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MRI Image Classification of Alzheimer's disease using a Deep Learning Model

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ABSTRACT: Alzheimer's Disease (AD) is a chronic and progressive neurodegenerative disorder that severely impacts memory, cognitive function, and the ability to perform everyday tasks. It represents a major public health concern, affecting millions of individuals worldwide and placing an emotional and financial burden on patients, families, and caregivers. Clinically, Alzheimer's Disease is often preceded by a condition known as Mild Cognitive Impairment (MCI), which involves subtle yet measurable changes in cognitive abilities that do not significantly interfere with daily life but can progress to AD over time. Currently, there is no known cure for Alzheimer's Disease. However, early diagnosis is crucial, as it allows for the implementation of therapeutic interventions that may slow the disease's progression and improve the quality of life for patients. One of the most common early symptoms of AD is memory loss. To assist in diagnosis, Structural Magnetic Resonance Imaging (sMRI) is widely used, particularly for assessing changes in brain regions such as the hippocampus, which is closely associated with memory and cognitive function. While sMRI provides valuable structural information, it has limitations. The imaging data often contain limited features and can be affected by segmentation errors, which may reduce the accuracy and reliability of diagnostic assessments. In light of these challenges, recent advancements in deep learning have shown great promise. Specifically, Convolutional Neural Networks (CNNs) have emerged as powerful tools for analyzing medical imaging data, including neuroimaging associated with AD. These networks are capable of automatically learning complex patterns and extracting relevant features from imaging data, making them highly effective for tasks such as classification and detection of Alzheimer's-related biomarkers. This project introduces a CNN-based approach enhanced with hyperparameter tuning techniques, specifically tailored to improve the classification of Alzheimer's Disease. The integration of these deep learning models enables more accurate segmentation of critical brain features, thereby improving the performance of the classifier. Although the development of such models requires extensive data preprocessing and computational resources, the resulting improvements in diagnostic accuracy highlight the potential of AI-driven solutions in advancing Alzheimer's Disease detection and patient care.

KEYWORDS: Classification, Machine Learning, Deep Learning, Disease and Structural Magnetic Resonance Imaging.

I. INTRODUCTION

1.1 DIGITAL IMAGING:

Digital image processing is a specialized field within digital systems that involves the manipulation and analysis of digital images through computational methods. It is activated whenever a digital system is employed to carry out operations on visual data in digital form. At its core, an image represents a projection of a three-dimensional scene onto a two-dimensional plane, essentially converting real-world spatial information into a format that can be processed digitally.

A digital image is more than just a visual display—it is a structured, stable representation of a physical or conceptual object, encoded in a format that computers can interpret and manipulate. This image is composed of a grid of tiny elements known as pixels, where each pixel contains data representing its position and visual intensity. Mathematically, a digital image can be represented as a function $f(x, y)$, where (x, y) denotes the spatial coordinates of a specific pixel and f refers to the corresponding intensity or color value. In the case of monochrome (grayscale) images, this value signifies the gray level, indicating the brightness of the pixel. For color images, the visual data is separated into three distinct channels: red, green, and blue. These components work together to form a full-color representation, with each channel capturing the intensity of its respective color at every pixel (Thanki & Kothari, 2019).

Digital image processing encompasses a broad range of operations that aim to enhance, analyze, and restore images to



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achieve various objectives. Three fundamental operations stand out as particularly significant: image acquisition, image enhancement, and image restoration. The first step, image acquisition, involves capturing images through digital sensors and then preparing them for analysis through processes such as preprocessing, scaling, and normalization. This foundational stage ensures that images are in a suitable format for subsequent processing.

The second major process is image enhancement, which is designed to improve the visual quality of an image or to highlight specific features that may be of interest. Techniques in this area can adjust contrast, sharpen edges, or suppress noise, all with the goal of making the image more interpretable for human observers or machine learning systems.

Following enhancement, image restoration aims to reconstruct or recover an image that may have been degraded due to factors such as motion blur, noise, or sensor errors. Unlike enhancement, which focuses on aesthetic or functional improvement, restoration seeks to recover the original structure of the image as accurately as possible.

Through a combination of these methods—supported by diverse algorithms and mathematical models—digital image processing provides a powerful platform for manipulating, analyzing, and interpreting digital images. This capability is crucial across a wide range of applications, from medical imaging and satellite image analysis to computer vision and artificial intelligence (Suresha & Chandrashekar, 2015).

