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EARLY DIAGNOSIS OF ALZHEIMER'S DISEASE USING DEEP LEARNING AND IMAGE PROCESSING ON BRAIN MRI IMAGES

Dr. Harish Barapatre [1], Dr. Nilesh Pawar [1], Shweta Mohite [1]

[1] Yadavrao Tasgaonkar Institute Department of Computer Karjat, India

Corresponding Author
Dr. Harish Barapatre,
harish.barapatre@tasgaonkartech.com

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ABSTRACT

To take preventative action, Alzheimer's disease (AD) must be identified early. Particularly in those over 60, Alzheimer's disease is regarded as one of the acute illnesses that kill people. Because of the diversity and complexity of brain tissue, using MRI (Magnetic Resonance Imaging) to classify Alzheimer's disease is thought to be a challenging process. As a result, the systems for Alzheimer's disease detection and classifi- cation comprise four stages: MRI pre-processing, segmentation, feature extraction, and classification. The primary goal of the first stage is to remove any noise from medical resonance images (MRIs) that could be caused by light reactions or errors in the imaging medium. The second step involves extracting the region of interest, which is the Alzheimer's disease zone. To prepare for the classification process, the third stage will involve obtaining and storing MRI image features in an image vector. The fourth stage will then involve the classifier, which will specify the Alzheimer-type picture segmentation, thereby recognizing the disease at an early stage. The hybrid methodology employed in this study blends deep learning-based convolutional neural networks (CNNs) with traditional classifiers such as support vector machines (SVM) and random forests. The interpretabil- ity of traditional classification methods is combined with the advantages of deep learning's feature extraction capabilities in this framework achieved higher accuracy when compared to the current CNN methods.

Keywords: Brain Segmentation, Skull Stripping, Threshold, Seed Region Growing, Alzheimer's Disease, Convolutional Neural Network, Deep Learning

1. INTRODUCTION

Alzheimer's disease (AD) must be identified early in order to take preventative action. The cognitive impairment tests used in current AD detection methods are regrettably insuf- ficient to provide a precise diagnosis until the patient has advanced past a moderate stage of the disease. Alzheimer's disease is regarded as one of the acute illnesses that kill people, particularly those over 60 [1]. Nowadays, a large number of computer-aided diagnosis systems are used to help diagnose Alzheimer's disease. As a result, a trustworthy and automatic computer-aided diagnostic method has been put forth for the diagnosis and categorization of brain disorders. Because of the diversity and complexity of brain tissue, MRI (Magnetic Resonance Imaging) is one method for detecting

brain illnesses; nonetheless, it is thought to be a challenging procedure to use for Alzheimer's disease classification [2].

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Computer-aided brain disease diagnosis systems using neuro- images like Diffusion Tensor Imaging (DTI), Positron Emis- sion Tomography (PET), Functional Resonance Imaging (FMRI), and Magnetic Resonance Imaging (MRI) have currently made extensive use of machine learning and pattern classification techniques. According to studies, structural MRI is the most often used imaging modality in clinical practice. It can also be used to monitor the various stages of AD's clinical progression. Therefore, structural MR images are used to evaluate our technique.

Recent years have seen a rise in the use of computer-aided diagnosis based on Neuroimaging, which uses artificial in- telligence (AI) to enhance the early detection of neurode- generative disorders including Parkinson's disease (PD) and Alzheimer's disease (AD). Structural MRI is an essential tool for detecting anomalies in brain morphology because it offers high-resolution anatomical features [3][4]. This study's main goal is to create an accurate and efficient CAD system by using machine learning techniques to structural MR data. In order to take preventative action, Alzheimer's disease (AD) must be identified early. Sadly, cognitive impairment testing, which is the foundation of current AD detection methods, cannot provide an accurate diagnosis until the patient has advanced past moderate AD [5]. Particularly in those over 60, Alzheimer's disease is regarded as one of the acute illnesses that kill people.

