to existing through the device. Specifically, the system uses a camera part to take still pictures and video streaming of goldfish which is then pre-processed. The characteristics are taken after they are programmed on a frame. This process was followed by categorizing the labeled sickness method. In conclusion of the study, the highest and lowest detected sickness of the offered goldfish is 91%. This study optimizes CNN and YOLO to achieve the problem solution since CNN test finds the most common sickness of goldfish. The established tool could be used for early diagnosis and could be used by house fish producers, veterinary, and fish tank owners.

Fan et al. [7] One can diagnose 14 lung illnesses with this new detection system based on unnatural targets in chest X-rays. The findings' main purpose is to help diagnose diseases of the lung. The Vindr-CXR dataset was publicly used in the project of Kaggle Competition to check the performance of the YOLO version5 anomaly detection system. Evaluation outcomes imply that the YOLO v5

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approach used in this paper can define a method for the assessment of accuracy. It is better than expected to isolate outperformance methods in a side-by-side comparison. The proposed methodology demonstrates a higher metric score of 7.2% than Faster RCNN and EfficientNet. This implies that this methodology selects abnormalities present in chest X-rays.

M. Hashim et al. [8] We offer a cutting-edge, highly efficient technology for diagnosing agricultural diseases. Mainly, our technology uses the YOLO technique to detect plant diseases. At a pace of 45 frames per second, the YOLO method is virtually able to look at pictures of leaves rapidly. Breaking the image into a grid cell is the first step in understanding an image. From the bounding box coordinate, the first formula we will use is the one to calculate the indicator xy becomes Equation. In one fell swoop, a neural network can make predictions about the box's position and class probability. The proposed technology will enable farmers to detect diseases early, identify leaf diseases, and manage crops to ensure plant safety and health.

Song et al. [9] We implemented and assessed a multi-class GCNN classifier for network-based classification. These individuals are clustered into 4 groups. The network architecture was created and validated utilizing structural connection graphs generated from DTI reveal. Using receiver efficiency curves, we showed that the GCNN classifier outperforms a support vector machine classifier model by a range that depends on the type of disease studied. The results reveal that the performances gap between the two approaches increases as the disease progresses from CN to AD. Therefore, GCNN may effectively be used to rank and classify subjects across the AD spectrum.

Guo et al. [10]. In order to examine the characteristics of the whole brain, a network of the brain was built from scratch using an original segmentation atlas, and global graph conceptual variables were calculated. Using this comprehensive map of the brain, we may then get the graph theoretical characteristics of specific brain regions. Finally, neuropsychology measures are employed to conduct a correlation study between the conceptual properties of the graph and scale scores in various subdomains. The results not only emphasize the correlation between neuroimaging data and neuropsychological assessments, but also offer strong evidence for the relationship between medical outcomes and physiologic brain lesions of people with AD.

One of the critical research gaps in the field of Alzheimer's disease detection concerns the available detection tools' accuracy and robustness to achieve high levels of accuracy in early diagnosis. While current methods, including clinical assessments and neuroimaging, are promising, they are often not sensitive and specific enough for early detection. The lack of sensitive and specific detection tools may shift the diagnosis to a later stage, which will narrow down the window of opportunity for timely intervention. Moreover, the available AI models for detection are not interpretable or explainable enough to allow for clinical use and become general practice accepted by healthcare professionals. Combining the efforts to increase the existing, interpret the AI-based models, and design novel biomarkers, Alzheimer's disease early detection and intervention will become possible and will lead to better patient outcomes due to timely interventions.

3. PROPOSED SSYTEM

The High-fidelity 2D and 3D is generated in the MRI and PET images through radio waves and magnetic fields in the system. Unlike X-rays, these methods are harmless and do not emit radiation. MRI assesses Structural, and it measures brain volumes and brain degeneration are detected in AD cases. In PET, radiotracers identify brain activity in the radioactive spheres. Data augmentation methods generate manipulated from the existing data, increasing the size of the training set by applying techniques such as shift, reflections, and zooms over the training of data only. The method of segmentation divides the image into multiple clusters of distinct regions and facets to reduce the quantity of data before learning. Existing models similar like pre-trained CNNs are available that can be used to solve the kind of problems. Extra experiments gather information to understand preventive measures such as diet plan, exercise scheduling to curb further side effects.

