

## PAPER

# Neural Network-Based Support System to Improve Alzheimer's Detection Using Magnetic Resonance Imaging

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## ABSTRACT

Early and accurate detection of Alzheimer's is crucial for the quality of life of patients and families. Given the limitations of traditional methods, neural networks offer a promising alternative. This study implemented a neural network-based system to analyze brain magnetic resonance imaging (MRI) scans and detect Alzheimer's. Using the SCRUM methodology, data acquisition and preparation, network training, and system evaluation were managed. The Inception V3 model achieved 98% accuracy, outperforming other models. This efficacy suggests that convolutional neural networks can significantly improve early detection, reducing the time to diagnosis. The findings support the use of advanced artificial intelligence to improve clinical outcomes and enable more timely interventions in Alzheimer's patients.

## KEYWORDS

Alzheimer's, neural networks, magnetic resonance imaging (MRI), early detection, artificial neural network, diagnosis

## 1 INTRODUCTION

Alzheimer's disease (AD), a progressive neurodegenerative pathology, represents a growing challenge for global health systems due to its devastating impact on the quality of life of patients and their families. Early and accurate detection of this disease is crucial to implementing timely therapeutic interventions and improving clinical outcomes. However, traditional diagnostic methods have significant limitations in terms of sensitivity and specificity, underscoring the urgent need to explore innovative technologies to improve detection and diagnosis. In this context, artificial neural networks and advanced magnetic resonance imaging analysis emerge as promising tools to revolutionize the field of Alzheimer's diagnosis. This study aims to evaluate the efficacy of a neural network-based support system in detecting the disease by analyzing brain magnetic resonance imaging (MRI) imaging. The main objective is to determine whether the implementation of these artificial intelligence technologies can

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significantly reduce the time to diagnosis, which could have a transformative impact on the medical care and therapeutic management of patients. For this purpose, we reviewed studies covering various artificial intelligence and machine learning techniques applied to the diagnosis of AD, as well as [1] covering the use of artificial intelligence and deep learning for the diagnosis of Alzheimer's through magnetic resonance imaging. Despite limitations such as overfitting, the study highlights the application of convolutional neural networks (CNNs) and the VGG16 model, which showed an accuracy of 69% and validation of 47%, so, despite the fact that the models were not perfect, they provide a significant advance for the early detection of the disease. They also [2] investigate the use of machine learning techniques to identify Alzheimer's using magnetic resonance imaging, so they trained models of SVM, decision trees, and neural networks, finding that the neural network was the most effective with high accuracy; the study highlights the importance of selecting for relevant traits and the need to continuously improve these techniques for earlier and more accurate detection. In [3], the potential of convolutional neural networks for detecting AD using magnetic resonance imaging is explored. Models such as AlexNet and VGG16 were compared, finding that VGG16 had better performance in accuracy and validation. Although the results are promising, it is suggested to validate the models with global data to ensure their robustness. The study [4] proposes a model that combines discrete wavelet transform (DWT) and a CNN to classify brain MRI images. The process includes pre-processing with a median filter, feature extraction using 3-level Haar DWT, and classification with CNN. The method achieved 99% accuracy in identifying normal and abnormal brain images, outperforming other algorithms compared. Its practical application in medical diagnosis is suggested. Research [5] explores the use of deep learning to detect markers of cognitive decline early in 3D MRI images of the brain in order to diagnose Alzheimer's early. Existing and new models are compared, analyzing the performance of 2D and 3D convolutional networks. The DNI database is used. Preliminary results reveal challenges such as limited dataset size, class imbalance, and technical issues. Despite the limitations, the study highlights the importance of this approach for the early detection of neurodegenerative diseases. In [6], it explores the use of the Random Forest algorithm to classify patients into three categories: control, mild cognitive impairment (MCI), and AD. The approach is based on analyzing MRI of the brain to improve the early detection of Alzheimer's. The model achieves 70% accuracy in classification and an area under the ROC curve of 72% when differentiating between MCI and EA. It uses Euclidean distance characteristics and displacement vectors obtained by deformable registration with the CPD algorithm. Although there are limitations, the results are promising for identifying early stages of Alzheimer's. It is recommended that scaling normalization be adjusted in future studies to improve visualization of brain deformities. The study [7] focuses on early detection of Alzheimer's to facilitate timely treatment and minimize the impact on patients and families. The developed system uses the VGG16 algorithm, which consists of 16 layers, to analyze MRI images and has achieved an accuracy of more than 82% in identifying early signs of the disease. The article presents visual diagnoses that demonstrate the system's ability to classify patients into different stages of Alzheimer's. The need to validate results with medical specialists is highlighted, and improvements such as investment in more powerful hardware and the use of cloud solutions for future projects are suggested. Research [8] develops a convolutional neural network to classify MRI scans with intracranial lesions. The network, trained with a specific database, uses filtering and segmentation techniques to facilitate medical diagnosis. Network performance is validated with physical testing and adjustments, and an extensive database ensures accurate detection of injuries.

