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Deep Learning for Detection and Predictive of the Progression of Alzheimer's Disease

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Abstract

Alzheimer's disease is a degenerative neurological disorder that primarily strikes older people. Alzheimer's disease is now a major health problem for anyone over the age of 65. The inability to remember what has been said or done before is the first symptom of the condition. Memory loss becomes severe, and daily functioning declines as the disease progresses. The memory-controlling region of the brain shows signs of impairment years before any symptoms occur. There are three possible disease stages: mild, moderate, and severe. The early stage, sometimes known as the middle stage, mild demented (MCI), is an intermediate state between Alzheimer's patients and healthy individuals When someone is diagnosed with MCI, there is an opportunity to treat or stop the development of the disease into AD, which is the only solution to avoid AD. Therefore, the early detection of AD plays a crucial role in preventing and controlling its progression. The main objective is to design an end-to-end framework for The Early detection of Alzheimer's disease and medical image classification for various AD stages. A deep learning approach, specifically convolutional neural networks (CNN), is used in this work. Based on MRI scans, The four phases of Alzheimer's disease are correctly categorized by the suggested technique with an accuracy of 95.17 % performance, 86.82 % precision, and 93.13 f1 score.

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1. Introduction

A neurological condition known as Alzheimer's disease (AD). Some of its symptoms include memory loss, interaction, understanding problems, loss of thinking and judgment, and cognitive skill impairment [1]. The brains of people who have Alzheimer's include more amyloid tau protein, the main cause of the disease, than the brains of typical older persons. [2]. So also, The emergence of tau neurofibrillary tangles and amyloid plaques results in a breakdown of nerve cell connection and, ultimately, cell death. The hippocampus is the first part of the brain to suffer damage of Disease [3]. The first sign of AD is forgetting names and dates because the hippocampus is so crucial for memory and learning. When life expectancy increases, the number of people with Alzheimer's disease will rapidly increase. According to projections from the World Alzheimer's Report, 50 million people worldwide were estimated to have Alzheimer's in 2015 [4]. By 2050, this number is anticipated to increase to 131.5 million people worldwide. Alzheimer's disease cannot currently be treated with medication, but early diagnosis can halt the disease's progression to more severe stages [5]. One of the primary objectives of artificial intelligence research is the classification of disease [6]. A range of neuroimaging techniques, such as, (fMRI) Functional MRI, (MRI) Magnetic Resonance Imaging, (PET) Positron Emission Tomography, (CT) Computed Tomography magnetoencephalography and (EEG) electroencephalography, are useful in the categorization of AD. The most widely utilized MRI technology is because the pictures it produces reveal the afflicted cells to be darker than the healthy areas [7]. Many brain MRI pictures showing different phases of Alzheimer's disease are shown in Figure (1). Dechter introduced the idea of deep learning (DL) in 1986 [8]. Its methods, and its ability to process and analyze images. Convolutional neural networks (CNN) are one of the most significant networks utilized in computer vision applications in the field of medicine [9]. where it has successfully demonstrated its accuracy in effectiveness and rapidity in analyzing medical pictures [10]

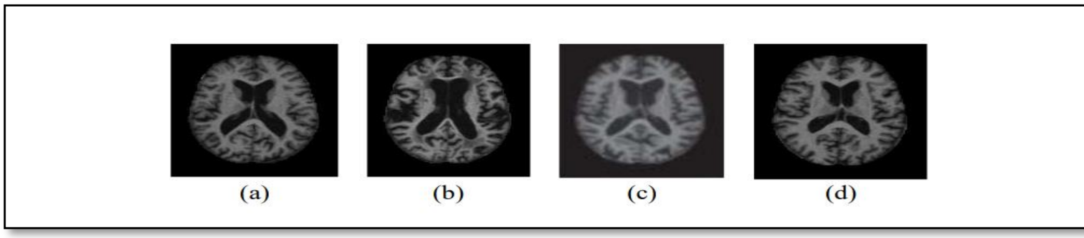

Figure 1. MRI of Alzheimer's disease stages.
(a) cognitively normal (CN), (b) mild demented (MCI), (c) moderate demented (MD), and (d) very mild demented (AD) [10].

2. Literature Review

a) Jyoti Islam and Yanqing Zhang 2017, "An Ensemble of Deep Convolutional Neural Networks for Alzheimer's Disease Detection and Classification" analyzed brain MRI data to offer a Alzheimer's Disease detection and classification model. On the Open Access Series of Imaging Studies (OASIS) dataset, a group of deep convolutional neural networks was created and their better performance was demonstrated. presented a one-step analysis from the 3D brain MRI data for the diagnosis and categorization of Alzheimer's disease. The distinction between the extremely mild and mild classes would make it easier to determine the patient's present stage of Alzheimer's disease. The accuracy of the proposed ensemble model was 93.18% [11].

b) Md Rishad Ahmed et al. 2018: "Neuroimaging and Machine Learning for Dementia Diagnosis: Recent Advancements and Future Prospects". This study can be broken down into two main sections: (1) a discussion of the most recent neuroimaging techniques in the field of dementia diagnosis for important clinical applications like (MRI, PET, and SPECT), and (2) a systematic description of machine learning techniques and, in particular, deep learning approaches for early detection of dementia. Discovered the performance of deep learning systems for analyzing brain pictures produced using cutting-edge imaging techniques is better than traditional imaging and machine learning techniques where the results of Accuracy 73.75% and 67.01% [12].

c) Deepthi, L. Dharshana et al 2020: "An intelligent Alzheimer's disease prediction using convolutional neural network (CNN)". The Electroencephalogram (EEG) signal is employed because it is less expensive than MRI and other tests. The collected features from the pre-processed signals are sent into the Convolutional Neural Network (CNN). The suggested approach uses input signals to train an algorithm to classify the disease as Mild or Severe. The EEG signal is obtained via physionet and is in European Data Format (EDF) EEG is a technique for measuring the neural electric activity of the brain from the scalp of the head. Classification accuracy of 85.7% [13].

