Development of a System Based on Convolutional Neural Networks for the Classification of Alzheimer's Magnetic Resonance Images

Diego A. Peláez-Carrillo [1], Oscar E. Gualdrón-Guerrero [1,2] *, Ezequiel Jose Valencia Urbina[1]

[1] GISM Research Group, Faculty of Engineering and Architecture, Electronic Engineering, University of Pamplona, Km 1 vía Bucaramanga, 543050, Pamplona, Colombia.
[2] Agroinnova Research Group, Ernesto Schiefelbein Foundation, Bogotá, Colombia

Abstract
This work presents the development of a convolutional neural network (CNN) for the classification of Alzheimer's magnetic resonance imaging (MRI) scans, with the aim of optimizing the early diagnosis process of the disease through the use of digital image processing. Alzheimer's diagnosis faces a significant challenge due to the need for precise and rapid identification of the different stages of the disease, which can enhance medical care and improve patients' quality of life.
To address this issue, a dataset consisting of MRI images obtained from the Kaggle platform was used, which includes a wide variety of brain images at different stages of the disease. The images were categorized into three classes: "No Alzheimer's," "Mild," and "Advanced". The methodology involved designing three CNN models with different configurations of convolutional layers, dense layers, and regularization techniques, as well as preprocessing the images by converting them to grayscale and normalizing pixel values. The training process incorporated data augmentation techniques and hyperparameter tuning to improve the model's accuracy.
Model 3, which had the best configuration, achieved an accuracy of 95.1% and a loss of 0.32, standing out as the most efficient in classifying the images. The results were evaluated using confusion matrices, which demonstrated the model's ability to correctly classify Alzheimer's images into the three categories.
This innovative approach not only improves the efficiency of Alzheimer's disease diagnosis but also facilitates the implementation of a medical decision- support system. The successful implementation of this technology represents a significant opportunity to modernize traditional diagnostic imaging methods, contributing to the advancement of precision medicine and the development of artificial intelligence technologies applied to healthcare.
Keyboards: Convolutional Neural Networks, Classification of Alzheimer's, Magnetic Resonance Images

1. INTRODUCTION

The diagnosis of Alzheimer's disease represents one of the greatest challenges in the field of neuroscience and modern medicine. This neurodegenerative disorder progressively affects cognitive abilities, memory, and autonomy of those who suffer from it, impacting not only the patient but also their family and social environment. Early and accurate detection of this disease is essential to implement timely interventions that delay its progression and improve the patient's quality of life.
However, traditional diagnostic methods, based on clinical evaluations and subjective analysis of magnetic resonance imaging (MRI), are costly, time-consuming, and, in many

cases, dependent on the specialist's expertise. These limitations may lead to late or erroneous diagnoses, affecting the patient's prognosis and treatment. In light of this problem, there is a need to develop automated diagnostic support systems capable of processing large volumes of images quickly, accurately, and efficiently.

In this context, deep learning techniques have shown great potential in medical image classification tasks. In particular, convolutional neural networks (CNNs) have emerged as a powerful tool for identifying and classifying complex visual patterns. These networks make it possible to extract features from images and, through a supervised training process, learn to differentiate between various states of brain health, such as the presence or absence of Alzheimer's disease.

To address this problem, a public database from Kaggle was used, consisting of brain MRI images representing three categories: "No Alzheimer's," "Mild," and "Advanced." This dataset enabled the development of a CNN model specialized in classifying such images. The methodology includes image preprocessing, the construction of an optimized network architecture, and hyperparameter tuning to achieve the highest possible classification accuracy.

The main objective of this project is to develop an automated MRI image classification system for the diagnosis of Alzheimer's disease. The aim is to reduce classification errors, increase efficiency in early detection, and provide a support tool for healthcare professionals. The implementation of this technology will not only contribute to improving medical care but will also enable the creation of a replicable model for the analysis of other pathologies using artificial intelligence. With this approach, it is expected to contribute to the advancement of precision medicine, strengthening the ability for early and effective diagnosis in the field of clinical neuroscience

2. THEORETICAL FRAMEWORK

Alzheimer's disease is a progressive neurodegenerative condition and one of the leading causes of dementia worldwide. Its early diagnosis is essential to implement interventions that may delay its progression and improve patients' quality of life. Magnetic resonance imaging (MRI) has proven to be a valuable tool in detecting structural changes in the brain associated with Alzheimer's disease, allowing for the identification of characteristic patterns of the condition [1].