Nowadays, a lot of computer-aided diagnosis tools are used to help diagnose Alzheimer's disease. For the purpose of identifying and categorizing brain disorders, a dependable and automatic computer-aided diagnostic system has been put forth. Our study uses a hybrid methodology that combines conventional classifiers like support vector machines (SVM) and random forests with deep learning-based convolutional neural networks (CNNs) [6]. This framework combines the interpretability of conventional classification techniques with the benefits of deep learning's feature extraction capabilities [7].

1) Motivation

The development of a computer-aided brain disease diag- nosis system using Neuroimaging techniques like magnetic resonance imaging (MRI), Positron Emission Tomography (PET), functional MRI (fMRI), and diffusion tensor imaging (DTI) has made extensive use of machine learning and pat- tern classification techniques. The most widely used imaging modality in clinical practice, according to studies, is structural MRI, which is also helpful for monitoring the various stages of AD. Consequently, structural MR images are used to assess our approach [8][9].

2. LITERATURE REVIEW

In the diagnosis of Alzheimer's disease, the examined litera- ture shows a rising trend away from conventional feature-based machine learning and toward sophisticated deep learning and hybrid systems. The next research horizon is the intersection of progression tracking, model interpretability, and multimodal data. Despite tremendous advancements, problems with ex- plain ability, standardization, and practical implementation still exist. Clinically proven pipelines for scalable diagnosis, longitudinal data integration, and model transparency should be the main focus of future research. The comparative ad- vantages of CNNs, Autoencoders, and hybrid systems across AD, Parkinson's, and schizophrenia are highlighted in broad surveys like the one conducted by M. B. T. et al. (2020), which provides an overview of deep learning applications in neurological disorder identification.

The Alzheimer's Association (2021) highlights the increasing need for technology intervention in early detection and offers crucial epidemiological statistics. The multi-task deep recur- rent network suggested by Liang et al. (2021) concurrently predicts cognitive scores and classifies AD stages in order to capture disease progression. Task-sharing networks and atten- tion processes were employed by Du et al. (2022) and Liu et al. (2021) to better manage clinical and imaging information for nuanced classification. A multi-stage deep learning framework based on residuals that refines features layer-by-layer was proposed by Najmul et al. (2024) and demonstrated higher performance in computer-aided AD detection tests.

It has proven successful to improve diagnosis reliability by integrating multimodal imaging data (such as MRI and PET). A GAN-based model called BPGAN was presented by Zhang et al. (2022) and allows for multimodal diagnosis by synthe- sizing PET pictures from MRI data. Pan et al. (2019) also distinguished between AD and healthy people using multilevel feature representation of FDG-PET images. Zheng et al. (2019) used multimodal imaging-derived brain connectivity characteristics to predict AD in patients with MCI. There has also been investigation into hybrid methods that combine clinical and imaging data. Altaf et al. (2018) introduced a multi-class AD classification model that incorporates clinical factors and MRI characteristics. Deep ensemble models with fine-tuned architectures were shown to be useful in the clas- sification of AD and brain tumours by Neelum et al. (2020, 2021).

Because deep learning can automatically extract and learn hierarchical patterns from imaging data, it has completely changed the diagnosis of AD. An ensemble of deep convolu- tional neural networks (CNNs) was used by Islam and Zhang (2018) to identify MRI data with encouraging accuracy. A volumetric CNN with transfer learning was presented by Oh et al. (2020) to improve AD classification and visualization. Similarly, depth wise separable CNNs were used by Liu et al. (2021), greatly lowering model complexity without sacrificing accuracy. Convolutional and recurrent neural networks offer superior diagnostic performance, according to a comparative study of several deep learning models by Hazarika et al. (2022). A fuzzy LS-TWSVM-based deep learning network (FDN-ADNet) that integrates interpretability and accuracy was proposed by Sharma et al. (2022) employing sagittal MRI planes for prognosis.