d) Lin, Weiming, et al. 2021: "Multiclass diagnosis of stages of Alzheimer's disease using linear Discriminant Analysis scoring for multimodal data". The goal of this study is to develop a framework for AD multiclass diagnosis utilizing a linear discriminant analysis (LDA) scoring approach to more effectively fuse multimodal data. Using feature reduction and selection, biomarkers have been identified in MRI and PET scans. They were subsequently given individual grades based on LDA and AD pathology scores. Finally, using these values, we developed a decision tree using an extreme learning machine for performing multiclass diagnosis. The Alzheimer's Disease Neuroimaging Initiative data collection was used in the experiments and the results of accuracy57.3% and 66.7% respectively [14].

e) Kavitha, C., et al. 2022: "Early-Stage Alzheimer's Disease Prediction Using Machine Learning Models ". Using a number of classification techniques, the most effective factors for Alzheimer's disease prediction have been identified,including, decision trees, random forests, and support vector machines. to make predictions for Alzheimer's disease, the Open Access Series of Imaging Studies (OASIS) data is utilized. In cases of early diagnosis, ML algorithms have the potential to drastically lower the annual death rates from Alzheimer's disease. With the best validation average accuracy of 80%, 83%, and 88% respectively on the test data of AD, the suggested study demonstrates improved outcomes. Comparing this test accuracy score to previous efforts reveals a substantial improvement [15].

3. Problem Statement and Plan of Solution

As may be observed in the "Related Work" section, various designs have recently been described in the literature that can support both AD detection and medical image categorization. However, few of them use multi-class medical image classification. The literature lacks a substantial amount of discussion on these topics. In light of the other cutting-edge methods discussed in the "Related Work" section, we can categorize the innovative aspects of this study as follows.

1. An end-to-end framework is applied for the early detection of Alzheimer’s disease and medical image classification.
2. The method is based on simple CNN architectures that deal with 2D structural brain MRI. These architectures are based on 2D convolution.
3. The main challenges for medical images are the small number of the dataset. So, data augmentation techniques are applied to maximize the dataset’s size and prevent the overfitting problem.

4. Motivation

There is yet no effective treatment for Alzheimer's disease [8, 9], which is the main obstacle facing the field. Despite this, modern AD treatments can alleviate symptoms and even reduce the disease's course. Therefore, prodromal stage diagnosis of Alzheimer's disease is crucial. Foreseeing the substantial care expenses associated with AD patients, a computer-aided system (CAD) is used for accurate and early identification [16]. Traditional machine learning algorithms often use two types of features, namely region of interest (ROI)-based features and voxel-based features, in the early detection of AD. Specifically, they rely significantly on assumptions about the brain's structure and function, such as differences in regional cortical thickness, hippocampus volume, and gray matter volume. Therefore, many of motives led to the use of deep learning model for early detection and prognosis. of Alzheimer's disease [17]:

1. Among One of the most important research fields in medical imaging is Deep learning has been used to analyze MRI, where Deep learning models have shown great promise in enhancing the accuracy of Alzheimer's disease diagnosis. These models can learn complex patterns and features from large-scale datasets, enabling them to make more accurate predictions based on various input data.
2. Traditional methods of diagnosing Alzheimer's disease often involve invasive procedures, such as cerebrospinal fluid analysis or brain biopsies, which can be discomforting for patients Deep learning models provide an opportunity to diagnose Alzheimer's disease using non-invasive techniques, such as neuroimaging scans (e.g., MRI, PET scans), thereby reducing the burden on patients and healthcare systems.
3. Early Detection and Intervention: Detecting Alzheimer's disease in its early stages is crucial for effective intervention and treatment. Deep learning models can be trained to recognize subtle patterns and predictive biomarkers in patient data that might indicate the onset or progression of the disease before noticeable symptoms appear.

5. Methodology of Proposed System

In this part, we lay out the basic structure of the proposed framework. Data collection, data cleaning, model selection, model training, model validation, and model evaluation are all part of the proposed framework. Each phase functions autonomously to carry out its designated goal. Since the output from one stage becomes the input for the next, the stages can communicate with one another in Real-time. The recommended framework is presented in Figure 2.

