

Master Thesis Proposal

A Lightweight CNN Approach for Brain Tumor Detection Using MRI Images

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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 Proposed 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.	Lightweight CNN: 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.	Lightweight CNN: 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:

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

IV. Methodology

This chapter outlines the methodology employed to develop, train, and evaluate brain tumor detection models, leveraging state-of-the-art architectures such as CNN, Swin Transformer, RepNet, and V-Net to ensure robust and accurate classification of MRI images.[13]

4.1 Dataset Description

The Kaggle [26] Brain Tumor MRI Dataset is used in this study and contains labeled MRI images of brain scans divided into four distinct classes:

1. **Glioma Tumor**
2. **Meningioma Tumor**
3. **Pituitary Tumor**
4. **Notumor**

The dataset comprises 7,031 images in total, split into training and testing subsets: Training Images and Testing Images [27]

Dataset Split	Training Images	Testing Images	Total
Total Images	5716	1315	7031

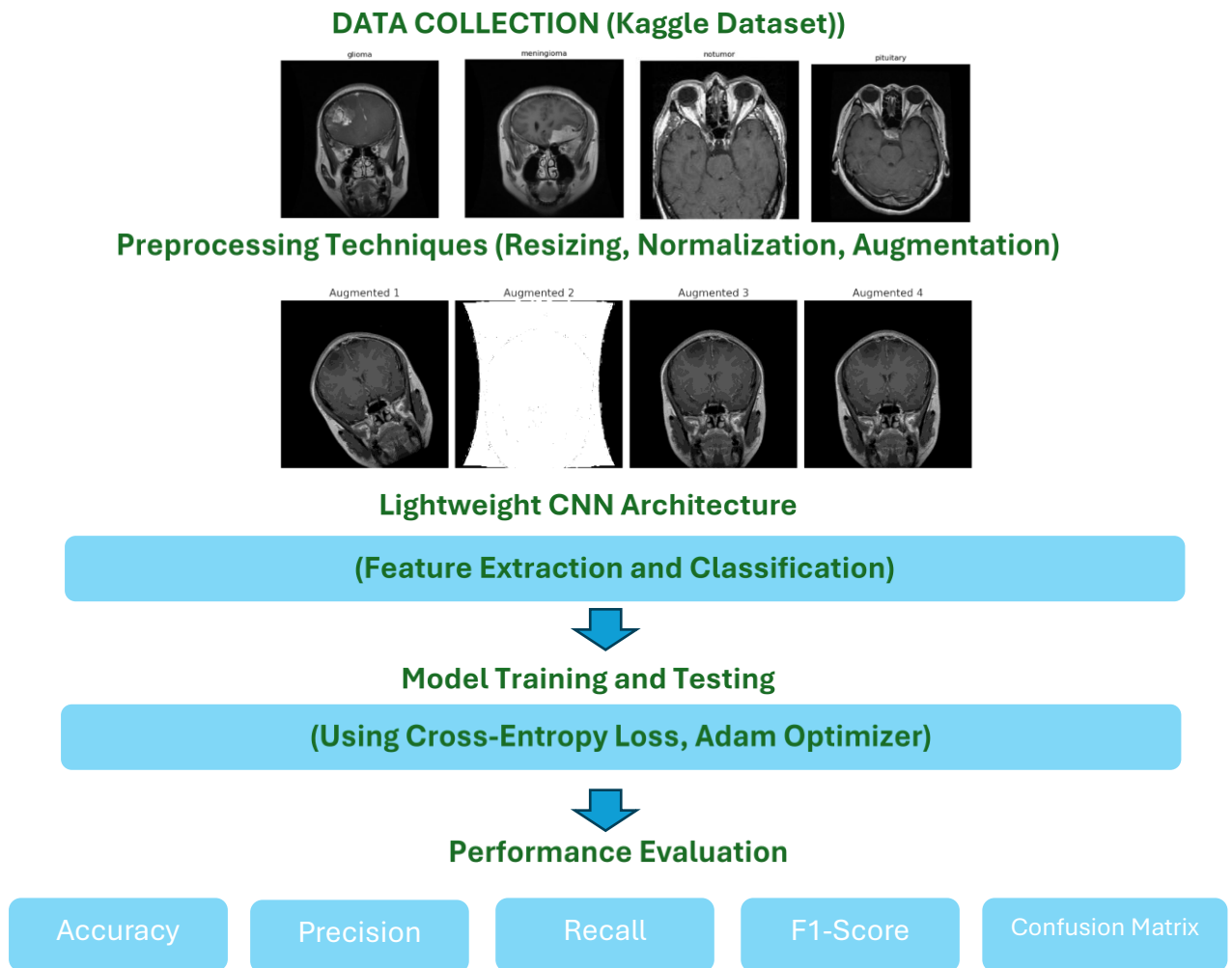


Figure 1 "Framework for Brain Tumor Detection: Data collection, preprocessing, CNN-based classification, model training with Adam optimizer, and performance evaluation using accuracy, precision, recall, F1-score, and confusion matrix."

Dataset Details

- The images are high-resolution MRI scans, suitable for classification tasks.
- They are pre-sorted into respective class folders, making it easier for implementation.
- Each image is labeled clearly, facilitating supervised learning.