1.2 HUMAN BRAIN:

The human brain is a compound neurological structure that is placed in the Center of the nervous organism and used to control the overall function of the human body. It is a collection of more than 100 billion neurons, cells, and blood vessels with around 1.5 kg weight and each neuron have a greater number of connections with other neurons which constitute the whole brain nervous system. The neurons perform the communication among the different parts of the human body by using its synapses (Thanki & Kothari 2019; Shebiah, Newlin Shebiah & Aruna Sangari 2019).

A neurotransmitter is a small burst of chemicals used to transmit information among the synapses. The synapses permit the fast transmission of neuronal information including feelings, thoughts, senses, and physical movements. Any injuries, diseases, and disorders of the normal age human brain that destroy and release the synapses cause the slowdown of the communication speed among the neurons. The changes in memory observation, confusion, perception impairments are the effects of demolishing nerve connections. But, in aged people, these symptoms usually occur, and lose the neurons if they are growing older (Dworkin & Kennedy 2018).

The human brain recognizes the strength and design of the neural connections that are responsible for human body functions. The brain controls the different functions of the human body including speech, imagination, movement of human body parts to the emission of hormones, and control the other organs in the human body by using its sub-regions structure. The brain is enclosed by a caring cover built by bones named as skull enclosed by colorless less fluid named cerebrospinal fluid (CSF) that provides headrest, protection alongside shock and flexibility of the brain (Shebiah, Newlin Shebiah & Aruna Sangari 2019). The structure of the brain is divided into three sub-regions including cerebellum, cortex or cerebrum, and brain stem as revealed in Figure 1.

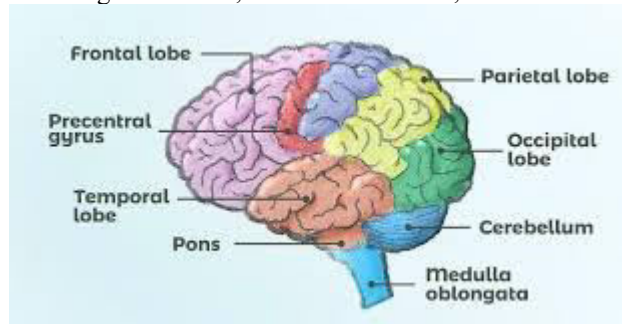


Figure 1 Anatomy of the Human Brain.

Gray Matter (GM) is the surface regions of the cerebral cortex that are used to build the neuron cell bodies and are accountable for memory functions, emotions, and intellect activities. White Matter (WM) is the network branch of nerve fibers used to observe the communication among the brain regions (Gordon Betts et al. 2013). The cerebral cortex is divided into four sections: the frontal, parietal, temporal, and occipital lobes. The frontal cortex is a structure that develops in the brain's frontal lobes. They're all termed what they are based on the way the skull's bones are arranged on them.



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The frontal lobe is placed in the front part of the brain which is used for problem-solving and decision making. The motor cortex available in the frontal lobe is used to collect the information from the other three lobes and command the body activities. The exceptional expression of emotions, activities, behaviors, and finally high risk-taking are the symptoms of the injured frontal lobe.

The temporal lobe is an important part located at the bottom of the brain used for storing and thinking. Auditory observation, sensory input, language, and memory are supervised by this temporal lobe. Difficulties in visual and hearing, language, and speech delivery are the symptoms of temporal lobe injuries. The occipital lobe is placed in the back most portion of the brain and performs visual processing. This lobe covers the most important visual cortex which is used for receiving and collecting information from the retina of the eyes. The visual challenge is the symptoms of occipital lobe injury and damage (Gordon Betts et al. 2013).

The parietal lobe is situated in the central part of the brain and it is mainly coordinating all sensual information collected from the different parts of the human body. It also performs visual and spatial relationship processing and increases the ability of understanding. Difficulties in storing the verbal words, language, and controlling the eyeball movements are the symptoms of injuries of the parietal lobe (Coslett, Branch Coslett & Schwartz 2018).

