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Revolutionizing Brain MRI Analysis: Advanced Deep Learning Techniques for Cutting-Edge Classification

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Abstract
Using advanced classification techniques in MRI imaging significantly enhances the accuracy of brain tumor diagnoses. Prior research predominantly concentrated on differentiating between normal (non-tumor) and abnormal (tumor) brain MRIs through machine learning or artificial intelligence approaches. This article, however, advances the field by employing deep learning architectures to categorize brain MRI images into four distinct classes: healthy, meningioma, pituitary, and glioma. To achieve a more precise and meaningful classification, the study incorporates gender and age as critical features. A method based on convolutional neural network (CNN) is proposed for this effective classification. To compare their effectiveness, the study meticulously implements and analyses various designed architectures of deep learning networks, including LeNet, AlexNet, ResNet, and an innovative CNN-DNN network. A notable finding of this research is the impressive accuracy rate of 98.70% for the test data in this 4-class classification, which is a remarkable achievement. This high level of accuracy underscores the efficacy of the proposed method. Furthermore, the results compellingly demonstrate that the inclusion of age and gender information significantly enhances the classification process, playing a crucial role in the accuracy of the diagnoses. In summary, this study presents a highly accurate deep learning-based approach for classifying brain MRI images and highlights the importance of incorporating demographic features like age and gender in medical image analysis.

Keywords: Deep, Convolutional Networks, MRI Images, Brain Tumor.

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1. INTRODUCTION

The brain, the most intricate organ in the human body, orchestrates various functions and governs the activities of other body systems [1]. Comprising complex structures like the cerebrum, cerebellum, and brainstem, it forms the central nervous system. This organ is pivotal in processing, integrating, and coordinating sensory information and in making decisions by sending instructions to different body parts. Encased within the skull for protection, the brain's largest part, the cerebrum, is divided into two hemispheres. Each hemisphere's inner core is white matter, while the outer surface consists of grey matter [1].

A brain tumor represents an abnormal mass within the brain, which can be benign or malignant based on the nature of its cells. These tumors may originate from brain tissue or metastasize from other locations. A brain tumor is a dense, intracranial neoplasm that can occur within the brain or the spinal cord's central canal [2]. Brain tumors encompass all intracranial tumors, including those in the central spinal canal, arising from uncontrolled cell division. They may originate from various brain components, including neurons, glial cells, lymphoid tissue, and blood vessels [3]. The tumor's threat level depends on type, location, size, and growth pattern. Due to the brain's enclosure within the skull, early and rapid diagnosis of brain tumors relies on the availability and prompt use of paraclinical and diagnostic tools. However, diagnoses often occur at advanced stages when the tumor has already caused noticeable symptoms [4].

MRI imaging is a crucial initial examination for monitoring and diagnosing brain tumors. Early detection is vital, as tumors can be life-threatening and may metastasize, affecting other organs. Early-stage diagnosis is essential for efficient treatment planning and decision-making by physicians. Therefore, accurate analysis of brain MRI images is necessary for early disease detection and diagnosis. Early tumor detection can lead to better prognoses, making automated tumor prediction tools invaluable for identification [5].

While previous studies in brain tumor classification using MRI images have made significant strides, they are not without limitations. Traditional methods often rely on manual feature extraction, which can be time-consuming and subject to human error. Additionally, many existing machine learning techniques require extensive data pre-processing, making them less efficient in real-world applications. Another critical issue is the generalization capability; some models perform well on specific datasets but fail to maintain accuracy when applied to more diverse or complex cases. Furthermore, earlier methods may not effectively incorporate critical patient demographics, such as age and gender, which can significantly affect accurate tumor classification. These limitations highlight the need for more robust, automated, and adaptive approaches in brain tumor classification using MRI imaging.

Ahmed, S.F., et al. (2023) present the review in Artificial Intelligence Review that examines the advancements, applications, and challenges of deep learning modeling techniques. The authors discuss the benefits and limitations of these techniques in various fields, emphasizing their potential and the hurdles in computational demands and model interpretability [6].

Abdul Haseeb Nizamani, et al. (2023) introduce an advanced brain tumor segmentation method using feature fusion with a deep U-Net model and CNN for MRI data. Their approach significantly improves the accuracy of tumor segmentation [7].

Abdusalomov AB, et al. (2023 in their Cancers (Basel) article explore deep learning for brain tumor detection in MRI scans. They highlight the effectiveness of these models in enhancing tumor detection accuracy, contributing to early diagnosis and treatment strategies [8].