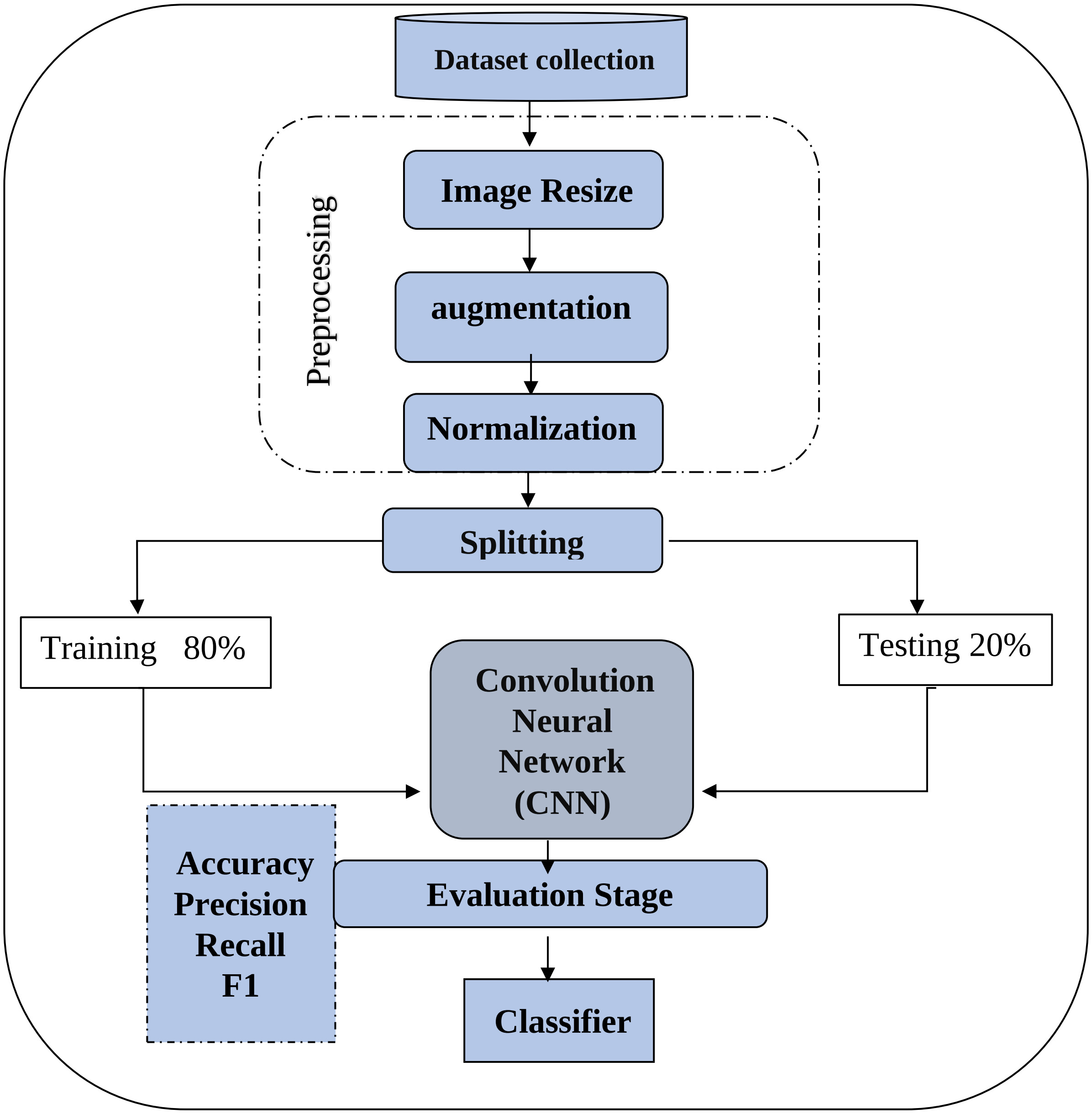

Figure2. A flowchart of the suggested method for detecting Alzheimer's disease at an early stage.

5.1 Dataset collection

Data collection is an important phase in deep learning (DL) because it entails acquiring and preparing the data required to train and evaluate deep learning models. To learn and create accurate predictions or classifications, labeled data in huge amounts is essential for deep learning models. As a result, the first stage in the range of the proposed work in this thesis is to gather data and obtain it from relevant data sources in order to handle the research problem, test the hypothesis, and assess the results. The dataset utilized in this research is from Kaggle®, it provides a credible online dataset for research and analytics in various domains, the collected dataset includes 6400 images with a size of 176×208 pixels for Alzheimer's Images of MRI. Including four classes, the train set with 4098 images while the test set with 1279 images, and the validation set with 1023 images. It has four classes (Non-Demented (2560 images), Mild Demented (717 images), Moderate Demented (52 images), and Very Mild Demented (1792 images),) as illustrated in Figure (3,4,5,6) [18] [19].

1. Class 0 " MildDemented"

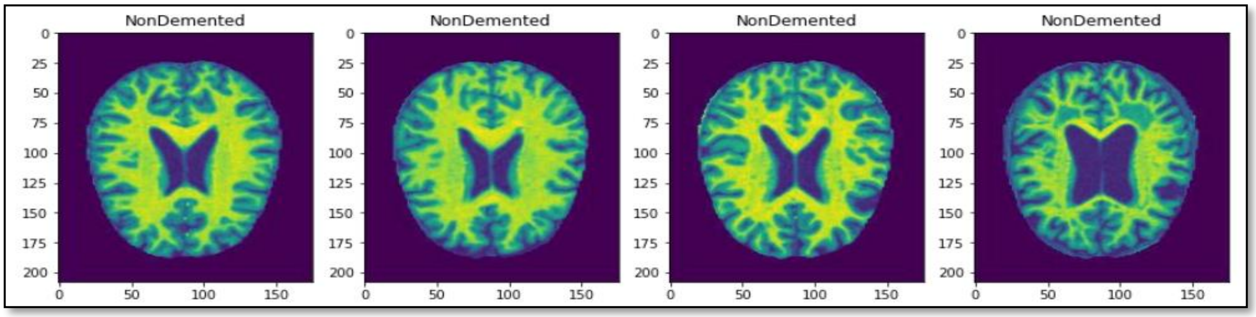

Figure 3. Alzheimer's Disease images (MildDemented).

2. Class 1 " ModerateDemented"

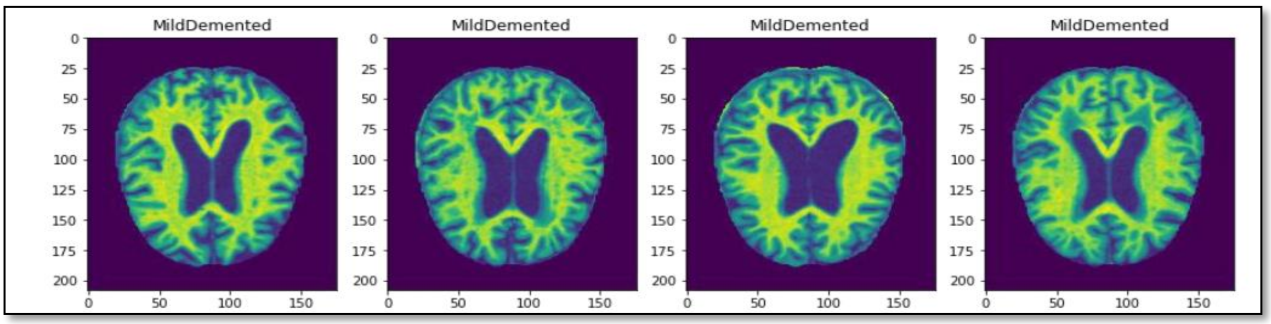

Figure 4. Alzheimer’s Disease images (Moderate Demented).