Therefore, the importance of continuing to refine these approaches and validate the models with diverse data to improve the robustness and effectiveness of detection

is highlighted. The study was conducted following an experimental approach, which included the acquisition of a public MRI dataset, meticulous preparation of the data, training of various neural network architectures, and a thorough evaluation of the system's performance.

## 2 METHODOLOGY

Experimental research will be conducted to evaluate the efficacy of a neural network-based support system for the detection of AD by analyzing brain magnetic resonance imaging. A public dataset and the SCRUM methodology will be used for project management. The main objective is to evaluate whether the implementation of artificial intelligence technologies can significantly reduce the time needed to make a diagnosis. The study will include data acquisition and preparation, neural network training, and evaluation of system performance.

### 2.1 Alzheimer's pathology

The author [9] states that Alzheimer's is the leading cause of dementia and one of the main reasons for morbidity and mortality in the elderly population. This disease is distinguished by a progressive and irreversible deterioration of cognitive functions, especially short-term memory, and is associated with the accumulation of  $\beta$ -amyloid and hyperphosphorylated tau in the brain.

### 2.2 Convolutional networks

For [10] [11] [12] [13], they are an advanced unsupervised learning technique widely used in image recognition. These networks have the ability to detect everything from edges and corners to more complex features in images, thanks to training with extensive datasets. They are very effective in the analysis of medical images, with promising applications in organ segmentation and in the identification and classification of different lesions. However, these types of networks require large amounts of labeled data for training and face difficulties such as the need for processing power and memory, as well as problems related to overfitting and under tuning (see Figure 1).

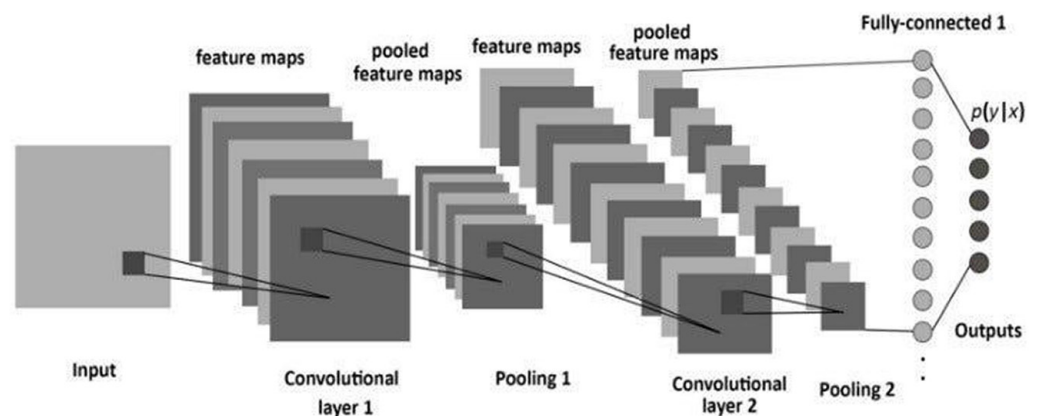


Fig. 1. Convolutional neural networks

## 2.3 Artificial intelligence

The author [14] mentions that it is inspired by the functioning of the human nervous system; it is composed of elementary units called neurons, organized in layers and connected by weighted links. Each neuron performs a weighted sum calculation of its inputs and employs a nonlinear firing function to generate an output signal. Based on the book [15], they have various applications such as image and character recognition, natural language processing, image compression, economic and financial forecasting, noise filtering, process control, and combinatorics troubleshooting.