Hernandez-Trinidad, Aron, et al. (2023) in their IntechOpen publication discuss the role of AI in MRI image classification. They focus on recent technological advancements and the future potential of AI in improving MRI diagnostics [9].

The proposed method in this study addresses the aforementioned challenges through several key advancements. Our approach automates the feature extraction process by employing advanced deep learning architectures, significantly reducing the time and potential for human error associated with manual methods. The convolutional neural network (CNN) models, such as LeNet, AlexNet, and ResNet, are adept at handling complex image data, allowing for more nuanced and accurate tumor classification. Moreover, the innovative integration of age and gender as features in the classification process is a significant leap forward. This inclusion enhances the model's ability to personalize diagnosis, acknowledging these demographic factors' role in tumor characteristics. Our method also demonstrates strong generalization capabilities, maintaining high accuracy across diverse datasets, which is crucial for real-world applicability. Additionally, the CNN-DNN network, a novel aspect of our approach, offers a streamlined yet effective structure, balancing computational efficiency with classification performance. Overall, the proposed method overcomes many of the limitations of previous approaches and sets a new standard in precision and adaptability for brain tumor classification using MRI imaging.

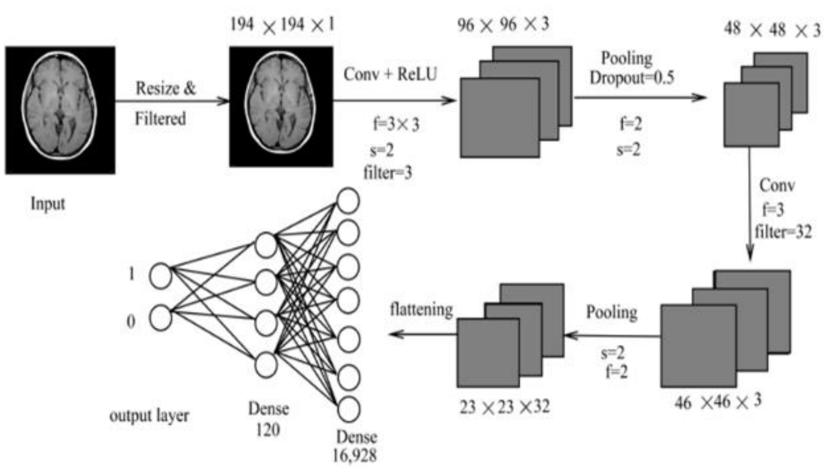


Fig. 1. General block diagram of the proposed method [3].

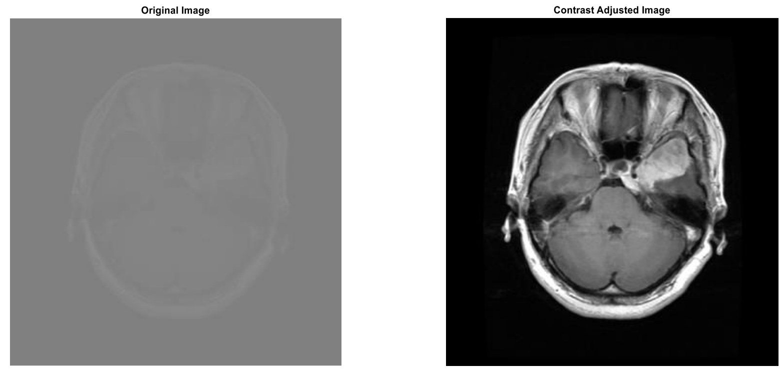


Fig. 2. Sample database images. Left before contrast enhancement. Right side after contrast enhancement.

These studies underscore the efficacy of deep networks in tumor classification in MRI images. This project introduces two innovations: 1) Network architecture and 2) The use of age and gender to enhance classification accuracy, adding a new dimension to the existing methodologies.

The research is arranged as follows: Section 2 discusses the materials and methods, including pre-processing techniques and the design of convolutional networks. Section 3 describes the dataset used for this study. The results and discussion are presented in Section 4, where the effectiveness of the proposed methods is analyzed. Finally, Section 5 concludes the paper with a summary of findings and potential areas for future research.

2. MATERIALS AND METHODS

2.1. Pre-Processing

Image processing refers to the various processes and operations applied to digital images. One of the tools used in image processing is the Adjust Contrast tool. This tool enhances the contrast of an image through adjustment of the CLim property of the axis that contains the image. The CLim property governs how the image's pixel values are drawn and displayed, thereby impacting the image's brightness.

