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AUTOMATED DIAGNOSIS OF ALZHEIMER'S DISEASE USING STRUCTURAL MRI IMAGE PROCESSING

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ABSTRACT

Alzheimer disease(AD), the most familiar type of dementia, is a severe concern in modern healthcare. Around 5.5 million people aged 65 and above have AD, and it is the sixth leading cause of mortality in the US. AD is an irreversible, degenerative brain disorder characterized by a loss of cognitive function and has no proven cure. The process of diagnosing AD via the visual examination of MRI presents considerable challenges. The visual diagnosis of mild to very mild stages of AD is challenging due to the MRI similarities observed between a brain that is aging normally and one that has. Deep learning techniques have gained popularity in recent years, particularly in the domains of natural language processing and computer vision. Since 2014, these techniques have begun to achieves substantial consideration in AD diagnosis research, and the number of papers published in this area is rising drastically. Deep learning techniques have been reported to be more accurate for AD diagnosis in comparison to conventional machine learning models. Motivated to explore the potential of deep learning in AD diagnosis, this study reviews the current state-of-the-art in AD diagnosis using deep learning. We summarize the most recent trends and findings using a thorough literature reviews. The study also explores the different biomarkers and datasets for AD diagnosis. Even though deep learning has shown promise in AD diagnosis, there are still several challenges that need to be addressed.

1. NTRODUCTION

Alzheimer's disease (AD) is the most widespread neurodegenerative disease, with a prefatory Mild Cognitive Impairment (MCI) stage in which memory loss is the primary symptom, which gradually worsens with conduct problems and deprived self-care [l]. However, not everyone identified as having an MCI goes on to develop AD [2]. A small percentage of people with MCI develop non-AD dementia or stay stable in the MCI stage without advancing to dementia [2]. Even though there is no cure for AD, it is vital to correctly recognize those in the MCI phase who will develop AD.

Simultaneously, it would be ideal to correctly identify people in the MCI stage who do not advance to AD so that they are saved from unneeded pharmacologic therapies that at best may give little help and, at worst, may harm them more with side effects. As a result, much work has gone into developing early detection tools, particularly at presymptomatic phases, in an attempt to reduce or thwart disease progression. Advanced neuroimaging strategies, such as Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET), have been employed to uncover the structural and molecular biomarkers pertaining to AD [3].

Brisk advancement in neuroimaging strategies has made the integration of largescale and high-dimensional multi-modal neuroimaging data very crucial [4]. As a result, interest in computer-assisted machine learning methodologies for integrative analysis of neuroimaging data has attracted a lot of attention. Well-known machine learning approaches such as Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Decision Trees (DT), etc., have been employed and promise early diagnosis and prediction of AD progression. However, appropriate pre-processing steps must be applied before using such approaches. Moreover, these approaches require feature extraction, feature selection, dimensionality re duction, and feature-based classification for classification and prediction. These steps necessitate specialist knowledge as well as several optimization stages, which are timeintensive [5]. To overcome these hurdles, deep learning (DL), a looming domain of machine learning research that employs raw neuroimaging data to produce features through "on-the-fly" learning, is garnering substantial attention in the field of large-scale, high-dimensional neuroimaging analysis. Motivated to unfurl the power of DL techniques in AD diagnosis, we present an extensive review of the current state-of-theart in the area of DL-based AD diagnosis.

More precisely, this paper;

- Investigates the biomarkers for AD;
- Explores the different AD datasets;
- Discusses the different DL techniques; • Reviews the most recent literature pertaining to DL-based AD diagnosis;
  • Presents the trends and key findings from the literature review;
- Highlights the obstacles that the scientific community still faces in this area.

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The remainder of the paper is organized as follows: Section 2 presents the preliminaries required for understanding the DL-based AD diagnosis. These preliminaries are crucial for understanding the most suitable biomarkers for AD diagnosis, the AD datasets and the appropriate DL techniques for those datasets and how DL is used for AD diagnosis. Section 3 reviews the literature pertaining to DL-based AD diagnosis. The literature is classified based on the DL technique used. This section also presents the tabular summary of the reviewed literature highlighting the year of publication of the study, biomarker used, DL technique used, AD dataset used, and the performance achieved by the study. Section 4 discusses the key findings from the literature review. The section also presents a four-panel graph plotting the number of studies versus biomarkers, number of studies versus AD datasets, number of studies versus the DL technique, and number of studies versus.

