

# Master Thesis Proposal

## A Lightweight CNN Approach for Brain Tumor Detection Using MRI Images

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Submitted by

Mahmoud Fasfos

Siraj Ahmedin Mussa

Master's Students, Master of Artificial Intelligence

Under the Supervision of

Prof. Dr. Hager Saleh

Department of Artificial Intelligence

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## Abstract

Brain tumor detection is a critical challenge in medical diagnostics, as timely and accurate detection can significantly improve patient outcomes. Traditional manual methods are time-consuming and prone to errors, necessitating automated solutions. Convolutional Neural Networks (CNNs) have demonstrated notable success in medical image classification tasks. This study introduces a Lightweight CNN architecture, optimized for computational efficiency compared to standard CNN models like ResNet and DenseNet. The lightweight model is designed to process MRI images faster with fewer computational resources while maintaining high accuracy. This efficiency makes it suitable for real-time deployment in clinical settings, particularly in resource-constrained environments. The proposed approach includes preprocessing techniques such as data augmentation, normalization, and resizing to improve robustness and generalization. Comparative analysis with standard CNN-based models highlights the performance and computational efficiency of the lightweight architecture. Experimental results demonstrate that the proposed lightweight CNN achieves high accuracy, precision, recall, and F1-score, providing an efficient solution for brain tumor detection in clinical settings.

**Keywords:** Brain Tumor Detection, Convolutional Neural Networks (CNN), Lightweight Model, MRI Imaging, Deep Learning, Kaggle Dataset.

## I. Introduction

Brain tumors are abnormal growths of cells in the brain that can be life-threatening if not detected and treated early. Accurate diagnosis of brain tumors from MRI (Magnetic Resonance Imaging) scans is critical for determining appropriate treatment strategies. However, manual interpretation of MRI images by radiologists is often subjective, time-consuming, and prone to human error [1].

Recent advancements in deep learning, particularly **Convolutional Neural Networks (CNNs)**, have significantly improved medical image analysis, automating the detection and classification of brain tumors. Standard CNN architectures like ResNet, DenseNet, and VGG16 have shown remarkable accuracy in tumor classification tasks but suffer from:

- **High computational demand:** Requiring significant memory and processing power.
- **Overfitting:** Often overfitting small datasets due to their complexity.

In clinical settings, particularly in hospitals with limited computational resources, these architectures are impractical for real-time applications. Lightweight CNN models address this limitation by reducing the model size, computational complexity, and inference time while maintaining high performance. **For example, lightweight CNNs**

**have successfully been deployed on mobile devices and edge computing systems for rapid diagnosis.**

The **proposed lightweight CNN** in this study aims to classify brain tumors into four categories: glioma, meningioma, pituitary tumor, and normal. By leveraging advanced preprocessing techniques and optimizing the architecture, the model achieves a balance between **accuracy** and **computational efficiency**, ensuring suitability for real-time deployment.

### **Motivation**

Brain tumors are among the most life-threatening conditions, requiring early and accurate detection. Despite the success of deep learning methods, key challenges persist:

1. **Small Datasets:** Limited labeled MRI datasets hinder model generalization.
2. **Overfitting:** Complex models tend to memorize training data instead of generalizing patterns.
3. **High Computational Demands:** Transformer-based models and deep CNNs are computationally expensive, restricting deployment in real-time clinical scenarios.

**Gap Addressed:** This research develops a **Lightweight CNN model** that bridges the gap between performance and computational efficiency. Unlike Transformer models or deep CNNs, the lightweight model is tailored for brain tumor detection in small datasets with minimal computational resources, making it ideal for clinical use.

### **Problem Definition:**

Manual diagnosis of brain tumors is inefficient and prone to subjectivity. Existing deep learning solutions face issues such as overfitting, dataset dependency, and computational complexity. This research addresses the need for a lightweight, efficient, and automated CNN-based brain tumor detection system.[\[19\]](#)

### **Research Objectives:**

1. Develop an optimized Lightweight CNN model for classifying brain tumors into four categories: glioma, meningioma, pituitary tumor, and normal.
2. Apply advanced preprocessing techniques, including data augmentation, resizing, and normalization, to improve dataset variability and model performance.
3. Evaluate the proposed model using metrics such as accuracy, precision, recall, and F1-score.
4. Address overfitting and improving generalization using regularization and augmentation.