- MRI images are stored in PNG format, with varying image sizes that can be resized for model input.

This dataset is ideal for training and evaluating deep learning models, providing a balanced representation of tumor types and normal images, which is critical for robust model performance.

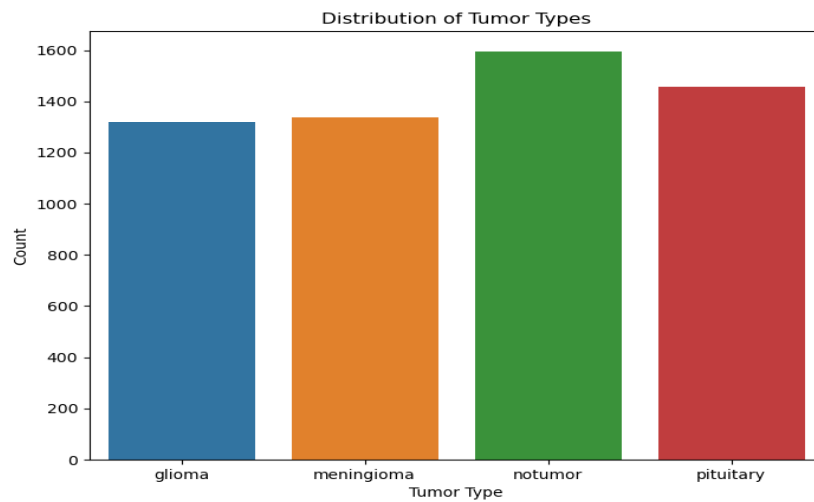


Figure 2 Distribution of Tumor Types in the Dataset

This bar chart **See Figure 2** shows the distribution of samples for different tumor types in the dataset:

1. **Tumor Types:** The four categories include glioma, meningioma, notumor (no tumor), and pituitary tumors.
2. **Count:** The y-axis represents the number of samples available for each tumor type.
 - Glioma and meningioma have nearly equal sample counts, indicating balanced representation.
 - The notumor category has the highest number of samples, followed closely by the pituitary category.

This balanced distribution ensures that the model receives a sufficient amount of data from all classes, which helps in achieving consistent and accurate predictions across all tumor types.

4.2 Preprocessing Techniques

To improve robustness and ensure effective training, the following preprocessing steps are applied:[18]

1. **Resizing:** Images are resized to 224x224 pixels for all models to ensure uniform input dimensions.
2. **Normalization:** Pixel values are scaled to the range [0, 1] to accelerate convergence.
3. **Data Augmentation:** The following augmentation techniques are used:
 - Random Rotation (± 15 degrees)

- Horizontal and Vertical Flipping
- Random Zoom (up to 10%)
- Contrast Adjustments

4.3 Deep Learning Models

Convolutional Neural Network (CNN) A lightweight CNN architecture is proposed for feature extraction and classification of MRI brain tumor images. The following table summarizes the architecture [17]