3. Class 2 " Nondemented"

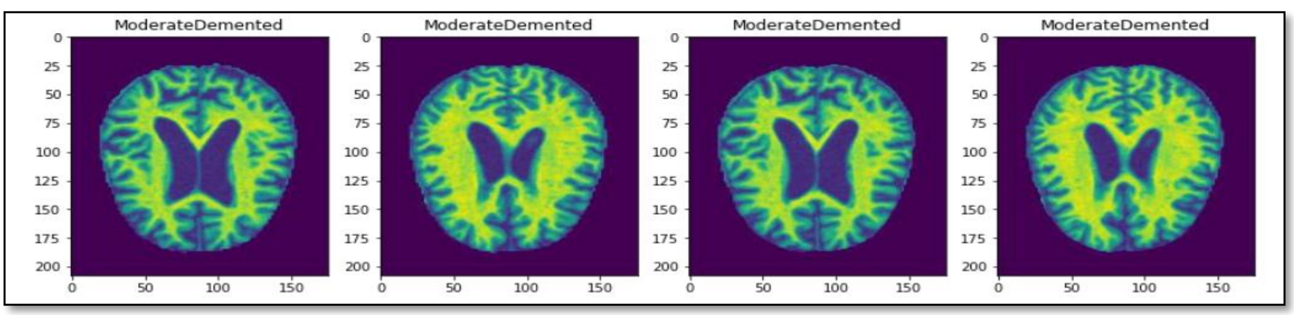

Figure 5. Alzheimer's Disease images (Nondemented).

4. **Class 3 " VeryMildDemented"**

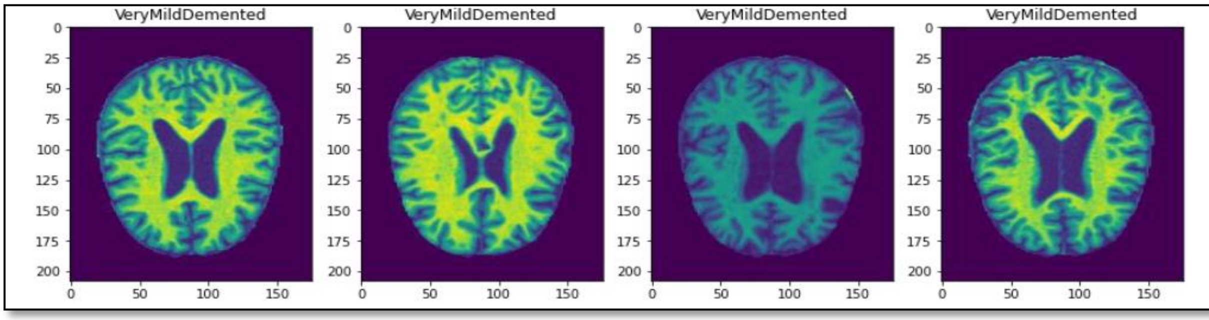

Figure 6. Alzheimer's Disease images (Very Mild Demented).

5.2 Preprocessing

Image pre-processing is the first stage in displaying various useful image features for subsequent usage. are described in the following subsections [20][21].

1. **Image Resize:** Images are resized and converted into a pixel array during this stage before being sent to CNN. image size is 224* 224 by using the bilinear interpolation due to their numerical simplicity.
2. **Augmentation Technique:** The augmentation technique was used to increase the generalization capacities of deep neural networks. Because of the non-uniform spread of images in each class, overfitting may occur. The Alzheimer's Disease dataset in the proposed system utilizes data augmentation, increasing the total number of images in the dataset to 8,810 after the augmentation technique.The augmentation technique utilized in this stage is:
   1. Rotation range: This augmentation technique helps the network identify the object in any direction in the image. The rotation angles used for all the photos in this work ranged from 0° to 20°.
   2. Brightness is more precisely defined as the measured intensity of each pixel in an ensemble that comprises the digital image after it has been captured, processed, and displayed. Figure (7) illustrates the brightness of a few MRI images.

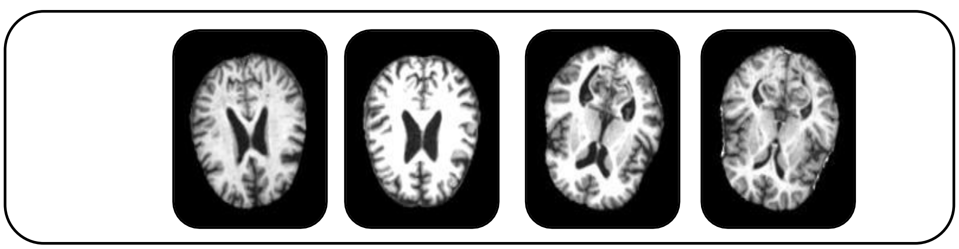

Figure 7: The Brightness and Rotation on MRI.

3. **Normalizing:** is the process of changing the range of pixel density values to a new range between (0,1) of the original range image and making it more stable to make the matching process compatible to achieve the highest accuracy and to balance the implementation before applying the CNN. Among the many benefits of normalization are the following:
   1. improving training by reducing the internal covariate shift. By keeping weights from bursting out of control and confining them to a particular range.
   2. lowering network overfitting by promoting regularization.

5.3 Dataset Splitting

After the preprocessing phase, the dataset is split. Dividing the dataset into two sets: a training set and a testing set. The training set is used to estimate the model parameters. sometimes referred to as the estimation set. The validation set of tests is used to evaluate the performance of the model. The data division 80%:20% ratio, meaning that 80% of the data is used to train the model and the remaining 20% is used to evaluate the model.