## 2.4 Image processing

According to [16], the field of image processing encompasses various methods for analyzing and transforming digital images. These techniques are applied in different phases, from initial pre-processing to final analysis, including segmentation and object identification. Artificial neural networks play a crucial role in this field, particularly excelling in image segmentation and categorization. Its effectiveness is due to its ability to recognize complex patterns in visual information.

## 2.5 Image segmentation

According to [17], image segmentation involves dividing an image into significant regions or segments to facilitate detailed analysis and extraction of relevant information. This process allows different areas of interest within an image to be identified and isolated, thus improving the ability to make accurate interpretations and obtain useful data.

## 2.6 SCRUM

Is an agile methodology focused on the collaborative development of new product. Its main objective is to improve communication and integration between different areas. By adopting SCRUM, you are looking to optimize the work process, create effective products, and increase customer satisfaction. This methodology is based on three key pillars: transparency, inspection, and adaptation, which guarantee clarity in the work and regular evaluations and adjustments necessary to improve results [18]. The phases are illustrated in Figure 2.



Fig. 2. SCRUM methodology

## 2.7 Planning

Table 1 presents the compilation of system requirements, detailing both the type of system and the specific items to be implemented.

**Table 1.** Compilation of requirements

| Type of System | ID-RR | Item Statement  |
|----------------|-------|---|
| Web system     | RR01  | The system must allow users to upload MRI images in an accepted format. |

Table 2 presents user stories, which allow describing user needs and expectations in simple and understandable terms, facilitating communication between the development team and stakeholders.

**Table 2.** User history

| ID   | User Story                          | Description  |
|------|-------------------------------------|--|
| HU1  | Uploading MRI images                | Allows you to upload MRI images  |
| HU2  | Finding Processing Methods          | Allows you to search for and select MRI image processing methods.          |
| HU3  | Image Preprocessing                 | Applies selected methods to prepare images for analysis.                   |
| HU4  | Pattern Comparison                  | Looks for possible signs of Alzheimer's.                                   |
| HU5  | Neural Network Training             | It trains a convolutional neural network to improve Alzheimer's detection. |
| HU6  | Comparison with Alzheimer's insoles | Compare MRI images with templates of known Alzheimer's cases.              |
| HU7  | Neural Network Model Comparison     | Select the neural network model that best suits Alzheimer's detection.     |
| HU8  | Performance Optimization            | Improves the accuracy and efficiency of the Alzheimer's detection system.  |
| HU9  | Diagnosis of Alzheimer's            | Provides a clear diagnosis of Alzheimer's with a confidence level.         |
| HU10 | Visualizing Results                 | It displays MRI images, results, and diagnostics in a graphical interface. |

## 2.8 Data processing

In the dataset selection phase, a set of previously processed MRI images, specifically designed for the detection of Alzheimer's, will be selected and prepared. This step is critical to ensure that the data used in training and validating neural network models is of high quality and relevant.

The MRI images will be obtained from Kaggle, a platform recognized for its wide range of freely accessible datasets. The dataset includes 6400 images collected from various websites, hospitals, and public repositories. They are divided into two subsets: 5121 images will be used to train the models, while the rest will be used for validation. Table 3 shows the division between the training images.

**Table 3.** Number of images per category

| Category   | Description        | Number of Images |
|------------|--------------------|------------------|
| Category 1 | Mild Demented      | 896              |
| Category 2 | Moderate Demented  | 64               |
| Category 3 | Non-Demented       | 3200             |
| Category 4 | Very Mild Demented | 2240             |

These images are classified into four categories of Alzheimer's diagnosis: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. The images come from various sources, such as websites, hospitals, and public repositories.

The dataset consists of pre-processed MRI images, with a size of 128×128 pixels. They are all in JPG format, which makes them easy to handle and process. All available images will be used to ensure a large and representative sample covering all diagnostic categories. Some of them can be seen in Figure 3.

Because the images have already been pre-processed, no additional steps such as normalization or resizing will be required. This ensures that the images are consistent and ready for analysis. In addition, they all comply with current data protection regulations and will be used exclusively for research and model development purposes.

