# Using Artificial Intelligence to Diagnose Demented in the Elderly

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# استخدام الذكاء الاصطناعي لتشخيص الخرف لدى كبار السن

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## Abstract

— In addition to possible other symptoms, memory loss and impairment are the hallmarks of Demented or alzahimar disease (AD). Despite the fact that Demented disease is incurable and has a significant negative impact on patients' lives, an early diagnosis can help start the right treatment and prevent additional brain damage. Over the years, machine learning techniques have been used to classify AD; nevertheless, the efficacy of the results depends on the use of multi-step classifiers and manually created features. Thanks to recent advances in deep learning, patterns may now be classified using neural networks' final stage.

In order to diagnose Demented disease early, convolutional neural networks (CNN, VGG16) were utilized in conjunction with magnetic resonance imaging to extract features from images of individuals with the condition and classify them. This research focuses on this process (MRI). Gray and white matter MRI image slices were employed as inputs for categorization. The output of deep learning classifiers was combined using group learning techniques to enhance classification after convolutional operations. We assessed the usefulness of our approach in the early detection of this illness with a collection of data from the Demented Disease Neuroimaging Initiative. Our accuracy rate for Demented disease evaluations was 95.4762%.


**Keywords- Demented disease, Deep learning, CNN, AI.**

## المستخلص

بالإضافة إلى الأعراض الأخرى المحتملة، يعد فقدان الذاكرة وضعفها من السمات المميزة لمرض الخرف أو مرض الزاهيمار (AD). على الرغم من أن مرض الخرف غير قابل للشفاء وله تأثير سلبي كبير على حياة المرضى، إلا أن التشخيص المبكر يمكن أن يساعد في بدء العلاج الصحيح ومنع حدوث تلف إضافي في الدماغ. على مر السنين، تم استخدام تقنيات التعلم الآلي لتصنيف مرض الزهايمر. ومع ذلك، فإن فعالية النتائج تعتمد على استخدام المصنفات متعددة الخطوات والميزات التي تم إنشاؤها يدويًا. بفضل التطورات الحديثة في التعلم العميق، يمكن الآن تصنيف الأنماط باستخدام المرحلة النهائية للشبكات العصبية.

من أجل تشخيص مرض الخرف مبكرًا، تم استخدام الشبكات العصبية التلافيفية (CNN، VGG16) بالتزامن مع التصوير بالرنين المغناطيسي لاستخراج الميزات من صور الأفراد المصابين بهذه الحالة وتصنيفهم. يركز هذا البحث على هذه العملية (التصوير بالرنين المغناطيسي). تم استخدام شرائح صور التصوير بالرنين المغناطيسي للمادة الرمادية والبيضاء كمدخلات للتصنيف. تم دمج مخرجات مصنفات التعلم العميق باستخدام تقنيات التعلم الجماعي لتعزيز التصنيف بعد العمليات التلافيفية. قمنا بتقييم مدى فائدة النهج الذي نتبعه في الكشف المبكر عن هذا المرض من خلال مجموعة من البيانات من مبادرة التصوير العصبي لمرض الخرف. كان معدل الدقة لدينا في تقييمات مرض الخرف هو 95.4762%.


**الكلمات المفتاحية: مرض الخرف، التعلم العميق، CNN، الذكاء الاصطناعي.**

# 1- Introduction

A neurodegenerative condition that mostly affects the elderly is Demented disease. Timely intervention and efficient management of Demented disease depend on an early and precise diagnosis. Techniques utilizing artificial intelligence (AI) have demonstrated significant promise in aiding medical practitioners in the diagnosis of Demented disease. Through the application of AI algorithms and machine learning models, scientists are creating novel methods for identifying and forecasting the start of Demented disease in older adults (Arafa, *et al.*, 2024) One of the most prevalent causes of cognitive deterioration in the elderly is Demented disease. The stage between normal cognitive functioning and dementia known as mild cognitive impairment (MCI) has a yearly progression rate of 10 to 15 percent to Demented disease (Borchert, *et al.*,2023), Even though there isn't a conclusive medical diagnosis or therapy for MCI at this time, there are certain strategies that can assist delay its progression(Bucholc, *et al.*,2023). Impeding the disease's course requires an early and precise medical diagnosis (Lyall, *et al.*,2023)To evaluate maze function, several techniques have been developed, including as transcranial magnetic stimulation (TMS), near-infrared spectroscopy (NIRS), magnetoencephalography (MEG), electroencephalography (EEG), positron emission tomography (PET), and functional magnetic resonance imaging (fMRI) (Tsoi, *et al.*,2023) These methods aid in the diagnosis of brain tumors and problems in maze adaptations, as well as the identification of neural activity and disease's physiological impacts. While fMRI generally looks at maze performance without taking its structure into account, resting state fMRI (RS-fMRI) is especially helpful in evaluating the physiological consequences of the condition (Ford, *et al.*,2023).

Using image zoning methods is another way to diagnose Demented disease. For this, several image partitioning techniques are used, such as thresholding, clustering, machine learning, and deep learning. For image zoning and illness detection, statistical techniques are frequently employed because thresholding techniques like Otsu are incapable of learning . Even though these techniques might not work by themselves, they might work well in combination with other strategies. Although they can't learn, clustering techniques like k-means and fuzzy clustering are good in identifying and classifying zones (Rogeau, *et al.*,2024) Accurately calculating the right number of clusters is the difficult part since mistakes might happen if this is done incorrectly. If the cluster centers are not accurately established, another problem with clustering algorithms is the lack of accuracy in the clustering region. In order to overcome these obstacles, several research have optimized cluster center selection by using group intelligence and meta-heuristic algorithms. Although this enhances clustering techniques, uncertainty may lead to longer execution times and a decreased ability to consistently identify illness sites.

