Smart Techno (Smart Technology, Informatic, and Technopreneurship)
Volume 7, Number 1, 2025 pp. 38-44
E-ISSN: 2541-0679
Open Access: https://lppm.primakara.ac.id/jurnal/index.php/smart-techno/


# Improving MRI Classification through Layered Convolutional Neural Networks Configuration

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**ARTICLE INFO**

***Article history:***
Initial submission
20-04-2025
Received in revised form
21-04-2025
Accepted 22-04-2025
Available online 25-04-2025

***Keywords:***
*MRI, Artificial Intelligence, Convolutional Neural Networks, Layered Architecture*

**DOI:**
https://doi.org/10.59356/smart-techno.v7i1.154

## ABSTRACT

Timely and accurate classification of brain tumors using Magnetic Resonance Imaging (MRI) is critical for effective treatment planning. This study proposes a layered Convolutional Neural Network (CNN) configuration to enhance the classification of brain tumors, addressing the limitations of traditional machine learning approaches that rely heavily on manual feature extraction. Utilizing a dataset sourced from Kaggle, comprising 7023 MRI images categorized into glioma, meningioma, no tumor, and pituitary tumor classes, the research implements data augmentation techniques such as rotation and flipping to increase the dataset size by 20%. Images were standardized to 128x128 pixels and normalized for model compatibility. The core model architecture was built using 2D CNNs with configurations ranging from one to three layers. The models were trained and tested using TensorFlow and Keras on Google Collaboratory, and evaluated based on accuracy, loss, and computational efficiency. The findings revealed that among all the configurations tested, the three-layered CNN model delivered the best performance. It achieved an accuracy value of 89.79% with a corresponding loss of 0.469. In terms of processing time, the model completed training in 59.8894 seconds and performed inference in 5.1099 seconds, highlighting its suitability for real-time diagnostic applications despite the longer training duration.

## 1. INTRODUCTION

Brain tumors are often defined as abnormal, frequently aggressive cellular growths within the brain or central nervous system, which represent a significant threat to patient survival, where timely detection and precise characterization are pivotal for optimizing treatment strategies. This study centers on brain tumor classification via Magnetic Resonance Imaging (MRI), a cornerstone of modern diagnostic radiology due to its non-invasive ability to produce high-resolution soft tissue visualization. Despite its clinical ubiquity, consistently differentiating healthy brain anatomy from tumorous lesions, including low-grade gliomas, glioblastomas, or metastatic tumors. Radiologists must meticulously analyze numerous cross-sectional images per patient, yet discrepancies between observers and the potential for oversight continue to hinder both the reliability and efficiency of diagnoses.

Traditional approaches to brain MRI analysis have hinged on manually identifying regions of interest and extracting hand-engineered features, such as texture metrics, intensity distributions, and shape characteristics, which are then processed using conventional algorithms like support vector machines (SVMs) or random forests (Shimanto, Hosain, Biswas, & Islam, 2023). While effective in idealized settings, these methods struggle with real-world variability in imaging equipment, scan parameters, and tumor heterogeneity, constrained further by the time-intensive, subjective nature of manual feature selection (Kaifi R, 2023).

These limitations highlight the urgent need for techniques capable of interpreting the intricate 3D spatial and textural complexity of brain tumors directly from raw imaging data (Yin

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et al., 2021). Artificial intelligence (AI), particularly deep learning, addresses this gap: by training neural networks on large-scale, annotated MRI datasets, models can autonomously uncover subtle, discriminative features beyond human-defined criteria. Convolutional Neural Networks (CNNs), optimized for grid-based data like MRI, excel in this domain by hierarchically detecting edges, textures, and advanced patterns. This capability is critical for mapping tumor boundaries and distinguishing subtypes. Innovations such as 3D convolutions (for volumetric context), synthetic data augmentation (to enhance generalization), and transfer learning (leveraging pretrained models from non-medical imaging datasets) further bolster their adaptability across diverse clinical scenarios (Anaya-Isaza, Mera-Jiménez, Verdugo-Alejo, & Sarasti, 2023). Integrating CNN-driven tools into diagnostic workflows promises to standardize tumor classification, minimize diagnostic variability, and provide clinicians with rapid, data-driven insights to guide personalized treatment plans. However, the advancement of the technique often increases the complexity of the program, resulting in a less efficient system, in terms of processing time.

The main contributions of this work are as follows:

a. Developed a layered CNN architecture for classifying brain tumor based on magnetic resonance imaging data, accompanied by an ablation study.
b. Incorporated data augmentation techniques to further improve the proposed model's accuracy and loss performance.