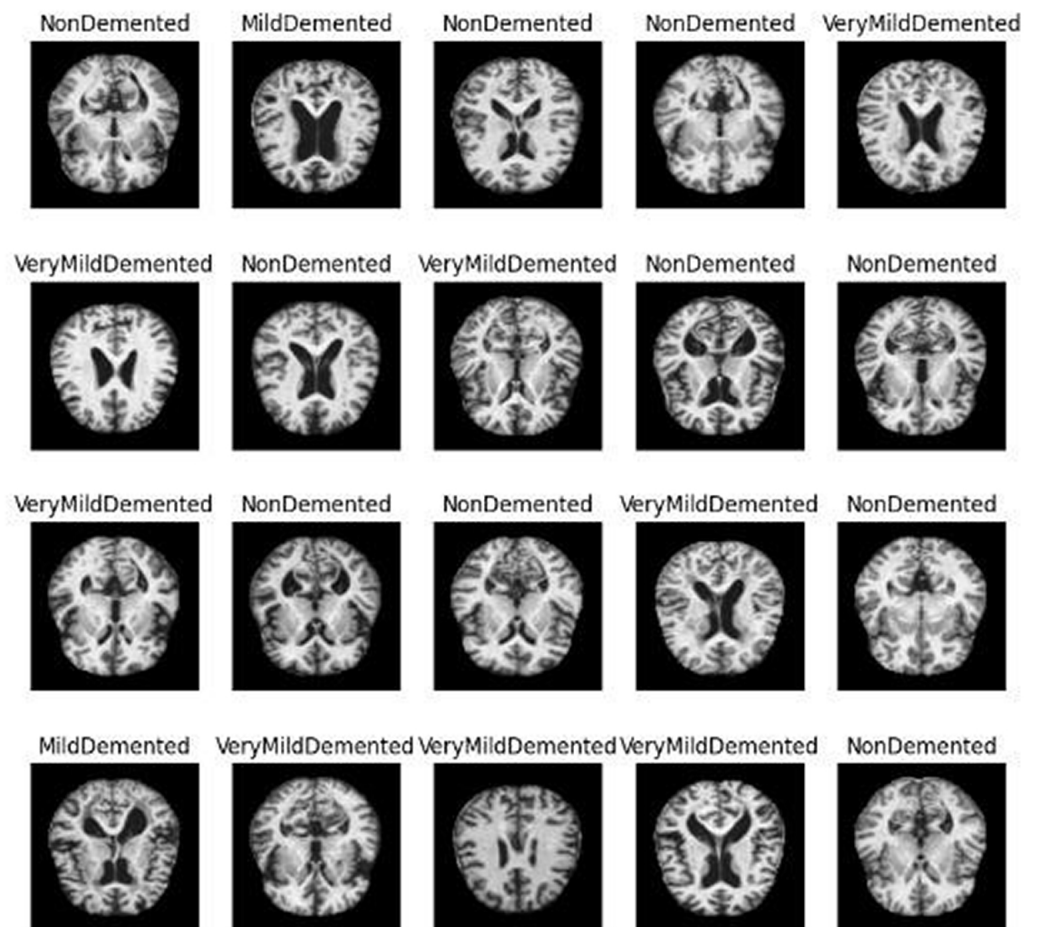


Fig. 3. Random MRI images with their respective label

## 2.9 Training and validation sets

The code in Figure 4 divides the data into three sets for training and evaluating a machine learning model: training, validation, and testing in two stages:

```

X_train, X_test1, y_train, y_test1 = train_test_split(train_data, train_labels, test_size=0.3, random_state=42, shuffle=True, stratify=train_labels)
X_val, X_test, y_val, y_test = train_test_split(X_test1, y_test1, test_size=0.5, random_state=42, shuffle=True, stratify=y_test1)
print('X_train shape is ', X_train.shape)
print('X_test shape is ', X_test.shape)
print('X_val shape is ', X_val.shape)
print('y_train shape is ', y_train.shape)
print('y_test shape is ', y_test.shape)
print('y_val shape is ', y_val.shape)

X_train shape is (8960, 176, 176, 3)
X_test shape is (1920, 176, 176, 3)
X_val shape is (1920, 176, 176, 3)
y_train shape is (8960, 4)
y_test shape is (1920, 4)
y_val shape is (1920, 4)

```

Fig. 4. Training and validation sets

First stage: The initial dataset is divided into training ( $X_{train}$ ,  $y_{train}$ ) and initial test ( $X_{test1}$ ,  $y_{test1}$ ). 30% of the original data is mapped to the initial test set. The division is done in a random and stratified manner, ensuring that the proportion of classes is the same in both sets.