The cerebellum is placed in the lower rear side of the brain under the occipital lobe. It coordinates all movements of the body and sustain the balance among all movements. For the last part of the brain, we have the brainstem, which is the bottom part of the brain that is utilized to connect the spinal cord and brain. A sturdy skull and CSF protect the brain, yet the brain is nevertheless susceptible to injury and a variety of neurological illnesses. There are various factors for brain disorders such as heredities, diseases that degenerate the neuron cells, painful injuries, and uneven growth of neuron cells that increase the sudden growth of neuron cells. The sudden growth of neuron cells is creating brain tumors and brain injuries including blood clots and shocks that harm the brain cells and nerves. Neurodegenerative diseases, such as Parkinson's, Alzheimer's, and Huntington's, cause brain cell death, and this is referred to as a "brain ailment" (Pinto & De Carvalho 2008).

1.3 ALZHEIMER'S DISEASE

Dementia is not a huge health concern because of the aging population. Multiple cognitive deficiencies that are severe enough to interfere with day-to-day activities describe this clinical condition. The deficits include impairment of memory and any other cognitive domain disorder like agnosia, apraxia, aphasia, and so on. 60 to 70 percent of all cases of dementia in the elderly are caused by Alzheimer's disease (AD). A combination of several factors has made this a relevant issue in science and public health. The need to identify prophylactics that can reduce risk or delay the onset of this is critical from the standpoint of choices of lifestyle. Here is an increase in a body of evidence to support the premise that intake of coffee/caffeine can bring down the risk of AD or delay its onset. This began with an epidemiologic human study and was supported by a controlled study in AD transgenic mice. These studies gave an insight into the mechanisms where coffee/caffeine protects against AD even in the case of Mild Cognitive Impairment (MCI) (Heidari & Gobato 2019).

The studies of Epidemiology have supported coffee/caffeine as being protective against such impairment and AD these studies though insightful will not be providing direct evidence to the prophylactic effect of coffee/caffeine against AD as this is all largely based on the recall which will not be able to isolate unequivocally the intake of coffee/caffeine from that of the other factors which may affect cognition over an entire lifetime (if they are not fully controlled). Luckily, creating the AD transgenic mice has permitted a highly controlled study that was performed to delve into the details of AD pathogenesis as well as its therapeutic development (Cornelis 2019).

Individuals who have a family history of dementia may be more interested in learning about genetic testing alternatives because they are concerned about their own risk of acquiring dementia. Even though genetic testing for AD is now more accessible, understanding the genetics of AD is still difficult for clinicians owing to its evolution. The main purpose of this type of practice is to provide them with a proper framework for assessing the genetic risk of their patients and for identifying which of the individuals can benefit from this testing and also providing certain key elements for AD counseling which is critical for this protocol. An Alzheimer's disease brain is seen in Figure 2, which displays a normal brain as well as one with Alzheimer's disease.



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Figure 2 Alzheimer Brain (left) and Normal Brain (right)

II. LITERATURE SURVEY

In AD, the brain shrinks, and the memory cells in the human brain are destroyed, causing the illness to continue to progress. AD is the most general reason for dementia that continuous degeneration in human memory, intellectual skills gradually and finally, it destroys the ability of the person to perform simple tasks. Nearly 5.8 million individuals in the United States are equal and above age 65 living with Alzheimer's disease. Alzheimer's disease affects 60 to 70 percent of the world's estimated 50 million dementia patients. Symptoms of Alzheimer's disease include losing recent memories and conversations (Covel 2009). Deterioration of memory and everyday function are hallmarks of Alzheimer's disease as it advances in the human brain. Researchers and pharmaceuticals have lately been able to enhance the health of people with Alzheimer's disease and the loved ones who care for them by slowing or even stopping the course of the illness' symptoms temporarily. As Alzheimer's disease progresses in the human brain, no medication can entirely cure or alter this process. Memory loss became more of an issue in the human brain as Alzheimer's disease progressed (Parvanta et al. 2010).

