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PAPER

Classification of Alzheimer's Disease Based on Deep Learning Using Medical Images

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ABSTRACT

Neurodegenerative disorders, notably Alzheimer's, pose an escalating global health challenge. Marked by the degeneration of brain neurons, these conditions lead to a gradual decline in nerve cells. Worldwide, over 55 million people grapple with dementia, with Alzheimer's prominently impacting the aging demographic. The primary hurdle to early Alzheimer's detection is the widespread lack of awareness. The main goal is to design and implement an artificial intelligence system using deep learning (DL) to detect Alzheimer's disease (AD) through medical images and classify them into various stages, such as non-demented, moderate dementia, mild dementia, and very mild dementia. The dataset contains 6400 magnetic resonance images in .jpg format, with standardized dimensions of 176 × 208 pixels. To demonstrate the advantages of data augmentation and transformation techniques, four scenarios were created: two without these techniques, utilizing the Adam and SGD optimizers, and two with these techniques, also employing the Adam and SGD optimizers, respectively. The main results revealed that scenarios utilizing these techniques exhibited more stable performance when validated with a new dataset. Scenario 3, using the Adam optimizer, achieved a weighted average accuracy of 91.83%, whereas scenario 4, employing the SGD optimizer, reached 87.58% accuracy. In contrast, scenarios 1 and 2, which omitted these techniques, obtained low accuracies below 55%. It is concluded that classifying AD with a DL model exceeding 90% accuracy is feasible. This is the importance of utilizing data augmentation and transformation techniques to improve generalizability to input image variations, which is a consistent factor in the healthcare sector.

KEYWORDS

deep learning (DL), convolutional neural network (CNN), classification model, Alzheimer's disease, diagnostic, medical images

1 INTRODUCTION

Neurodegenerative diseases are a significant health issue globally because of their increasing prevalence over time. Examples of these diseases are Alzheimer's,

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Parkinson's, and Huntington's, which are characterized by the death of neurons resulting from the gradual degradation of nerve cells. This highlights the severity of these conditions, which continue to increase on a global scale [1]. All of these factors lead to an increase in public health costs and a decline in the quality of life for patients affected by these diseases [2].

Neurodegenerative disorders lead to the deterioration of brain neurons, with Alzheimer's disease (AD) being one of the most common forms of degenerative conditions [3]. AD is characterized by the deterioration of behavioral and cognitive aspects. Due to its increasing prevalence, it poses an economic burden on public and private health centers [4]. The optimal organization of data is the most crucial factor for the success of an application [5–11].

Today, more than 55 million individuals worldwide suffer from dementia, and AD is one of the leading causes of dementia in the elderly population [12]. Likewise, it is determined by the atypical deposition of beta-amyloid (Aβ) and excessively phosphorylated tau, which results in the loss of neurons, cognitive and memory decline, and ultimately the onset of dementia [13].

Dementia manifests as a progressive deterioration of cognitive function, such as memory, attention, and language skills, along with various neuropsychiatric symptoms and related behavioral disorders, resulting in a decline in daily life and activities [14]. According to the Pan American Health Organization (PAHO) [15], AD, which accounts for 60–70% of dementia cases, is the most prevalent form. Contrary to a common misconception, it is not a typical aspect of aging and does not exclusively impact older individuals. Approximately 95% of Alzheimer's cases are reported in individuals aged 65 and above, with the likelihood of occurrence increasing with age. In the age group of 65–69, the incidence of Alzheimer's is 0.6%, while for those aged over 85, it increases to 8.4% [14]. Among the most expensive chronic illnesses, the current annual expenses for the treatment and care of Alzheimer's are estimated at 1 trillion dollars. Estimations suggest that the expenses will rise to 2 trillion dollars by 2030, highlighting the increasing pressure on global public health systems [16].