Second stage: The initial test set ( $X_{test1}$ ,  $y_{test1}$ ) is subdivided into two parts: validation ( $X_{val}$ ,  $y_{val}$ ) and final test ( $X_{test}$ ,  $y_{test}$ ). The validation set corresponds to 50% of the initial test set, also with a random and stratified division to maintain the class ratio.

Finally, the code prints the dimensions of each set to verify the correct division of the data. The training set has 8960 images of 176×176 pixels, three channels (RGB), and four classes on the labels. Both the validation and test sets contain 1920 images with the same characteristics and four classes in the tags.

## 2.10 Model comparison

In the comparison of models carried out, different architectures for the detection of Alzheimer's were evaluated, as shown in Table 4. The following is a brief description of the models evaluated and their main characteristics:

**Self-organizing map (SOM) network:** Created by Teuvo Kohonen, it is a neural network technique that organizes and represents patterns in multidimensional data in a two-dimensional space. They group similar elements together, preserving their topological relationships, so that similar objects are closer together on the map, and different objects are farther away. SOMs are useful in fields such as architecture and urban planning to identify and analyze patterns, making it easier to understand the characteristics of the data. In addition, through a heuristic process, SOMs eliminate irrelevant variables and highlight significant relationships between the variables analyzed [19].

**Conventional neural network** are a type of neural network that is primarily used for processing data with a grid structure, such as images. A classic convolutional neural network uses convolutional layers to extract features from images, followed by clustering and full-connection layers for classification [20].

**ResNet-18:** ResNet models form a number of deep architectures that have shown strong performance in terms of convergence and accuracy. These networks use residual units, which integrate convolutional and clustering layers, and are available in several configurations that vary in number of layers: 18, 34, 50, 101, 152, and 1202. In particular, ResNet 18, which consists of five convolutional layers, an average clustering layer, and a fully connected layer, provides an effective balance between network depth and network performance [21].

**Inception V3:** Inception V3 is a deep convolutional neural network that is widely used in image classification. It was developed as an evolution of the initial GoogleNet module by Szegedy. This architecture features a variety of both symmetrical and

asymmetric blocks, each with multiple branches including convolutions, average clusters, maximum clusters, concatenations, dropout, and fully connected layers [21].

In the evaluation, the InceptionV3 model stood out with an accuracy of 98%, outperforming other models such as conventional CNN networks and ResNet-18. Therefore, InceptionV3 was chosen to continue the research due to its high performance in the task of diagnosing the disease.

**Table 4.** Comparison of models

| Models       | Precision | AUC  | Loss |
|--------------|-----------|------|------|
| SOM Network  | 78.5%     | –    | –    |
| CNN Networks | 63.07%    | 0.83 | 1.83 |
| Resnet-18    | 92.18%    | 0.99 | 0.21 |
| InceptionV3  | 98.64%    | 0.99 | 0.04 |

## 2.11 Inception V3 model performance

Inception V3 is a CNN architecture optimized for image classification and object recognition. Being based on CNN, Inception V3 takes advantage of convolutional layers to extract key features from images, being very efficient and accurate in computer vision tasks.

The performance of this model is evaluated by means of a classification report, as shown in Figure 5. This report presents key metrics that allow us to analyze the effectiveness of the model in classifying different categories related to the diagnosis of Alzheimer's. Metrics that stand out include precision, recall, F1-score, and the number of examples per class, each providing important insights into the model's behavior.

**Accuracy:** Measures the ratio of true positives to the total number of positive predictions. In this case, the model has very high accuracy in all classes, which means that the number of false positives is low.

**Recall:** Measures the ratio of true positives to the total true positives plus false negatives. Here too it is very high in all classes, indicating that the model correctly identifies most cases in each category.

**F1-Score:** It is the harmonic average between accuracy and recall, providing an overview of both metrics. All values are close to 0.99 or 1.00, suggesting that the model has excellent performance balanced between accuracy and sensitivity.