5.4 CNN Architecture Design

This part explains the structure of the Convolution Neural Network (CNN)and its components in detail. CNN is a common deep learning network because it offers several advantages over other networks, including the usage of fewer parameters with fewer neurons, which results in a quicker training period. The proposed research makes use of a customized CNN structure . the layers that make up the CNN architecture are as follows: an input layer, three hidden layers, and an output layer. Examples of CNNs' most often hidden layers are convolution layers, max-pooling layers, and flatten layers. Figure (7) illustrates the whole structure used for the CNN design.

1. Input Layer

The input layer contains the input image as well as its pixel values. The input layer in the proposed work comprises images of Alzheimer's (Non-Demented, Mild Demented, Moderate Demented, Very Mild Demented) inserted as a matrix of pixels. the size of images is changed to a fixed size (224*244) during the preprocessing stage.

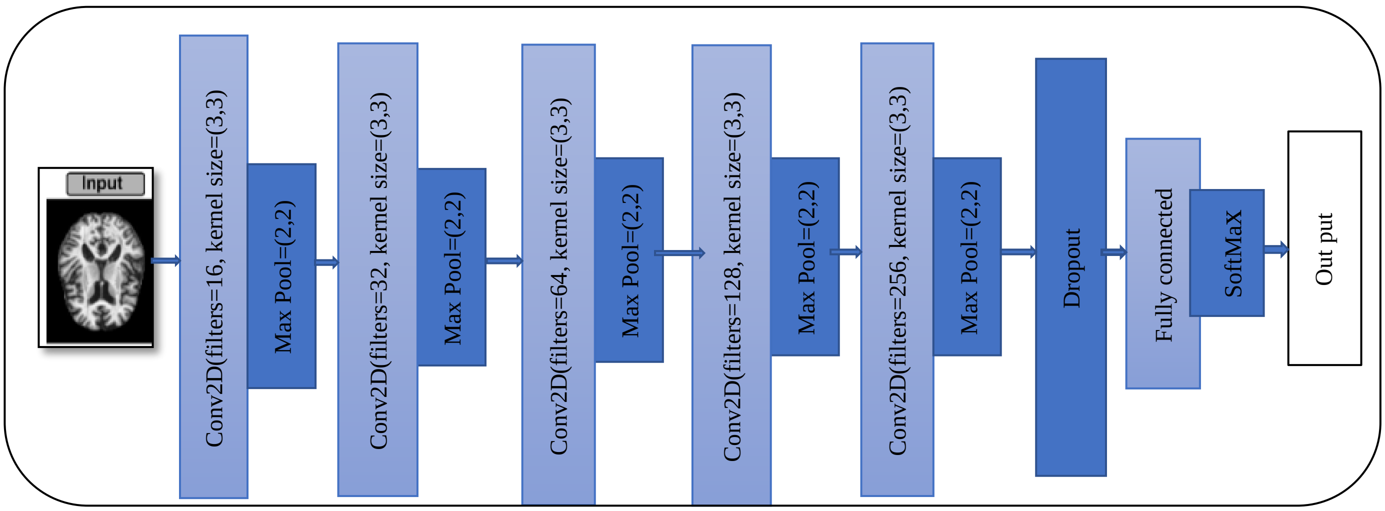

Figure7. Block Diagram of the Proposed CNN Structure.

2. A Convolutional Layer

The most important component of CNN's structure is accountable for for feature extraction and feature map creation. The convolution layer filters in this layer have weight arrays, and each member in the array denotes the weight being taught. In other words, the kernel or filter of this layer is a matrix consisting of an array of integers. These filter arrays are applied to the entire image in order to extract features. A convolutional layer contains.

1. The first convolution layer has 16 filters.
2. The second convolution layer has 32 filters.
3. The third convolution layer has 64 filters.
4. The fourth convolution layer has 128 filters.
5. The fifth convolution layer has 256 filters.

3. Pooling Layer

The pooling layer is put after the non-linear layer. This layer has. MaxPooling2D (pool_size= (2,2)), Throughout forward and backward propagation, the pooling layer is responsible for sending values to the following and preceding levels. The max pooling is employed in the suggested job following numerous testing due to its effectiveness and ability to give the best outcomes. When using max pooling, there are choices for the window size and stride. The suggested technique uses two as the window size and two as the stride, which are standard parameters for maximum pooling. The network's convergence rate is accelerated by these configurations.

4. Fully Connected Layer

Feature vectors are sent to the FC layer, which is used to analyze the best features that the model learns to use these characteristics to categorize the inputs into distinct groups. 64 units (weights) are used in two fully connected layers, represented by (Dense), with ReLU serving as the activation function. To extract the outcome from a model, the last fully connected layer employs four units (nodes) reflecting the number of categories, which are appended with the softmax activation function. The softmax's main responsibility is to calculate probabilities; based on these probabilities, Alzheimer's Disease is classified into any appropriate class according to the data used. This model utilizes one flatten layer and one dropout.

5.5 Evaluation Stage

To evaluate the efficacy of the analytical or Deep Learning model, evaluation measures are used. For each project, evaluating Deep Learning models or algorithms is crucial. There are four possible outcomes when making classification predictions. In order to analyze all phases of Alzheimer's disease (AD), a number of criteria are employed to evaluate the classification model using testing data, including precision, recall, and F1-measure, as indicated in (1) to (4), respectively [22].