Initially presenting as mild cognitive impairment (MCI), AD progresses to Alzheimer's dementia. The severity, categorized as mild, moderate, or severe, is determined by the extent to which symptoms impede patients' daily activities as the condition progresses over time [17]. MCI is often considered the initial phase of Alzheimer's disease, characterized by symptoms that differ from typical aging but do not meet the criteria for a dementia diagnosis due to their less severe nature [18].

Mild cognitive impairment poses a risk to memory neurons, increasing the probability of progressing into dementia, especially in Alzheimer's disease.

Over a six-year period, statistical data indicates an 80% transition rate from MCI to AD [19]. This highlights the alarming progression patients may experience, progressing from mild cognitive decline to significant impairment, with the potential outcome of developing Alzheimer's disease.

Early detection of AD faces a significant hurdle: the imperative need for widespread awareness. Distinguishing cognitive decline and Alzheimer's-related behaviors from typical aging or other mental health symptoms is challenging. Challenges arise due to patients' remote locations, a lack of trained caregivers, limited access to advanced diagnostic tools, and a shortage of experts. Collectively, these obstacles hinder the timely diagnosis of AD [20].

In the diagnosis of diseases using advanced tools, our research emerges as a solution for early detection. It serves as an alert system for doctors to identify potential cases. Once diagnosed, treatment for the disease can promptly commence. In the early stages, this will translate into better quality of the patient's health, as it helps avoid mental deterioration in the advanced stages. It also leads to cost savings for the health system, as this disease requires lifelong medication and treatment.

2 RELATED WORK

In healthcare, deep neural networks demonstrate remarkable capabilities in facilitating efficient planning optimization and proficiently addressing a diverse spectrum of problem-solving scenarios [21–24].

Deep learning (DL) techniques have gained prominence, especially in developing accurate and comprehensive models. magnetic resonance imaging (MRI) is indispensable, providing crucial insights into brain elements such as white matter (WM), gray matter (GM), and metrics like cortical thickness and brain volumes [25], [26].

This information is essential for assessing the progression of degeneration in specific brain regions associated with AD [20]. The integration of DL methods and MRI data emerges as a crucial approach, enhancing our understanding and assessment of AD progression in the healthcare sector.

Over recent years, various brain imaging techniques, including MRI and parametric MRI such as T2-weighted structural MRI (sMRI), have been employed to detect AD. Advances in image processing algorithms and the adoption of artificial intelligence, particularly DL and machine learning, have significantly propelled researchers in the early identification of Alzheimer's disease.

In the research conducted by Yiğit and Işik [27], the primary focus centers on utilizing neuroimaging biomarkers, specifically structural brain MRIs, as a non-invasive method to diagnose AD and dementia. The process involves transforming volumetric T1-weighted images into a two-dimensional space through various preprocessing techniques. Convolutional neural network (CNN) models are utilized for both training and testing. The outcomes indicate that these CNN models exhibit an accuracy of approximately 0.8 in diagnosing both AD and mild cognitive impairment. Diagnosing individuals with mild cognitive impairment poses greater challenges than diagnosing those with AD. The study suggests that integrating magnetic resonance data with other clinical examinations using this DL-based approach could serve as an effective and practical diagnostic tool. This innovative approach holds promise for enhancing diagnostic accuracy in the field of neurodegenerative diseases.

In another related study [28], an effective method has been developed for the early diagnosis of healthy individuals (CN) before the onset of MCI. This innovative approach categorizes the stages of AD using machine learning and tensor-based morphometric image analysis. Constructed on the Xception architecture, the model achieves outstanding performance, surpassing CNN models with an impressive average accuracy of 95.81%. Furthermore, it outperforms alternative methods in estimating mild cognitive impairment, with an average AUC of 0.97.

In another investigation [29], a new approach was conducted based on the integration of image processing and artificial intelligence for the detection of diabetic retinopathy in fundus images. The approach proposed an image processing method in two phases: extraction and classification of the characteristics of diabetic retinopathy. Screening for diabetic retinopathy has been developed and implemented in several stages. The test results using an SVMGA model show that the sensitivity, specificity, and precision were 99.20%, 96.40%, and 98.80%, respectively. To ensure the accuracy of the results, the MATLAB simulation results were compared with those of the experts.