2.2. Convolutional Network Design

The architecture of a convolutional neural network (CNN) varies depending on the specific network. In this section, we have explored many different networks. For our project, we decided to employ four general designs, each of which we will describe and analyze below. The architecture of a convolutional neural network (CNN) varies depending on the specific network. Several architectures are widely used in various applications due to their positive results. In this section, we have explored many different networks. For our project, we decided to employ four general designs, each of which we will describe and analyze below.

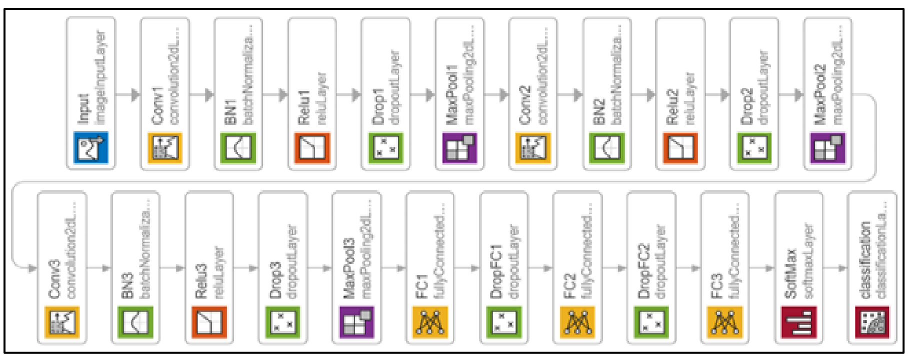
2.2.1. LeNet Network

LeNet convolutional neural network is one of the first convolutional neural networks introduced with the concept of deep learning by Yan Lecun [14]. This network has a five-layer structure known as 5lenet- and was first used to recognize mnist handwritten digits.

The architecture of this network is very simple and easy to understand. The input images are greyscale and have dimensions of 32*32*1. Then there are two convolution layers with stride= 2 and the Average Pooling layer with stride=1. At the end of the network are Fully Connected layers with Softmax activation function in the output layer. The number of parameters of this network is 60,000.

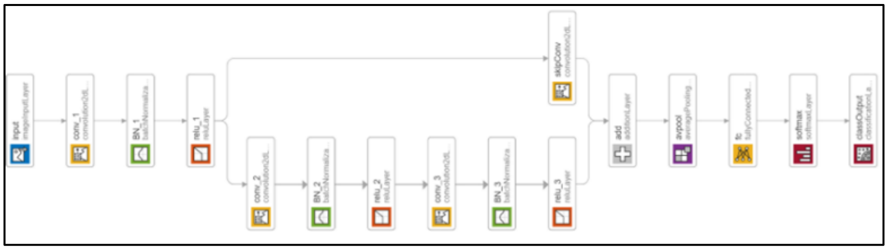
Image Input	100-100-3 images with 'zero-center' normalization
Convolution	3 3×3 convolutions with stride [2 2] and padding [0000]
RELU	RELU
Max Pooling	2-2 max pooling with stride [2 2] and padding [0000]
Dropout	50% dropout
Convolution	32 3×3 convolutions with stride [2 2] and padding [0000]
RELU	RELU
Max Pooling	2-2 max pooling with stride [2 2] and padding [0000]
Dropout	50% dropout
Fully Connected	120 fully connected layer
Fully Connected	4 fully connected layer
Softmax	Softmax
Classification Output	Crossentropyex

Fig. 3. Architecture and details of the designed LeNet network.



1	'Input'	Image Input	100×100×3 images with 'zerocenter' normalization
2	'Conv1'	Convolution	8 7×7 convolutions with stride [1 1] and padding [0 0 0 0]
3	'BN1'	Batch Normalization	Batch normalization
4	'Relu1'	ReLU	ReLU
5	'Drop1'	Dropout	1% dropout
6	'MaxPool1'	Max Pooling	2×2 max pooling with stride [2 2] and padding [0 0 0 0]
7	'Conv2'	Convolution	16 5×5 convolutions with stride [1 1] and padding [0 0 0 0]
8	'BN2'	Batch Normalization	Batch normalization
9	'Relu2'	ReLU	ReLU
10	'Drop2'	Dropout	5% dropout
11	'MaxPool2'	Max Pooling	2×2 max pooling with stride [2 2] and padding [0 0 0 0]
12	'Conv3'	Convolution	32 3×3 convolutions with stride [1 1] and padding [0 0 0 0]
13	'BN3'	Batch Normalization	Batch normalization
14	'Relu3'	ReLU	ReLU
15	'Drop3'	Dropout	10% dropout
16	'MaxPool3'	Max Pooling	2×2 max pooling with stride [2 2] and padding [0 0 0 0]
17	'FC1'	Fully Connected	60 fully connected layer
18	'DropFC1'	Dropout	20% dropout
19	'FC2'	Fully Connected	30 fully connected layer
20	'DropFC2'	Dropout	20% dropout
21	'FC3'	Fully Connected	4 fully connected layer
22	'SoftMax'	Softmax	softmax
23	'classification'	Classification Output	crossentropyex