Deep learning techniques, on the other hand, have been effective in medical image zoning research. They are frequently utilized in this context because they provide great accuracy in data analysis. The problem with these approaches is that they rely on long-term learning for zoning. Using group intelligence techniques to improve learning can be a useful tactic to solve this (Tsoi, *et al*,2023) It is crucial to remember that machine learning techniques are more constrained than deep learning techniques, and they do not have an automated feature selection process (Akan, *et al.*,2024).

## 2. Literature Review

The variety of studies on Demented disease that have been utilized in this paragraph:

Because disease-modifying medications are most effective when begun early in the course of the illness, before permanent brain damage develops, early symptom identification, or "pre-detection," is crucial. Consequently, using automated techniques to predict AD symptoms from such data is crucial. The system was built using the Open Access Series of Imaging Studies (OASIS) dataset. The data was analysed and then used in many machine learning models. Support vector machines, random forests, logistic regression, and decision trees were employed in the prediction process. The SVM beats all other neural networks with an accuracy of 88.88, the only exception being a manually controlled neural network that needs a significantly longer training time. have been present (Ebell, *et al.*,2024) Diagnosed and classified using thick layers, conv2D, maxPooling2D, and a sequential model. A 4-class dataset has been utilized in this work to diagnose Demented disease, according to the Kaggle dataset. The Demented MRI dataset has been used to classify the disease as non-demented, moderately demented, mildly demented, and very mildly demented, in that order. Diagnosed and classified using thick layers, conv2D, maxPooling2D, and a sequential model. A 4-class dataset has been utilized in this work to diagnose Demented disease, according to the Kaggle dataset. The Demented MRI dataset has been used to classify the disease as non-demented, moderately demented, mildly demented, and very mildly demented, in that order have been presented (Karnik, *et al.*,2024). Diagnosed and classified using thick layers, conv2D, maxPooling2D, and a sequential model. A 4-class dataset has been utilized in this work to diagnose Demented disease, according to the Kaggle dataset. The Demented MRI dataset has been used to classify the disease as non-demented, moderately demented, mildly demented, and very mildly demented, in that order. have been presented (Perluigi, *et al.*,2024). Evaluate a state-of-the-art deep learning method for diagnosing Demented disease (AD) and collaboratively predict the MMSE scores of AD patients in South Korea. Using resting-state functional magnetic resonance imaging (rs-fMRI) scans of 331 people, we generated functional 3-dimensional (3-D) independent component spatial maps to be used as features in classification and regression tasks. A three-dimensional convolutional neural network (CNN) architecture was developed for the classification task. Support vector regression, bagging-based ensemble regression, tree regression employing group independent component analysis (gICA) features, and linear least square regression were the techniques employed to predict MMSE scores (LLSR). To improve MMSE regression performance, we employed feature optimization methods such support vector machine-based recursive feature reduction, least absolute shrinkage and selection operator, and so forth (SVM-RFE). The average balanced examination have been presented(Mattsson-Carlgren, *et al.*,2024)

## 3. Deep Learning

Because deep learning can handle large amounts of data, it has become a particularly important technology in the last several decades. Hidden layers have recently attracted attention in fields such as pattern recognition where traditional techniques have failed. Convolutional neural networks are a common kind of deep neural networks (CNN).

During the 1950s, when artificial intelligence was still in its infancy, researchers attempted to develop a system that could interpret visual input. The field that this research was conducted in later years grew to be known as computer vision. Computer vision took a quantum leap in 2012 when a group of academics from the University of Toronto developed an AI model that considerably surpassed the top picture recognition algorithms.

With an incredible accuracy rate of 85%, the artificial intelligence system known as AlexNet—named after its principal creator, Alex Krizhevsky—won the 2012 ImageNet computer vision competition. The runner-up received a commendable 74 percent on the exam. AlexNet used convolutional neural networks, a kind of neural network that mimics human vision. Since CNNs have become an essential component of many computer vision applications, they are now included in all online computer vision training courses. Let's now look into how CNNs function. Artificial neural networks (ANNs), a kind of machine learning called deep learning, are systems that use vast amounts of data to learn by modeling the structure of the human brain. For example, machine learning makes it possible for computers to grow and learn from their experiences without the need for human interaction. A deep learning algorithm will repeat a job and improve the result each time by making small tweaks, much as how it learns from experience. Deep learning neural networks are neural networks that include several (deep) layers for learning. Through deep learning, any issue that requires "thinking" may be taught to be solved. Through the utilization of large, unorganized, and interconnected data sets, deep learning empowers computers to address complex (Ebrahim, *et al.*,2020).

## A. Convolutional Neural Network (CNN)

Convolutional neural networks are a kind of deep learning that operates by extracting features from image and video data, building neural networks by allocating weights, and selecting and classifying images via filter transformations. CNN is the first tool that every data scientist will use to handle any image or video processing data. The transfer learning methodology is quite simple to use and adapt when using our layers. The most prominent use for CNNs, a particular kind of directed neural network, is in computer vision problems. CNN provides answers to a variety of AI and computer vision issues. Because at least one of the layers in convolution acts as a foundation step, the technology is known as "convolutional neural networks." The CNN is made up of several levels between the input and output layers. Layers include convolutional, pooling, and fully connected layers. Depending on the application, different CNN designs use different numbers and types of layers (Ebrahim, *et al.*,2020). CNN layers may have tens of thousands of filters that go through the input and look at every channel.

Sequential To extract more abstract characteristics, CNN layers are used. Beginning with edges and corners in the early levels, work your way up to whole faces and artifacts in the deeper layers. During training, the network learns which features need to be eliminated in order to provide a solution. Due to its flexibility in solving a wide range of computer vision issues, CNN does not need human labor or sophisticated expertise for feature building (Dubois, *et al.*,2020).

The following subsections describe several terminology and jargon related to CNN:

### I. CNN Input layer

The input layer encompasses all of CNN's data. Typically, in an image processing neural network, the input is the pixel matrix of the picture. The dimensions of the grayscale picture can be used to determine the size of the input image (Ravi, *et al.*,2023).