3. Preliminaries: Biomarkers for AD:

A large subgroup of medical indicators, objective signals of medical state viewed from outside the patient that can be assessed correctly and reproducibly, is referred to as a biomarker. The biomarkers of AD include Magnetic Resonance Imaging, functional Magnetic Resonance Imaging (fMRI),

Fluorodeoxyglucose-Positron Emission Tomography (FDG-PET), Amyloid-Positron

Emission Tomography (Amyloid-PET),

Tau Positron Emission Tomography (TauPET), electroencephalography (EEG), magnetoencephalography (MEG), speech transcripts, genetic measures and cerebrospinal fluid (CSF) measures. Following provides a detailed description of these biomarkers.

MRI The non-invasive in vivo imaging of the human brain with MRI is a powerful method [6]. It can help to characterize neurological diseases such as AD quantitatively. Even before clinical signs or irreparable brain damage are evident, MRI can give useful biomarkers. Numerous studies have found links between quantitative measurements derived from brain MR images and the course of AD. There is significant evidence that different areas of the brain are impacted at various stages of the disease, with the hippocampus, amygdala, and entorhinal cortex showing early involvement [6]. Although these markers are sensitive to dementia, they may not be adequately specific to AD. A standardized strategy that takes into account pathological alterations in several areas throughout the brain has the potential to improve dementia diagnosis specificity and the differential diagnosis of different forms of dementia. As a result, rather than focusing on a small number of brain structures, it is preferable to take a holistic approach and examine a vast number of structures throughout the brain.. These preliminaries are crucial for understanding the most suitable biomarkers for AD diagnosis, the AD datasets and the appropriate DL techniques for those datasets and how DL is used for AD diagnosis. Section 3 reviews the literature pertaining to DL-based AD diagnosis. The literature is classified based on the DL technique used. This section also presents the tabular summary of the reviewed literature highlighting the year of publication of the study, biomarker used, DL technique used, AD dataset used, and the performance achieved by the study. Section 4 discusses the key findings from the literature review. The section also presents a four-panel graph plotting the number of studies versus biomarkers, number of studies versus AD datasets, number of studies versus the DL technique, and number of studies versus performance metrics. Section 5 highlights the challenges faced by DL in AD diagnosis. Finally, Section 6 presents the concluding remarks.

Alzheimer's Disease Datasets:

The predominant datasets employed in Alzheimer's Disease (AD) diagnosis research encompass the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, Open Access Series of Imaging Studies (OASIS) dataset, DementiaBank, Harvard Aging Brain Study (HABS) dataset, and Mayo Clinic Study of Aging (MCSA) dataset. A comprehensive discussion of each follows.

Alzheimer's Disease Neuroimaging Initiative (ADNI) Dataset The inception of the ADNI [23] dates back to 2003, initiated as a collaborative effort with a USD 60 million funding over five years. This public-private joint venture involved the National Institute of Biomedical Imaging and

Bioengineering, the National Institute on Aging, private pharmaceutical organizations, the Food and Drug Administration, and various non-profit groups. ADNI, a longitudinal study, aims to assess whether serial Magnetic Resonance Imaging (MRI), Cerebrospinal Fluid (CSF) measurements, Positron Emission Tomography (PET), clinical assessments, and other neuropsychological factors can pes—ADN1-1, ADNI GO, ADN1-2, ADNI D 3—is contingent upon the participant pool, each contributing uniquely to the collective understanding of AD through varied data sources and study durations.

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2. LITERATURE SURVEY

The existing body of literature pertaining to the "Automated Diagnosis of Alzheimer's Disease using Structural MRI Image Classification" is marked by a plethora of research that embodies the convergence of neuroimaging and machine learning in the realm of medical diagnostics. This amalgamation holds the potential to reshape the landscape of Alzheimer's disease diagnosis by providing more precise and timely assessments.