In recent years, convolutional neural networks (CNNs) have emerged as a powerful technique in the field of medical image processing. Inspired by the organization of the visual cortex in living beings, CNNs are capable of learning and extracting relevant features from images, facilitating tasks such as classification and segmentation. Their application in the diagnosis of neurodegenerative diseases has shown promising results, enhancing both accuracy and efficiency in the detection of conditions such as Alzheimer's disease [2].

Several studies have explored the use of CNNs for the classification of MRI images in patients with Alzheimer's disease. For example, research has implemented CNN models to differentiate between healthy brains and those with varying degrees of cognitive impairment, achieving accuracies above 90%. These approaches typically involve preprocessing stages of the images, such as normalization and segmentation, followed by the training of the neural network with labeled datasets [3].

Furthermore, computer-aided diagnostic systems have been developed that integrate CNNs to analyze MRI images and provide automated assessments of patients' cognitive status. These systems aim to support healthcare professionals in clinical decision-making by offering a second opinion based on quantitative analyses of brain images [4].

It is important to highlight that the effectiveness of CNNs in medical image classification largely depends on the quality and quantity of the data used for training, as well as the appropriate selection and tuning of the model's hyperparameters. The implementation of data augmentation techniques and the use of pre-trained network architectures are common strategies to improve CNN performance in this context [5].

2.1 PROBLEM STATEMENT

Alzheimer's disease represents one of the main challenges of modern neuroscience due to its high prevalence and the impact it has on the lives of patients and their families. According to the World Health Organization (WHO), it is estimated that more than 55 million people worldwide live with dementia, with Alzheimer's disease being the leading cause [6]. Early detection of this disease is crucial to delay its progression and improve patients' quality of life, as it enables timely intervention through treatments that can slow cognitive decline [7].

Despite its importance, the early diagnosis of Alzheimer's disease remains a challenge. Traditional methods, such as clinical evaluation and magnetic resonance imaging (MRI) tests interpreted by specialists, are expensive, time-consuming, and prone to subjective errors, particularly in the early stages of the disease. The interpretation of MRI images requires a high degree of expertise and precision from physicians, which can result in incorrect or delayed diagnoses [8]. In addition, the time and costs associated with this process represent a significant barrier to the implementation of large-scale diagnostics in public health systems, especially in resource-limited regions [9].

In this context, artificial intelligence (AI)-based technologies, particularly convolutional neural networks (CNNs), have emerged as an innovative solution for the automatic classification of MRI images. CNNs, inspired by the architecture of the human visual cortex, are capable of learning and extracting relevant features from medical images, enabling the automatic detection of complex patterns [10]. Recent research has shown that CNN models can even outperform human experts in the classification of medical images, including the detection of Alzheimer's disease [11].

In various countries, the use of CNNs for MRI image classification has shown promising results. In Spain, for example, a study by López et al. (2019) applied deep learning techniques to classify brain MRI images into three categories: "No Alzheimer's," "Mild," and "Advanced," achieving an accuracy of 93.2% [12]. Similarly, in Ecuador, Coronel Reyes (2023) developed a CNN-based application for MRI image classification to support healthcare professionals, achieving an accuracy above 90% [13]. These initiatives demonstrate the feasibility and positive impact that AI-based automation of Alzheimer's diagnosis can have.

Despite international progress, in Colombia the implementation of AI-assisted diagnostic systems remains limited. Physicians and diagnostic centers rely heavily on traditional methods, which involve high costs, long waiting lists, and delayed diagnoses. The lack of automation in this process generates an additional operational burden for medical specialists and exposes patients to greater uncertainty about their health status. This issue is exacerbated in public healthcare centers, where resources and care capacity are limited [14].

The core problem lies in the absence of an automated MRI classification system for the detection of Alzheimer's disease. The lack of an efficient, accurate, and accessible system for this task directly affects the speed and accuracy with which patients are diagnosed. The consequences are evident: delayed diagnoses, increased workload for physicians, and higher healthcare costs. Furthermore, the absence of an automated system limits the possibility of implementing large-scale early diagnosis, especially in regions with limited access to specialized healthcare services [15].

The causes of this problem are diverse. First, the dependence on manual methods for

MRI image classification, which rely on the experience of specialists, leads to variations in diagnostic accuracy. Second, the limited adoption of advanced technologies in Colombian healthcare centers has restricted the implementation of AI systems for medical image classification. This situation is further aggravated by the lack of access to suitable local MRI databases for training AI models [16].