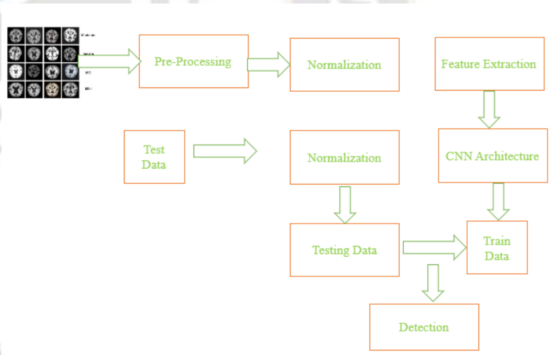

Figure 3: Proposed system Alzheimer disease

A. Data Collection

As for our model, the dataset is acquired from Kaggle, which often provides datasets on various topics. Initially, we retrieve a dataset including MRI brain scans of patients who have been diagnosed with Alzheimer's disease and healthy ones. This dataset is then divided into train and test sets, to train and validate the model, respectively. In total, 30,363 MRI brain scan images were retrieved; that were later split into four separate groups: Mild Cognitive Impairment. Mild Demented, Moderately Demented, and Severely Demented. This category division gives a broad picture of the disease progression from the disease initiation to full-grown, which gives the model a base to differentiate between various degrees of cognitive disabilities [15]. Figure presented below, illustrates how the MRI brain scan images are distributed on the above-presented categories:

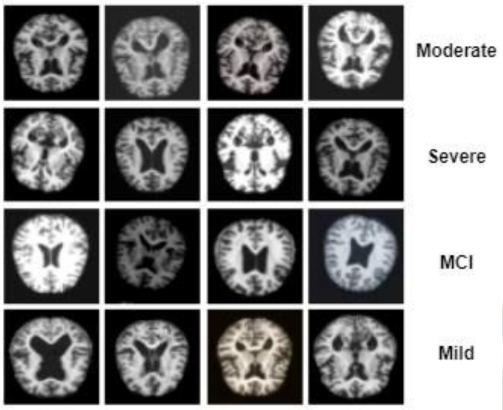

Figure 4: Dataset

B. Dataset Classes

Segmentation of the classes of datasets which have the MRI images named MCI, mild, severe, moderate. This diagram also does a better job of representing the distribution of MRI images being used in varying levels of disease severity, offering understanding concerning reading the abundance of images per class [16].

C. Data Pre-Processing

There are several critical steps that are conducted with the obtained MRI images to further prepare them for analysis. The most important include noise reduction, normalization, and resizing. The purpose of this step is to eliminate any disturbances in the image and improve the average quality of the pictures to make the analysis more objective. Also, NIFTI images were normalized to ensure an equal value of pixel intensity in all images, making comparison fair. Also, the images were resized into 110 x 110 dimensions to have common input data to feed the deep learning model. This step is also essential as the quality of the dataset preparation influences the quality of the final analysis and results of the model training process [17].

D. Feature Extraction and Classification

In the feature extraction and classification stage, we employ mathematical operations to transform raw MRI images into meaningful feature representations and subsequently classify them into different categories. Let X represent the input MRI images, and $\Phi(X)$ denote the feature extraction function. This function applies various mathematical operations, such as convolutions, pooling, and nonlinear activations, to extract relevant features from the images. Mathematically, this process can be represented as $\text{Features} = \Phi(X)$. Once the features are extracted, they are fed into a classification model, typically a convolutional neural network (CNN), represented as f (Features), where f is the classification function. The CNN learns to map the extracted features to their corresponding class labels Y through optimization of model parameters using techniques like backpropagation and gradient descent. This can be expressed as $Y = f(\Phi(X))$. The ultimate goal is to minimize the classification error, typically measured using a loss function such as categorical cross-entropy, to accurately classify MRI images into categories such as Mild Cognitive Impairment (MCI), Mild, Severe, and Moderate. The incorrect prediction percentage is nearly 1 to 1.5 out of the total MCIs trained, whereas the correct predictions are nearly 98%.