The remainder of this article is organized as follows: Section 2 reviews related work in this field; Section 3 details the proposed methodology and its implementation; Section 4 presents the performance evaluation; and Section 5 offers concluding remarks and discusses directions for future research.

## 2. RELATED WORKS

Recent advances in medical image analysis have seen a significant shift from traditional machine learning techniques to deep learning approaches, particularly CNNs, for tasks such as brain tumor classification. Earlier studies typically relied on handcrafted features like texture, shape, and intensity metrics, processed through classifiers such as SVM and Random Forests (Pallavi & Vidhya, 2024). While these methods achieved moderate success in controlled environments, they lacked robustness in real-world scenarios due to variations in imaging protocols and tumor morphology. Deep learning, particularly CNNs, has emerged as a powerful alternative by enabling automated feature extraction directly from raw image data. Saeedi et al. (2023) shown the efficacy of 2D CNNs in detecting tumor regions in MRI scans by leveraging hierarchical learning of spatial features. Notable architectures like AlexNet, VGG, and ResNet have been adapted for brain tumor classification, often improving diagnostic performance and minimizing inter-observer variability. However, the tradeoff between accuracy and efficiency from those architecture was significant (Priya & Vasudevan, 2024)

Recent efforts have explored deeper CNN models and the use of 3D CNNs to capture volumetric context in MRI scans (Lu, Wang, Zhang, Yoon, & Won, 2019). However, deeper models often increase computational complexity and inference time. Data augmentation and transfer learning techniques have also been applied to enhance model generalization, especially when medical datasets are limited in size (Alomar, Aysel, & Cai, 2023). This study builds upon these foundations by proposing a layered CNN approach that balances classification accuracy with computational efficiency, specifically optimized for multi-class brain tumor identification.

## 3. PROPOSED METHODOLOGY

In this section, the proposed methodology is detailed into three different subsections, starting with the general overview, dataset collection and preprocessing using data augmentation, along with model development and ablation study.

### 3.1. General Overview

The overall process carried out in this work is depicted in Figure 1. Initially, the datasets were collected and augmented using various methods to generate larger MRI dataset. This data was then processed before divided into two-part, train and test dataset. The train data used to support the learning process of the proposed CNN model to achieve accuracy performance larger than 95%. When the training accuracy passed the 95% threshold, the inference conducted using test dataset. The results obtained from this test data were used as final indicator of the model performance.

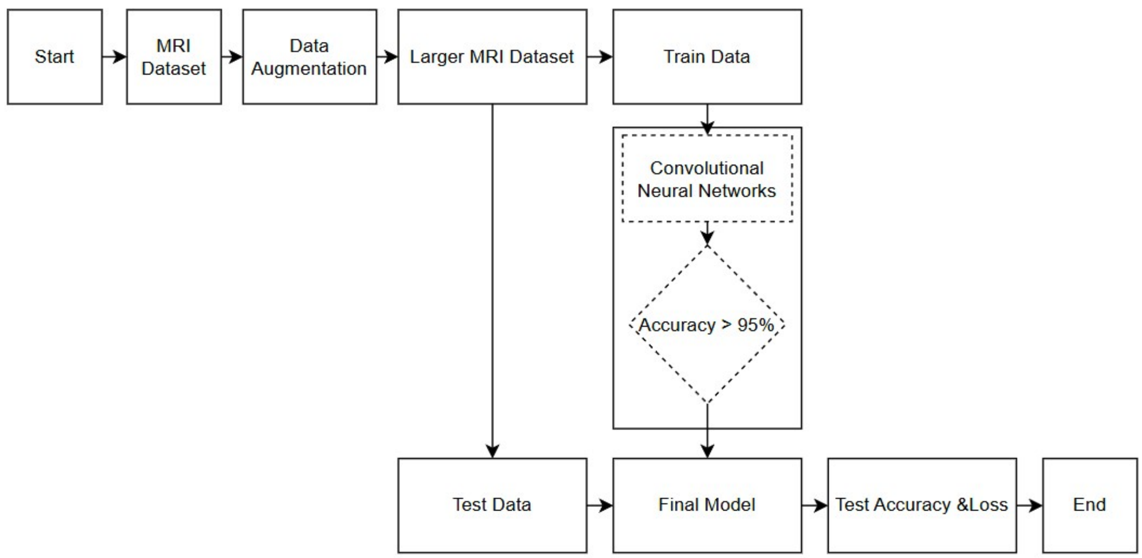


**Figure 1**. The general overview of the proposed Layered CNN-based MRI Classification.

### 3.2. Data Collection and Preprocessing

The availability of health-related datasets is limited. In this work, we utilized the MRI dataset that is collected from Kaggle (Nickparvar, 2021). The dataset was a combination of three different datasets and consist of a total of 7023 images of human brain MRI images which are classified into 4 classes, such as glioma, meningioma, no tumor and pituitary. The distribution of data for each class is detailed in Table 1.