In Neuroimaging, there are three main methods for extracting characteristics from the data. Methods that use Voxels, Surfaces, and Regions of Interest are all available. (Ashburner et al. 2001) have proposed Statistical Parametric Mapping (SPM) methods that analyze the brain anatomy to find the focal differences. This technique extracts voxel-based features that can effectively discriminate between healthy control, MCI, and AD. It is used to extract voxel-based features from a voxel-based representation of the brain's gray matter, white matter, and cerebrospinal fluid (CSF). (Desikan et al. 2009) also, contribute towards Dementia diagnosis apart from other volumetric methods. A study by (Querbes et al. 2009) has employed an automatic technique for the detection of Alzheimer's Dementia with cortical thickness measurement. Another study by (G Li et al. 2004) indicates that cortical thickness measurement is more valuable than measurement of hippocampus volume since the former is less independent of the operator. Research-based on clinical trials indicates some of the limitations of the vertex-based diagnosis of AD. Detection of Region of Interest is another dimension in this study. It has been reported in the literature that Cingulum, corpus callosum, and hippocampus are some of the major areas affected due to AD (Clement, Braak & Arenales 1995). On the other hand, pathological studies by the National Institutes of Health (2005) indicate that neurodegeneration caused by AD begins in the medial temporal lobe and then extends towards neocortical areas. Hippocampus volume adjusted to total cerebral volume was used to diagnose illness in research by (De Winter et al. 2017). The volume of the hippocampus nucleus is calculated using cortical maps of GM, WM, and CSF in a standard area. While some studies have concentrated on the volume of specific areas like the hippocampus or the Entorhinal cortex, other studies take multiple regions of interest for the diagnosis instead of a single section.

Pharmacy Data Management software is used to compute a series of spherical harmonics that describes the hippocampi details and its coefficients. There has been researching work that revealed that areas other than hippocampi are also affected in AD (Pertuzé, Ji & Chetelat 2003). Hence new studies have focused on feature extraction from multiple Regions of Interest in brain MRI. One such work utilized the AAL cortical parcellation map to study the varied levels of hypo-metabolism observed in MCI and AD. The above method has used the FDG-PET modality and reported 21 brain regions that could aid as biomarkers in differentiating between AD and MCI. Since there is an overlap of biomarkers in AD and MCI, there is a need to find specific biomarkers for differentiation of AD from MCI.

Hussain et al. 2020 introduced an algorithm to extract and classify features from MRI images. Pretrained models such



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as VGG16, Xception, MobilenetV2, and InceptionV3 were compared using the OASIS dataset. The experimental results demonstrated that the suggested CNN network performed well. Yue et al. (2019) performed feature extraction and classification of MCI and AD pictures using MRI scans from the ADNI dataset. An SVM classifier was then used to identify MCI and AD images after duplicate features had been eliminated using a feature selection strategy.

Using deep learning algorithms, (Ebrahimighahnavieh, Luo & Chiong 2020) examined the current status of AD categorization. Pre-processing characteristics and biomarkers for single- and multi-modality neuroimaging data were examined by the authors. The deep models performed better in detecting and classifying AD, however, there were significant limitations, mostly related to datasets and training methods.

III. METHODOLOGIES AND IMPLEMENTATION

3.1 Existing System

It has been common practice in recent years to use medical image segmentation to see the brain's structures and to undertake volumetrically and shape comparisons in the structures. Medical image segmentation is a challenging task that leads to the complexity of this segmentation. Certain methods are based on the intensity that is vulnerable to noises. Many strategies have been used since the beginning of medical image segmentation to segment the brain using MRI.

Imaging in several planes and with high contrast in soft tissues are only a few of the benefits of MRI, which is a non-invasive, painless procedure. The process of image enhancement targets making it suitable for a particular task by altering the attributes of the image. Research on Fuzzy C Means for successful medical picture segmentation, particularly in the case of data sets with noisy images, is the key objective of this study, and fuzzy segmentation of bees is recommended to improve segmentation. The categorization of brain pictures may be improved even in aberrant images by using the surrounding information.

It is difficult to tell whether a person has Alzheimer's disease with the current system. Only a thorough clinical history and knowledge of a patient's genetic background will allow this to be accomplished. Doctors are not always successful in detecting sickness, though. People with AD, a form of dementia, have gradually worsening mental and behavioral issues that begin in middle or late age. Most of the time, the symptoms appear gradually and become severe enough to cause problems in everyday living. Despite the fact that old age is the primary risk factor, AD is not only an aging illness. Early on, the patient has very little memory loss, but as the disease progresses, their capacity to converse and react rapidly decreases. AD cannot be halted by existing therapies, but early detection may assist to reduce the severity of the illness and provide patients a better quality of life. One in every 85 people will be affected with AD by the year 2050, according to projections. So the importance of accurately diagnosing the early stages of Alzheimer's disease cannot be overstated.

