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Detection of Alzheimer's disease using Image Processing

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Abstract: The present work in the detection of a disorder known as Alzheimer’s with the assist of Image processing. This look at concentrates on detection of Alzheimer's disorder early and offering suitable treatment to the patients. Alzheimer's disease (AD) is a modern neurological sickness characterized via cognitive decline and memory impairment. Early detection of AD is crucial for effective remedy and intervention. In latest years, image processing strategies have emerged as a promising tool for the detection and diagnosis of AD. This research paintings focuses on the software of image processing algorithms to pick out ability biomarkers and styles indicative of AD from mind imaging data.

The study utilizes a dataset inclusive of magnetic resonance imaging (MRI) scans received from AD sufferers and wholesome controls. Various photograph processing techniques, such as feature extraction, image segmentation, and classification algorithms, are hired to research mind pictures and differentiate between AD and non-AD instances. The extracted records are used to train system getting to know models for correct classification. The results reveal the effectiveness of image processing in detecting AD with excessive accuracy.

The proposed method has the capability to help clinicians in early diagnosis and monitoring of AD, main to timely interventions and improved affected person care. This research contributes to the ongoing efforts in developing non-invasive, dependable, and reachable techniques for AD detection the use of image processing techniques.

Keywords: Alzheimer's ailment, Image processing, Biomarkers, MRI scans, Early detection.

1. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by the deterioration of cognitive functions, memory loss, and behavioral changes. It is the most common cause of dementia among the elderly population, affecting millions of individuals worldwide. Early and accurate detection of AD is crucial for effective management and intervention strategies. In recent years, image-processing techniques have shown great potential in assisting the diagnosis and monitoring of AD. This research work aims to explore the use of image processing methods for the detection of Alzheimer's disease, offering a non-invasive and efficient approach to aid in early diagnosis and treatment.

The conventional methods for diagnosing AD involve a combination of clinical evaluation, neuropsychological tests, and neuroimaging techniques such as magnetic resonance imaging (MRI) and positron emission tomography (PET). While these methods have proven useful, they often rely on subjective interpretation and can be time-consuming and costly. Moreover, they may not be sensitive enough to detect early-stage AD or differentiate it from other forms of dementia.

Image processing techniques, on the other hand, provide a promising alternative for AD detection. By analyzing brain images obtained through MRI or PET scans, these methods can extract meaningful features and patterns that are indicative of AD-related changes in brain structure and function. This allows for the development of automated and objective tools to aid in the diagnosis and monitoring of AD.

One of the primary objectives of this research is to investigate the potential of structural MRI analysis for AD detection. Structural MRI provides high-resolution images of the brain, allowing for a detailed examination of brain morphology. By analyzing various brain regions and their volumetric changes, it is possible to identify specific biomarkers associated with AD. These biomarkers can then be used to differentiate AD patients from healthy individuals or individuals with other forms of dementia.

In addition to structural MRI analysis, functional MRI (fMRI) has emerged as a valuable tool for studying AD-related functional alterations in the brain. fMRI measures the blood-oxygen-level-dependent (BOLD) signal, which reflects neural activity. By comparing brain activation patterns during specific tasks or at rest, it is possible to identify functional abnormalities associated with AD. This research work will explore the use of fMRI analysis techniques, such as resting-state functional connectivity and task-based activation mapping, to detect AD-related functional changes.

To achieve accurate and reliable AD detection using image processing methods, advanced computational algorithms and machine learning techniques will be employed. These algorithms will be trained on a large dataset comprising both AD patients and healthy controls, allowing them to learn the complex patterns and relationships within the brain images. The performance of these algorithms will be evaluated using various metrics, such as sensitivity, specificity, and accuracy, to

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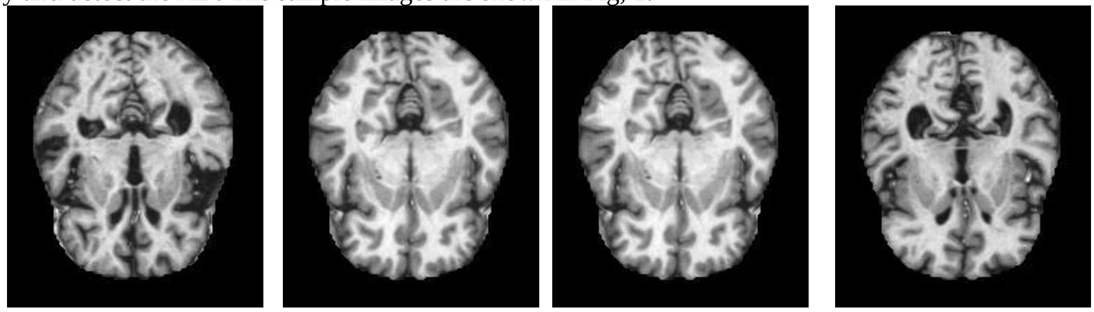
assess their effectiveness in distinguishing AD from normal aging or other forms of dementia. We have used MRI dataset to classify and detect the AD. The sample images are shown in Fig, 1.