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FN+FP} \qquad (1)$$

$$\text{Recall}= \frac{TP}{TP+FN} \qquad (2)$$

$$\text{precision} = \frac{TP}{TP+FP} \qquad (3)$$

$$\text{F1score} = \frac{2 * \text{Precision} * \text{Racall}}{\text{Precision} + \text{RacaLL}} \qquad (4)$$

6. Experimental Results with Convolutional Neural Network (CNN)

This part provides a full discussion while also outlining the research's findings. Training for the proposed network lasted 14 hours, 55 minutes, and 58 seconds. On a 25 GB Nvidia Tesla P100 GPU, tests were run using the Pytorch framework and Python 3.7.10. After scaling the photos to 224x224 pixels, we used the original Alzheimer's disease dataset, which consisted of 6400 images. Data was split into training (80%), and validation (20%).

a) Experiment (1) Result CNN without augmentation

The results of experiment (1) are shown in Table (5.1). In contrast, the performance of the model was shown in the Train accuracy , Validation accuracy ,Train loss and Validation loos , throughout Epochs figure 8. illustrated Loss Function for Training and Validation.

Table (5.1) The result of CNN without augmentation

Train Loss	1.22
Val loss	1.21
Train Accuracy	75%
Validation Accuracy	86%

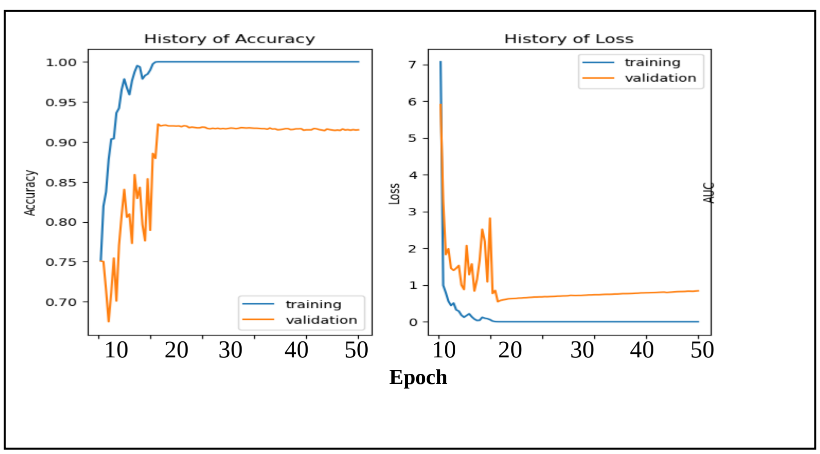

Figure 8. Loss Function for Training and Validation

Where was Test Accuracy 65%, Precision50%, and F1-score50% after epoch 50 This demonstrates conclusively that the suggested model is not an optimization fluke and that overfitting exists. The dataset's small number of images is the primary cause of overfitting, therefore augmentation is recommended to overcome this problem

b) Experiment (2) Result CNN with augmentation

when augmentation techniques are utilized to improve results. The final result of experiment (2) is shown in Table (5.2). In contrast, the performance of the model was shown in the accuracy of Validation,train loss and Validation,train accuracy across epochs

Table (5.2) The result of CNN with augmentation

Train Loss	2.44
Val loss	2.19
Train Accuracy	95 %
Validation Accuracy	95.17%

where was test Accuracy 95%, Precision 86.82%, and F1-score 93.13% . The experiments' results to which we mentioned above demonstrates, dataaugmentation techniques achive best accuracy it requires many experiments and iterations until a satisfying result is achieved. Finding suitable parameters for a specific problem is simply an optimization task in itself Figure 8. shows the accuracy of training and validation across epochs while Figure 9. shows the training and validation loss across epochs.

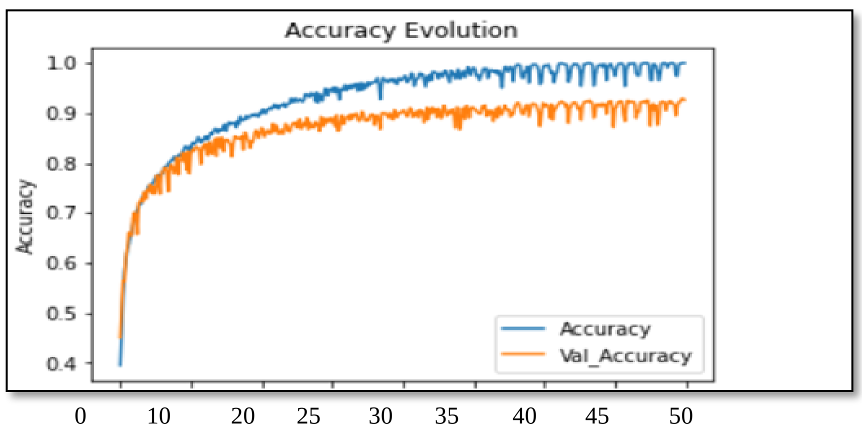

Figure 8. The Accuracy of Training and Validation Across Epochs.

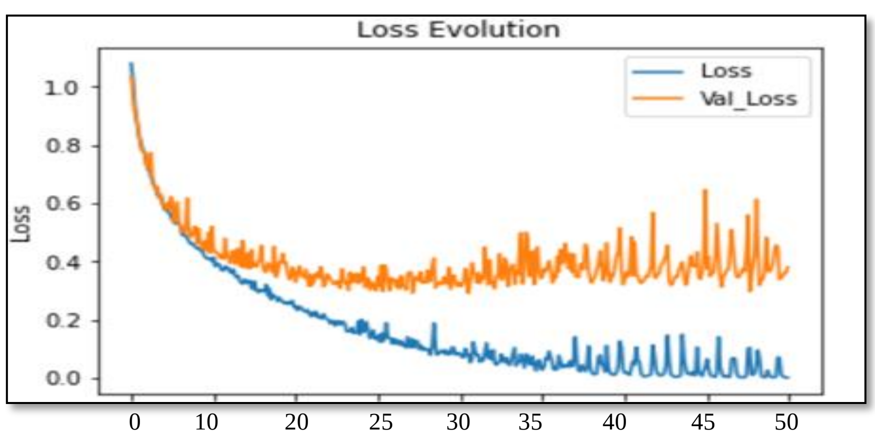

Figure 9. The training and validation loss Across Epochs.

