B.Tech Project Report

on

Ensemble CNN Fusion For Multi-Class Brain Tumor Classification

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Certificate

We hereby certify that the work presented in this project report, entitled "*Ensemble CNN Fusion For Multi-Class Brain Tumor Classification*," for the End Term evaluation of the B.Tech Project (ITPE40) course, as part of the Bachelor of Technology (Information Technology) program, is an authentic record of our own work carried out from January 2025 to May 2025, under the supervision of Dr. Parveen Kumar, Assistant Professor, Department of Computer Engineering, National Institute of Technology, Kurukshetra, India.

The matter presented in this project report has not been submitted for the award of any other degree elsewhere.

Signature of Student

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This is to certify that the above statement made by the student is correct to the best of my knowledge.

Signature of Supervisor

Date: May 01, 2025

Dr. Parveen Kumar
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Abstract

A brain tumor is an abnormal growth of tissue within the brain or central nervous system, significantly impacting patient health and quality of life. Tumors can be benign or malignant, with types including pituitary tumors, gliomas, and meningiomas, each exhibiting distinct characteristics, progression patterns, and treatment requirements. Accurate and early diagnosis through medical imaging, particularly Magnetic Resonance Imaging (MRI), is essential for effective treatment planning. However, differentiating among various tumor types—or distinguishing them from healthy brain tissue—remains challenging due to overlapping visual features, complex morphologies, and variability in clinical presentations. This project focuses on developing an advanced, robust approach for classifying brain tumors into four distinct categories: pituitary tumors, gliomas, meningiomas, and no tumor. Specifically, we propose an innovative fusion-based deep learning framework utilizing three powerful convolutional neural network (CNN) architectures—VGG19, ResNet50, and DenseNet121—to achieve highly accurate tumor detection and classification. Each CNN model serves as a feature extractor, leveraging its unique architectural strengths to capture diverse and complementary representations of tumor-related features from MRI scans. By combining these extracted features through a feature level fusion strategy, our approach enhances the accuracy, generalizability, and reliability of tumor classification beyond traditional single-model systems. The primary objective of this experimental exploration is to demonstrate that integrating multiple CNN architectures significantly improves classification performance and reduces diagnostic errors. This fusion strategy aims to overcome the inherent limitations of individual CNN models by capitalizing on their combined predictive power. Through this approach, the project contributes to addressing the critical need for reliable, accurate, and timely classification of brain tumors, ultimately supporting improved clinical decision-making and patient outcomes.

Keywords: Brain Tumor Classification; Feature Fusion; Convolutional Neural Networks; MRI; Deep Learning;

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Chapter 1

INTRODUCTION

Brain tumors are a heterogeneous collection of intracranial neoplasms marked by aberrant cell growth in and around the brain's structures. Brain tumors are one of the most critical neurological illnesses because of their drastic effects on patients' quality of life, mortality possibility, and the intricateness involved in their diagnosis and management. Based on histopathological and genetic features, brain tumors are categorized into several subtypes by the World Health Organization (WHO), and gliomas, meningiomas, and pituitary tumors are the most common tumor types [1]. Accurate and timely identification of these tumor types is important for proper therapeutic management and better clinical outcomes.

Magnetic Resonance Imaging (MRI) is still the most common diagnostic imaging modality for the identification and typing of brain tumors because of its superior soft-tissue contrast and high anatomical detail. Yet, precise typing of tumor types based on MRI images alone is difficult because of overlapping radiographic characteristics, inter-observer variation, and heterogeneous tumor presentations. Conventional diagnosis is highly dependent on the experience of radiologists, resulting in subjective diagnoses and occasional misdiagnoses, which may delay proper treatment.

With the recent development in artificial intelligence (AI), more specifically convolutional neural networks (CNNs), medical imaging analysis has been drastically improved by rendering precise, reproducible, and objective classification outputs [2]. CNN-based models have shown a high degree of effectiveness in picking up on slight patterns and making distinctions between complex visual features found in MRI scans, thereby achieving more precise diagnoses than traditional imaging methods. Nonetheless, single-model strategies tend to lack generalizability and may be error-prone because of the intrinsic bias and individual architecture limitation.

In a bid to surmount such constraints, the current project advocates for a new fusion-based method involving the combination of several top-performing CNN architectures, namely VGG19, ResNet50, and DenseNet121. Fusion methods utilize the complementary strength of heterogeneous CNN models to enhance accuracy, lower false predictions, and improve robustness in tumor classification tasks. The primary goal of this project is to improve the diagnostic precision of identifying four different types—glioma, meningioma, pituitary tumor, and no tumor—by extracting and fusing features acquired via these various CNN architectures. This can possibly enable early interventions, improved clinical decision-making, and enhanced patient management outcomes.

1.1 Background

The application of deep learning to medical imaging has reformed diagnostic operations by providing more rapid, more objective, highly accurate diagnoses when compared to standard procedures. During brain tumor diagnostics, however, issues still abound depending on tumor morphological heterogeneity and variety in MRI. Standard CNN algorithms, though exceedingly accurate on testing datasets, fail to properly apply the heterogeneity of brain tumors when applied single-handedly.