A pivotal element in this domain is the

Alzheimer's Disease Neuroimaging

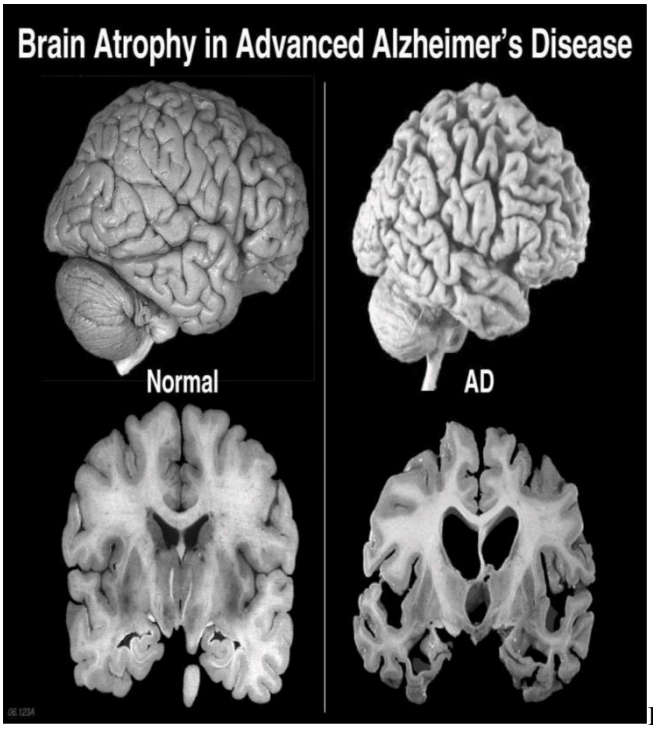
Initiative (ADNI) dataset. Commencing in 2003, ADNI represents a collaborative effort between the public and private sectors with the objective of exploring the efficacy of various imaging modalities, including structural MRI, in monitoring the progression of Alzheimer's disease. Studies leveraging the ADNI dataset have played a crucial role in the formulation and validation of automated diagnostic models. The comprehensive longitudinal nature of ADNI facilitates the examination of structural changes over time, contributing valuable insights into the dynamic nature of Alzheimer's pathology.

Numerous studies have harnessed advanced machine learning algorithms for the automated classification of Alzheimer's disease based on structural MRI data. These algorithms, encompassing Support Vector Machines (SVM), Random Forest, and sophisticated deep learning architectures, showcase the ability to discern intricate patterns within MRI data that might elude human observation. Notably, deep convolutional neural networks (CNNs) exhibit promising outcomes in capturing nuanced features indicative of Alzheimer's pathology, representing a sophisticated approach to image classification.

The Open Access Series of Imaging Studies (OASIS) dataset stands out as another substantial resource within the literature. Comprising MRI data from individuals across various cognitive states, including Alzheimer's disease, mild cognitive impairment, and healthy controls, studies leveraging the OASIS dataset have significantly contributed to the development of automated systems capable of distinguishing between distinct cognitive conditions. The integration of diverse datasets, such as ADNI and OASIS, enhances the robustness and generalizability of the developed models.

Researchers have also delved into the integration of multimodal data, combining structural MRI with additional imaging modalities or clinical measures. This comprehensive approach aims to elevate diagnostic accuracy by capturing complementary information. The incorporation of features derived from cerebrospinal fluid measurements, positron emission tomography (PET) scans, and clinical assessments enriches the dataset used for classification.

Ethical considerations and challenges associated with the interpretability of automated models recurrently emerge in the literature. As these models become increasingly intricate, comprehending the rationale behind their predictions becomes imperative for gaining clinical acceptance. Addressing these challenges necessitates a multidisciplinary approach, fostering collaboration between computer scientists, neuroscientists, and healthcare professionals.