3. METHODS AND MATERIALS

In order to assess medical data, artificial intelligence (AI) uses a variety of computing methods that simulate human intellect. In order to increase early detection, decrease human error, and improve diagnostic accuracy, AI incorporates ML and DL algorithms in tumour detection [10]. In machine learning, algorithms are trained using medical data, such as histopathology pictures, CT scans, and MRIs as shown in Fig. ?? A branch of machine learning called deep learning

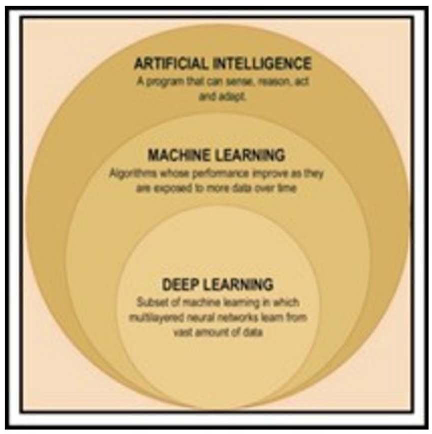

Figure 1 Realation Between the AI, ML and Deep Learning

uses multi-layered neural networks to analyze intricate medical images. Recurrent Neural Networks (RNNs) are utilized in sequential medical data processing, whereas Convolutional Neural Networks (CNNs) are widely employed in radiol- ogy and pathology for automated tumor segmentation and classification [11][12]. This research has been used hybrid pattern because research follows the integrated platform like AI, Machine Learning and deep learning with KNN algorithm [13]. In the existing research they detected the AD detection but our research aim to detect the AD with continues regional growth by using KNN algorithm [14].

4. METHODOLOGY

A branch of machine learning called deep learning uses multi-layered neural networks to analyse intricate medical images. Recurrent neural networks (RNNs) are utilized in sequential medical data analysis, whereas convolutional neural networks (CNNs) are widely employed in radiology and pathology for automated tumour segmentation and classifica- tion [15[16]. Alzheimer's disease (AD) is a neurological condi- tion that worsens over time and affects behaviour, memory, and thinking. For an intervention to be effective, early detection is essential. By integrating machine learning (ML), deep learning (DL), KNN and other computational methods as Shown in Fig. 2, a hybrid methodology improves the precision and dependability of AD detection and region growth using KNN [17]. The Complete research has been divided into two parts- Training and testing mode. In the training mode used machine learning algorithm that a critical stage in medical image analysis, particularly for the diagnosis of Alzheimer's disease, is pre-processing. Accurate feature extraction is guaranteed, and image quality is improved. This method utilizes the efforts made to make AD detection more effective. Deep learning models, data management tactics, assessment, pre-processing methods, and brain scans are just a few of the crucial elements that this system leverages through their synergistic integration.

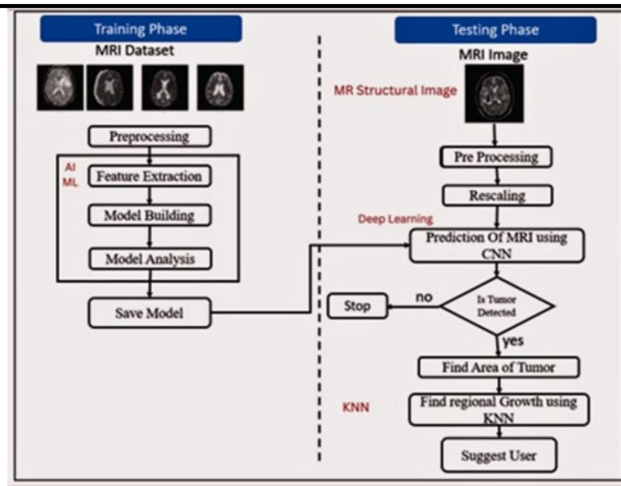

Figure 2 System Flow for AD detection and Region Growth

We can now train a classification model to identify Alzheimer's disease (AD) after extracting features (Gray Mat- ter, White Matter, and Hippocampus) and choosing pertinent ones using PCA, LASSO, or auto encoders. Convolutional neural networks, or CNNs, are used to extract high-level information from magnetic resonance imaging (MRI) data also In order to find similar regions based on intensity and geographical closeness, K-Nearest Neighbors (KNN) is fre- quently employed in medical picture segmentation. KNN is the most significant method for detecting Alzheimer's disease since it groups pixels or voxels with comparable intensity growth values to identify regions of interest (such as the hippocampus, grey matter, or white matter) and categorizing the portions into three groups: Alzheimer's disease (AD), mild cognitive impairment (MCI), and normal (NC). The growth of patterns of which analysis brain atrophy using voxels-based morphometric (VBM) [19].