**Table 1.** Initial dataset sizes for brain tumor classification using MRI images.

| No | Class Name | Training Instance | Testing Instance |
|---|---|---|---|
| 1 | Glioma | 1321 | 300 |
| 2 | Meningioma | 1339 | 306 |
| 3 | Notumor | 1595 | 405 |
| 4 | Pituitary | 1457 | 300 |

Based on the detailed dataset above, the data preprocessing was conducted. The initial stage is the data augmentation. In order to further enhance the information from the dataset, augmentation using rotation and flip image. After the augmentation process is finished, the next step is to ensure that the images are of the same sizes. This is important as the model requires the specific number of image pixels as an input. In this case, we utilize 128x128 as the standard image size for the proposed model. Additionally, the normalization stage was also incorporated in this work, which allows the proposed brain tumor detection using MRI images to perform better. In addition, Table 2 shows the difference between initial image and augmented image in terms of quantity.

**Table 2.** Augmented dataset sizes for brain tumor classification using MRI images.

| No | Class Name | Augmented Training Instance | Augmented Testing Instance |
|---|---|---|---|
| 1 | Glioma | 1585 | 360 |
| 2 | Meningioma | 1606 | 367 |
| 3 | No tumor | 1914 | 486 |
| 4 | Pituitary | 1748 | 360 |

The augmentation process shows the average dataset increment is 20% from the initial dataset detailed in Table 1.

### 3.3. Model Development

The proposed model for brain tumor classification introduced in this work utilizes the CNN as the basis for the development stage. In specific, 2D Convolutional Neural Networks were used to comply with MRI images. The architecture of the proposed CNN network is detailed in Table 3.

**Table 3.** The summary of the basis proposed CNN-based model for brain tumor classification.

| No | Layer Basis | Output Shape | Param # |
|---|---|---|---|
| 1 | Conv2D | (None, 126, 126, 128) | 3,584 |
| 2 | MaxPooling2D | (None, 63, 63, 128 | 0 |
| 3 | Flatten | (None, 508032) | 0 |
| 4 | Dense | (None, 32) | 16,257,056 |
| 5 | Dense | (None, 4) | 132 |

It is worth noting that Table 2 shows the basis model proposed in this work, which is called single layer CNN model. Those models were then implemented using a layered approach. Thus, the configuration complexity of the network slightly increased. In this work, we incorporated three different configurations of the layer. In order to further detail the proposed model configuration, the optimizer used in this work is Adam with loss metrics in categorical cross entropy. The learning rate designed for the proposed model is 0.001 and batch size of 32. Additionally, the framework used in this model development process is Keras and TensorFlow with Google Collaboratory as the training devices.

## 4. RESULT AND DISCUSSION

In this section, we present the results of the proposed model for classifying brain tumors based on MRI images. The performance metrics used to evaluate the model are accuracy and loss, calculated using Equation (1) and Equation (2), respectively.

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

$$Cross\ Entropy\ Loss = -\sum_i^n yi\, .\log \hat{y}i \quad (2)$$

In context of accuracy metrics, $TP$ represent true positive, whereas the $TN$ denotes the true negative of the prediction results. In terms of loss metrics, $n$ represent the total number of test data, followed by $yi$ and $\hat{y}i$ denotes the predicted and actual value, respectively.

First, we show the performance of one layer CNN model, followed by two layers and three layers configuration.

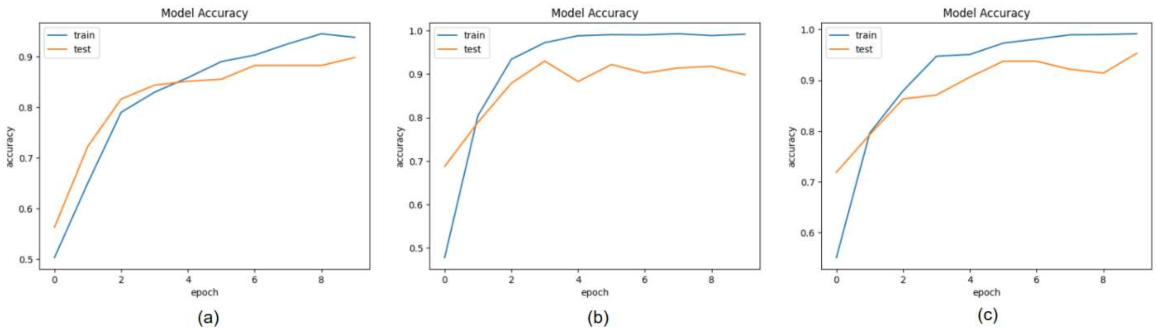


**Figure 2**. The training improvement of three different model configurations; (a) 1-Layered CNN; (b) 2-Layered CNN; (c) 3-Layered CNN.