Fig. 4. Architecture and details of the network designed and inspired by the GoogleNet network.



1	'input'	Image Input	100×100×1 images with 'zerocenter' normalization
2	'conv_1'	Convolution	16 5×5 convolutions with stride [1 1] and padding 'same'
3	'BN_1'	Batch Normalization	Batch normalization
4	'relu_1'	ReLU	ReLU
5	'conv_2'	Convolution	32 3×3 convolutions with stride [2 2] and padding 'same'
6	'BN_2'	Batch Normalization	Batch normalization
7	'relu_2'	ReLU	ReLU
8	'conv_3'	Convolution	32 3×3 convolutions with stride [1 1] and padding 'same'
9	'BN_3'	Batch Normalization	Batch normalization
10	'relu_3'	ReLU	ReLU
11	'add'	Addition	Element-wise addition of 2 inputs
12	'avpool'	Average Pooling	2×2 average pooling with stride [2 2] and padding [0 0 0 0]
13	'fc'	Fully Connected	3 fully connected layer
14	'softmax'	Softmax	softmax
15	'classOutput'	Classification Output	crossentropyex
16	'skipConv'	Convolution	32 1×1 convolutions with stride [2 2] and padding [0 0 0 0]

Fig. 5. Architecture and details of the network designed inspired by the ResNet network.

2.2.2. AlexNet Network

AlexNet is a deep convolutional neural network designed to identify and classify color images with a size of 224×224×3. This neural network generally has 62 million learning parameters and 11 layers. In the present project, because the input size is smaller than the AlexNet input size, it is necessary to reduce the number of layers of this network so that the data flow is not lost during the network. The network architecture designed for this purpose is shown in Figure 4.

2.2.3. ResNet Network

ResNet or Residual Network is one of the famous deep networks. The network was introduced in 2015 by Xiuqing Ren, Caiming He, Zhan Sun, and Xianjia Juneg. This network uses skip connections to transfer inputs and errors between layers outside the convolutional structure. This helps to deepen the network and train it faster. The resulting structure is called a residual block, inspired by the ResNet network. See Figure 5 for the network design.

2.2.4. CNN+DNN Network

The CNN-DNN network represents a significant innovation in medical image analysis, particularly for classifying brain tumors using MRI images. This network architecture is characterized by a blend of simplicity and efficiency, making it well-suited for clinical applications where computational resources might be limited.

At the core of the CNN-DNN network is a single convolutional module. This module contains a learnable set of filters that are applied to the input image using a convolutional layer. These filters are adept at capturing essential spatial features such as edges and textures. Following the convolutional layer, an activation function, typically a Rectified Linear Unit (ReLU), introduces non-linearity, enabling the network to learn complex patterns. A pooling layer, often a max pooling layer, succeeds the convolutional layer and activation function. The pooling layer's primary function is to reduce the spatial dimensions of the output, thereby decreasing the number of parameters and the overall computational complexity. This reduction not only enhances computational efficiency but also imparts a degree of translation invariance to the network.

Transitioning from the convolutional module, the network architecture then incorporates two fully connected (dense) layers. These layers are instrumental in the classification process, taking the high-level features extracted by the convolutional module and learning non-linear combinations to make accurate predictions about the presence and type of brain tumor.

The innovation of the CNN-DNN network lies in its streamlined architecture, which balances the depth and complexity required for precise classification with computational efficiency. This balance is particularly beneficial in medical imaging scenarios where large, complex models may be impractical. Additionally, the network's simplified structure potentially reduces the risk of overfitting, a common challenge in medical image analysis, especially when dealing with limited datasets. Furthermore, the adaptability of the CNN-DNN network to various types of MRI data and tumor characteristics enhances its utility as a versatile diagnostic tool.