1) Extracting the region of interest

One crucial aspect of image processing is the extraction of regions of interest. We divide the job into chunks using a variety of methods, some of which are more effective than others. The idea behind this technique is to split the image into 32*32 pixel square chunks. After that, only the blocks that contain the brain's hippocampus (blocks with the numbers 43, 44, 45, and 46) should be extracted. The remainder will then be removed from the block, as illustrated in Fig. 2

2) Procedures for the Hybrid CNN-SVM-KNN Model

- To diagnose Alzheimer's illness, you should optimize your Hybrid CNN-SVM-KNN model by: Improving CNN Feature Extraction (Pretrained models, Data Aug- mentation)
- SVM classification optimization (Regularization, Kernel tweaking)
- Reducing Feature Dimensions (PCA, Autoencoders)
- Optimizing KNN for Region Growth (Distance metric, Nearest Neighbors)
- Hyper parameter Adjustment (Bayesian Optimization, Grid Search)
- Integrating Datasets Make use of the ADNI dataset or other real-world MRI datasets related to Alzheimer's.
- Hyper parameter Tuning: For increased accuracy, opti- mize the SVM kernel, CNN layers, and KNN neighbors.
- Use Grad-CAM in Explainable AI (XAI) to see which parts of the brain affect predictions.
- Performance Metrics: Evaluate the model's efficacy by measuring its accuracy, precision, recall, and F1-score.
- Implementation: Take into account utilizing an Edge AI solution for real-time MRI analysis or Flask/Fast API for a web-based interface.

3) Hybrid Implementation Model Detail

This CNN architecture is intended to process 200x200x1 grayscale images for four classes of multi-class categorization. It consists of pooling layers for down sampling, convolutional layers for spatial feature extraction, and fully linked layers for classification as shown in Table I When four different categories are included in an image classification challenge, this CNN architecture performs well. With a modest amount of parameters, the network may learn rich characteristics by gradually increasing the filters and decreasing the spatial dimensions.

5. DATA SET DESCRIPTION

The four classification groups for Alzheimer’s disease are Non, Very Mild, Mild, and Moderate. There is a pronounced class disparity, as the ”Dataset Size” graphic shows. About 2400 samples belong to the ”Non” class, which predominates

Table I

HYBRID PARAMETER DETAIL

Layer (Type)	Output Shape	Parameters	Details
Input	(200, 200, 1)	0	Input grayscale image (1 channel)
Conv2D	(198, 198, 16)	448	3×3 kernel, 1 input channel, 16 filters: (3×3×1×16 + 16)
MaxPooling2D	(99, 99, 16)	0	Pool size = (2×2), stride = 2 (default)
Conv2D_1	(97, 97, 32)	4,640	3×3 kernel, 16 input channels, 32 filters: (3×3×16×32 + 32)
MaxPooling2D_1	(48, 48, 32)	0	Pool size = (2×2)
Conv2D_2	(46, 46, 64)	18,496	3×3 kernel, 32 input channels, 64 filters: (3×3×32×64 + 64)
MaxPooling2D_2	(23, 23, 64)	0	Pool size = (2×2)
Conv2D_3	(21, 21, 64)	36,928	3×3 kernel, 64 input channels, 64 filters: (3×3×64×64 + 64)
MaxPooling2D_3	(10, 10, 64)	0	Pool size = (2×2)
Conv2D_4	(8, 8, 64)	36,928	3×3 kernel, 64 input channels, 64 filters: (3×3×64×64 + 64)
MaxPooling2D_4	(4, 4, 64)	0	Pool size = (2×2)
Flatten	(1024,)	0	Flattens 4×4×64 into 1024
Dense	(128,)	131,200	Fully connected: 1024×128 + 128
Dense 1 (Output)	(4,)	516	Fully connected: 128×4 + 4 (for 4-class classification)

in the dataset. The ”Very Mild” group comes in second with about 1700 samples. In comparison, the ”Moderate” class contributes less than 100 samples, making it substantially underrepresented, whereas the ”Mild” class has over 600 samples, which graphically shows in Fig. 3 This mismatch