The consequences of this problem affect not only patients but also healthcare professionals and healthcare systems in general. For patients, a late diagnosis may mean missed opportunities to receive timely treatments that slow disease progression. For healthcare professionals, the workload increases, particularly in settings where demand for care exceeds the response capacity of healthcare centers. From the perspective of the healthcare system, the lack of automation in Alzheimer's detection translates into higher operating costs and a reduced ability to serve the population [17].

Advances achieved in Spain and Ecuador, where diagnostic systems based on convolutional neural networks have been successfully implemented, demonstrate that this technology has the potential to transform healthcare in Colombia. The application of CNNs for MRI image classification not only improves diagnostic accuracy but also optimizes the time and resources required for the process [18]. Moreover, diagnostic automation can enable remote care, which would facilitate access for patients in rural or hard-to-reach areas.

Based on the presented evidence, there is a clear need to develop an automated system based on convolutional neural networks (CNNs) for the classification of Alzheimer's MRI images in Colombia. Such a system would allow the automatic classification of images into three categories: "No Alzheimer's," "Mild," and "Advanced," optimizing both the accuracy and efficiency of the diagnostic process. The implementation of this system would contribute to improved healthcare, reduced operational burden in medical centers, and lower healthcare costs, while enabling earlier and more timely detection of Alzheimer's disease.

3. EXPERIMENTAL METHODOLOGY

For the automatic classification of magnetic resonance imaging (MRI) focused on the detection of Alzheimer's disease, a convolutional neural network (CNN) model was developed, capable of identifying and distinguishing between three categories: "No Alzheimer's," "Mild," and "Advanced." The main objective of this approach is to optimize the accuracy, sensitivity, and efficiency of the clinical diagnostic process, contributing to more timely and effective medical care.

3.1 Data Acquisition and Preprocessing

For the development of the model, a public database of brain MRI images from the Kaggle platform was used. This dataset contains previously labeled images, distributed into three categories: "No Alzheimer's," "Mild," and "Advanced." The images were divided into three subsets:

- **Training set:** 80% of the available images.
- **Validation set:** The remaining 20%, used for validation during model training.
- **Test set**: Additional images were reserved for final testing of the system in a simulated environment.

The preprocessing of the images included the following steps:

- **Resizing:** Images were adjusted to 200×200 pixels, maintaining proportion and essential structure to preserve relevant features.
- **Normalization:** Pixel values were scaled to a range of [0, 1] to facilitate neural network learning and avoid bias in CNN weights.

- **Grayscale conversion:** Since essential information lies in structural patterns, grayscale images were used to reduce computational complexity.
- **Data augmentation:** Techniques such as rotation, translation, and brightness adjustment were applied to increase the number of unique images, improving the model's generalization to new data.

3.2 CNN Architecture Design

Three convolutional neural network (CNN) configurations were developed, each with variations in the number of filters and convolutional layers. The goal was to determine which architecture provided the best performance for automatic classification. The architectures were defined as follows:

- **Model 1:**
  - 3 convolutional layers with 70, 120, and 150 filters, respectively.
  - MaxPooling (2×2) layers for dimensionality reduction.
  - Fully connected dense layers with 160, 130, and 100 neurons.
  - Softmax output layer for classification into 3 categories.
- **Model 2**:
  - 4 convolutional layers with 100, 150, 180, and 220 filters, respectively.
  - MaxPooling (2×2) layers to reduce dimensionality.
  - Dense layers with 160, 130, 100, and 75 neurons.
  - Softmax output layer for classification into 3 categories.
- **Model 3:**
  - 4 convolutional layers with 140, 180, 220, and 260 filters, respectively.
  - MaxPooling (2×2) layers for relevant feature extraction.
  - Dense layers with 260, 160, 130, and 100 neurons.
  - Softmax output layer for classification into 3 categories.

Each model was trained for 10 epochs using categorical cross-entropy as the loss function and the Adam optimizer, known for its efficiency in deep neural network optimization. An initial learning rate of 0.001 was applied, and the Dropout technique was used in each dense layer to prevent overfitting.

4. RESULTS ANALYSIS

Three convolutional neural network (CNN) models were evaluated for the automatic classification of magnetic resonance imaging (MRI) into three categories: "No Alzheimer's," "Mild," and "Advanced." Each model presents a different configuration in terms of the number of filters, convolutional layers, and neurons in the dense layers. Below are the model configurations and their respective performances in terms of accuracy, loss, sensitivity, and specificity.