It is noticed that the accuracy increases, and the loss is decreased for the models according to the findings of our experiments. We found that the model outperforms and after implementing augmentation, obtains an improvement in accuracy. Figure 10. presents the confusion matrix between true labels and predicted labels.

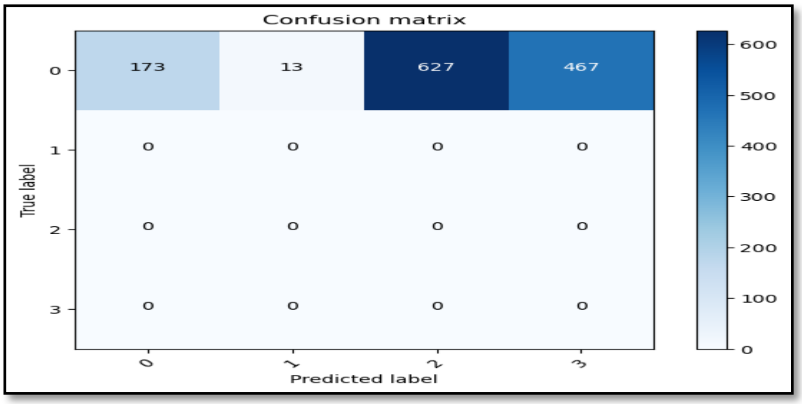

Figure 10. Confusion Matrix of CNN

The confusion matrix is one of the major metrics used in the classification process in CNN architectures. where the confusion matrix shows the number of correct and wrong predictions resulting from the classification model in comparison to the actual output.

In summary, the train loss and validation loss are used to adjust the model's parameters during the training stage, while the validation accuracy and test accuracy are used to measure how well the model performs on unseen data and gauge its generalizability. A good model should have high test and validation accuracy, as well as minimal train and validation loss.

5. Comparison with Related Works

A comparison is made between the suggested system and the relevant works presented in chapter one. The comparison shows in Table (3). the table below appears that our models achieves encouraging results after pre-processing the data set and applying the augmentation to increase the data with increase appropriate number of layers that were the reason for increasing the accuracy of the proposed system.Table (7.1) shows the comparison between the proposed model and previous studies.

Table (7.1) Comparison between the Proposed Model and previous studies.

Author	**Accuracy**
Jyoti Islam et al. 2017	93.18%
Md Rishad Ahmed et al 2018	73.75%
Deepthi et al.2020	85.7%
Lin, Weiming, et al. 2021	66.7%
Kavitha, C., et al. 2022	88%
proposed system	**95.17 %**

6. Conclusion

Alzheimer's disease is a degenerative neurological illness that worsens with age. It is also considered the most common cause of dementia. Alzheimer's disease develops in different stages, so early diagnosis and A correct diagnosis of Alzheimer's disease is crucial because early intervention in Alzheimer's disease slows the progression of the disease and accelerates the development of treatment options of future, and reduces the financial burden on patients' families. Therefore, researchers have created a variety of computer-aided diagnostic (CAD) techniques to identify AD ,which lowers this difficult effort. This work has aimed to find out whether the early diagnosis of Alzheimer's disease can be reliably performed by using magnetic resonance imaging of the brain together with a deep learning algorithm known as a convolutional neural network. We trained the network without augmentation techniques and noticed few results. Then we used augmentation techniques to increase the size of the data which become (8.810). This augmentation improved the classification accuracy of the MRI images achieving 95.17 % of accuracy. The proposed model was trained using 80% of the imagery data and validated using 20% of the image data. This model was created using the Python programming language.

7. References

[1] N. J. Herzog and G. D. Magoulas, “Brain Asymmetry detection and machine learning classification for diagnosis of early dementia,” Sensors, vol. 21, no. 3, Jan. 2021, doi: 10.3390/s21030778.

[2] D. J. Selkoe and J. Hardy, “The amyloid hypothesis of Alzheimer’s disease at 25 years,” EMBO Molecular Medicine, vol. 8, no. 6, pp. 595–608, Jun. 2016, doi: 10.15252/emmm.201606210.

[3] W. Qiang, W.-M. Yau, J.-X. Lu, J. Collinge, and R. Tycko, “Structural variation in amyloid-β fibrils from Alzheimer’s disease clinical subtypes,” Nature, vol. 541, no. 7636, pp. 217–221, Jan. 2017, doi: 10.1038/nature20814.

[4] D. Bachstetter et al., “Disease-related microglia heterogeneity in the hippocampus of Alzheimer’s disease, dementia with Lewy bodies, and hippocampal sclerosis of aging,” Acta Neuropathologica Communications, vol. 3, no. 1, Dec. 2015, doi: 10.1186/s40478-015-0209-z.

[5] M. Prince, A. Wimo, M. Guerchet, A. Gemma-Claire, Y.-T. Wu, and M. Prina, “World Alzheimer report 2015: the global impact of dementia - an analysis of prevalence, incidence, cost and trends,” 2015. doi: 10.1111/j.0963-7214.2004.00293.x.

[6] H. A. Lafta, Z. F. Hasan, and N. K. Ayoob, “Classification of medical datasets using back propagation neural network powered by genetic-based features elector,” International Journal of Electrical and Computer Engineering (IJECE), vol. 9, no. 2, pp. 1379– 1384, Apr. 2019, doi: 10.11591/ijece.v9i2.pp1379-1384.

[7] A. Hussein, “Improve the performance of k-means by using genetic algorithm for classification heart attack,” International Journal of Electrical and Computer Engineering (IJECE), vol. 8, no. 2, pp. 1256–1261, Apr. 2018, doi: 10.11591/ijece.v8i2.pp1256-1261.