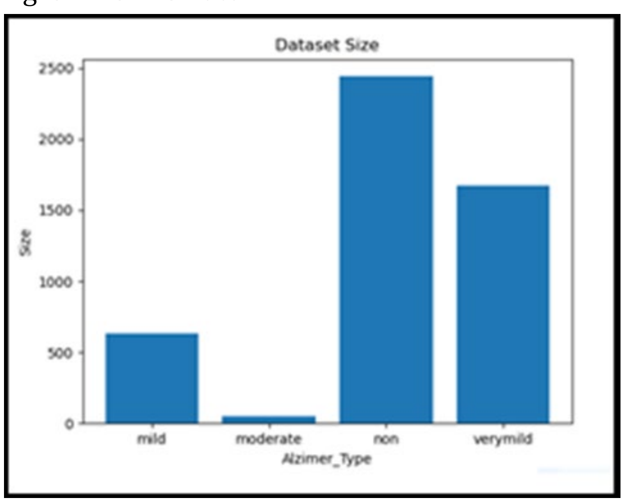

Figure 3 Data Set Description For Early stage Alzmier

may have a negative impact on the model’s performance, particularly when it comes to correctly classifying situations as Moderate. Data augmentation, synthetic sampling approaches (like SMOTE), or class weighting during model training are some ways to counteract this and make sure the network pro- vides minority classes enough weight.

Addressing this problem successfully is essential to creating a strong, equitable model that functions well at every stage of Alzheimer's disease.

6. RESULT AND DISCUSSION

This CNN architecture is intended to process 200x200x1 grayscale images for four classes of multi-class categorization. It consists of pooling layers for down sampling, convolutional layers for spatial feature extraction, and fully linked layers for classification when four different categories are included in an image classification challenge, this CNN architecture performs well. With a modest amount of parameters, the network may learn rich characteristics by gradually increasing the filters and decreasing the spatial dimensions.

1) Results

A generator was used to train the hybrid model over three epochs as shown in Table. II The model.fit generator () method was used for the training process; however, it is now deprecated and is advised that model.fit() be used instead in future implementations to ensure compatibility and main- tainability. Throughout the three epochs, the model shows a

Table II

TRAINING SUMMARY

Epoch	*Loss*	*Accuracy*
1	1.0321	50.01%
2	9.024	57.45%
3	0.8089	62.44%

steady improvement in both loss reduction and classification accuracy. By the third epoch, the accuracy has increased from 50.01% in the first to 62.44%, suggesting that the model is improving over time in terms of learning and generalization. A graph showing the model's training progress over three epochs plotted accuracy and loss. Both metrics' values are shown on the y-axis, and the epoch number (0–2) is represented on the x-axis. The loss curve, which is depicted in orange, shows a sharp decline, going from roughly 2.0 in the first epoch to almost 0.0 by the third. This steep drop shows that with each new epoch, the model is learning efficiently and reducing its prediction error. The accuracy curve, which is depicted in blue, also shows a steady upward trend, indicating that the model's performance is getting better as training goes on. Even while the accuracy rises more slowly than the loss decline, it nevertheless shows a consistent improvement in the model's