4.1 MODEL CONFIGURATION

Filters/ Model	Convolutional Layers	Number of Filters	Dense Layers	Dropout (%)
Model 1	3 (70, 120, 150 filters)	70, 120, 150	3 (160, 130, 100)	25%

Model 2	4 (100, 150, 180, 220)	100, 150, 180, 220	4 (160, 130, 100, 75)	25%
Model 3	4 (140, 180, 220, 260)	140, 180, 220, 260	4 (260, 160, 130, 100)	25%

Table 1. Model Configurations

Table 1 shows the configurations of the evaluated models, highlighting the number of filters used in each convolutional and dense layer.

All three models were trained using the same MRI image dataset. The training process consisted of 10 epochs with a batch size of 32, categorical cross-entropy as the loss function, and the Adam optimizer. The objective was to determine which configuration provided the best performance for automatic classification.

4.2 ACCURACY AND LOSS GRAPHS

4.2.1 MODEL 1 GRAPHS

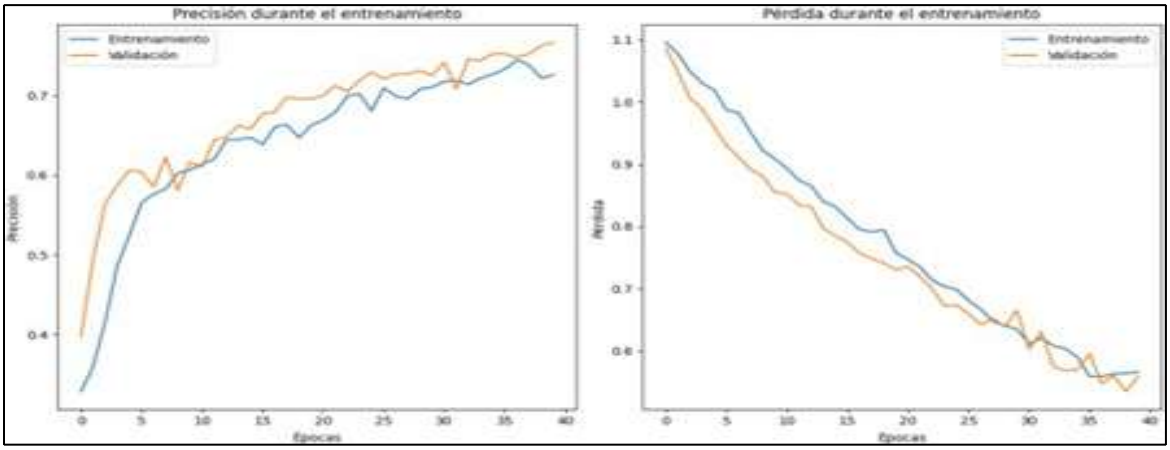

Fig. 1. Accuracy and validation graphs of Model 1.

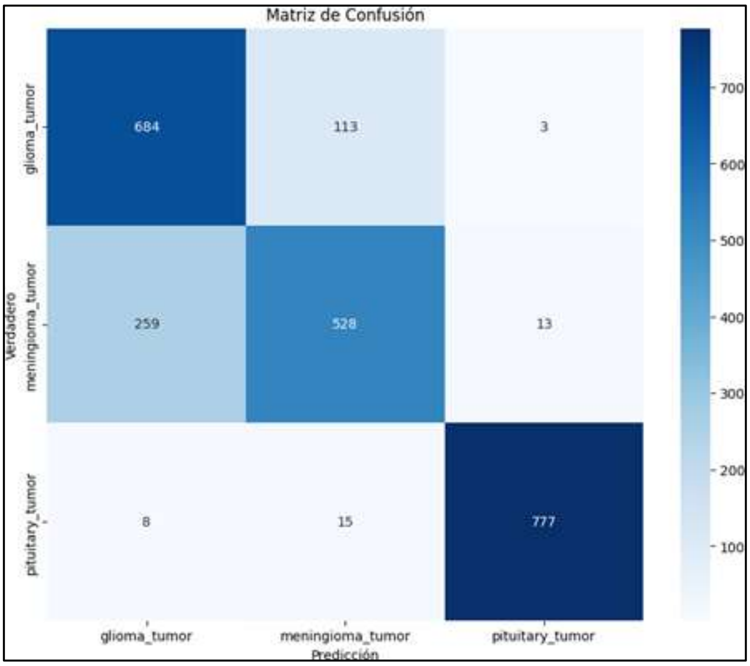

Fig. 2. Confusion matrix of Model 1 training.