The training process of all model configuration observed in this work depicted in Figure 2. It can be shown that the total iteration of the learning process chosen in this work is 10 epoch. This value selection is due to the early observations of model capabilities to learn the pattern of the MRI images. Based on the results, most of the model is able to achieve satisfactory performance in detecting the tumor in brain utilizing MRI images. To further understand the importance of the layered architecture, test accuracy and loss were also considered in this work.

**Table 4.** The performance of different layer configurations in the proposed work.

| No | Model Configuration | Test Accuracy (%) | Test Loss |
|---|---|---|---|
| 1 | Single Layered CNN | 84.78 | 0.974 |
| 2 | Two Layered CNN | 86.12 | 0.559 |
| 3 | Three Layered CNN | 89.79 | 0.469 |

Table 4 shows the performance of various layered CNN models proposed in this work. It can be observed that the three-layered CNN is able to achieve better performance compared to others, as shown by the greater test accuracy value of 89.79% and lower loss of 0.469. The results also show that the deeper the layer of the CNN network able to produce better model performance. Additionally, we calculate the total training time, and the time required for each model to perform a prediction or often called inference time.

The training and inference time information is detailed in Figure 3. The 1-layered CNN recorded the shortest training time at 51.0964 seconds and inference time at 2.6081 seconds. The 2-layered CNN required 54.5401 seconds for training and 3.7155 seconds for inference. The 3-layered CNN, while the most computationally intensive, had the highest training time of 59.8894 seconds and inference time of 5.1099 seconds. This trend indicates a trade-off between model complexity and processing time, with deeper models demanding more computation but potentially offering improved performance.

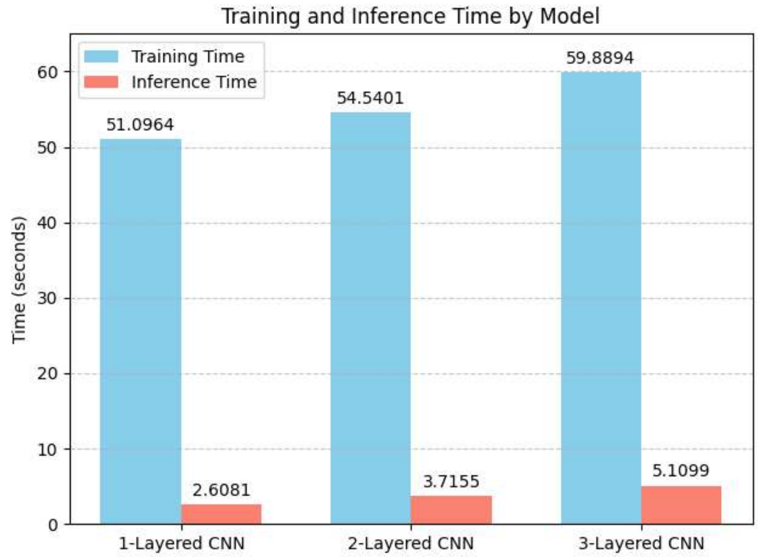


**Figure 3**. The training and inference time information for three different model configurations.

Based on presented results, the tradeoff between performance in terms of accuracy and efficiency is clear. Deeper CNN model layer resulting in better performance but consequently have longer training time as well as inference time. To accommodate both performance criteria, the three layered is suitable compared to another variations. Even though the training time is longer, the inference time difference is negligible.

## 5. CONCLUSION

This work introduces various variations of layered CNN approach for brain tumor classification using MRI images. As the state-of-the-art mainly utilizes machine learning approaches, the proposed work incorporates deep learning methods. The dataset was collected from various sources, especially from Kaggle. The data augmentation process and preprocessing of the data were then performed sequentially. The model developed with three different variations of CNN layered. The results showed that the performance of the three-layered CNN model is superior compared to other configurations investigated in this work. Three-layered model successfully achieved 89.79% accuracy with 0.469 loss. The proposed model took 59.8894 and 5.1099 seconds for training and inference, respectively.

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