**Support:** The number of true examples that belong to each class. In this case, there are 480 examples for each class (in total, 1920 examples).

|                  | precision | recall | f1-score | support |
|------------------|-----------|--------|----------|---------|
| MildDemented     | 0.99      | 0.99   | 0.99     | 480     |
| ModerateDemented | 1.00      | 1.00   | 1.00     | 480     |
| NonDemented      | 0.97      | 0.99   | 0.98     | 480     |
| VeryMildDemented | 0.99      | 0.96   | 0.98     | 480     |
| micro avg        | 0.99      | 0.99   | 0.99     | 1920    |
| macro avg        | 0.99      | 0.99   | 0.99     | 1920    |
| weighted avg     | 0.99      | 0.99   | 0.99     | 1920    |
| samples avg      | 0.99      | 0.99   | 0.99     | 1920    |

**Fig. 5.** Classification report

This report reflects that the model performs excellently in all classes of Alzheimer’s diagnosis, with accuracy, recall, and f1-score values close to 1.00 in all categories. This suggests that the model correctly classifies both patients with different degrees of dementia and those who are not insane, with very few errors.

In addition to these metrics, it is important to analyze other variables that allow a broader view of the model’s performance, such as the overall accuracy (accuracy), the AUC curve (Area under the ROC curve), and the loss function during training and validation.

### 2.12 Support system design

In the design phase of the support system, a user interface was developed that will allow interaction with the Alzheimer’s detection system.

The app is an “Alzheimer’s MRI Classifier,” as shown in Figure 6 that has a title at the top indicating its purpose. Below the title are three interactive buttons: one to choose an image, another to classify it, and a third to reset the process. An MRI image is shown in the center along with text indicating the predicted class. In this case the class is “Moderate\_Demented,” which means that the image has been classified as corresponding to a patient with moderate dementia. The design is straightforward and makes it easy for the user to upload images and get results.

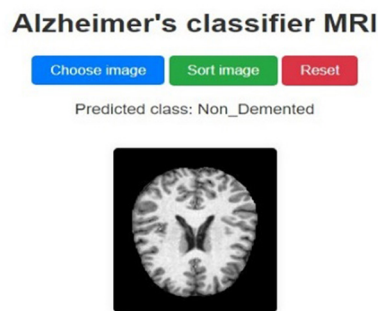


Fig. 6. Final user interface

A visual architecture was created as seen in Figure 7, showing how the MRI classifier works in the system.

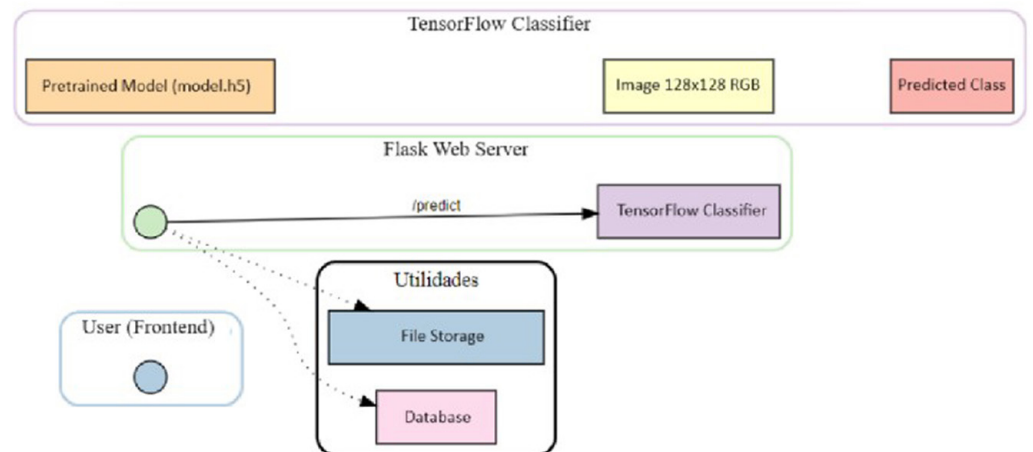


Fig. 7. MRI classifier architecture

The image shows the application architecture: below are the key components of the architecture:

- **Frontend:** This is the part of the application that the user interacts with directly. Here, the user can upload an MRI image from their device, triggering the flow to the backend for sorting.
- **Web Server (Flask):** It is built using Flask, a microframework in Python. It is responsible for receiving user requests, managing image processing, and returning results. The /predict path is where the frontend sends the image to be processed by the TensorFlow Flask model, passes the image to the classifier, and sends the prediction back to the frontend.
- **TensorFlow Classifier:** Here is the pre-trained model in .h5 format, which has been pre-trained to detect Alzheimer's using MRI imaging. The images sent must be 128×128 pixels in size in RGB format, as it is the format required by the model. The model returns a predicted class, which corresponds to one of the four levels of Alzheimer's diagnosis.
- **Utilities:** File Storage When the user uploads an image, it is temporarily stored before being processed by the classifier. Database: Here additional information could be saved, such as records of classified images or details of the model used.
- **Workflow:** The user loads an image from the Flask frontend, receives the image, and redirects it to the /predict path. The image is processed and passed to the TensorFlow model, which performs the classification. Flask receives the predicted class from the model and sends it back to the frontend to show it to the user.