### II. Convolution Operation

The convolutional layer extracts picture features, identifying basic visual elements like edges, lines, and corners. It generates feature activation maps by applying a convolution kernel to the preceding layer.The convolutional layer extracts picture features, identifying basic visual elements like edges, lines, and corners. It generates feature activation maps by applying a convolution kernel to the preceding layer.

$$X_j^l = f\left[\sum_{\in M_j} (X_i^{l-1} * K_{ij}^l + b_j^l)\right], \qquad (1)$$

The kernel, a scaled-down version of the original, is arranged in a specific order, modified during training to align with the neural network's weights, and convolution combines two functions.

The image's kernel moves from left to right, and the convolutional process starts in the upper-left corner. The kernel moves one item downhill and then turns back to the left when it reaches the upper-right corner of the picture. This operation is continued until the kernel reaches the input image's bottom-right corner. The feature map is the outcome of this method (Mahendran, *et al.*,2021). The stride variable controls how quickly the filter scans the picture. The filter will only move one pixel across the picture if the stride is set to one.

## III. Image Features

A picture's borders, lines, areas of interest, and other characteristics may reveal a lot about its content. They are used in a number of image analysis applications, including as matching, identification, and reconstruction, to characterize certain regions of an image (Mehmood, *et al.*,2021).

## IV. Zero Padding

To ensure that every convolution stage can preserve the original input size, zero padding is the technique of appending zeros to the input image's matrix. There are two different kinds of padding. The first, called genuine, claims that the convolutional layer is never padded at all and that, as a result, the input size is lost. The second kind is similar in that it uses padding to convolve the original input picture until it does. This results in the identical sizes for the input and output. In there is no padding. In short, our input's volume indicates how much padding our kernels need to handle the input matrices. We have two options for padding: either add one row or column on each side of zero matrices (zero padding) or remove the part of the picture that does not fit (valid padding) (Boualouache, *et al.*,2018).

## V. Batch Size, Iterations and Epoch

In machine learning, for example, batch sizes, iterations, and epochs all become important when working with enormous volumes of data. In order to get beyond this obstacle, we must divide the input into manageable chunks and feed it into our model in real time, modifying the neural network weights at the end of each step to better suit the data. An epoch is the period of time the network will keep evaluating data. The full dataset is used to train the network for a single iteration inside an epoch. The batch size controls how many I/O pairs are shown on the network at any one time. Iterations are the number of batches required to finish a project in a single time frame (Zhang, *et al.*,2019).

### VI. Cost Function

This technique is used to provide network performance feedback. This is a deep learning-related trait that the network is attempting to eliminate. An optimizer is needed to reduce the functionality of the network cost. In this instance, the optimal option is the Adaptive Moment Estimation Optimizer, or ADAM Optimizer. Rather than using the conventional random gradient descent approach, ADAM is an optimization methodology that may be used to recursively update network weights depending on training data (Ahmadlou, *et al.*,2018).

### B. CNN Layers

A CNN is composed of many layers. The important levels are explained in the subsections that follow.:

### Convolution Layer

The convolution procedure learns the properties of the picture and extracts features while preserving the spatial relationship between the image's pixels by applying a filter (kernel) to the input data. The core of a convolutional neural network is the convolution layer. performs a wrap operation on the supplied picture. It's used to get the properties of the picture. The first convolution layer extracts low-level features like edges, corners, and lines. XT-level layers are used to extract the extachigher level characteristics from the input picture. According to Balodi, *et al.*, (2021), equation (2) displays the layer equation.

$$^{1}\,xt = \sigma\,(\,a1+ * a^{0}\,) \qquad (2)$$

The set activations generated by the feature map are denoted by a1, the input activations by a0, the activation function by w, the bias by b, and the convolution process by *. The kernel's width and height are less than those of the input picture. As it advances over the picture, the kernel builds a feature map (convolve with). The outcome of multiplying the original picture by the kernel element is convolution.

## b) Pooling Layers

This layer reduces neural network instability and computational complexity (NN). The assembly method is often used by beginners who are unaware of its purpose. A comparison of three typical, daily assembly techniques is shown below.

The three types of aggregating operations that follow are:

Maximum pooling: The batch's maximum pixel value is stated.

establishes the minimum pixel value for the batch using min pooling.

Average pooling: An average is calculated between the batch's pixel values.

In this context, "batch" refers to a collection of pixels that match the filter's size, which is determined by the image's dimensions. A 9x9 filter was used in the example that follows. The result of the aggregation process is impacted by the variable value of the filter size. Consequently, the feature maps have a large number of convolutional layers. The pooling layer decreases the features' accuracy. Consequently, instead of removing each and every item, we provide an overview of all the data discovered when we aggregate a picture.

### c) Fully Connected Layer(FC)

This layer connects neurons between levels and also includes of weights and biases. These layers come before the output layer in the CNN architecture. The FC layer receives the input picture from the preceding layers and flattens it. To allow arithmetic function operations, more FC layers are stacked on top of the flat vector. The process of categorizing now begins.

### d) Dropout

The basic idea behind dropout is to continuously train on different networks, losing a portion of the neurons in the hidden layer each time, which weakens the connections between the neurons. The Dropout Strategy Is Included in the Calculation Method for Redirecting Diffusion from Equation (1) to Equation (2) and (3).

$$r^{(-1)} \sim Bernolli\,(p)$$

$$x_j^l = f[\sum_{i \in M_j} (r^{(l-1)} * x_i^{l-1}) * W_{ij}^l + b_j^l] \qquad \mathbf{3}$$

When every feature is connected to the FC layer, overfitting occurs often in the training dataset. Equation (3) shows that each value in the vector (1) or− is a Bernoulli distribution with probability p to generate values of 0 and 1, meaning that each layer of the model blocks is part of the 1lix− input vector from the first layer l through the vector (1) LR−, which approximates the subnetwork model taken from the overall network model. This means that the output of the lth layer is obtained by forwarding propagation. The model performs well on the training data but poorly on new data.