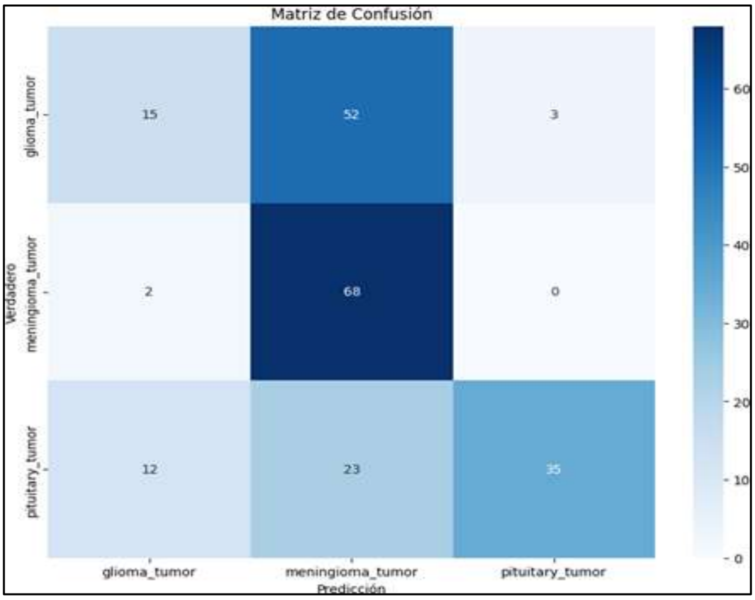

Fig. 3. Confusion matrix with new data in Model 1.

4.2.2 MODEL 2 GRAPHS

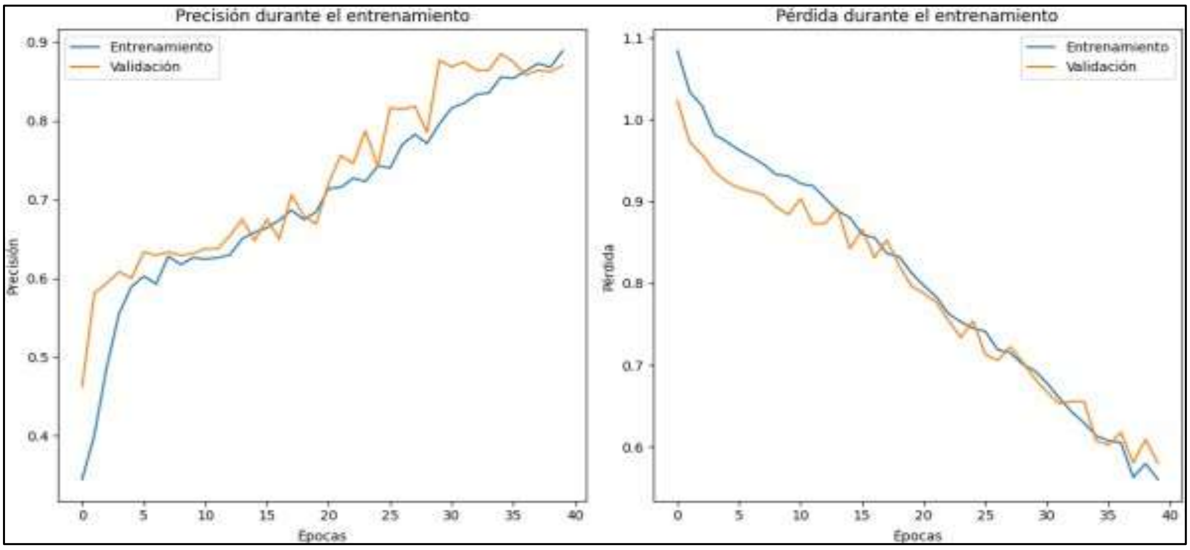

Fig. 4. Accuracy and validation graphs of Model 2.