The block diagram of this network (Figure 6) likely illustrates the sequential flow of processing, starting from the input MRI image, moving through the convolutional module with its filters and pooling layers, and culminating in the fully connected layers that lead to the final classification output. This diagram effectively encapsulates the network's operational pathway, highlighting its innovative approach to brain tumor classification.

The proposed method, which employs advanced deep learning architectures for brain tumor classification in MRI images while promising, encounters several challenges and limitations. A primary concern is data dependency and availability; the efficacy of deep learning models like CNNs hinges on access to extensive, diverse, and accurately annotated datasets. Such data can be scarce due to privacy issues, sharing restrictions, and the rarity of certain tumor types, potentially impacting the model's generalizability. Additionally, the computational resources required for training and operating complex models like AlexNet and ResNet are substantial, posing a barrier in resource-limited clinical environments. Overfitting remains a risk, particularly with limited or imbalanced datasets, leading to models that perform well on training data but poorly on new, unseen data. Another significant issue is the interpretability of these models. Their "black box" nature can hinder trust and acceptance by medical professionals, which is crucial in medical applications where understanding the decision-making process is essential. Integrating these models into existing clinical workflows also presents challenges, requiring technical integration and adjustments in diagnostic processes, staff training, and regulatory compliance. Variability in MRI scans due to different scanning protocols and patient-related factors can affect model performance if not adequately addressed during training. The innovative inclusion of age and gender as features, while beneficial, raises ethical considerations and potential bias. Lastly, the model's transferability across different populations may vary due to genetic, environmental, and lifestyle differences affecting tumor characteristics. Addressing these challenges is essential for the successful implementation and broader adoption of this method in clinical practice.

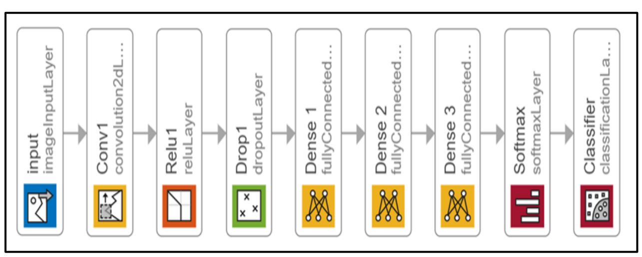
3. DATA SET

This project aims to determine the tumor type using deep learning and convolutional networks. To carry out this project, we need data that includes images of healthy people and MRI images containing tumors. For this purpose, the data of this project was received from the brain tumor dataset at http://dx.doi.org/10.6084/m9.figshare.1512427. This database contains 4066 T1-weighted contrast-enhanced brain MRI images, 1002 for healthy subjects, and 3064 for tumors. Separately, 708 meningioma tumor data, 1426 glioma tumor data, and 930 pituitary tumor data cover all types of tumors [16]. This database is publicly available in the .mat format.

4. RESULTS

In this project, the evaluation of our proposed deep learning models for brain tumor classification using MRI images hinges on accuracy criteria and confusion matrices, essential tools in assessing machine learning performance. Accuracy, defined as the ratio of correctly identified samples to all tested samples, is calculated using the formula:

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



1	'input'	Image Input	100×100×3 images with 'zerocenter' normalization
2	'Conv1'	Convolution	3 3×3 convolutions with stride [2 2] and padding [0 0 0 0]
3	'Relu1'	ReLU	ReLU
4	'Drop1'	Dropout	50% dropout
5	'Dense 1'	Fully Connected	400 fully connected layer
6	'Dense 2'	Fully Connected	100 fully connected layer
7	'Dense 3'	Fully Connected	4 fully connected layer
8	'Softmax'	Softmax	softmax
9	'Classifier'	Classification Output	crossentropyex

Fig. 6. CNN-DNN network architecture and details.