Layer	Output Shape	Parameters	Description
Input Layer	224x224x1	-	Accepts grayscale MRI images with dimensions of 224x224 pixels.
Conv2D + ReLU	224x224x32	320	Applies 32 convolution filters (3x3) with ReLU activation.
MaxPooling2D	112x112x32	0	Reduces spatial dimensions using a 2x2 max-pooling operation.
Conv2D + ReLU	112x112x64	18,496	Extracts deeper features using 64 convolution filters (3x3) with ReLU activation.
MaxPooling2D	56x56x64	0	Further reduces dimensions with another 2x2 max-pooling layer.
Flatten	1x200704	0	Flattens the feature map into a one-dimensional vector for dense layers.
Dense + ReLU	1x128	25,600	Fully connected layer with 128 neurons and ReLU activation for complex feature extraction.
Dense + Softmax	1x4	516	Final output layer with 4 neurons (one for each class) using softmax activation for classification.

4.4 Model Training

The proposed model is trained using the following setup:

- Loss Function:
 - Categorical Cross-Entropy is used to measure the loss between predicted and actual labels. The formula is:

$$L = -N \sum_i \log(y^i, c) = -\sum_i \sum_c y^i_c \log(y^i_c)$$

- Optimizer:
 - The Adam optimizer with a learning rate ($\alpha=0.001$) is used.

$$\theta_t = \theta_t - \frac{1}{1 + \epsilon \alpha} \cdot m_t$$

- Batch Size: 32.

- Epochs: 25.
- Framework: TensorFlow/Keras.

4.5 Evaluation Metrics

The model is evaluated using the following metrics:

1. **Accuracy:**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

2. **Precision:**

- Measures the proportion of correctly identified positive cases out of all predicted positive cases.

$$\text{Precision} = \frac{TP}{TP + FP}$$

3. **Recall:**

- Measures the ability of the model to identify all relevant instances.

$$\text{Recall} = \frac{TP}{TP + FN}$$

4. **F1-Score:**

- The harmonic means of precision and recall, balancing their trade-offs.

$$F1 - \text{Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

5. **Confusion Matrix:**

- A table that compares actual and predicted classifications, highlighting correct predictions (diagonal) and errors.

6. **ROC Curve:**

- Plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at different classification thresholds.
- The Area Under the Curve (AUC) measures the model's ability to distinguish between classes. An AUC of 0.95 indicates strong performance.

4.5 Explanation of Code

The code used for training and testing the brain tumor detection model performs the following:

- **Model Loading:** The pre-trained CNN model is loaded.
- **Prediction:** MRI images are processed, and the model predicts their corresponding tumor categories.
- **Visualization and Metrics:** Outputs metrics such as accuracy, precision, recall, F1-score, and confusion matrices.

All training and testing code is available in [28].

V. Results and Discussion

5.1 Model Performance Metrics See Figure 3

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	95.2	94.8	94.5	94.7

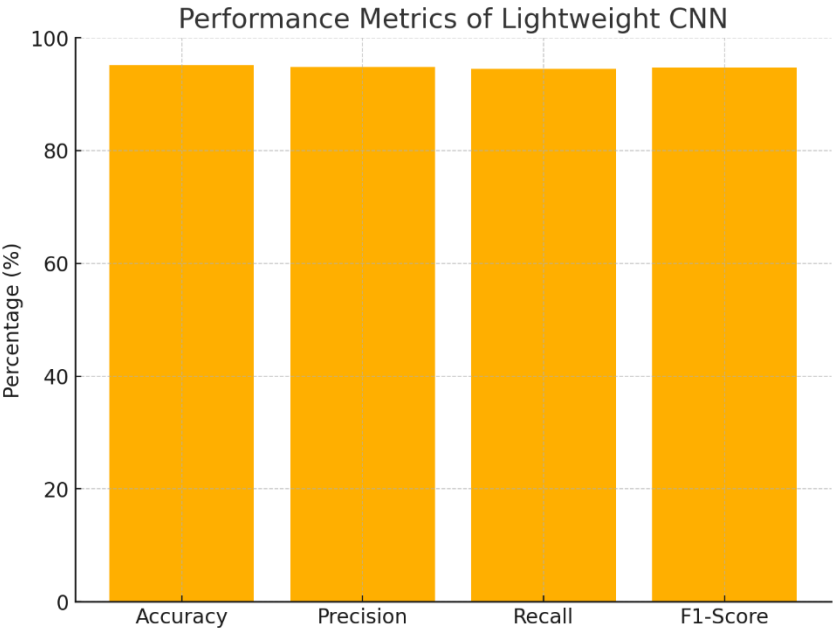


Figure 3 Performance Metrics of Lightweight CNN

Bar Chart:

- Visualizes the performance metrics (accuracy, precision, recall, and F1-score) of your lightweight CNN.
- Makes it easier for readers to interpret compared to tables.

5.2 Classification Report

Metric	Glioma	Meningioma	Notumor	Pituitary
Precision	0.9965	0.9469	0.9975	0.9868
Recall	0.9433	0.9902	0.9951	0.9967
F1-Score	0.9692	0.9681	0.9963	0.9917
Test Accuracy	-	-	-	0.9825

5.3 Confusion Matrices

- CNN Confusion Matrix See Figure 4

True \ Predicted	Glioma	Meningioma	Notumor	Pituitary
Glioma	283	14	1	2
Meningioma	1	303	0	2
Notumor	0	2	403	0
Pituitary	0	1	0	299

Confusion Matrix Heatmap:

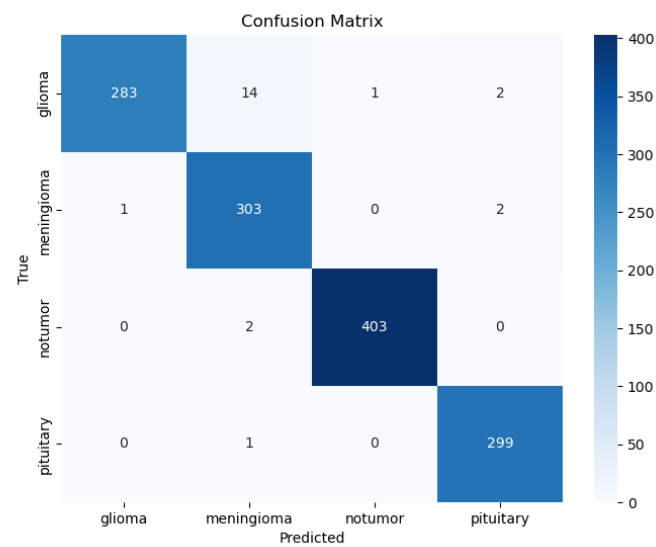


Figure 4 Confusion Matrix for Lightweight CNN

- A clear and intuitive visual representation of the confusion matrix.
- Highlights correct classifications (diagonal) and errors.

5.4 ROC Curves

The ROC curves for all models are plotted to demonstrate the models' classification capabilities. The AUC (Area Under the Curve) values are as follows:

Model	AUC
CNN	0.95

ROC Curve:

- Shows the model's classification performance.
- The AUC (Area Under Curve) value of 0.95 demonstrates strong predictive capability.