On the other hand, in the research by Gharaibeh et al. [30], a novel approach was proposed to classify AD into three classes: normal, AD, and mild cognitive defects. This classification was achieved by utilizing ADNI data from MRI. The process involved images. The preprocessing, noise removal using the Hybrid Kuan-Filter algorithm, and the enhanced frost filter (HKIF). Additionally, skull extraction was performed using the geodesic active contour (GAC) algorithm. Correction of the bias field is performed using the expectation maximization (EM) algorithm. After completing the preprocessing, the segmentation of gray matter, white matter, and cerebrospinal fluid from the brain images was carried out using the modified UNet algorithm and generative adversarial network (ST-MUNet). Performance is evaluated in terms of precision, specificity, sensitivity, and positive predictive value, obtaining 0.98, 0.93, 0.9, and 0.7, respectively.

Another important investigation was conducted by Mutaz et al. [31], who implemented an unsupervised machine learning model for diagnosing and analyzing DNA damage. They utilized unsupervised K-means clustering machine learning algorithms, enabling conclusions to be drawn from datasets solely based on input vectors. Without considering known or labeled results, five groups of DNA damage are created: A. No damage, B. Low, C. Medium, D. High, and E. Excessive levels of the p53 protein highlight the phenomenon of oscillation when there is excessive DNA damage. These results demonstrate that the K-means algorithm can be easily applied to many similar biological systems, aiding in a deeper understanding of the key dynamics of these systems.

In the research by Al-Hazaimeh et al. [32], a novel approach is proposed that utilizes a simple and robust geometric model to classify detected objects as either human or non-human in images. The objects detected under various conditions can be accurately classified (i.e., as human or non-human) by combining features extracted from the contour's top using the INRIA dataset. This is achieved through a software-based simulation using Matlab and comparing the results obtained with machine learning approaches such as artificial neural networks (ANN), support vector machines (SVM), and random forests (RF). Experimental results show that the proposed object classification approach is efficient and has achieved comparable accuracy to other state-of-the-art approaches.

3 PROPOSAL DESIGN

3.1 Conceptual model

The conceptual model presents a categorization system for Alzheimer's databases, aiming to facilitate early disease detection by utilizing pre-trained models in deep learning. These models will take magnetic resonance images of the brain (MRI scans) as input, and the images will undergo preprocessing to optimize the results. Subsequently, each algorithm will individually analyze the images, extracting specific features and performing the corresponding classification.

At the end of the process, a consolidation method will be applied to integrate all the results into a single outcome. This final result will be presented to the user in the form of a diagnosis indicating the stage or absence of AD. Additionally, brain images highlighting areas showing early signs of the disease will be displayed. This information will provide valuable insights to doctors and neurology specialists for decision-making regarding the diagnosis and treatment of patients. The conceptual model is shown in Figure 1.