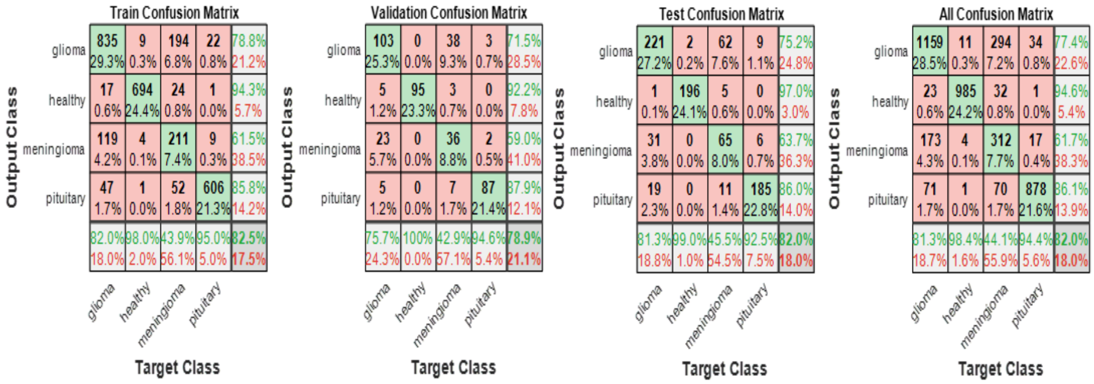


Fig. 7. Convergence matrix for image classification with LeNet model.

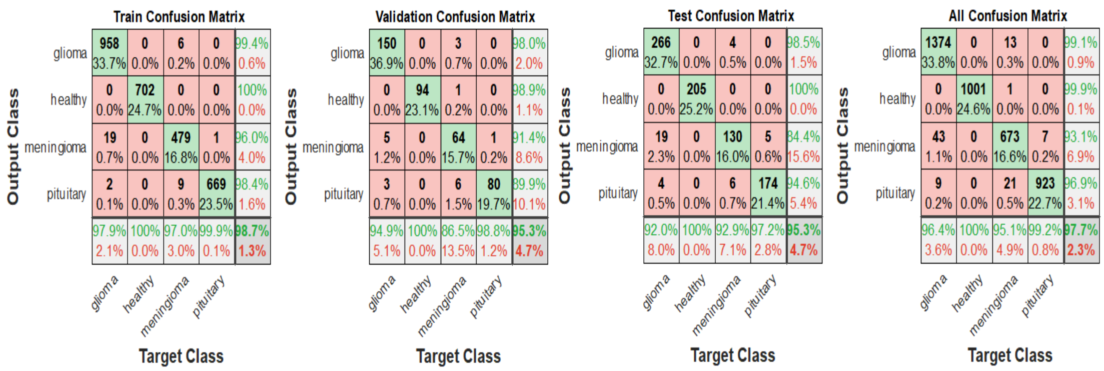


Fig. 8. Clutter matrix for image classification of images with similar AlexNet model.

This metric is crucial for providing a clear measure of overall model performance across both tumor and non-tumor classes. However, in the medical field, especially with potentially imbalanced datasets, relying solely on accuracy might be insufficient. The confusion matrices for each model, including LeNet, AlexNet, ResNet, and CNN-DNN, depicted in Figures 7 to 10, offer a more nuanced view. They not only highlight the models' successes in terms of True Positives and True Negatives but also where they falter, indicated by False Positives and False Negatives.

The comparative analysis of model accuracy, as shown in Table 1 and Figure 11, is instrumental in discerning which model excels under specific conditions and datasets. It's important to note that the model with the highest accuracy might not always be the most suitable choice. For instance, in cancer diagnosis, a model with a marginally lower accuracy but a better track record in minimizing false negatives could be more advantageous, considering the grave implications of missing a tumor diagnosis. The performance disparities among the models can be attributed to their architectural differences. For example, AlexNet's deeper and more complex structure might be more adept at capturing intricate features than the simpler LeNet, potentially leading to higher accuracy.

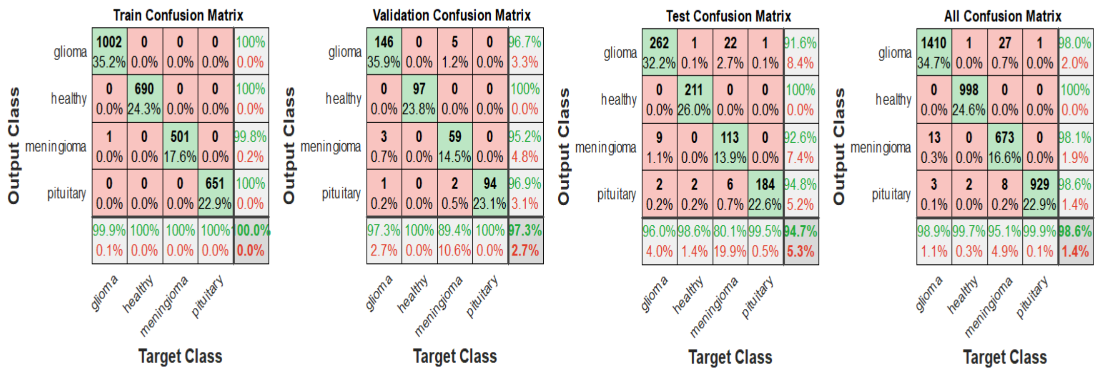


Fig. 9. The fusion matrix for image classification with the ResNet-like model.