[8] Puente-Castro, E. Fernandez-Blanco, A. Pazos, and C. R. Munteanu, “Automatic assessment of Alzheimer’s disease diagnosis based on deep learning techniques,” Computers in Biology and Medicine, vol. 120, May 2020, doi: 10.1016/j.compbiomed.2020.103764.

[9] H. Abdulkarim and M. Z. Al-Faiz, “Online multiclass EEG feature extraction and recognition using modified convolutional neural network method,” International Journal of Electrical and Computer Engineering (IJECE), vol. 11, no. 5, pp. 4016–4026, Oct. 2021, doi: 10.11591/ijece.v11i5.pp4016-4026

[10] Q. Dou et al., “Automatic detection of cerebral microbleeds from MR images via 3D convolutional neural networks,” IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1182–1195, May 2016, doi: 10.1109/TMI.2016.2528129.

[11] Islam, Jyoti, and Yanqing Zhang. "An ensemble of deep convolutional neural networks for Alzheimer's disease detection and classification." arXiv preprint arXiv:1712.01675 (2017).

[12] Ahmed, Md Rishad, et al. "Neuroimaging and machine learning for dementia diagnosis: recent advancements and future prospects." IEEE reviews in biomedical engineering 12 (2018): 19-33

[13] Deepthi, L. Dharshana, D. Shanthi, and M. Buvana. "An intelligent Alzheimer’s disease prediction using convolutional neural network (CNN)." International Journal of Advanced Research in Engineering and Technology (IJARET) 11.4 (2020): 12-22.

[14] Lin, W., Gao, Q., Du, M., Chen, W., and Tong, T.: ‘Multiclass diagnosis of stages of Alzheimer's disease using linear discriminant analysis scoring for multimodal data’, Computers in Biology and Medicine, 2021, 134, pp. 104478

[15] Kavitha, C., et al. "Early-stage Alzheimer's disease prediction using machine learning models." Frontiers in public health 10 (2022): 240.

[16] S. Basaia, F. Agosta, L. Wagner, E. Canu, G. Magnani, R. Santangelo, et al., "Automated classification of Alzheimer's disease and mild cognitive impairment using a single MRI and deep neural networks," NeuroImage: Clinical, vol. 21, p. 101645, 2019.

[17] A. Akhtar, S. Minhas, N. Sabahat, and A. Khanum, "A deep longitudinal model for mild cognitive impairment to Alzheimer’s disease conversion prediction in low-income countries," Applied Computational Intelligence and Soft Computing, vol. 2022, 2022.

[18] S. Lu, S.-H. Wang, and Y.-D. Zhang, “Detecting pathological brain via ResNet and randomized neural networks,” Heliyon, vol. 6, no. 12, Dec. 2020, doi: 10.1016/j.heliyon.2020.e05625.

[19] M. S. AL-Huseiny and A. S. Sajit, “Transfer learning with GoogLeNet for detection of lung cancer,” Indonesian Journal of Electrical Engineering and Computer Science (IJEECS), vol. 22, no. 2, pp. 1078–1086, May 2021, doi: 10.11591/ijeecs.v22.i2.pp1078-1086.

[20] Z. A. Khalaf, S. S. Hammadi, A. K. Mousa, H. M. Ali, H. R. Alnajar, and R. H. Mohsin, “Coronavirus Disease (COVID-19) detection using deep features learning,” Scientific Reports, 2020, doi: 10.21203/rs.3.rs-60331/v1.

[21] H. H. Alasadi and A. K. H. Al-Saedi, "A method for microcalcifications detection in breast mammograms," Journal of Medical Systems, vol. 41, no. 4, Apr. 2017, doi: 10.1007/s10916-017-0714-7.
[22] D. Soydaner, "A Comparison of Optimization Algorithms for Deep Learning," Int. J. Pattern Recognit. Artif. Intell., vol. 34, no. 13, pp. 1–26, 2020, doi: 10.1142/S0218001420520138.

التعلم العميق للكشف عن مرض الزهايمر والتنبؤ به

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الخلاصه :

مرض الزهايمر هو مرض عصبي يصيب كبار السن بشكل متكرر. أولئك الذين تزيد أعمارهم عن 65 عامًا يعانون الآن من مرض الزهايمر. العلامة الأولية للمرض هي نسيان المناقشات أو الأحداث السابقة. عندما تسوء الحالة ، يحدث فقدان خطير للذاكرة وتقلص القدرة على ممارسة الأنشطة اليومية. قبل سنوات من ظهور أي أعراض ، يبدأ الضرر في الظهور في منطقة الدماغ التي تتحكم في الذاكرة. قد يكون المرض في واحدة من ثلاث مراحل: خفيف أو متوسط أو خطير. تظهر الصعوبات الناشئة في المرحلة المبكرة ، والتي يشار إليها أحيانًا بالمرحلة المتوسطة. المصابة بالخرف الخفيف ، هي حالة وسيطة بين مرضى الزهايمر والأفراد الأصحاء عندما يتم تشخيص شخص ما مع الخرف الخفيف ،فأن هناك فرصة لعلاج أو توقف تطور المرض إلى الزهايمر ، وهو الحل الوحيد لتجنب مرض الزهايمر. لذلك ، فإن الاكتشاف المبكر لمرض الزهايمر يلعب دورًا حاسمًا في منع والسيطرة على تقدمه. الهدف الرئيسي هو تصميم إطار عمل شامل للكشف المبكر عن مرض الزهايمر وتصنيف الصور الطبية لمراحل الزهايمر المختلفة. تم استخدام نهج التعلم العميق ، وتحديداً الشبكات العصبية التلافيفية (CNN) ، في هذا العمل. استنادًا إلى فحوصات التصوير بالرنين المغناطيسي ، تم تصنيف المراحل الأربع لمرض الزهايمر بشكل صحيح من خلال التقنية المقترحة بدقة أداء95.17 ٪ ودقة 86.82٪ ودرجة 93.13 f1.