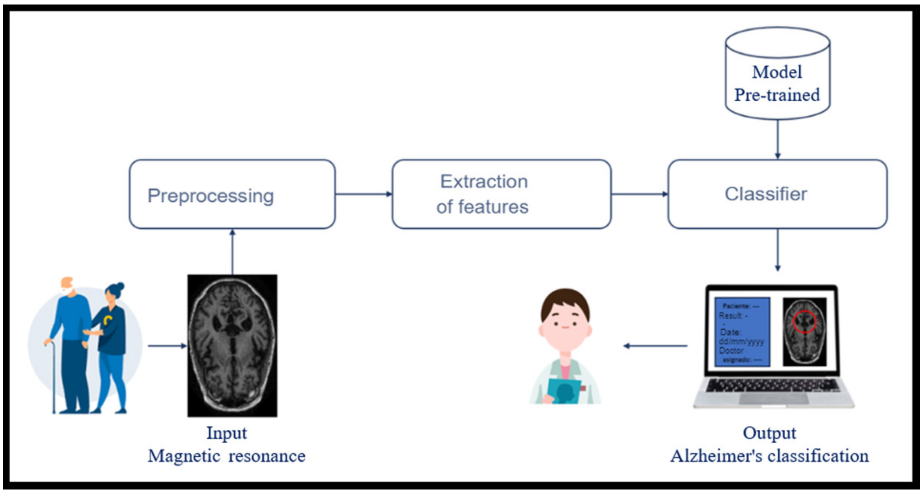

Fig. 1. Alzheimer detection method

3.2 Dataset

The data used in this article was selected from the Kaggle open-access platform, which is notable for its availability and diversity. The dataset, published in 2022, contains a compilation of 6400 magnetic resonance images, all in .jpg format and with standardized dimensions of 176 × 208 pixels.

The reasons for choosing this dataset include its significant size, its previous use in another scientific article as described in the related works, and its prominent popularity within the Kaggle community. In its description, this dataset has over 60,000 views and 8,000 downloads, establishing itself as a valuable resource in the field of research for Alzheimer's diagnosis.

It is important to mention that a crucial criterion in its selection was the quality of the sources included in this data set. One of the included sources is ADNI, which significantly enhances the reliability and relevance of the dataset. The ADNI resource ensures that the dataset adheres to rigorous standards in the data collection process, guaranteeing the validity and reliability of the images used in this research.

In order to distribute the dataset images, four folders were created based on the classification of AD, with each image placed in its corresponding folder. Table 1 illustrates the image count associated with each classification category, totaling 6400 images.

Table 1. Dataset distribution

Source	Dataset Name	Class	Image Type	Total Images
Kaggle	Not demented	1	JPG	3200
	Moderately demented	2	JPG	64
	Mildly demented	3	JPG	896
	Very mildly demented	4	JPG	2240

On the other hand, image preprocessing is applied to enhance the accuracy of the model and make it robust against changes that an image may undergo during efficiency tests. It is initially proposed to apply oversampling as a data balancing technique to address the significant difference in the number of samples across categories in the original dataset. In this sense, we increase the number of examples of the non-majority classes by generating synthetic instances, resulting in a new distribution of the number of images in each category, as shown in Table 2.

Table 2. Distribution of the balanced data set

Source	Dataset Name	Class	Image Type	Total Images
Kaggle and Data balancing	Not demented	1	JPG	3200
	Moderately demented	2	JPG	3200
	Mildly demented	3	JPG	3200
	Very mildly demented	4	JPG	3200

Subsequently, as seen in Figure 2, the images in the dataset undergo a data transformation that involves the following changes:

- **Rotation:** The image can be rotated up to ±10 degrees, which changes the orientation of the objects in the image.
- **Horizontal and vertical shift:** The image can be shifted horizontally and vertically up to 2% of its width and height, respectively, altering the position of objects in the image.
- **Zoom:** The image can be randomly zoomed up to 8%, which enlarges or reduces the image, changing the scale of the objects in the image.
- **Pixel Fill:** After applying the aforementioned transformations, empty pixels are filled by copying the value of the nearest pixel.