5. Compare the proposed lightweight CNN with standard CNN architectures.
6. Create a practical model for real-time clinical integration to assist radiologists in decision-making.

### **Contributions**

The key contributions of this work include:

1. **Development of a Lightweight CNN Model**

- A novel, computationally efficient CNN architecture tailored for MRI brain tumor classification.

2. **Enhanced Data Preprocessing**

- Application of augmentation, normalization, and resizing to improve performance.

3. **High Accuracy and Robustness**

- Achieves competitive accuracy while addressing overfitting and ensuring generalization.

4. **Comparative Analysis**

- Performance evaluation against standard CNN-based models.

5. **Clinical Applicability**

- Design of an efficient system for real-time clinical deployment.

### **Thesis Structure**

The remainder of this thesis is organized as follows:

- **Section 2: Literature Review**

This section briefly reviews techniques for brain tumor detection using MRI images, with **Convolutional Neural Networks (CNNs)** like ResNet, DenseNet, and VGG16 being widely used for their feature extraction capabilities, despite challenges like **overfitting** and **high computational demands**.

- **Section 3: Related Work**

- A comprehensive review of existing research on brain tumor detection using deep learning techniques, with a focus on CNNs and related methods. The section discusses the strengths and limitations of previous approaches and identifies the research gaps addressed in this thesis.

- **Section 4: Methodology**

This section presents the proposed approach for brain tumor detection. It includes:

- **Dataset Description:** Overview of the MRI dataset used, including data classes and structure.
- **Preprocessing Techniques:** Details on image preprocessing methods such as resizing, normalization, and data augmentation.

- **Proposed CNN Model:** The architecture, layers, and hyperparameters of the CNN.
  - **Model Training and Evaluation:** Description of the training process, loss function, optimizer, and evaluation metrics.
- **Section 5: Results and Discussion**  
The experimental results of the proposed model are presented in this section. Key performance metrics such as accuracy, precision, recall, F1-score, and the confusion matrix are discussed in detail. Comparative analysis with existing models is also provided to validate the effectiveness of the proposed approach.
- **Section 6: Conclusion and Future Work**  
This section summarizes the findings of the study, highlighting the significance and contributions of the proposed model. It also discusses limitations and outlines directions for future research, such as integrating hybrid deep learning models and expanding datasets for better generalization.
- **References**  
A list of all cited references, formatted according to the required citation style.

## II. Literature Review

This section outlines the evolution of brain tumor detection methods using **deep learning techniques**, particularly **Convolutional Neural Networks (CNNs)**, which have shown remarkable success in **extracting spatial features** from MRI images for precise tumor classification. CNNs, such as **AlexNet**, **VGG**, **ResNet**, and **DenseNet**, have significantly contributed to automating tumor detection and segmentation tasks. These architectures utilize **convolutional layers** to identify complex patterns, enabling accurate classification of brain tumor types, such as **glioma**, **meningioma**, and **pituitary tumors**.

Despite their effectiveness, several challenges persist:

1. **Limited labeled datasets:** Acquiring annotated MRI datasets requires extensive time and expertise from radiologists, resulting in smaller datasets that hinder model generalization.
2. **Computational inefficiency:** Standard CNN architectures are computationally intensive, making them unsuitable for real-time applications, particularly in clinical environments with resource constraints.
3. **Overfitting:** Small datasets often lead to models learning noise instead of meaningful patterns, reducing performance on unseen data.

To address these issues, **three primary approaches** have emerged:

- **Transformer-Based Models:** Recent advancements, such as **Swin Transformers** ([1], [4]), achieve superior accuracy through **self-attention mechanisms** that capture both **local and global features**. These models excel in feature representation, particularly for complex and high-resolution MRI images. However,

their **high computational cost** and **memory requirements** restrict real-time deployment, limiting their practicality for clinical use.