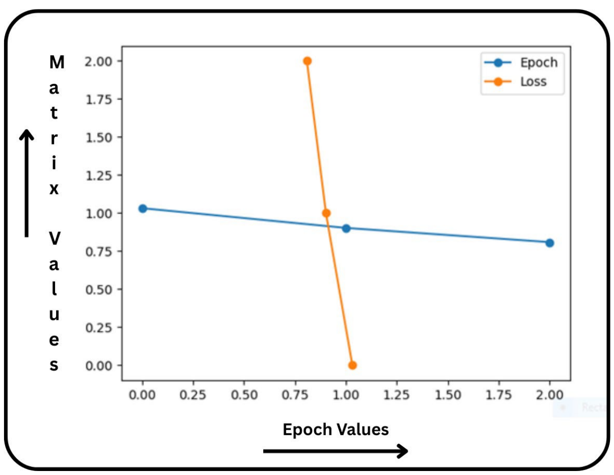

Figure 4 Model's training progress over three epochs plotted accuracy and loss

capacity to categorize input data accurately.

This graph illustrates how a well-trained model should behave, with accuracy rising and loss falling over time. Furthermore, it demonstrates that the model is convergent and not over fitting during the initial epochs. Training could be continued for several epochs in the future to see if the improvement keeps up or stops.

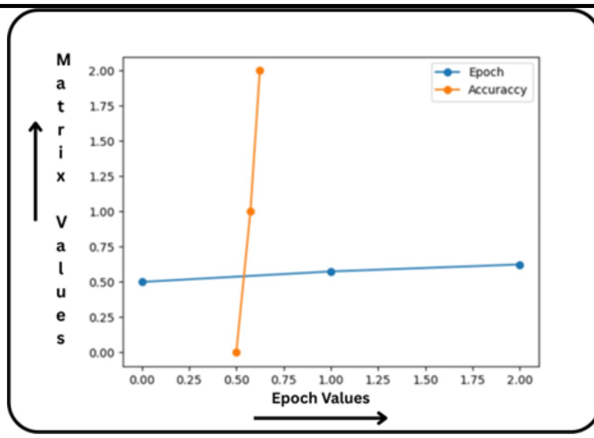

Figure 5 Model Accuracy Plot

The blue line, labelled as ”Epoch”, exhibits a gradual upward trend from approximately 0.50 to 0.65. Although labelled as “Epoch”, this line likely represents model accu- racy, showing improvement over time, which aligns with the expected behaviour during model training. The orange line, labelled as ”Accuracy”, demonstrates a steep upward curve from 0.0 to nearly 2.0, which is unrealistic for accuracy values. Accuracy is conventionally bound between 0 and 1, indicating a possible labelling or plotting error. The plot suggested that model performance improved slightly over the epochs, but due to potential inconsistencies in the metric labelling and scale, the graph fully relied upon for accurate performance analysis.

7. DISCUSSION

The Hybrid Alzheimer’s detection algorithm has examined the uploaded image, which is an MRI scan of the brain. The MRI provides structural information that is frequently used to categorize Alzheimer’s disease stages. Features in the brain scan that are compatible with Stage 2 (moderate) Alzheimer’s disease have been discovered by the system. This stage is usually characterized by memory loss, cognitive decline, and decreased reasoning.

It is advised that you see a doctor and take your prescription as prescribed. It is highly recommended that you visit a neurol- ogist or other appropriate medical expert as away. Symptom management and progression slowing can be achieved with early and regular medical intervention. A Convolutional Neu- ral Network (CNN) model that has been trained to classify MRI pictures into different phases of Alzheimer’s disease pro- duced this result. It is meant to supplement medical diagnosis rather than take the place of expert opinion.

8. CONCLUSION

Using Python, we have developed a platform for identifying Alzheimer’s disease in this system that is designed to run on Windows. The method helps diagnose Alzheimer’s disease early by classifying brain MRI pictures using deep learning and image processing techniques. By promoting early inter- vention and awareness, the incorporation of technology into healthcare not only improves individual diagnostic support but also favourably impacts society well-being.

The viability and significance of automated diagnostic tools in healthcare are illustrated in this paper, which provides an additional method for clinical evaluations. Future intelligent diagnostic platforms can be based on this system’s promising performance and easy-to-use implementation.

CONFLICT OF INTERESTS

None.

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None.

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