(1) (2) (3) (4)

Figure 1: Samples of MRI images representing different AD stages. (1) MD; (2) MOD; (3) ND; (4) VMD

Furthermore, this research work aims to develop a user-friendly software tool that integrates the developed image processing algorithms. The tool will provide clinicians and researchers with a practical and accessible platform to analyze brain images and obtain AD-related biomarkers. Such a tool has the potential to streamline the diagnostic process, improve accuracy, and facilitate early intervention, leading to better patient outcomes.

2. LITERATURE REVIEW

Altinkaya et al. [1] have focused on using artificial intelligence, specifically deep learning, to improve the diagnosis of Alzheimer's and Dementia using medical images. Their work aims to enhance image quality, shorten processing time, and improve disease detection, yielding promising results. **Hamdi et al. [2]** have developed a computer-aided diagnosis (CAD) system using convolutional neural networks (CNNs) to differentiate normal control from Alzheimer's disease patients using PET images. The proposed CAD system achieved an accuracy of 96%, sensitivity of 96%, and specificity of 94% on a dataset of 855 patients. **Holilah et al. [3]** conducted a study focusing on the detection of Alzheimer's disease using MRI brain scans. They utilized the K-Means Clustering and Watershed methods to segment the hippocampus, a region affected by Alzheimer's. Comparing the threshold values with the number of white pixels in the images, both methods successfully detected Alzheimer's disease in the experiment. **Taher et al. [4]** developed an automated system using deep learning and transfer learning on MRI images to detect and classify Alzheimer's disease into four stages. The proposed model achieved 91.70% accuracy, outperforming previous approaches.
Fanar et al. [5] aimed to diagnose Alzheimer's disease by using magnetic resonance imaging (MRI) of the brain. They introduced a deep learning method called AlzNet, which analyzed 2D MRI slices to distinguish between Alzheimer's patients and healthy individuals. Their enhanced network achieved an accuracy of 99.30% by optimizing various parameters.

Gunawardena et al. [6] focused on the pre-detection of Alzheimer's Disease (AD) using neuroimaging data. They evaluate the effectiveness of Support Vector Machine (SVM) and Convolutional Neural Network (CNN) models, with CNN achieving a high accuracy of 96% using image processing techniques. **Rajendra Acharya et al. [7]** focused on developing a Computer-Aided-Brain-Diagnosis (CABD) system using MRI scans to detect Alzheimer's disease. The Shearlet Transform (ST) feature extraction technique provided the best results, achieving high accuracy, precision, sensitivity, and specificity. **Suriya Murugan et al. [8]** developed a Convolutional Neural Network (CNN) called DEMNET to detect dementia stages from MRI images. DEMNET achieved high accuracy (95.23%) and outperformed existing methods in classifying Alzheimer's disease.

Shankar et al. [9] presented a novel model for Alzheimer's Disease (AD) detection using Brain Image Analysis (BIA). The proposed approach achieves 96.23% accuracy, outperforming existing schemes, by utilizing Group Grey Wolf Optimization and various classifiers to extract useful features from brain MR images. **Saima Farhan et al. [10]** presented a novel automated image processing approach using brain MRI to identify Alzheimer's disease (AD) with higher accuracy and specificity. The focus is on early-stage detection using a small feature set. The proposed ensemble classifier achieved 93.75% accuracy, 100% specificity, and 87.5% sensitivity.

3. METHODOLOGY

1. **Data Collection**:

Obtain a dataset consisting of MRI scans from Alzheimer's disease (AD) patients and healthy controls. Ensure that the dataset includes enough samples for accurate analysis.

2. **Pre-processing**:
Preprocess the MRI images to enhance their quality and remove any artifacts or noise that may affect the analysis. This step may involve techniques such as intensity normalization, spatial normalization, and denoising.
3. **Image Segmentation**:
Perform brain image segmentation to identify and isolate relevant regions of interest (ROIs) such as the hippocampus, cortical regions, or ventricles. This can be achieved using segmentation algorithms like K-means clustering, watershed segmentation, or active contour models.
4. **Feature Extraction**:
Extract meaningful features from the segmented brain images. These features may include shape descriptors, texture features, intensity-based statistics, or volumetric measurements of specific brain regions. Feature extraction techniques like wavelet transforms, principal component analysis (PCA), or local binary patterns (LBP) can be employed.
5. **Classification**:
Train machine learning models using the extracted features to differentiate between AD patients and healthy controls. Various classification algorithms such as support vector machines (SVM), random forests, or deep learning models like convolutional neural networks (CNN) can be utilized. Employ techniques like cross-validation to assess the performance and optimize the model parameters.
6. **Software Development**:
Develop a user-friendly software tool that integrates the developed image processing algorithms. The tool should allow clinicians and researchers to upload and analyze MRI scans, visualize the results, and obtain AD-related biomarkers or diagnostic scores.