- **CNN Architectures:** Methods employing **ResNet** and **DenseNet** ([2], [3]) leverage deeper layers to extract hierarchical features, improving classification accuracy. However, these models often rely on **pre-trained weights** through transfer learning, which may not fully adapt to domain-specific nuances of brain MRI data. Additionally, class imbalance in datasets can lead to biased predictions, particularly for underrepresented tumor classes.
- **Hybrid Approaches:** Techniques like **CNN-SVM hybrids** ([5]) combine the feature extraction capabilities of CNNs with traditional classifiers, such as **Support Vector Machines (SVMs)**, to mitigate overfitting and improve robustness. While promising, these approaches face challenges with **generalization** when applied to small or diverse datasets, limiting their scalability.

**next studies** ([1–5]) reveal persistent research gaps:

- Transformer-based models offer excellent performance but are **computationally expensive**.
- Traditional CNNs require **extensive fine-tuning** and fail to address issues like class imbalance without augmentation.
- Hybrid models attempt to address overfitting but often struggle with **generalizability** across varied datasets.

From this review (detailed in **Chapter 3: Related Works**), the need for a **lightweight, robust CNN** is evident. A model that:

1. Optimizes **computational efficiency** for real-time deployment,
2. Effectively handles **small datasets** through advanced **preprocessing** and **regularization**, and
3. Maintains **high accuracy** comparable to transformer-based methods while **reducing complexity** remains unaddressed.

This research bridges the gap by proposing a **Lightweight CNN model** specifically designed for brain tumor detection in MRI images. By incorporating **data augmentation**, **normalization**, and an **optimized architecture**, the model achieves a balance between **accuracy**, **robustness**, and **computational efficiency**, enabling its use in real-world clinical applications.

### III. Related Works

Recent advancements in **deep learning** and **transformer-based architecture** have significantly enhanced the accuracy of brain tumor classification using MRI images. However, achieving a balance between **accuracy** and **computational efficiency** remains a challenge. Several studies have explored different models and preprocessing techniques to improve performance. This section reviews the most prominent studies in this domain and compares their outcomes with the proposed **lightweight CNN models**.

**AlMohimeed et al. [1]** applied **Swin Transformers** combined with deep learning techniques to classify brain tumor sizes in MRI scans. The authors employed preprocessing techniques such as **flipping, rotation, and normalization** to standardize the input data and enhance the model's performance. The **Swin Transformer demonstrated an impressive accuracy of 97.4%**, outperforming traditional CNN-based models in handling complex tumor images. However, the study highlighted the **significant computational cost** associated with transformer-based architectures, which limits their application in **real-time clinical settings**.

**Nayak et al. [2]** explored the use of **ResNet50** and **VGG16** architectures for brain tumor classification. To address **class imbalance issues**, **data augmentation** and **weight loss functions** were implemented, ensuring that the models were effectively learned from underrepresented classes. The results revealed that **ResNet50 achieved a higher accuracy of 91.2%**, whereas **VGG16 reported a slightly lower accuracy of 88.5%**. This outcome underscores the strength of **deeper networks** like ResNet50 in extracting hierarchical features, while VGG16 faced limitations in capturing **deeper representations** due to its relatively shallow architecture.

**Ali et al. [3]** utilized **transfer learning** with pre-trained models such as **ResNet, DenseNet, and InceptionV3** to classify brain tumors in MRI datasets. By fine-tuning these models and incorporating **data augmentation techniques**, the study effectively addressed the challenges posed by **limited datasets**. Among the tested architectures, **ResNet achieved the highest accuracy of 93.5%**, while **DenseNet** and **InceptionV3** recorded accuracies of **92.8%** and **90.7%**, respectively. Although **transfer learning** demonstrated its advantages in enhancing classification performance, the study noted that **reliance on pre-trained models** limits the customization required for **domain-specific tasks**.

**Wang et al. [4]** introduced a **Swin Transformer-based model** for brain tumor detection, leveraging **attention mechanisms** to capture both **local and global features** effectively. Preprocessing methods such as **resizing** and **normalization** were applied to standardize the MRI data. The **Swin Transformer achieved state-of-the-art accuracy of 98.1%** and a **Dice coefficient of 0.95**, surpassing other deep learning approaches. However, similar to AlMohimeed et al., the **computational cost** associated with the transformer-based models was identified as a limitation, making them less suitable for **real-time deployment in clinical environments**.