### e) Activation Function Layer

Neurons in a neural network have activating activities, which alter the received input to maintain values within a tolerable range. These functions are non-linear and constantly differentiable, allowing for efficient error back-propagation across the network. The nonlinearity of the neural network allows it to be used as a global approximation.

The neuron's interior:

- A neuron or the entire neural layer receives the activation function.
- The input values' weighted total is added.
- The weighted total of the input values is applied to the activation function, and the transformation happens.
- This altered value is passed on to the next tier (Liu, Ryan Wen, *et al.*,2023):

$$\text{sigmoid:} \quad f(x) = \frac{1}{1+e^{-z}}, \quad 4$$

$$\text{tanh:} \quad f(x) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}, \quad 5$$

$$\text{ReLU:} \quad f(x) = \max(0, x), \quad 6$$

## 4. the proposed method

MRI is the data set utilized in half of the process. An MRI dataset has images for mild, moderate, and severe Demented disease, whereas a dataset with medical records is utilized to predict dementia. The process for identifying An Demented patient using deep learning techniques is shown in Figure (1).

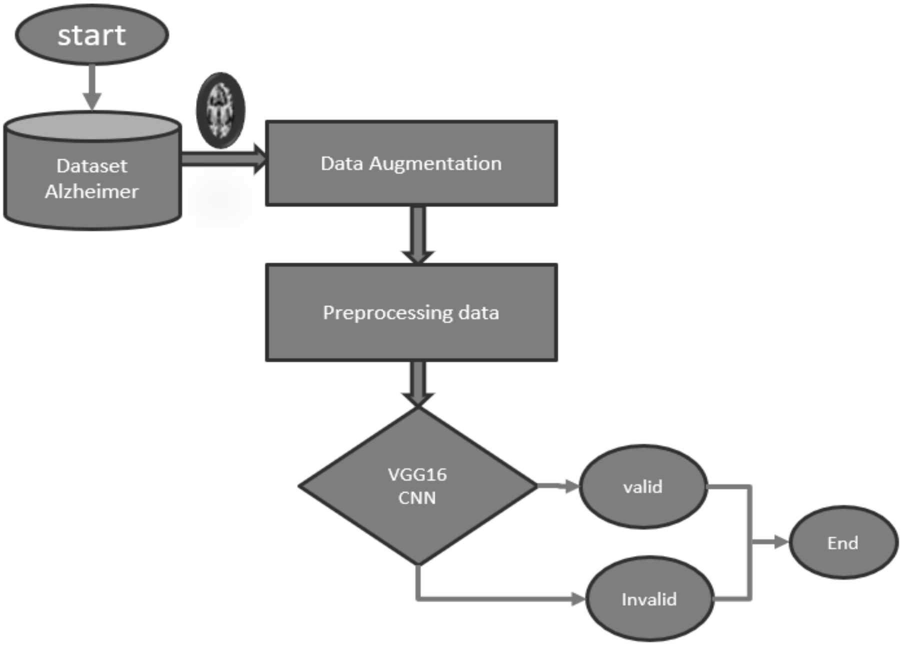



**Figure (1) Proposal Method**

## A. Data Collection

To start the process of creating an image classification network, the initial task is to gather a dataset of images that will be utilized for training the network. This step holds significant importance in the overall process. There are various methods to obtain data for image classification, and one approach is to utilize online resources. In this specific case, the dataset was obtained from the Kaggle Standard website and is referred to as "alzheimers-dataset-4-class-of-images". This dataset comprises four classes, with each class containing a total of 7000 labeled images. For the purpose of training and validation, the dataset will be split into 70% for training and 30% for validation. As shown in Table (1)

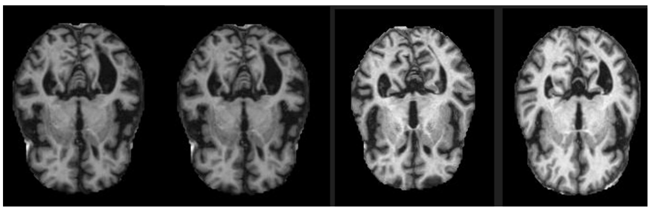
**Table (1) Alzheimers-dataset-4-class-of-images**

| Class Number | Class type | Total Images of Dataset | Training Images 70% | Validation Images 30% |
|---|---|---|---|---|
| Class 0 | Non-Demented | 7000 | 4900 | 2100 |
| Class 1 | Mild Demented | 7000 | 4900 | 2100 |
| Class 2 | Moderate Demented | 7000 | 4900 | 2100 |
| Class 3 | Very Mild Demented | 7000 | 4900 | 2100 |

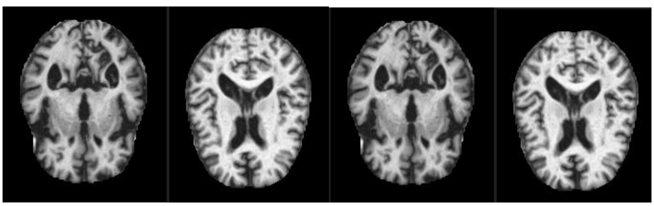
## 1- Standard Dataset

The data comprises MRI images from four classes in both training and testing sets: Mild Demented, Moderate Demented, Non Demented, and Very Mild Demented. The dataset aims to create a highly accurate model for predicting Alzheimer's stage, available at https://www.kaggle.com/datasets/tourist55/alzheimers-dataset-4-class-of-images. As shown in Figure (2).