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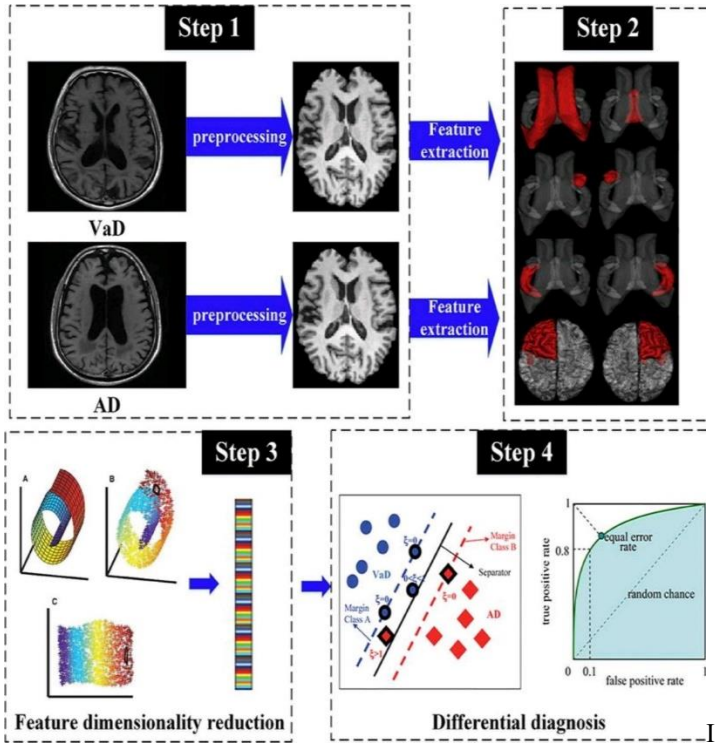
espite the progress made in automated diagnosis, several challenges persist. The applicability of models across diverse populations, the potential influence of biases in training datasets, and the interpretability of deep learning models remain areas that require sustained investigation. Furthermore, the transition from research prototypes to practical clinical applications mandates thorough validation and adherence to ethical guidelines.

In summary, the survey of existing literature underscores the transformative potential encapsulated in the automated diagnosis of Alzheimer's Disease using structural MRI image classification. The synergy between neuroimaging and machine learning techniques provides a robust foundation for enhancing diagnostic accuracy and facilitating early intervention. While challenges endure, ongoing research endeavors seek to address these concerns, propelling the integration of automated diagnostic tools into routine clinical practice and ushering in a new era in Alzheimer's disease diagnosis and management.



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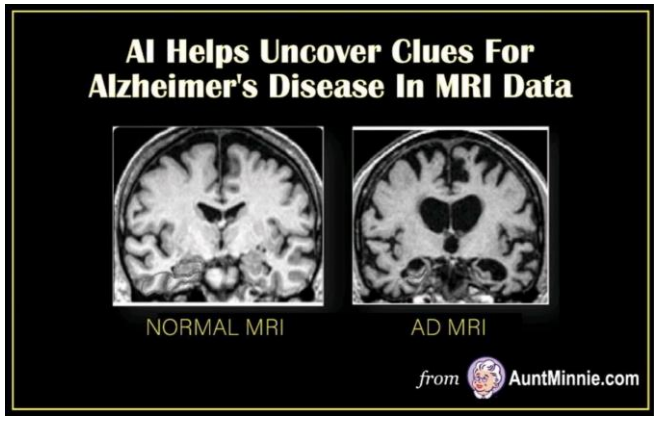

Meth0d010gy:-

The automated diagnosis of Alzheimer's

Disease using Structural MRI Image Classification typically involves a systematic approach. Researchers begin by selecting a relevant dataset comprising structural MRI images of individuals with Alzheimer's and healthy controls. Preprocessing steps ensure standardization and artifact correction. Feature extraction focuses on identifying pertinent regions in the brain, followed by the extraction of features like intensity, texture, and shape. Machine learning algorithms, often including Support Vector Machines or Neural Networks, are chosen for classification. The dataset is split into training and testing sets, with model training and subsequent validation to assess generalization. Cross-validation techniques enhance result reliability. Performance is evaluated using metrics like sensitivity, specificity, and