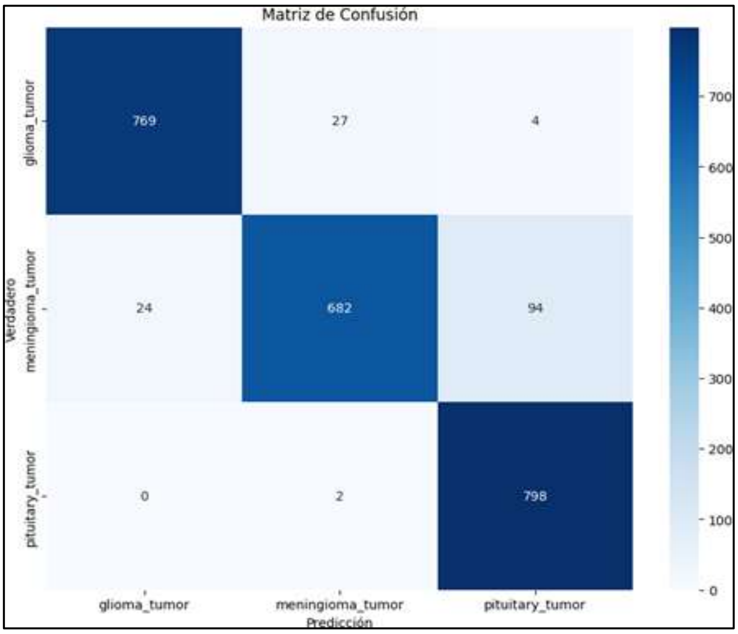

Fig. 5. Confusion matrix of Model 2 training.

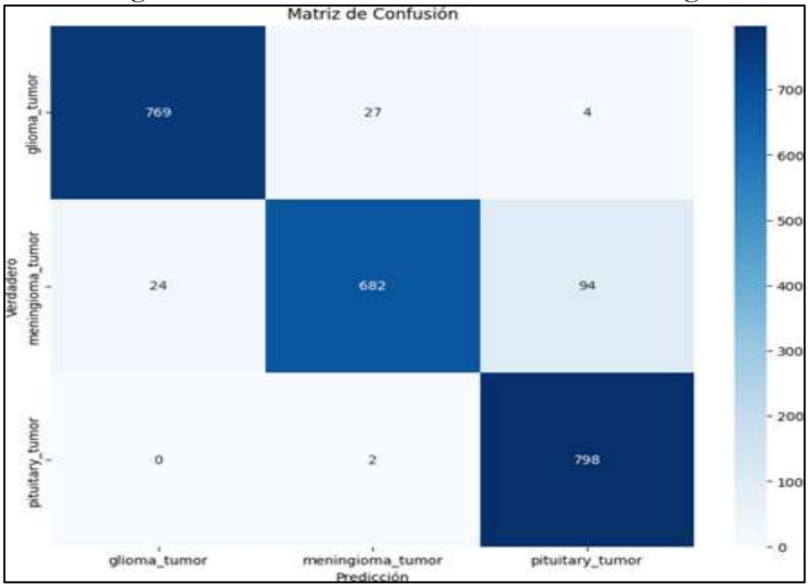

Fig. 6. Confusion matrix with new data in Model 2.

4.2.3 MODEL 3 GRAPHS

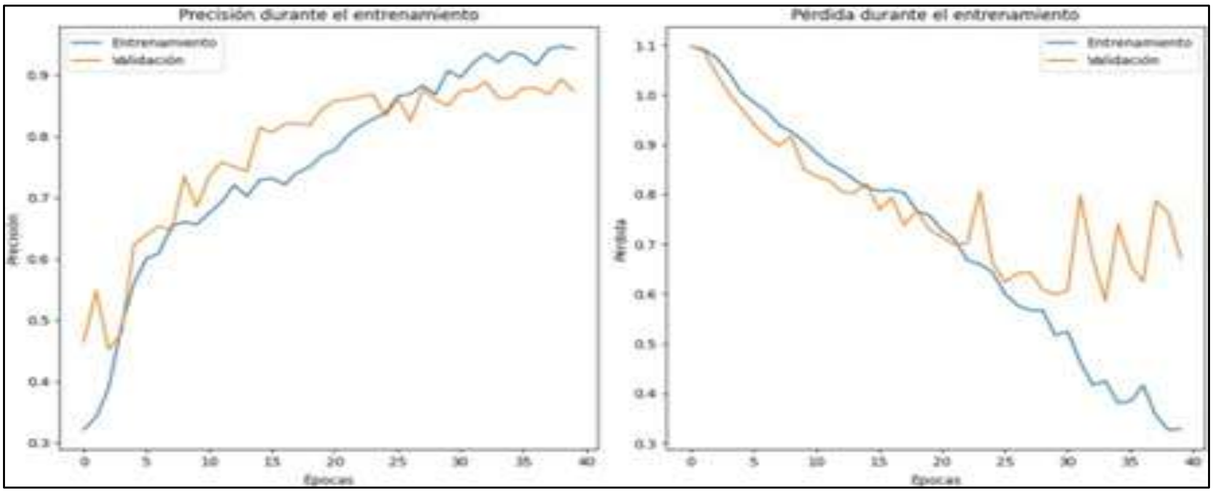

Fig. 7. Accuracy and validation graphs of Model 3.