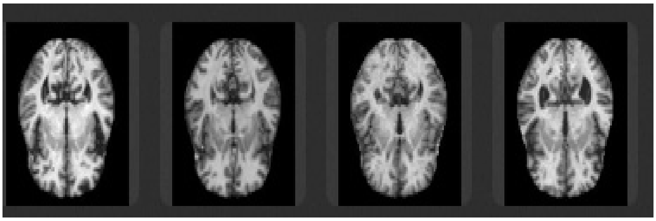
Mild Demented



Moderate Demented



VeryMild Demented



Non Demented

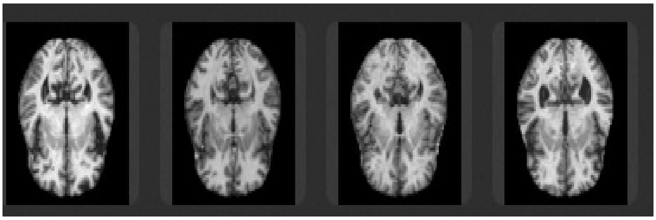


**Figure (2) Sample of MRIS Datasets of Demented Disease**

## .2 Data Augmentation

The augmented image data-store applies random transformations to images in the mini-batch of training data, without changing the actual number of images at each epoch. Random rotation, reflection, and translation are used.

## 3. Data Pre-processing

The images in the dataset need to be preprocessed before they can be used to train the network. This involves steps such as resizing the images, normalizing the pixel values, and removing noise.

**Resizing**: The images in the dataset need to be resized to a common size 28x28x1.

**Normalizing**: The pixel values in the images may need to be normalized. This means that the pixel values are all scaled to a range of 0 to 1.

**Removing noise**: The images in the dataset may contain noise, it will be removed using a Medem filter.

## 4.VGG16 CNN Model

The system uses a VGG-16 convolutional neural network with 41 layers, including 16 learnable layers, 13 convolution layers, and 3 fully connected layers. It applies sliding filters, performs threshold operations, down-samples, and multiplies input by weight matrix and bias vector.

1. Input Layer

   The image dimensions are 28 x 28 x 1, with three colour channels, and no data shuffle is needed for the Demented disease layer due to the train network's initial processing.

2. Convolutional Layer

   The feature map is created through dot product multiplication and weight slide mask, which is randomly generated and adjusted through BN, Pooling, and RleU Layers. As shown in Figure (3).

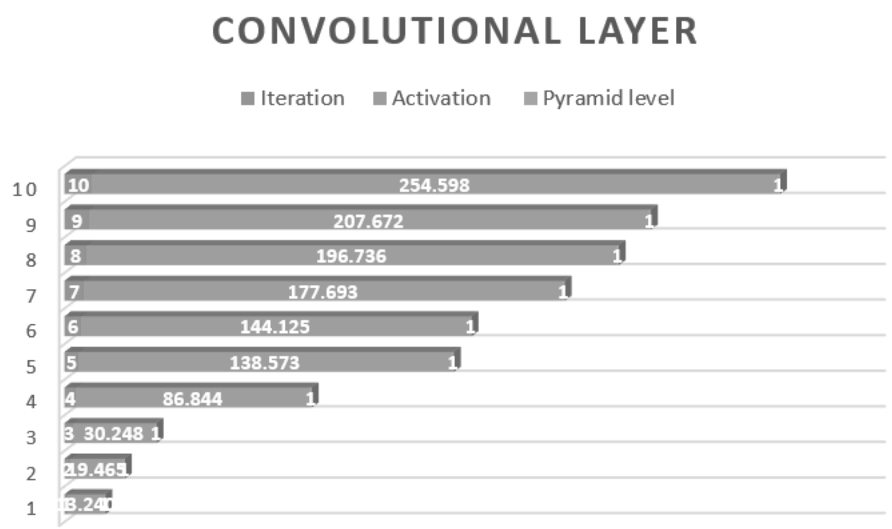



**Figure (3) Convolutional Layer**

## 3. Batch Normalization Layer (BN)

This layer reduces network initialization sensitivity by reducing channel numbers and normalizing activation before relocating input. It's used alongside convolutional and RleU layers.as shown in Figure (4).

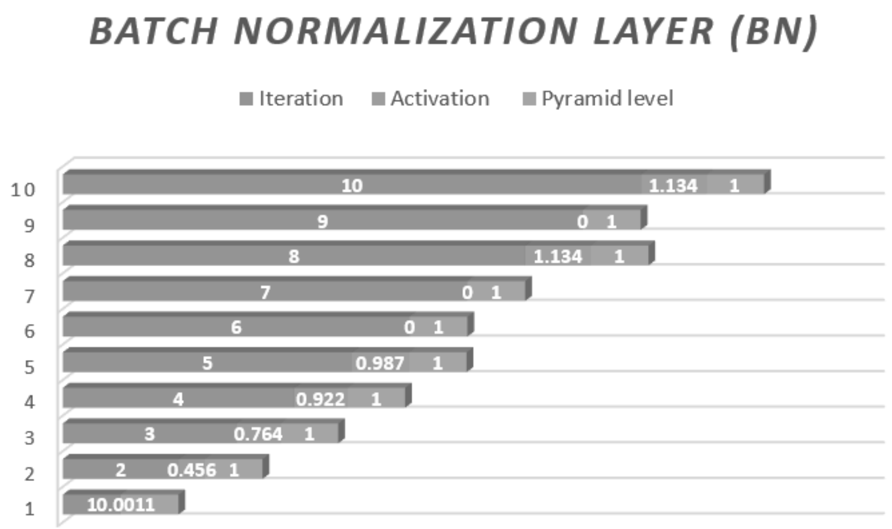



**Figure (4) Batch Normalization Layer.**

## 4. Max Pooling Layer

The layer removes unwanted features by applying a mask over the feature map, ensuring the largest value falls inside the mask at each stride. As shown in Figure (5).