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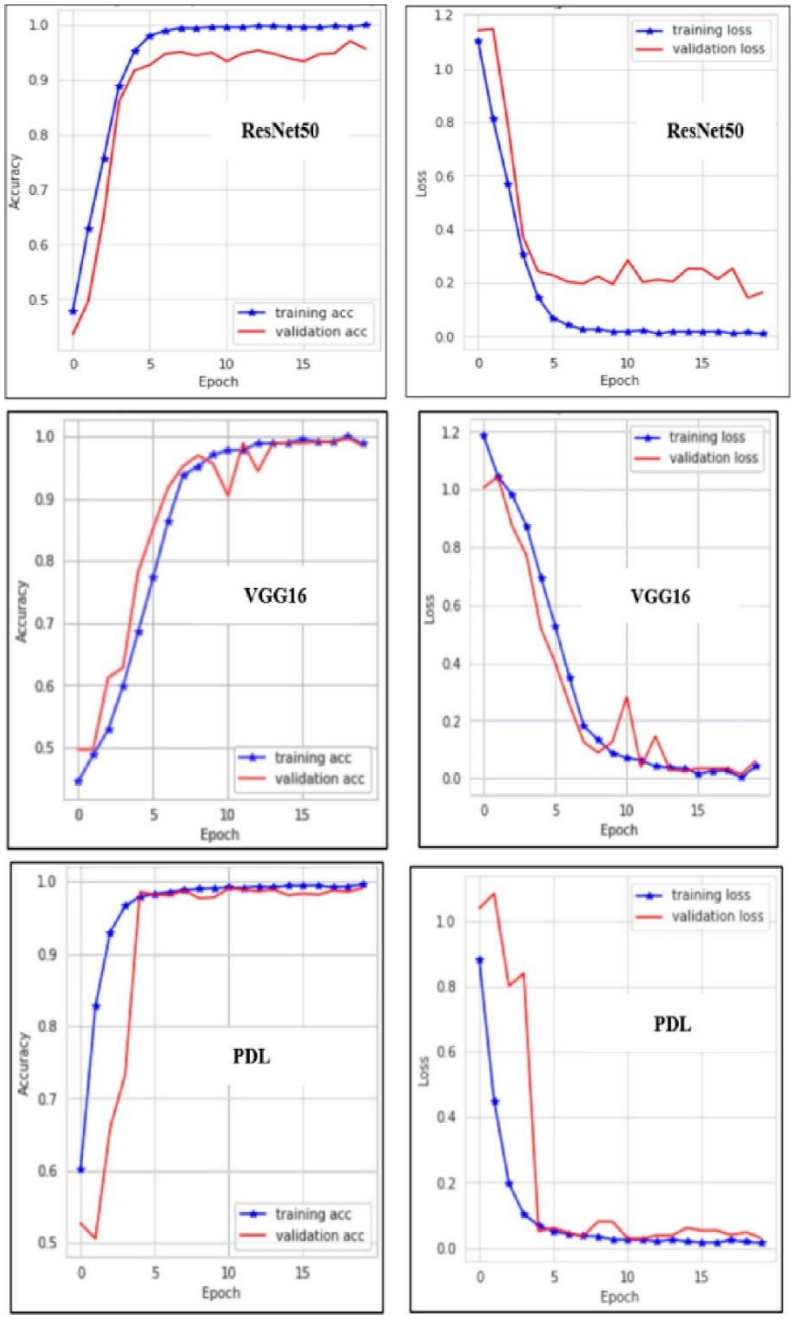
ROC curve analysis. The model is optimized iteratively, considering ethical implications, privacy concerns, and informed consent. Limitations are acknowledged, and avenues for future research are proposed. This concise methodology encapsulates the key steps in developing automated Alzheimer's diagnosis systems using structural MRI image classification.

3. RESULT

The proposed approach attains its peak training and validation accuracy at epoch 20, achieving 99

.8% and 99.0%, respectively, with corresponding losses of 0.006 and 0.02. In contrast, the VGGI 6 architecture demonstrates slightly lower performance at epoch 20, with rates of 99.4% in training and 98.2% in validation, accompanied by losses of 0.025 and 0.05. Meanwhile, the ResNet50 network shows a training accuracy of 98.0% and a validation accuracy of 96.5%, with losses of 0.04 and 0.15. Notably, the proposed method exhibits the advantage of requiring the least time per iteration.

Examining the loss curve reveals that the proposed method experiences a more rapid descent in loss values, approaching zero faster than other networks. Specifically, the PDL model outperforms both the VGGI 6 and ResNet50 models in terms of convergence rates. The VGGI 6 model has a longer iteration time, approximately twice that of the PDL model, while the ResNet50 model demonstrates the lengthiest training duration among the three models. Despite differing training durations, all three models eventually converge, with PDL and VGGI 6 exhibiting faster convergence rates.