**Kumar et al. [5]** proposed a **hybrid approach** combining **convolutional neural networks (CNN)** for **deep feature extraction** and **Support Vector Machines (SVM)** for classification. To mitigate the risk of **overfitting** on small datasets, the authors employed **regularization techniques** and **data augmentation**. The **hybrid CNN-SVM model achieved a competitive accuracy of 93.0%**, showcasing its potential for brain tumor classification. However, the

study acknowledged challenges related to the **generalizability** of the model due to **dataset limitations**.

**Contributions to our Work**

While existing methods have shown promising results, challenges remain in balancing **accuracy, computational efficiency, and generalizability**:

- 1. **High Computational Cost:** Transformer models achieve superior accuracy but are resource intensive.
- 2. **Overfitting:** Small datasets lead to overfitting in CNN-based and hybrid models.
- 3. **Limited Customization:** Transfer learning relies on pre-trained models, reducing adaptability.

To address these limitations, this study proposes a **lightweight CNN-based model** that:

- Incorporates advanced **preprocessing techniques** such as augmentation, resizing, and normalization to improve robustness.
- Mitigates overfitting through **regularization strategies** and optimized architecture design.
- Balances **accuracy and computational efficiency**, enabling practical deployment in real-time clinical applications.

**Comparison of Related Studies and Proposed Work**

| Study                 | Model/Technique  | Preprocessing                     | Accuracy (%)    | Limitations                                 | Our Proposed Work                                                                                 |
|-----------------------|------------------|-----------------------------------|-----------------|---------------------------------------------|---------------------------------------------------------------------------------------------------|
| AlMohimeed et al. [1] | Swin Transformer | Flipping, rotation, normalization | 97.4            | High computational cost.                    | <b>Lightweight CNN:</b><br>Reduces computational overhead while maintaining performance.          |
| Nayak et al. [2]      | ResNet50, VGG16  | Data augmentation, weighted loss  | 91.2 (ResNet50) | Class imbalance; shallow features in VGG16. | <b>Lightweight CNN:</b><br>Handles class imbalance more effectively and extracts deeper features. |

|                   |                                                   |                                         |                           |                                                                     |                                                                                                      |
|-------------------|---------------------------------------------------|-----------------------------------------|---------------------------|---------------------------------------------------------------------|------------------------------------------------------------------------------------------------------|
| Ali et al. [3]    | Transfer learning (ResNet, DenseNet, InceptionV3) | Data augmentation, fine-tuning          | 93.5 (ResNet)             | Reliance on pre-trained models.                                     | Lightweight CNN: Custom-built architecture tailored for MRI images without reliance on pre-training. |
| Wang et al. [4]   | Swin Transformer                                  | Resizing, normalization                 | 98.1                      | High computational cost.                                            | Lightweight CNN: Optimized for real-time clinical applications with reduced complexity.              |
| Kumar et al. [5]  | Hybrid CNN-SVM                                    | Regularization, data augmentation       | 93.0                      | Limited generalizability on small datasets.                         | Lightweight CNN: Enhances generalizability through robust regularization and augmentation.           |
| Our Proposed Work | Lightweight CNN Models                            | Enhanced augmentation, optimized layers | Target Accuracy: ~95%-98% | Optimized for efficiency, real-time processing, and small datasets. | Balances accuracy, efficiency, and robustness for clinical applications.                             |

Key Advantages of our Proposed Work:

- Efficiency:** Our lightweight CNN models reduce computational cost, making them suitable for **real-time clinical environments**.
- Robustness:** By incorporating advanced **data augmentation** and **regularization** techniques, your models perform well on small or imbalanced datasets.[15]
- Customization:** Unlike transfer learning approaches, our models are **tailored specifically for brain tumor detection** using MRI images.
- Accuracy:** Achieves competitive performance (targeting 95%-98%) while being computationally efficient.