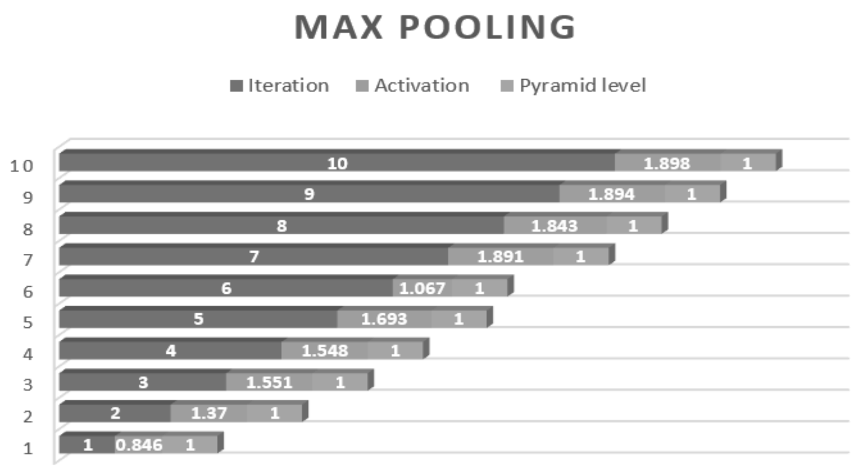



**Figure (5) Max Pooling Layer.**

## 5.RleU Layer

The layer removes extraneous elements from a feature map by overlaying a specified dimension mask, ensuring the largest value under the mask is the result.as shown in Figure (6).

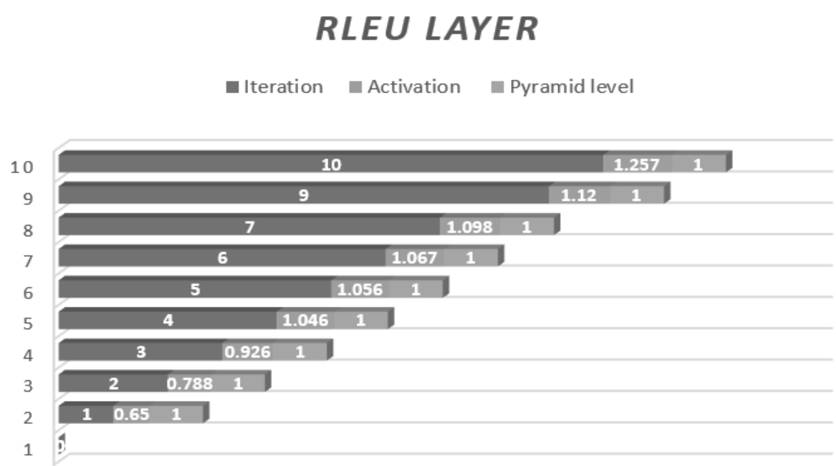



**Figure (6) RleU Layer**

## 6. Fully Connected Layer

A feature vector is a crucial input data from previous convolutional layers used in training for classification, allowing hidden layers to predict class likelihood. As shown in Figure (7).

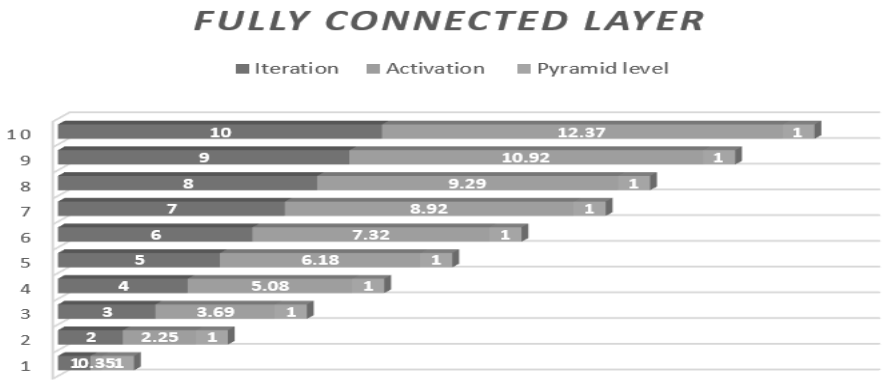



**Figure (7) FC Layer**

## 7. Softmax Layer

The Softmax layer assigns a probability value between 0 and 1, indicating a high likelihood for a candidate class while reducing the probability of other classes. As shown in Figure (8).

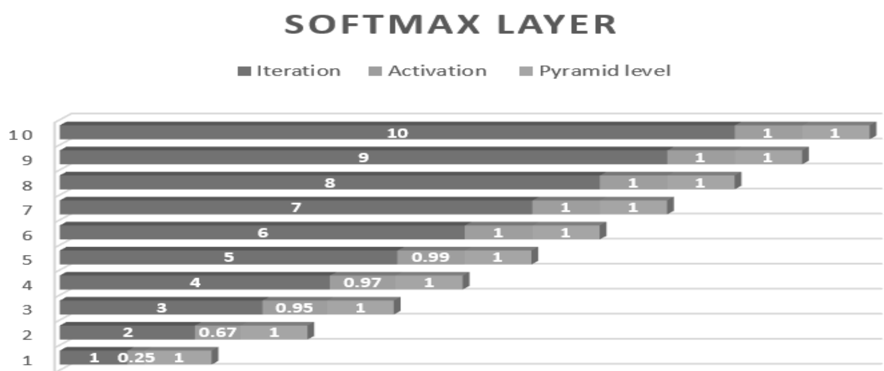



**Figure (8) Software Layer.**

### 8. Loss Function Layer

The loss function calculates the error of each trading epoch, crucial for weight update during backpropagation, illustrating the discrepancy between predicted output and real label.

## 5. Experimental Results

The MATLAB simulation on Alzheimer classifier demonstrates the effectiveness of CNN architecture for early detection of Alzheimer illnesses. The system can be trained and evaluated on a large dataset, achieving high accuracy in identifying the disease. This project explores deep learning's potential in biomedical applications, highlighting the importance of data pre-processing and feature extraction in developing effective Alzheimer classifying systems.

### 1. Evaluation Metrics

This section outlines the metrics used to evaluate the performance of a classification network, including accuracy, precision, recall, and F1-score. The parameters include True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). These metrics ensure the system accurately identifies diseases in images, ensuring accurate disease detection.