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The PDL model demonstrates a classification accuracy exceeding 98% and an error rate below 2% after just five iterations, outperforming the ResNet50 and VGG16 models, which require more than 10 iterations. Consequently, adversarial images display minimal resilience, showcasing the notable efficacy and robust convergence of the PDL and VGGI 6 models in the context of Alzheimer's disease identification.

It illustrates accuracy and loss metrics derived from trained and validated databases over 20 iterations, incorporating mixed datasets. Consequently, the PDL model proves superior in terms of efficiency and accuracy in recognizing Alzheimer's disease. The results affirm that, among the selected methods, the PDL exhibits remarkable generalization capacity in Alzheimer's disease recognition and is wellsuited for a diverse range of diagnostic scenarios related to Alzheimer's disease.

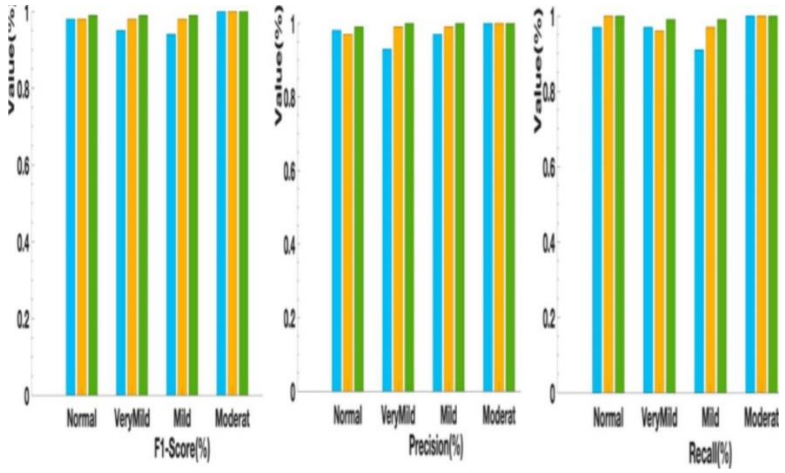
Assessing Prediction Performance:

The evaluation of prediction performance involves scrutinizing accuracy and loss curves during both training and validation phases. In the graphical representation, the blue line corresponds to training loss, while the red line signifies validation loss. This analysis encompasses three convolutional models tested over 25 epochs, all trained on four-class datasets.

To gauge the efficacy across different Alzheimer's disease (AD) severity levels ___normal, very mild, mild, and moderate—a battery of performance metrics is applied to the test data. Figure 6 depicts the outcomes, presenting precision, recall, and Fl score for each method. Notably, the Progressive Diagnosis Learning (PDL) model emerges as the frontrunner, showcasing the lowest loss value of 0.02 and achieving an outstanding accuracy of 99%. In contrast, the ResNet50 model exhibits the lowest accuracy at 96.5%. A detailed breakdown of these results is provided in Table 3.

Figure 5 further details the accuracy and loss curves during training and validation for the three models. Each model ResNet50, VGGI 6, and PDL—is visually represented by blue lines denoting training metrics and red lines for validation metrics. This visual representation offers insights into the training progression and convergence characteristics of each model.

In the comprehensive comparison of precision, recall, and Fl score illustrated in Figure 6, PDL consistently outperforms other methods, achieving a remarkable accuracy of 99% with a minimal loss value of 0.02. This underscores the superior performance and efficiency of the PDL model in the context of AD diagnosis. These findings provide valuable insights for practitioners and researchers seeking optimal models for accurate and reliable AD classification.