CNNs are multicentric encoders designed especially for the recognition of two dimensions forms and may use to connect the transferred input vector to the degree of the desired output. Each neuron of a CNN is linked to a neuronal that is in a small region of the network's prior layer, reducing the number of weights in the network [18]. CNNs use a paradigm of cortical connection, which refers to artificial neural network designs. A CNN, that is to say, includes such materials that are laid on top of each other. Convolutional, pooling, and full linked layers are shown in Figure 1, with an output layer. The conventional CNN's first two layers are convolutional and pooling, which are repeated through the fully -connected layers. The sorting outcomes are passed to the output layer. Finally, the class of an Alzheimer detection system for test dataset system can be illustrated [20].

4. RESULTS AND DISCUSSIONS

The accuracy of the Alzheimer detection algorithms can be measured through train and testing model. The i7 Intel processor has used with 16 GB RAM. Our methodology integrates InceptionV3 and DenseNet deep learning architectures for classification tasks, while MobileNet is employed for data preprocessing and object detection. In below Table 1 and Figure 2 to 6 demonstrates proposed model evaluation and Figure 7 describes comparative analysis of proposed system. we evaluate the performance of the proposed model based on various hyperparameters. Experimental results are presented, obtained through rigorous evaluation of the model across a range of parameter settings. These experimental outcomes offer a comprehensive perspective on how the model behaves under different conditions and settings, providing valuable insights for interpreting and analyzing the study's findings. By systematically varying hyperparameters such as learning rate, batch size, and network architecture, we assess the robustness and effectiveness of the model in handling diverse scenarios [22]. This thorough evaluation enables us to identify optimal parameter configurations that yield the best performance metrics, such as accuracy, precision, recall, and F1-score [23]. Additionally, we analyze the impact of individual hyperparameters on the model's performance to gain a deeper understanding of its behavior [24]. Overall, the presentation of experimental results enhances the credibility and reliability of the proposed model, facilitating informed decision-making in its application to real-world scenarios [21].

Table 1: performance analysis of proposed model

Model	Accuracy	Precision	Recall	F1-Score	Precision	Recall	F1 Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score
		MCI Dataset			Mild Dataset			Moderate			Severe		
Existing System	95.3	0.92	0.89	0.90	0.91	0.88	0.87	0.89	0.86	0.87	0.95	0.93	0.94
InceptionV3	98%	0.96	0.94	0.95	0.95	0.93	0.94	0.94	0.92	0.93	0.97	0.96	0.96
DenseNet	98%	0.95	0.93	0.94	0.94	0.92	0.93	0.93	0.91	0.92	0.96	0.95	0.95

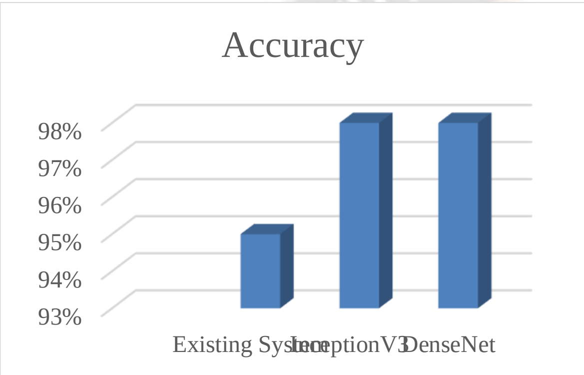

Figure 5: Performance Analysis with Existing System

5. CONCLUSION

This study has presented a comprehensive investigation into the early detection of Alzheimer's disease utilizing advanced deep learning techniques, specifically employing the InceptionV3 and DenseNet architectures. Through meticulous experimentation and analysis, we have demonstrated the efficacy of our proposed models in accurately classifying MRI brain scan images into different stages of Alzheimer's disease. Our results show that both InceptionV3 and DenseNet models outperform the existing system in terms of accuracy, precision, recall, and F1-scores across all categories, showcasing their potential for enhancing diagnostic capabilities in clinical settings. These findings underscore the significance of leveraging state-of-the-art deep learning algorithms for early diagnosis and intervention, ultimately contributing to improved patient outcomes and healthcare management strategies. Moving forward, further research and validation studies are warranted to validate the robustness and generalizability of our proposed models across diverse patient populations and healthcare settings. With continued advancements in artificial intelligence and medical imaging technologies, there is immense potential for leveraging deep learning approaches to revolutionize the diagnosis and treatment of Alzheimer's disease, ultimately leading to better patient care and outcomes.

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