### A. Accuracy

This is the percentage of images that are correctly classified by the system. It is calculated as the number of correctly classified samples divided by the total number of samples. Accuracy is a common metric used to evaluate the performance of any classification network. To calculate accuracy, we can use the following formula:

$$Acc\% = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{7}$$

Accuracy is a useful metric for evaluating the overall performance of a classification system, but it can be misleading if the class distribution is imbalanced (e.g. if there are many more samples from one speaker than from another). In this case, it may be more useful to look at other metrics such as F1-score.

**B. Precision**

This is the percentage of images that are correctly classified by the system with respect to the total number of images detected as normal, which indicate the correct “positive” predictions. Precision is a metric used to evaluate the performance of any classification system. To calculate the precision, we can use the following formula:

$$Precision\% = \frac{TP}{TP+FP} \times 100 \tag{8}$$

Precision is a useful metric for evaluating the overall performance of our classification network, but also it can be misleading if the class distribution is imbalanced

**C. Recall**

This is the percentage of images that are correctly classified as normal with respect to the total number of images labelled as normal, which indicate the percentage of “positive” class correctly identified. Recall is a metric used to evaluate the performance of any classification system. To calculate recall, we can use the following formula:

$$Recall\% = \frac{TP}{TP+FN} \times 100 \quad (9)$$

Recall is a useful metric for evaluating the performance of a classification system.

## D. F1-score

F1 score is another metric that indicate the accuracy of a model, which combine the recall rate and the precision rate of this model. The accuracy metric can be reliable only if the classes are balanced, which means that each class has the same number of samples, as in our case here. Real datasets are often imbalanced which makes this metric necessary.

The precision and the recall rate made a trade-off, for us ideally, we need to increase both recall and precision to classify perfectly the images. F1-score is the rate responsible of combining these two metrics, so maximizing F1-score leads to maximize both recall and precision rate. To calculate F1-score we use the harmonic means of both mentioned metrics, and we can use the following formula:

$$F1 - score = \frac{2 \times Recall \times Precision}{Recall + Precision} \quad (10)$$

## 2. Evaluation Results

Use standard metrics to determine an item's performance value. The factors known as hyper-parameters have an impact on the network's architecture and training process. The learning rate affects how quickly network parameters may be modified. The learning process slows down because of the low rate of learning, but it finally converges. A faster pace of learning encourages learning even though it might not converge. Usually, it is suggested to take your time studying. The number of periods indicates how many times the entire training set is transmitted to the network during training. The accuracy of the micro-batch reported during training has a positive correlation with the accuracy of the micro-batch stated at the given iteration. Iteratively generated averages do not represent running averages. The method splits the entire data set into several small groups while using momentum training and random gradient descent (SGDM). For each small batch, network gradients are computed during iteration. Every imaginable little impulse that might be felt has a time component. Even if the error is estimated for each image in the training dataset, the model is not changed until all training images have been examined.

## A. Accuracy and Loss Metrics

Depending on the conditions at the time we train the model, the accuracy and loss in the validation data model may change. In general, accuracy should increase with age and loss should decrease. Validation loss keeps going down as validation accuracy starts to go up. Additionally, this is wonderful since it demonstrates how the model is evolving and performing as expected. Table (2) shows that 95.4% of Demented illnesses can be correctly identified.

**Table 2: Accuracy of Demented diseases**

| |
|---|
| Epoch 10 (final iteration of epoch) /10 (max of epoch)<br>8020/8400 [=] - 220s 11ms/step - loss: 0.0065 - accuracy: 0.954762% |

## B. Training Progress Plot

1. **Training and Validation Losses**: The subplot displays training and validation losses over epochs, aiming to minimize training and validation losses while avoiding overfitting, based on the error between predicted and actual classes.
2. **Training and Validation Accuracy**: The subplot displays training and validation accuracy over epochs, with a typically decreased learning rate to ensure a good solution convergence.

Figure (9) shows our proposed classification model is convergent, accurate, and decreasing in learning rate over epochs, indicating low training and validation losses.