3.2 Proposed System

It is the combination of Image filter with region based segmentation combined with CNN with hyper parameter to detect the affected Alzheimer regions from the input images. The proposed System Architecture is shown in Figure 3.

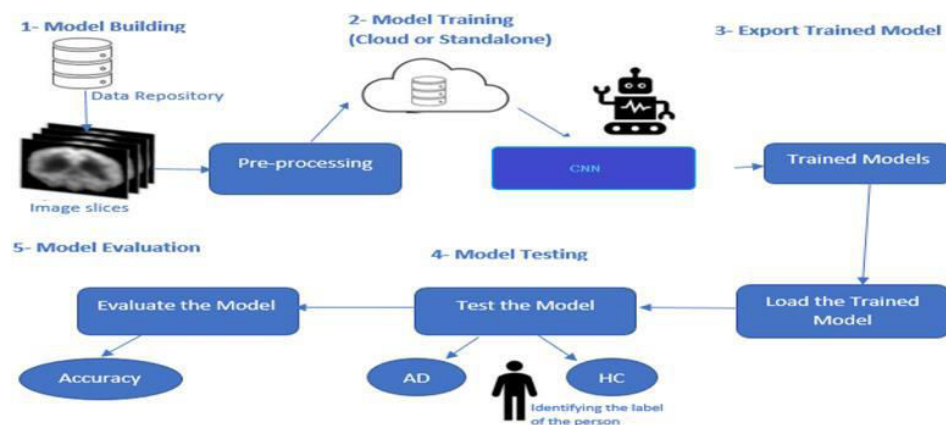


Figure 3: Proposed System Architecture



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3.3 Dataset Description:

One hundred and thirty-three people with an average age of 73.3 years, including 38 females, were included in the Alzheimer's disease Neuroimaging Initiative (ADNI) picture collection at rsfMRI. The participants were chosen based on the ADNI dataset's availability of rsfMRI pictures. Most of the ADNI individuals were included in the current study. Patients with Alzheimer's disease scored between 0.5 and 1.0 on the Clinical Dementia Rating Scale and between 20 and 30 on the MMSE (CDR). To put it another way, they had scores of 25-32 on the MMSE, a loss of objective memory deficit determined by education-adjusted scores of 23-29 Logical Memory II and 0.5 on the CDR, and no dementia. MMSE scores ranged from 23 to 32, while CDR values were found to be close to zero in the healthy patients.

3.4 Image Filter:

Mean filtering is a basic, instinctive and simple to carry out strategy for smoothing pictures, for example diminishing how much force variety between one pixel and the following. Diminishing commotion in images is frequently utilized. Mean separating is just to supplant every pixel esteem in a picture with the mean ('normal') worth of its neighbors, including itself. This takes out pixel values which are unrepresentative of their environmental factors. Mean separating is normally considered a convolution channel. Like different convolutions it is based around a piece, which addresses the shape and size of the neighborhoods to be inspected while computing the mean.

3.5 Segmentation:

Image segmentation is a technique for dividing an image into different regions or segments based on specific properties or characteristics. Image segmentation can be used to identify and separate cancerous regions from healthy skin regions in the context of skin cancer images. Image segmentation of skin cancer is critical in computer-aided diagnosis and treatment planning. It enables doctors to accurately assess the extent of the cancerous area, determine the boundaries of the lesion, and monitor its progression.

3.6 Region-Based Segmentation:

A region may be delegated a meeting of related pixels displaying similar properties. The comparison among pixels may be regarding power, variety, and so on. In this type of department, a few predefined regulations are to be had which should be complied with the aid of using a pixel to be ordered into comparative pixel locales. Locale primarily based totally department strategies are preferred over edge-primarily based totally department techniques withinside the occasion of a noisy image. District Based approaches are moreover grouped into 2 kinds in mild of the methodologies they follow.