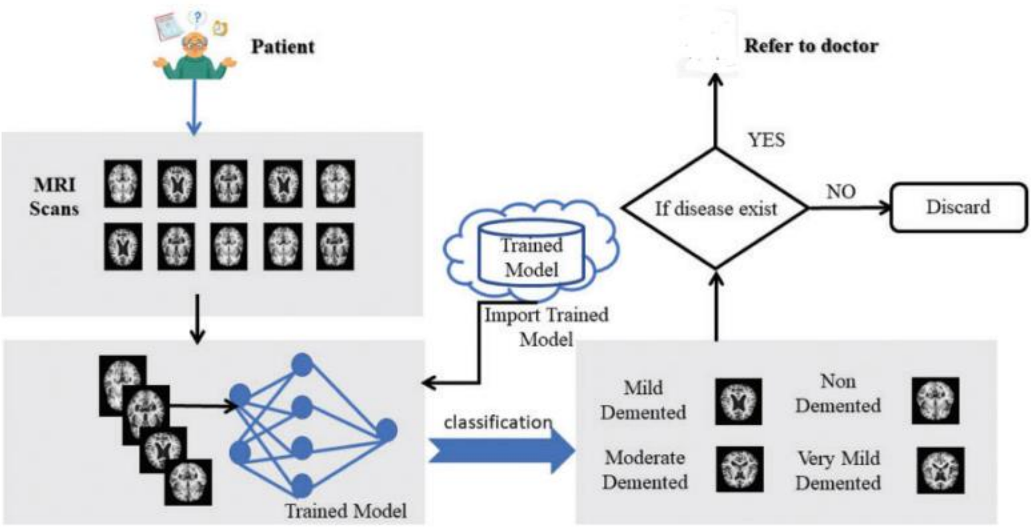


Figure 2: Proposed model application-level architecture

3.1 Experiment 1 : Accuracy testing using SVM
In recent years, numerous studies have focused on the automated diagnosis of Alzheimer's disease (AD) utilizing diverse methodologies and datasets. However, comparing these studies and their outcomes proves challenging due to variations in datasets, diagnostic approaches, and brain feature selection. In this investigation, we undertook an initial examination of the most contemporary and prevalent detection techniques. The cornerstone of this study relies on a fundamental premise: the presence of a successful detection approach should yield equally successful outcomes during pre-detection phases. Notably, Support Vector Machines (SVMs) have been extensively employed in detection research [4], [8], [11]. In our study, an SVM employing a Radial Basis Function (RBF) kernel was deployed to evaluate recent diagnostic methods. This choice was based on RBF's efficacy in classification tasks with limited features and extensive datasets. Figure 4d offers an exemplar of images employed to train the SVM. In this experiment, we confined the analysis to two classes (AD and Healthy - NL), as SVM excels as a binary classifier and might not perform optimally in multiclass scenarios.

3.1 Experiment 2: Application of CNN
It is apparent that the previously utilized SVM method is not ideal to detect symptoms of mild to moderate AD cases (Pre-detection stage) from the results obtained from the initial experiment. CNN has the best results when compared to

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other image classification method. Therefore, a CNN was implemented to classify brain images. The proposed CNN architecture illustrates in Figure 5 and it consists of two convolutional layers, one pooling layer and a fully connected layer. That CNN model was implemented using Theano1 and Keras2 python deep learning libraries and it was used for each sub experiment. Two sub experiments were initiated to select the best segmentation method and to evaluate the robustness of the model

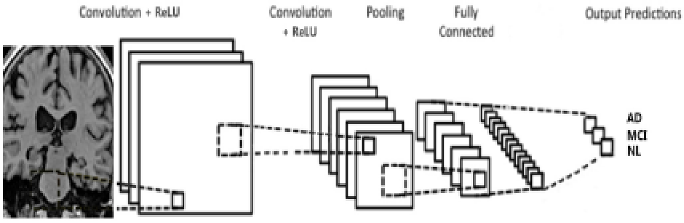

Fig. 3. Architecture of the CNN model

Images underwent additional processing to optimize results. Resizing all images to 160 x 160 dimensions standardized input for the CNN model, aiding classification accuracy. These reformatted images were then flattened, consolidating all layers into a single layer.