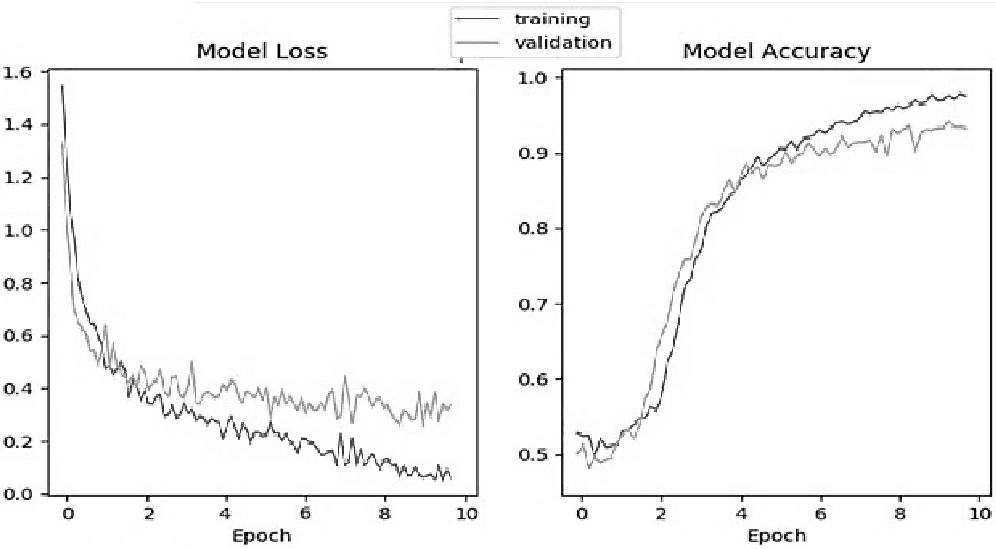



**Figure 9: Training Progress Plot**

Training Set

| TARGET / OUTPUT | Class0 | Class1 | Class2 | Class3 | SUM |
|---|---|---|---|---|---|
| Class0 | 2007<br>23.8929% | 66<br>0.7857% | 13<br>0.1548% | 18<br>0.2143% | 2104<br>95.3897%<br>4.6103% |
| Class1 | 51<br>0.6071% | 2004<br>23.8571% | 53<br>0.6310% | 033<br>0.3929% | 2141<br>93.6011%<br>6.3989% |
| Class2 | 24<br>0.2857% | 17<br>0.2024% | 2003<br>23.8452% | 43<br>0.5119% | 2087<br>95.9751%<br>4.0249% |
| Class3 | 18<br>0.2143% | 13<br>0.1548% | 31<br>0.3690% | 2006<br>23.8810% | 2068<br>97.0019%<br>2.9981% |
| SUM | 2100<br>95.5714%<br>4.4286% | 2100<br>95.4286%<br>4.5714% | 2100<br>95.3810%<br>4.6190% | 2100<br>95.5238%<br>4.4762% | 8020 / 8400<br>95.4762%<br>4.5238% |

**Figure 10: Confusion Matrix**

## C. Confusion Matrix

As mentioned in the Figure (10), the images are distributed equally between the four classes and these classes are numbered from class 0 to class 3. Python also can include some simulations to visualize the performance of our model. One simulation is a confusion matrix that shows the number of correctly and incorrectly classified disease. Figure (10) shows the result of our simulation applied to validation images of each class, this matrix can help to identify which class are most easily confused and can be used to improve the performance of the model.

## D. Other evaluation metrics

other evaluation metrics could be important to evaluate our classification model, here, we will compute them to demonstrate that are unnecessary when the dataset is class-balanced. In our case, as shown in the Figure (11) the F1-score is exactly matching the accuracy rate value which is normal for our balanced dataset.

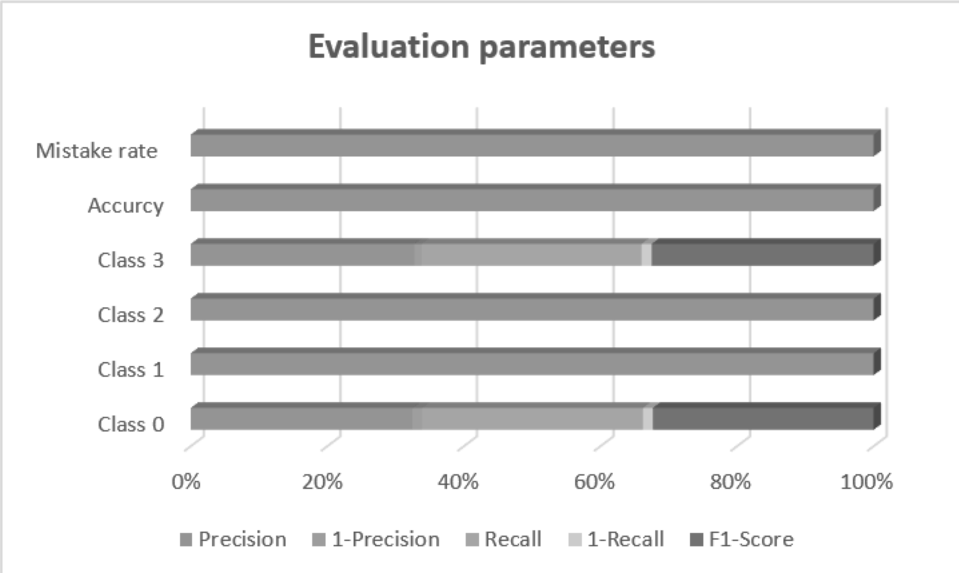



**Figure11. Evaluation Parameters**

## 3- Comparison with Related Work

In this paragraph, previous studies are compared with our work in terms of algorithms, data set, and accuracy ratio (Table 3).

**Table 3: Comparison with Related Work**

| Ref. | Method | Dataset | Accuracy |
|---|---|---|---|
| Ebell, M. H. *et al.*, | Decision trees, logistic regression, random forests, support vector machines | Open Access Series of Imaging Studies (OASIS) dataset | 88.88% |
| Karnik, S. *et al.*, | Sequential model, conv2D, maxPooling2D, dense layers | Kaggle dataset | 87.59% |
| Perluigi, M. *et al.*, | Support vector regression, tree regression, bagging-based ensemble regression, 3D convolutional neural network (CNN), and linear least square regression (LLSR) | 331 people's resting-state functional magnetic resonance imaging (rs-fMRI) scans | Mean balanced test accuracy: 85.27% |
| Our method | Using CNN and VGG16 | RMI alzahimer dataset | 95.4762% |

## 6- Conclusion

AI is being utilized more and more in image-based diagnostics, risk management, and illness detection. It still need a few technological and practical solutions to realize its full potential. We used CNN deep learning methods to construct a more accurate model, which has a little improvement in accuracy while addressing photo recognition challenges, considering the severity of the disease's spread in this study. It will, however, increase the difficulty of the model. Training will take longer, and there will be a higher chance of overfitting.

To simplify the model, more organizational elements need to be included. Here, we simply label the CNN as half if the patient has a mild nodule rather than mild, moderate, extremely mild, or non-in Demented in order to extract a feature from the CNN layer. There are other formulations and extraction techniques to research.

However, since it's possible that there might be noise during transmission, we reduce this uncertainty by overlooking the possibility that this data would be needed to pre-process the image. Images were improved using a number of methods before deep learning. Eight levels were chosen to achieve the best results when the image was once again fed into the system from the CNN layers to retrieve the attributes. After that, CNN levels were used to classify the data with high accuracy by category. The system has undergone 70% training and 30% testing, and the results show that it has a 95.4762% accuracy rate with little room for error and misclassification error is 0.0452%.

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