- Region growing method
- Region splitting and merging method

3.7 Region Growing Technique:

On account of the region growing approach, we begin with some pixel because the seed pixel and in a while clearly examine the contiguous pixels. In the occasion that the close by pixels observe the predefined regulations, that pixel is introduced to the location of the seed pixel and the accompanying machine move on until there may be no likeness left. This approach follows the granular perspective. In the occasion of a locale growing, the popular rule may be set as an edge. For instance: Consider a seed pixel of two withinside the given image and a restrict really well worth of 3, at the off risk that a pixel has a really well worth extra distinguished than 3, it is going to be regarded as in the seed pixel locale. Any different way, it is going to be regarded as in any other locale. Thus 2 locales are framed withinside the accompanying image in mild of a restrict really well worth of 3.

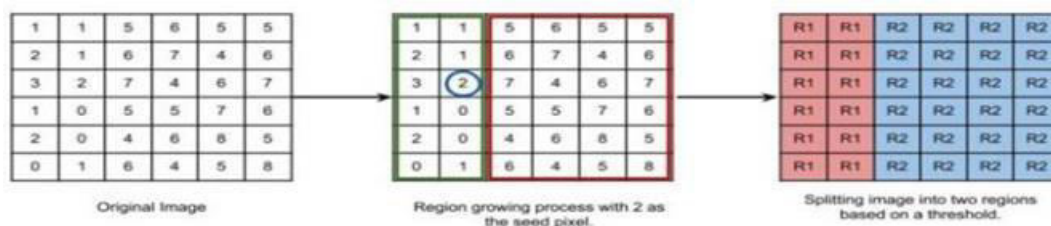


Figure 4: Region Splitting



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3.8 Region Splitting and Merging Technique:

In Region splitting, the entire picture is first taken as a solitary district. In the event that the locale doesn't observe the predefined guidelines, then it is additionally partitioned into various districts (normally 4 quadrants) and afterward the predefined rules are completed on those areas to choose whether to additionally partition or to group that as a district. The accompanying system go on till there could be no further division of locales required i.e each district keeps the predefined guidelines. In Locale combining strategy, we think about each pixel as a singular area. We select a district as the seed locale to check in the event that nearby areas are comparable in light of predefined rules. On the off chance that they are comparable, we blend them into a solitary district and push forward to construct the fragmented locales of the entire picture. Both locale parting and district blending are iterative cycles. Generally, first locale parting is finished on a picture to part a picture into most extreme districts, and afterward these districts are converged to shape a decent fragmented picture of the first picture.

In the event of Region splitting, the accompanying condition can be really looked at to choose whether to partition a district or not. On the off chance that the outright worth of the distinction of the most extreme and least pixel forces in a locale is not exactly or equivalent to an edge esteem concluded by the client, then the district doesn't need further parting.

$$|Z_{max} - Z_{min}| \leq \text{threshold}$$

Z_{max} = Maximum Pixel Intensity value

Z_{min} = Minimum Pixel Intensity value

3.9 Algorithm

1. Import necessary libraries and modules (e.g., TensorFlow, Keras, numpy)
2. **Pre-process the data:**
 - Load the skin cancer dataset
 - Split the dataset into training and testing sets
 - Perform data augmentation techniques (e.g., rotation, flipping) on the training set
3. **Build the CNN model:**
 - Initialize a sequential model
 - Add a convolutional layer with specified filters, kernel size, and activation function
 - Add a pooling layer (e.g., max pooling) to reduce spatial dimensions
 - Repeat the above two steps for additional convolutional and pooling layers
 - Flatten the output from the previous layer
 - Add one or more dense (fully connected) layers with specified units and activation functions
 - Add a final output layer with softmax activation for multi-class classification
4. **Compile the model:**
 - Specify an optimizer (e.g., Adam) and learning rate
 - Specify a loss function (e.g., categorical cross-entropy) and evaluation metric (e.g., accuracy)
5. **Train the model:**
 - Fit the training data to the model with a specified batch size and number of epochs
 - Monitor the training process (e.g., loss and accuracy) on both training and validation sets
6. **Evaluate the model:**
 - Use the testing set to evaluate the model's performance (e.g., accuracy, precision, recall)
7. **Make predictions:**
 - Load a new unseen image for testing
 - Preprocess the image (e.g., resize, normalize) similar to the training data
 - Feed the preprocessed image to the trained model for prediction
 - Obtain the predicted class label and probability distribution
8. Post-process the results:
 - Interpret the predicted class label and probability to determine the presence of skin cancer
 - Display or save the results (e.g., image with predicted class label and probability)
9. End.