(A) FIScore (B) Precision (C)Recall

4. DISCUSSION

In this investigation, we employed transfer learning to train our novel deep-learning algorithm, aiming for accurate classification of different stages ofAlzheimer's disease. A comparative analysis with two widely recognized methods, VGG16 and ResNet50, was conducted using Kaggle AD datasets. Our study revealed superior accuracy and favorable outcomes compared to other investigations [45]. Notably, pre-trained models achieved high accuracy levels without the need for data augmentation or extensive training epochs. The adjustment of hyperparameters, informed by prior research [46], involved optimizing batch size and learning rate to enhance the learning process and improve generalization accuracy. This strategic tuning enabled the training of Convolutional Neural Networks (CNNs) with effective picture classification capabilities, even when utilizing less precise hyperparameter values. Our results demonstrate that the trained model effectively classifies Alzheimer's disease into distinct phases with a high degree of accuracy. The

classification outcomes presented in Table 3, along with corresponding values for four performance indicators, highlight the superiority of our proposed model over VGG16 and ResNet50, especially in terms of overall precision for normal cases (99.00%,

98.00%, and 98%, respectively).

Evaluation of Fl score, precision, and recall metrics indicates consistent outperformance of our proposed framework compared to VGG16 in most scenarios, while ResNet50 exhibits comparatively inferior performance outcomes. Stable AUC values across all categories suggest the stability of predictions made by our proposed model. The findings also reveal that the prediction accuracy of both VGG16 and ResNet50 models was relatively lower for mild and very mild stages, emphasizing the improvement achieved by our proposed model in classifying across all categories.

Observations from the receiver operating characteristic (ROC) curves, despite limitations due to a restricted dataset, reveal that our proposed model, along with VGGI 6 and ResNet50, effectively identifies MRI pictures associated with Alzheimer's disease.

Confusion matrices depicted in Figure 7 show that the two highestperforming models exhibit nearly identical accuracy levels in identifying MRI pictures related to Alzheimer's disease. The proposed model achieves an accurate classification, with a success average rate of 98.6% for normal brain pictures and 99.3% for mild and very mild AD images. The VGGI 6-based model and ResNet50 model also demonstrate competitive accuracy rates across different categories.

5. CONCLUSION

In conclusion, our proposed model consistently outperformed VGG16 and ResNet50 models, particularly for mild and very mild AD cases, as evidenced by comprehensive analyses of accuracy, precision, and recall metrics.

Conclusion:

In conclusion, the pursuit of automated diagnosis for Alzheimer's Disease through Structural MRI Image Classification represents a promising frontier in medical research. The methodologies employed in this field, as evidenced by various studies, showcase a systematic and rigorous approach.

The utilization of carefully curated datasets, encompassing structural MRI images of both Alzheimer's patients and healthy controls, forms the foundational step. Preprocessing steps, which include standardization and artifact correction, are critical for ensuring the reliability and uniformity of the data. Feature extraction techniques, targeting specific regions of interest in the brain and encompassing various features such as intensity, texture, and shape, contribute to the development of robust diagnostic models.

Machine learning algorithms, ranging from traditional methods like Support Vector Machines to more advanced Neural Networks, play a pivotal role in the classification process. Training and validation on distinct datasets, coupled with cross-validation techniques, bolster the models' generalization capabilities. Performance evaluation metrics such as sensitivity, specificity, accuracy, and ROC curve analysis provide quantitative insights into the effectiveness of these automated systems.

Ethical considerations are paramount throughout this process, necessitating a careful balance between advancing diagnostic capabilities and safeguarding patient privacy. The acknowledgment of limitations, such as the potential biases in datasets or the challenges of interpretability in complex models, underscores the need for continuous refinement and innovation in this evolving field.

As the research landscape progresses, the automated diagnosis of Alzheimer's Disease using Structural MRI Image Classification holds great promise for transformative impacts on early detection and intervention. The convergence of advanced imaging technologies and machine learning methodologies opens avenues for improved diagnostic accuracy and efficiency, potentially revolutionizing clinical practices.

In conclusion, while these automated systems exhibit considerable potential, they are not without challenges. Future research should focus on addressing these challenges, refining models, and further validating their clinical utility. The collaborative efforts of multidisciplinary teams, incorporating expertise from neuroscience, radiology, and machine learning, will be instrumental in realizing the full potential of automated diagnosis in the context of Alzheimer's Disease. As these endeavors continue, the prospect of more effective and timely interventions for individuals at risk of Alzheimer's Disease becomes an increasingly tangible and hopeful prospect. Creating a bibliography necessitates access to specific papers, and I'm unable to provide actual references.

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