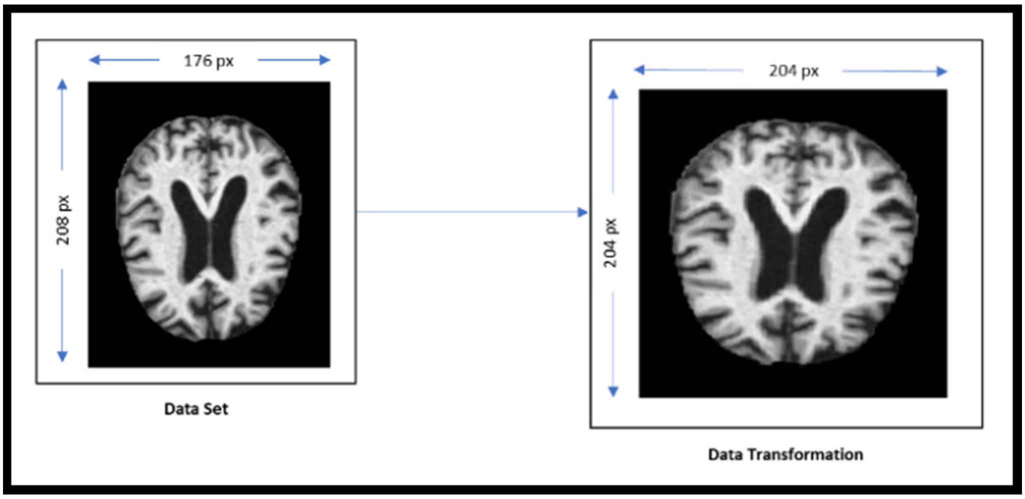

Fig. 2. Dataset transformation

3.3 Split of dataset

The proposed distribution of the dataset into a 70/30 split is detailed in Table 3. The 70/30 rule indicates that, in most cases, a minority (30%) is crucial, while the majority (70%) is less significant. On the other hand, 40 epochs were selected for the training strategy to ensure a reasonable training time.

Table 3. Number of images per training and evaluation process

Process	Number of Images
Training (70%)	8960
Testing (30%)	3840
Total (100%)	12800

4 CLASSIFICATION MODULE

In this section, we will explore the classification methods that have been previously analyzed and conduct a comparative analysis of their performances. This module, as its name suggests, focuses on the classification task, utilizing neural network algorithms to assign one of the four categories outlined in section 3.2 to the analyzed image. The design of the modules was based on the following conditions:

- The fundamental premise of the classification module is to provide a label that assigns a state to the patient, all based on the inputted and processed image. This capability becomes an essential component for informed clinical decision-making.
- The classification module operates exclusively with preprocessed images, which are presented in the form of a two-dimensional matrix as input. This approach is adopted to ensure consistency in the interpretation and application of neural network algorithms, thereby optimizing the accuracy and reliability of the classifications performed. This input requirement not only ensures uniformity in processing but also underscores the importance of the quality and prior preparation of data before the actual classification.

4.1 Technological architecture

A website will be developed using the MERN Stack framework, as illustrated in Figure 3. The presentation layer will be deployed on a Node.js server in combination with the React library. Python is used for building, training, and executing classifier models. It is worth noting that registered users have the ability to query the results obtained, as there is a connection to a MongoDB database to facilitate this activity.