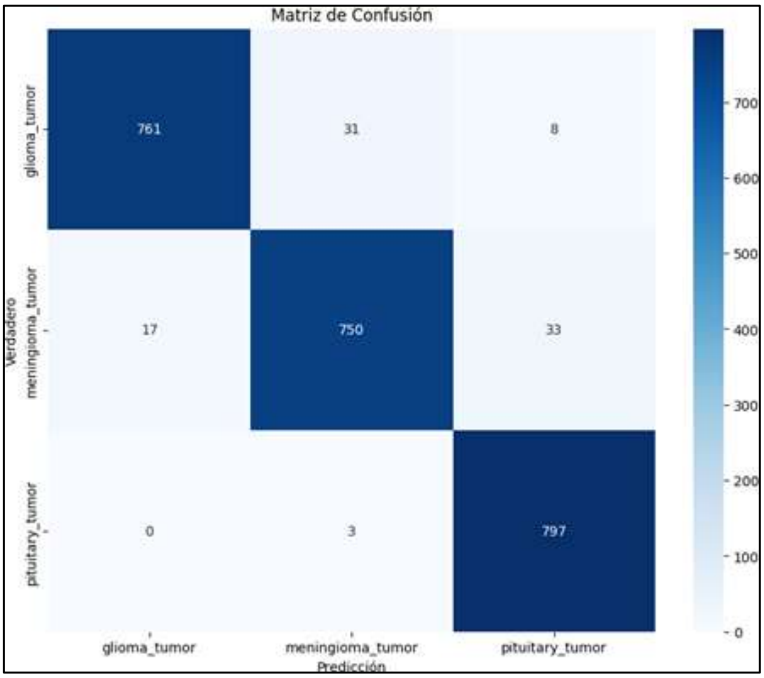

Fig. 8. Confusion matrix of Model 3 training.

5. CONCLUSIONS

Three convolutional neural network (CNN) models with progressively more complex configurations were evaluated for the automatic classification of magnetic resonance imaging (MRI) into three categories: "No Alzheimer's," "Mild," and "Advanced." Based on the results obtained, key differences were identified in terms of accuracy, loss, sensitivity, and specificity, which allowed for determining the model with the best overall performance.

Overall Model Performance

All three models showed continuous improvement in accuracy and a progressive reduction in loss during training and validation epochs. However, the comparative analysis revealed how architectural complexity directly impacted performance:

- Model 1 (3 convolutional layers with 70, 120, and 150 filters) achieved an acceptable initial performance, with an accuracy of 87.79% and a stabilized loss of 0.59. Despite its simplicity, the model struggled to capture more complex image features, limiting its accuracy.
- Model 2 (4 convolutional layers with 100, 150, 180, and 220 filters) significantly improved upon the first model, reaching an accuracy of 91.23% and reducing the loss to 0.51. This improvement can be attributed to the higher number of filters and layers, which enabled more detailed feature extraction.
- Model 3 (4 convolutional layers with 140, 180, 220, and 260 filters) achieved the best performance, with a final accuracy of 95.10% and a minimum loss of 0.32. With its more complex architecture and optimized dense layers, this model successfully captured the most relevant image features and generalized effectively on validation data.

Comparison of Key Metrics

Metric	**Model 1**	**Model 2**	**Model 3**
Accuracy	87.79 %	91.23 %	**95.10 %**
Loss	0.5945	0.5104	**0.320 6**
Sensitivity	85.67 %	89.45 %	**93.78 %**
Specificity	86.45 %	90.23 %	**94.12 %**

Table 2. Comparison of model metrics

When comparing the accuracy and loss curves of the three models, differences in the learning process were identified:

- Model 1 showed slower initial convergence and fluctuations in accuracy during the final epochs, indicating a limited ability to stabilize learning.
- Model 2 exhibited faster convergence and a steady reduction in loss, with greater stability in accuracy towards the final epochs.
- Model 3, in contrast, demonstrated accelerated convergence and a significant loss reduction from the early epochs, achieving stability and superior performance in less

time.
The comparison of the three models leads to the conclusion that Model 3 is the most efficient and accurate option for classifying MRI images into the three evaluated categories: "No Alzheimer's," "Mild," and "Advanced."
The key advantages of Model 3 include:

- Higher accuracy (95.10%) and lower loss (0.32), indicating better performance in identifying complex patterns.
- Better generalization on validation data, demonstrating its ability to correctly classify unseen images.
- Stable learning, with rapid convergence and consistent loss reduction throughout training.