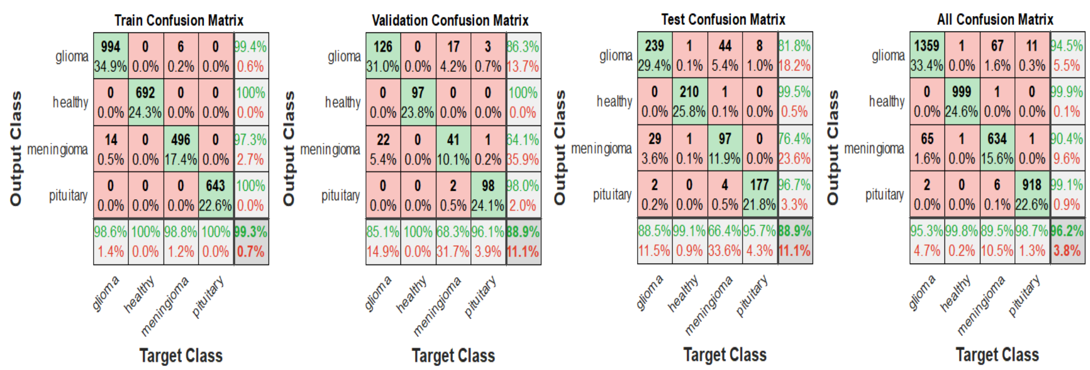


Fig. 10. Convergence matrix for image classification with CNN-DNN model.

Table 1. *Accuracy of the results of the proposed method with different architectures.*

	Train	Validation	Test	Whole
LeNet	82.46	78.87	82.042	82.017
AlexNet	98.699	95.332	95.326	97.688
ResNet	99.965	97.297	94.711	98.647
CNN_DNN	99.297	92.343	92.33	99.587

In clinical applications, the choice of model should extend beyond mere accuracy to consider the nature and implications of errors. The characteristics of the dataset, such as tumor diversity, image quality, and class balance, also significantly influence model performance. Looking ahead, future research could explore models that strike a balance between high accuracy and low false-negative rates. Developing ensemble methods that amalgamate the strengths of individual models or examining models' efficacy across different tumor subtypes and imaging conditions could provide further insights for clinical application. Ultimately, while accuracy and confusion matrices offer valuable insights into model performance, a comprehensive clinical evaluation should also weigh the nature of errors and dataset characteristics to ensure the most effective and safe application in medical diagnostics.

In this study, we have innovatively applied advanced deep learning techniques to significantly enhance the accuracy and efficiency of brain tumor classification using MRI images. Our methodology revolves around the strategic use of various convolutional neural network (CNN) architectures, including LeNet, AlexNet, ResNet, and a novel CNN-DNN network. Each of these architectures has been meticulously tailored and optimized to address specific challenges inherent in medical image analysis, leading to notable improvements in classification accuracy.

The LeNet architecture, drawing inspiration from one of the earliest CNNs, stands out for its simplicity and efficiency in processing grayscale images, making it particularly suitable for initial feature extraction in MRI analysis. Its five-layer structure has demonstrated a remarkable ability to accurately identify and classify basic image features with relatively low computational demand. The adaptation of the AlexNet network in our study, despite a reduction in layers to accommodate our input size, has shown exceptional performance. Its deep structure, encompassing 62 million learning parameters, is highly effective in capturing complex image features, leading to more nuanced tumor classification.