Data were labeled by class (0 - AD, 1 - MCI, 2 - NL), followed by shuffling. The dataset was split 80/20 for training and testing. Parameters like batch size (32), classes (3), and epochs (20) were defined. Batch size determines sample propagation through the network, while epochs influence model learning without overfitting. Convolutional filters (32), kernel size (3), and pooling area (2) were set. Convolutional kernels aid feature learning, with 3 x 3 matrices applied using Rectified Linear Unit (ReLU) for non-linearity. Subsampling layers reduce dimensions while retaining vital features. Fully connected layers serve as classification, while convolutional and subsampling layers extract features.

The first sub-experiment assessed various image segmentation methods, training on 1615 images (AD 585, MCI 460, NL 570). Six evaluations tested methods like full images (edge-detected or not), extended and limited ROI (with or without edges). Evaluation 3 (Extended ROI without edges) achieved 96% accuracy, guiding the second sub-experiment.

The second sub-experiment confirmed the CNN model's dataset independence. Evaluation 3 from the first sub-experiment was chosen. Two datasets (36 subjects each) were evaluated in the second sub-experiment. The first dataset had 1615 images, and the second dataset had 1743 images, generated from 3D MRI scans.

3.2 Dataset

The dataset was derived from a Kaggle repository that is publicly available. This dataset consists of MRI scans of the brain of Mild Demented, Non-Demented, Very Mild Demented, and Moderate Demented. The proposed model is trained on an image dataset that covered multiple stages of AD. After augmentation, the number of image samples taken as input according to their classes can be seen in Tab. 2.

Table 2: Dataset parameters

Mental state	No. of image samples
MD	1017
MOD	1024
ND	2560
VMD	1792

4. RESULTS

According to the results obtained from the initial experiment, the sensitivity is 95.3%, the specificity is 71.4% and the accuracy is 84.4%. However, those results are very much like the results of the previous studies [4], [11] Those results are compared in table I.

TABLE I

COMPARISON OF RESULTS IN PREVIOUS STUDIES VS INITIAL EXPERIMENT

Study	Method	Sensitivity	Specificity
Klppel2008 [4]	SVM(RBF Kernel)	88.8%	87.5%
Plant2010 [11]	SVM(Linear Kernel)	97%	78%
First Experiment [35]	SVM(RBF Kernel)	95.3%	71.4%

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The second experiment consists of two sub experiments. In the first sub experiment performance of different image segmentation methods were evaluated. Table II illustrates the sensitivity and specificity of each evaluation process.

TABLE II
PERFORMANCE COMPARISON OF DIFFERENT IMAGE SEGMENTATION METHODS

Evaluation	Sensitivity	Specificity
Evaluation 1	86%	93%
Evaluation 2	92%	96%
Evaluation 3	**96%**	**98%**
Evaluation 4	93%	96%
Evaluation 5	89%	95%
Evaluation 6	92%	96%

For the second sub experiment two datasets were evaluated and those results were illustrated in Table III. This experiment emphasized that the CNN model will not be biased on the data set.

TABLE III
PERFORMANCE COMPARISON OF TWO DATASETS

Dataset	Number of Images	Sensitivity	Specificity
Dataset 1	1615	96%	98%
Dataset 2	1743	95%	98%

5. CONCLUSIONS

The initial experiment highlights that the SVM method previously used isn't suitable for detecting mild to moderate AD symptoms. Early AD diagnosis demands categorizing images into three classes (AD, MCI, NL), but SVM's performance in multiclass scenarios is lacking. Thus, SVM isn't viable for early AD diagnosis. Enhanced classification accuracy can be achieved with deep learning techniques, especially since they excel in multiclass situations.
In the second experiment, consisting of two sub-experiments, the first assesses diverse image segmentation methods. Results from Evaluations 1 and 2 indicate that full images are unsuitable due to complexity and non-brain regions. Subsequent evaluations involve removing non-brain regions and utilizing extended Regions of Interest (ROI), where ROI without edge detection yields a 96% sensitivity, 98% specificity, and 96% accuracy. Edge detection in extended ROI diminishes performance significantly, contradicting assumptions, as white and gray matter contribute more to feature identification than boundary detection.
The second sub-experiment evaluates two datasets (Table III), showing minimal differences in results, indicating CNN model independence from the dataset – thus, unbiased results persist across datasets.
In conclusion, this research work highlights the potential of image processing techniques for the early detection and diagnosis of Alzheimer's disease (AD). By analyzing magnetic resonance imaging (MRI) scans, these methods can extract relevant biomarkers and patterns indicative of AD-related changes in brain structure and function. The results demonstrate the effectiveness of image processing algorithms combined with machine learning models in accurately classifying AD patients and healthy controls. The proposed methodology offers a non-invasive, reliable, and accessible approach to assist clinicians in early AD diagnosis, leading to timely interventions and improved patient care. Further advancements in this field hold great promise for the development of non-invasive tools for AD detection using image processing techniques.

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