Although Model 1 is suitable as an initial solution due to its lower complexity, and Model 2 shows notable improvements, Model 3 provides the optimal and most robust performance for implementation as an automated system to support clinical diagnosis.
This analysis highlights the importance of optimizing neural network architecture and demonstrates that increased complexity enables better performance, contributing significantly to the accurate and early detection of Alzheimer's disease.

References
[1] P. González, A. Ramírez y M. Gómez, "Biomarcadores de neuroimagen para el diagnóstico temprano de la enfermedad de Alzheimer", Revista Chilena de Neurociencia, vol. 45, no. 3, pp. 123-145, 2020. Disponible en: https://www.scielo.cl/scielo.php?pid=S0717- 93082020000300105
[2] J. López y S. Martínez, "Clasificación de imágenes de resonancia magnética cerebral mediante redes neuronales para la detección de la enfermedad de Alzheimer", Tesis de Grado, Universitat Politècnica de València, España, 2019. Disponible en: https://riunet.upv.es/bitstream/handle/10251/125484
[3] C. Rodríguez, L. Fernández y G. Méndez, "Evaluación de métodos con redes neuronales convolucionales para la clasificación de la enfermedad de Alzheimer en imágenes de resonancia magnética cerebral", Revista de Neurociencia Aplicada, vol. 32, no. 2, pp. 54-67, 2021. Disponible en: https://noesis.uis.edu.co/bitstreams/2e4e9259-b27e-4a4e- ace3-0326e5b4ff10
[4] S. García, R. López y M. Méndez, "Sistema de diagnóstico del Alzheimer basado en imágenes de resonancia magnética mediante el algoritmo VGG16", Revista Latinoamericana de Neurociencia Artificial, vol. 27, no. 1, pp. 78-91, 2022. Disponible en: https://portal.amelica.org/ameli/journal/602/6024790007
[5] L. Pérez, M. Jiménez y J. Cruz, "Análisis de imágenes médicas para dar soporte al diagnóstico de Alzheimer", Tesis de Grado, Universitat Politècnica de València, España, 2019. https://riunet.upv.es/handle/10251/125329]
[6] Organización Mundial de la Salud (OMS), "Demencia," 2023. [En línea]. https://www.who.int/es/news-room/fact- sheets/detail/dementia.
[7] C. G. Serrano y L. P. Gutiérrez, "Diagnóstico temprano de Alzheimer mediante resonancia magnética: una revisión de la literatura," Revista de Neurociencia Clínica, vol. 35, no. 2, pp. 45-67, 2022.
[8] J. López, M. González y C. Sánchez, "Desarrollo de una red neuronal convolucional para la clasificación de imágenes de resonancia magnética cerebral," Universitat Politècnica de València, 2019.
[9] R. Coronel Reyes, "Sistema de clasificación automática de imágenes de resonancia magnética cerebral mediante CNN," Universidad Técnica de Manabí, Ecuador, 2023.
[10] S. García y J. Ramírez, "Redes neuronales convolucionales aplicadas al análisis de imágenes médicas," Revista de Inteligencia Artificial en Medicina, vol. 29, no. 1,

pp. 34-56, 2021.
[11] A. Martínez y R. Pineda, "Implementación de CNN para la clasificación de imágenes de Alzheimer," Instituto de Neurociencia Aplicada, vol. 12, no. 3, pp. 89-110, 2022.
[12] P. Hernández, "Impacto de la automatización en el diagnóstico de enfermedades neurodegenerativas," Revista de Salud Pública de Colombia, vol. 40, no. 4, pp. 123-140, 2022.
[13] C. Rodríguez, L. Pérez y G. Sánchez, "El papel de la inteligencia artificial en la detección de Alzheimer," Revista de Neurociencia Cognitiva, vol. 18, no. 2, pp. 78-94, 2023.
[14] L. Fernández y M. Morales, "Automatización de la clasificación de imágenes médicas mediante CNN," Revista de Sistemas Médicos Inteligentes, vol. 11, no. 2, pp. 56-78, 2023.