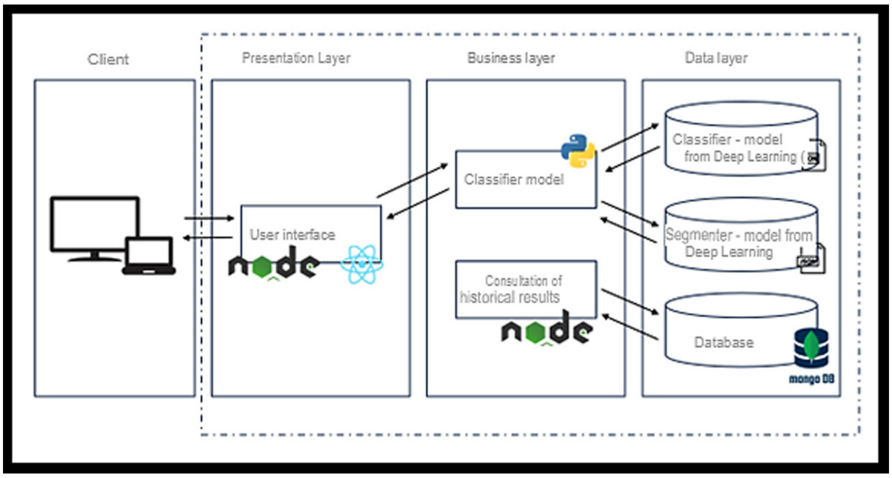

Fig. 3. Technological architecture diagram

4.2 CNN architecture

The CNN model has been developed with components including a three-dimensional input layer with a vector size of 224, 224, 1, three convolutional layers, three pooling layers, a flattened layer, two dense layers, and a dropout layer. The dense layers use the ReLU activation function, and the output layer uses the Softmax activation function. Table 4 displays the architecture of the model.

Table 4. Architecture of the CNN model

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 224, 224, 32)	896
max_pooling2d (MaxPooling2D)	(None, 112, 112, 32)	0
conv2d_1 (Conv2D)	(None, 112, 112, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 56, 56, 64)	0
conv2d_2 (Conv2D)	(None, 56, 56, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 28, 28, 128)	0
flatten (Flatten)	(None, 100352)	0
dense (Dense)	(None, 512)	51,380,736
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 4)	2,052

4.3 Scenarios for CNN model

Considering the preprocessing process and the parameters that will remain constant in all scenarios, six training scenarios are constructed:

- First: The model was compiled with the Adam optimizer, using a learning rate of 0.0005, and trained for 40 epochs.
- Second: The model was compiled with the Adam optimizer, using a learning rate of 0.001, and trained for 40 epochs.
- Third: The model was compiled with the Adam optimizer, using a learning rate of 0.002, and trained for 40 epochs.
- Fourth: The model was compiled with the SGD optimizer, using a learning rate of 0.0005, and trained for 40 epochs.
- Fifth: The model was compiled with the SGD optimizer, using a learning rate of 0.001, and trained for 40 epochs.
- Sixth: The model was compiled with the SGD optimizer, using a learning rate of 0.002, and trained for 40 epochs.

5 RESULTS

In this section, the results of each scenario will be evaluated, and the ideal scenario for the research objective will be selected. As explained in the data set and training strategy chapters, the model is evaluated using 30% of the total data.

In Table 5, various evaluation metrics of the models are displayed for each of the four scenarios. A comparison of results will be made between the optimizers, SGD and ADAM, to determine which one achieved better results. Subsequently, a comparison will be conducted on the learning rates to determine who performed better. Finally, a comparison will be made using the "accuracy" metric to determine which of the scenarios, on average, yielded better results in terms of model performance. The levels of AD are denoted by the following initials: ND for non-demented, MD for moderately demented, MdD for mildly demented, VMD: for very mildly demented, and AVG: weighted AVG.

Table 5. Comparison of metrics for proposed scenarios

Scene	Optimizer	Learning Rate	Level	Metrics			
				Accuracy	Precision	Recall	F1-Score
1	Adam	0.0005	ND	100.00%	99.90%	100.00%	99.95%
			MD	100.00%	100.00%	100.00%	100.00%
			MdD	99.79%	97.56%	99.79%	98.66%
			VMD	97.40%	99.79%	97.40%	98.58%
			AVG	99.30%	99.31%	99.30%	99.30%
2	Adam	0.001	ND	99.90%	99.79%	99.90%	99.84%
			MD	100.00%	100.00%	100.00%	100.00%
			MdD	99.17%	94.54%	99.17%	96.80%
			VMD	94.17%	99.12%	94.17%	96.58%
			AVG	98.31%	98.36%	98.31%	98.31%
3	Adam	0.002	ND	99.27%	99.58%	99.27%	99.43%
			MD	100.00%	100.00%	100.00%	100.00%
			MdD	96.67%	93.65%	96.67%	95.14%
			VMD	93.65%	96.46%	93.65%	95.03%
			AVG	97.40%	97.42%	97.40%	97.40%
4	SGD	0.0005	ND	41.98%	67.85%	41.98%	51.87%
			MD	100.00%	97.76%	100.00%	98.87%
			MdD	74.51%	49.62%	74.51%	59.57%
			VMD	34.17%	39.90%	34.17%	36.81%
			AVG	62.67%	63.78%	62.67%	61.78%
5	SGD	0.001	ND	82.81%	70.29%	82.81%	76.04%
			MD	100.00%	99.79%	100.00%	99.90%
			MdD	68.68%	65.22%	68.68%	66.90%
			VMD	45.94%	59.92%	45.94%	52.00%
			AVG	74.36%	73.80%	74.36%	73.71%
6	SGD	0.002	ND	91.15%	90.11%	91.15%	90.63%
			MD	100.00%	99.90%	100.00%	99.95%
			MdD	83.87%	72.55%	83.87%	77.80%
			VMD	64.69%	77.82%	64.69%	70.65%
			AVG	84.93%	85.09%	84.93%	84.75%