This scheme combines Flask's handling of requests and storage with the power of a neural network model in TensorFlow.

### 2.13 Population and sample

The study population for the present research consists of all the magnetic resonance images obtained from the public source Kaggle, consisting of a total of 6400 images ( $P$  = all the magnetic resonance images of the dataset). From this population, a sample of 5121 images that will be part of the training set ( $M$  = Images that will be part of the training) was selected.

### 2.14 Tests

Figure 8 presents four tests carried out using the system. On the left are the actual classifications and next to them, the classifications generated by the system.



Fig. 8. (Continued)

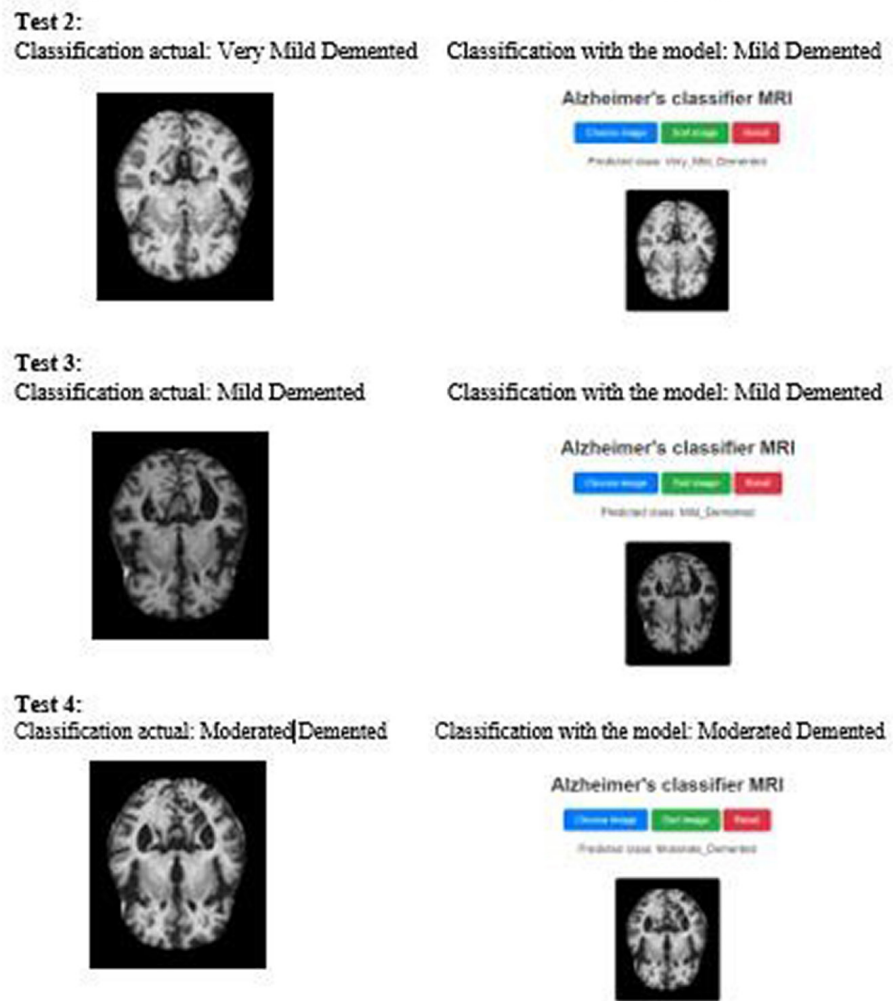


Fig. 8. Tests performed

Four cases are presented that cover different stages of the disease, from non-insane to moderate dementia. The model is correct in three of the four cases, correctly identifying the absence of dementia, one case of mild dementia, and another case of moderate dementia. However, it makes a mistake in classifying a case of very mild dementia as mild, suggesting some difficulty in distinguishing between very subtle early stages of the disease. Overall, the model demonstrates good accuracy, especially in detecting non-demented cases and identifying more advanced stages, although it presents a challenge in accurately differentiating between the earliest stages of dementia.