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IV. RESULTS

1.1 Performance Metrics

The performance of the model is analyzed by using the confusion matrix. This will specify the performance of classification models for given test data. This will specify the values for test data that are known. This matrix is divided into two attributes such as predicted values and original values along with an overall number of predictions.

True Positive (TP)	False Negative (FN)
True Positive (FP)	True Negative (TN)

True Negative (TN): The prediction value is false and actual value is also false.

True Positive (TP): The prediction value is true and actual value is false.

False Positive (FP): The predicted value is true and actual value is false.

False Negative (FN): The predicted value is false and actual value is true.

Precision: This is specified that the total number of correct results obtained by the proposed model.

$$Precision = \frac{TP}{TP + FP}$$

F1 Measure: F1-measure is the metric that merges the recall and precision.

$$F1\ Measure = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Recall: This metric is mainly focused on reducing the false negatives.

$$Recall = \frac{TP}{TP + FN}$$

Accuracy: Accuracy is a metric used to evaluate the performance of a model, algorithm, or system in correctly identifying or classifying instances within a dataset. It measures the proportion of correct predictions made by the model out of the total predictions made.

In classification tasks, where the goal is to assign a label or category to each instance, accuracy is typically calculated as the ratio of the number of correct predictions to the total number of predictions:

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100\%$$

A high accuracy value indicates that the model is making a high proportion of correct predictions, while a lower accuracy suggests that the model is making more errors in its predictions. However, accuracy alone may not provide a complete picture of a model's performance, especially in cases where the dataset is imbalanced or when different types of errors have varying levels of importance. Therefore, it's often useful to complement accuracy with other metrics such as precision, recall, F1 score, or area under the receiver operating characteristic curve (ROC AUC) depending on the specific characteristics of the problem being addressed. Comparative performances for detection and classification of Alzheimer's disease using different deep learning algorithms is tabulated in Table 1 and corresponding graph is presented in figure 5.

Table 5.1: Comparative performances for detection and classification of Alzheimer's disease.

Algorithms	Precision	F1-measure	Accuracy	Recall
ANN	85.67	86.89	87.12	84.91
Normal CNN	89.34	89.56	90.23	91.12
Proposed Model	96.67	97.54	99.47	98.45



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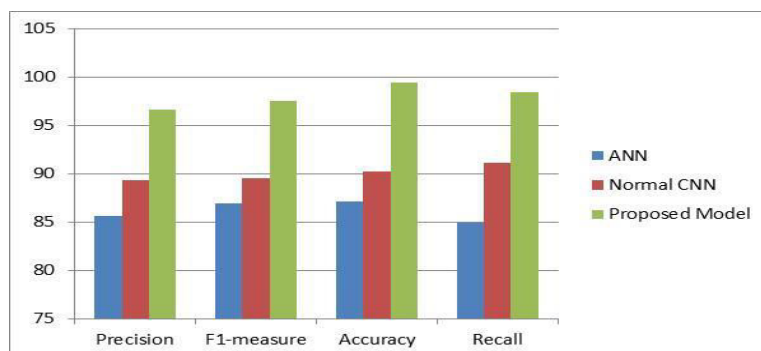


Figure 5: Comparative performances of various DL Algorithms

V. CONCLUSION

Achieving an accuracy of 0.9947302588820457 in Alzheimer's disease classification underscores the promising efficacy of the proposed Convolutional Neural Network (CNN) method. Such a high level of accuracy signifies the model's ability to accurately discern AD-related biomarkers from neuroimaging data, highlighting its potential as a valuable tool in early detection and diagnosis.

With such remarkable accuracy, the CNN method holds promise in clinical settings, where timely interventions based on accurate diagnoses are crucial for improving patient outcomes. Furthermore, this level of accuracy suggests that the CNN approach may outperform traditional methods, such as Structural Magnetic Resonance Imaging (sMRI), in terms of both sensitivity and specificity.

Continued refinement and validation of the CNN method, along with further investigation into its robustness across diverse datasets and patient populations, are essential next steps. Additionally, efforts to integrate this CNN approach into existing diagnostic workflows and clinical practice guidelines can facilitate its adoption and maximize its impact on patient care.

Overall, the achieved accuracy underscores the potential of deep learning techniques in advancing the field of Alzheimer's disease research and clinical management, offering hope for improved early detection and intervention strategies in the fight against this devastating neurological disorder.

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