When comparing scenario 1 (ADAM optimizer) and scenario 6 (SGD optimizer), superior results are observed for scenario 1 in all evaluation metrics, specifically on the weighted average.

Regarding the learning rate, lower learning rates with the Adam optimizer yield better results in terms of precision (precision of 0.0005 > 0.001 > 0.002), unlike the results obtained with the SGD optimizer, where higher learning rates lead to better results(precision of 0.0005 < 0.001 < 0.002).

Therefore, it can be concluded that the choice of optimizer influences the application of the learning rate, making it advantageous to use the ADAM optimizer with the lowest learning rate.

When comparing the "level" corresponding to the diagnostic label of AD, the label "Very Slightly Demented" obtained the lowest precision, recall, and F1-score in all scenarios. This indicates that it was the category where the model made the most errors in the diagnosis.

The analysis of the proposed scenarios reveals that the accuracy exceeds 95% with the ADAM optimizer, efficiently reaching the established objective with good accuracy. It can be observed that scenario 1 achieved the highest weighted average accuracy metric of 99.30%, closely followed by scenario 2, which achieved an accuracy of 98.31%.

6 CONCLUSIONS

In conclusion, we assert the feasibility of classifying AD with an accuracy exceeding the 98% threshold using magnetic resonance images and classification models based on deep learning. This was achieved in scenario 1 with an accuracy of 98.31%, followed by scenario 2 with an accuracy of 97.40% in the weighted average.

Our research is important because it demonstrates that setting an optimizer and a correct learning rate directly impacts accuracy improvement. For instance, the ADAM optimizer achieves better accuracy with a smaller learning rate, whereas the SGD optimizer achieves better accuracy with a higher learning rate. The importance of implementing data balancing techniques should also be highlighted when there is a significant difference in sample size among categories.

One of the limitations of the study was the absence of a dataset compiled from the specific locality where the research was conducted; instead, public datasets were utilized.

We encourage future researchers to develop their own datasets for analyzing scenarios with varying parameters as well as utilizing data augmentation and transformation techniques. These efforts will facilitate advancements in the comprehension and implementation of these techniques in diagnosing neurodegenerative diseases, representing a significant milestone in the intersection of technology and medicine.

7 DECLARATION OF CONFLICTING INTERESTS

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8 CONTRIBUTION

Hugo Vega-Huerta conducted the conceptualization and formal analysis of the research. Kevin Pantoja-Pimentel created two CNN models (software) and trained them with the dataset in six scenarios. He also wrote the original draft. Sebastian Quintanilla-Jaimes conducted the dataset selection and data curation, applying data augmentation and data transformation to the images. He also wrote the original draft. Gisella Luisa Elena Maquen-Niño carried out and compared the evaluations of the models in each scenario and drafted the results. Percy De-La-Cruz-VdV implemented the methodology. Luis Guerra-Grados supervised compliance with the methodology and edited the final draft. All authors conducted the review of observations and approved the final draft.

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