### 3 RESULTS

To evaluate the effectiveness of the support system, the time in seconds of diagnosis of Alzheimer's was measured with traditional methods, and after the implementation of the system. After analyzing the data, it was confirmed that they followed a normal distribution, so the Student t test was used to contrast hypotheses. The results of this test are detailed in Figure 9.

The alternate hypothesis ( $H_1$ ) is a statement that states that there is a significant effect or difference in the experiment or analysis being performed.

$H_1$ : The use of the support system improves the time to detect Alzheimer's (post-test) compared to the sample to which it was not applied (Pre-Test).

The null hypothesis ( $H_0$ ) is the opposite statement to the alternative hypothesis and states that there is no significant difference between the groups or conditions being compared. In this case, the null hypothesis would be:

$H_0$ : The use of the support system does not improve the time to detect Alzheimer's (Post-Test) compared to the sample to which the system was not applied (pre-test).

Solution:

Hypothesis statement:

$\mu_1$  = Mean time to detect Alzheimer's in the Pre-Test.  $\mu_2$  = Mean time to detect Alzheimer's in the Post-Test.

$H_0$ :  $\mu_1 = \mu_2$

$H_1$ :  $\mu_1 > \mu_2$

Calculation: 2-sample t-test

**Test:**

| Proof   |    |         |
|---|----|---------|
| Null hypothesis $H_0$ : $\mu_1 - \mu_2 = 0$         |    |         |
| Alternate hypothesis $H_1$ : $\mu_1 - \mu_2 \neq 0$ |    |         |
| T value   | GL | p value |
| 13.92   | 29 | 0.000   |

**Fig. 9.** Test report

Since the p-value = 0.000 is less than  $\alpha = 0.05$ , the results provide sufficient evidence to reject the null hypothesis ( $H_0$ ) and accept the alternative hypothesis ( $H_1$ ). The test turned out to be significant.

## 4 DISCUSSION

The results show a significant improvement in Alzheimer's detection times after implementing the proposed intervention. In the pre-test, detection times ranged from 900 to 3480 seconds, reflecting remarkable variability in participants' performance due to factors such as task familiarity, cognitive status, and differences in image interpretation.

After applying the intervention, detection times in the post-test were drastically reduced from an average of 2212 seconds to only 1.3392 seconds. This significant improvement was statistically confirmed by Student's t-test (p-value = 0.000, less than  $\alpha = 0.05$ ), which allows the null hypothesis to be rejected and the alternative hypothesis to be accepted.

This improvement can be attributed to increased familiarity with MRI and the use of advanced artificial intelligence and deep learning techniques, which have made it easier to quickly identify signs of Alzheimer's.

Reduced turnaround times can lead to faster diagnoses, which is crucial for initiating early treatments that slow disease progression and improve patients' quality of life. However, it is important to recognize that the study sample may not be representative of the general population and that individual factors may influence performance. These issues should be explored in future studies.

## 5 CONCLUSIONS

The MRI classification model has proven to be highly effective in the early detection of Alzheimer's, reducing the time to diagnosis by 99.94%. This technology, based on artificial intelligence and deep learning, offers a promising avenue for early identification of the disease, enabling more timely interventions and significantly improving clinical outcomes. The results of the comparison between pre- and post-intervention tests support the efficacy of the strategy used, confirming that it optimizes the detection of Alzheimer's. However, the limited size of the dataset and the imbalance of classes represent challenges that require attention. Despite these limitations, the results obtained underline the potential of advanced image processing and machine learning techniques in neuroscience. To improve the robustness and generalizability of the model, it is recommended to expand the dataset, address class imbalance, and explore the integration of additional biomedical data. It is also crucial to continue researching and optimizing these models, as well as to evaluate their long-term effects and their integration into health systems. Analysis of metrics such as AUC, accuracy, and loss indicates potential model overfitting. To mitigate this problem, it is suggested to review the quality and representativeness of the validation data, apply regularization techniques, and adjust the hyperparameters of the model.

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