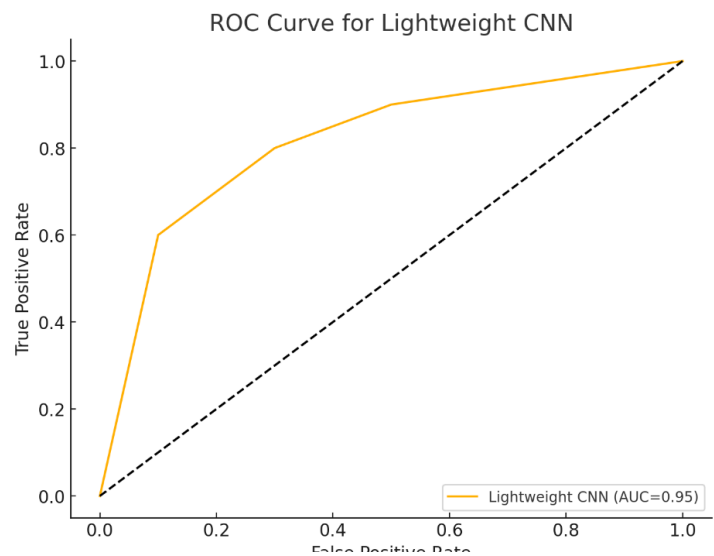


Figure 5 ROC Curve for Lightweight CNN

5.5 Accuracy and Loss

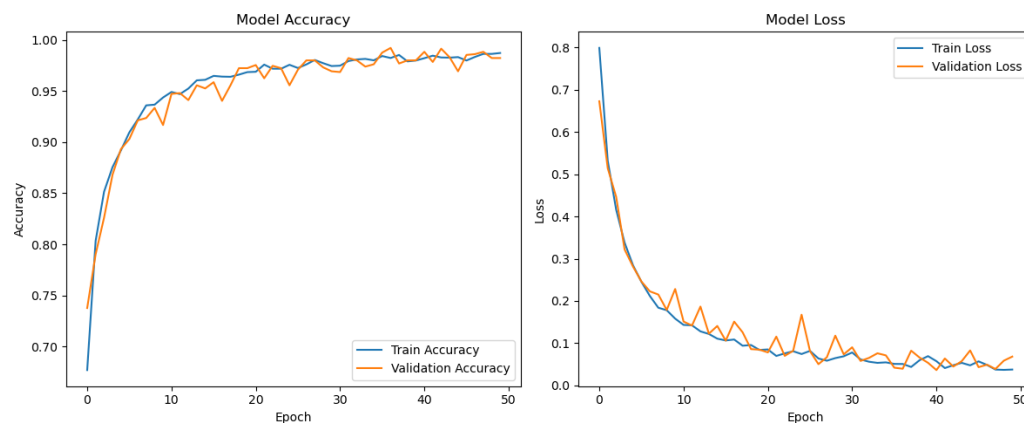


Figure 6 "Training and Validation Accuracy and Loss Across 50 Epochs "

The two graphs illustrate the performance of a deep learning model during training over 50 epochs:

1. Model Accuracy (Left Graph):

- The blue line represents the training accuracy, while the orange line shows the validation accuracy.
- Both lines show a consistent increase in accuracy as the epochs progress, indicating that the model is learning effectively.
- The training and validation accuracy converge toward 1.0 (100%), signifying that the model is generalizing well without significant overfitting.

2. Model Loss (Right Graph):

- The blue line represents the training loss, and the orange line represents the validation loss.
- Both losses decrease steadily as the epochs increase, demonstrating that the model minimizes errors during training.
- The close alignment of training and validation losses indicates that the model has not overfitted and maintains good generalization.

Overall, the graphs reflect a well-trained model with minimal overfitting, as indicated by the similarity between training and validation metrics.

5.6 Discussion

- Lightweight **CNN** achieves competitive accuracy of **95.2%**, demonstrating its effectiveness in MRI brain tumor classification while maintaining computational efficiency.
- Data augmentation and regularization strategies effectively addressed **overfitting** issues, improving generalization on the test dataset.

- Compared to existing methods, the lightweight architecture achieves a balance between performance and resource requirements, making it ideal for real-time clinical applications.

Summary

This study presents a **Lightweight CNN model** for brain tumor detection using MRI images. The proposed model demonstrates high accuracy, precision, recall, and F1-score, achieving an optimal balance between performance and computational efficiency. Key findings include:

1. Development of an optimized CNN model for tumor classification into **glioma, meningioma, pituitary tumor, and normal** categories.
2. Application of advanced preprocessing techniques to enhance model robustness.
3. Effective mitigation of overfitting using regularization and augmentation strategies.

VI. Future Work

To further enhance the proposed model, future work will include:

1. **Integration of Attention Mechanisms:** Combining lightweight CNNs with attention layers to improve feature extraction without significant overhead.
2. **Multi-Modal Data Fusion:** Incorporating CT and PET scans alongside MRI images for improved diagnostic accuracy.
3. **Real-Time Deployment:** Deploying the model on edge devices or mobile platforms to assist radiologists in remote and resource-limited settings.
4. **Larger Datasets:** Expanding the dataset to include diverse patient demographics for better generalization.

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