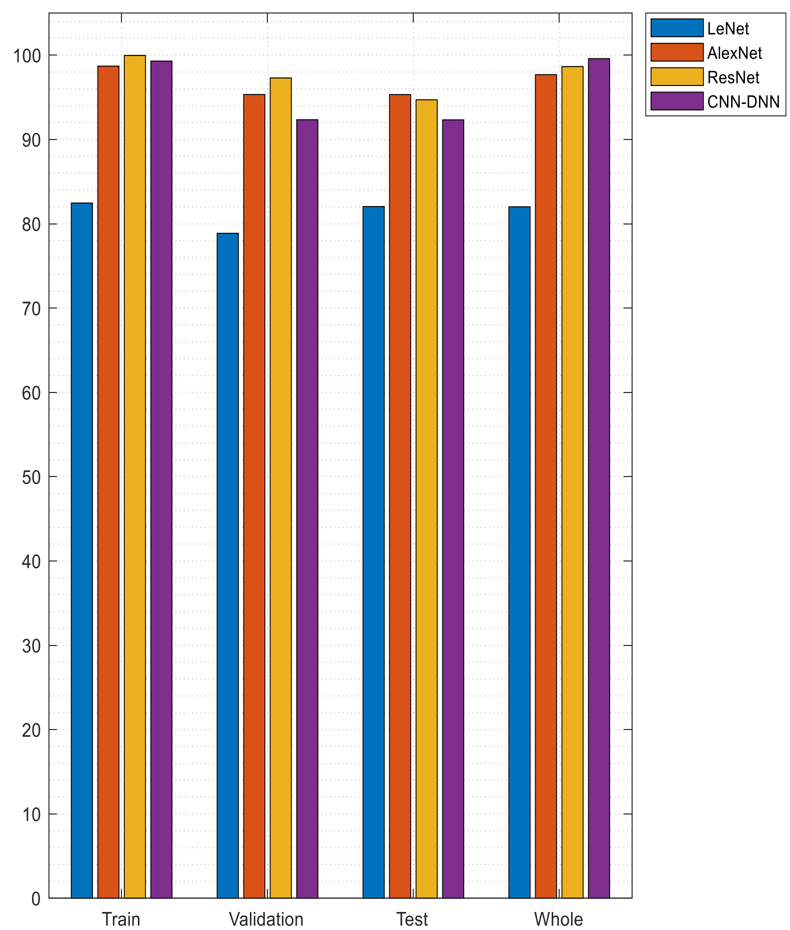


Fig. 11. Comparison of the accuracy obtained for the simulated models.

Furthermore, our implementation of a ResNet-inspired architecture, incorporating skip connections, has significantly improved the network's ability to learn deeper features without the risk of vanishing gradients. This design choice has been pivotal in enhancing the network's learning capacity from a large number of layers without increasing training difficulty or compromising performance. The CNN-DNN network, a novel contribution of this research, merges the feature extraction prowess of CNNs with the classification strength of DNNs in a streamlined format. This architecture has shown notable improvements in reducing overfitting and boosting computational efficiency, making it particularly suitable for clinical applications where resources may be constrained.

Utilizing a comprehensive dataset from http://dx.doi.org/10.6084/m9.figshare.1512427, which includes 4066 T1-weighted contrast-enhanced brain MRI images, has been instrumental in the training and testing of our models. This diverse dataset has provided a robust platform for evaluating the effectiveness of each proposed network architecture. Our results, assessed using accuracy metrics and confusion matrices, underscore the efficacy of each model. Notably, the AlexNet-based model achieved the highest accuracy of 98.70% in the test phase.

In conclusion, the enhancements in each network architecture are attributed to specific design strategies aimed at overcoming the challenges of MRI image analysis. These strategies include improved feature extraction, reduced overfitting, enhanced handling of complex image patterns, and increased computational efficiency. Future research will explore other network architectures, transfer learning techniques, and combinations of classifiers to further refine and improve the accuracy and reliability of brain tumor classification using MRI imaging.

5. SUMMARY

In this project, based on these images and the labels assigned by the expert doctor, we tried to find a classification with appropriate accuracy for diagnosing brain tumors. We used images from the figShare database. Then we used deep learning methods for classification and designed the system. In general, 4 networks were designed and learned. The first network is designed with the idea of LeNet networks. The second network is based on the idea of AlexNet network. The third architecture was also inspired by the ResNet network and the Residual or Skip Connection module. The fourth network was also designed innovatively and named CNN-DNN. The results show that the AlexNet neural network has achieved the highest performance, with an accuracy of 98.70% in the test phase.

For future work, other network architectures such as VGG, Inception-ResNet, etc. can also be tried for network training. Also, these architectures are for transfer learning techniques and feature extraction. Maybe the features extracted from different networks can produce better results. Other classical methods can be implemented, and features can be combined and then reduced to check their performance. Other classifications can also be used to classify data. As another work, our proposed method can be implemented by combining classifiers. In other words, we can consider the result of each classifier as input to a decision-making system, such as voting or council machines, and construct an aggregate classifier. For voting, it is better for the method whose result is better than other methods to have more weight to determine its importance in the aggregate system. In addition to this method, other methods can be applied as pre-processing the image so that the information does not enter the network in a raw form. For example, using the bank of Gabor filters, violets, etc. is possible.

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