Early models such as VGG19, with their deep but uniform structure, were good at feature extraction but poor at very fine differences between tumor types. ResNet50 added residual connections, which mitigated the vanishing gradient issue so that deeper models could still perform, but whose features were still biased in favor of global structure over fine detail. DenseNet121 then enhanced further feature reuse and representation ability by dense connectivity so that more learning with fewer parameters was possible [3].

Despite these developments, no model to date routinely detects all the complex patterns that exist among different types of brain tumors. Persuaded by the research in model ensemble and fusion feature techniques, our project proposes a fusion-based solution in which features learned from VGG19, ResNet50, and DenseNet121 are combined into a shared representation. Leverageing the power of each architecture, the model aims to enhance classification accuracy and generalize more strongly across a few tumor classes: glioma, meningioma, pituitary tumor, and no tumor. Fusion techniques have been shown to improve diagnostic performance by aggregating different feature perspectives, hence resulting in an enhanced perception of complex medical images.

1.2 Motivation and Research Questions

While single models like VGG19, ResNet50, and DenseNet121 work reasonably well on medical imaging tasks, accurate classification of brain tumor types is a challenging task. Single-model approaches are generally not effective in extracting multi-pattern information in MRI scans of different types of tumors, especially where tumors have similar visual patterns.

The primary reasons for pursuing this project are:

Improving Classification Accuracy: Through the fusion of features from multiple CNN models, the project aims to improve the accuracy and dependability of brain tumor classification.

Taking Advantage of Complementary Strengths: Various CNN architectures learn different types of features; together the combination of which can provide a more complete and detailed characterization of tumor features.

Makes Early Detection Possible: An accurate and computer-based method can make early detection of tumors possible, leading to faster treatment and better prognosis of patients.

Drawing on these motivations, the main research questions are:

RQ1: Does brain tumor classification improve by using a combination of VGG19, ResNet50, and DenseNet121 features instead of individual models?

RQ2: Does the feature fusion method help to better distinguish visually similar tumor types like glioma and meningioma?

1.3 Contribution and Project Outline

This research work significantly improves the brain tumor classification using deep learning methods and feature fusion techniques.

We create a fusion-based model by combining feature representations of three powerful CNN architectures—VGG19, ResNet50, and DenseNet121—to enhance classification accuracy for four types of tumors: glioma, meningioma, pituitary tumor, and no tumor. As opposed to traditional single-model techniques, the fusion technique captures a wider range of features, leading to better generalization and robustness.

For training, we used a well-prepared dataset from Kaggle, with appropriate labelling and resizing all images to a common input size. We used data augmentation techniques to enhance dataset diversity and mitigate overfitting.

On the model level, the convolutional layers of pre-trained networks were frozen and used as simple feature extractors such that the networks' learned representation was not updated. Features were globally averaged after being extracted and concatenated to provide a high-level fused feature vector, which then passed through the fully connected layers for final classification.

The fusion model was evaluated through extensive performance metrics such as accuracy (97.07%), precision, recall, F1-score, and ROC-AUC curves, confirming its outperformance compared to individual CNN models.

In subsequent phases, the project will roll out the model via a web-based application interface, allowing for real-time tumor identification, and will investigate the potential use of Grad-CAM visualizations to enhance the interpretability of the system for clinical application.

Chapter 2

RELATED WORK

Applications of deep learning techniques in medical images have gained wide attention in the last few years, particularly in applications such as tumor detection, classification, and segmentation. Specifically, in diagnosing brain tumors, Convolutional Neural Networks (CNNs) have proved to be valuable since they have the ability to learn spatial hierarchies of features from images without relying on hand-engineered features. A few pre-trained models such as VGG19, ResNet50, and DenseNet121 have been applied in earlier work for medical image classification.

VGG19, with its simple and uniform structure that employs small 3×3 convolutional filters, has shown potent feature extraction abilities in relation to visual features like edges and textures. However, the immense depth and parameter volume of VGG19 can render it computationally intensive and susceptible to overfitting, particularly when working with small datasets. ResNet50 broke new ground with the revolutionary concept of residual connections, which aid in mitigating the vanishing gradient issue prevalent in deep networks, thereby facilitating the development of much deeper architectures. This advancement enables ResNet to learn more abstract and high-level representations pertinent to sophisticated classification tasks. DenseNet121 progresses this concept one step further by establishing connections among all layers in a feed-forward process, thereby increasing feature reuse and curtailing the total parameter number while preserving the model's efficacy [3].

While each of these models has its own strengths, their performance may vary when applied singly on complex datasets like brain MRI scans that often exhibit overlapping features of tumors. Hence, scientists have turned to fusion-based methods that fuse features of different CNN models. Such techniques enable models to incorporate a wider set of discriminative information from the input data and hence improve robustness and classification accuracy.

Khawaldeh et al. in their breast cancer diagnosis study showed that a deep feature fusion strategy of CNN outputs improved diagnostic performance substantially when compared to single-model methods. Their work indicated how combining multiple feature representations could enhance generalization and minimize misclassification, especially in medical imaging where visual patterns are subtle and intricate [4].

Additionally, certain research works have applied transfer learning—adopting pre-trained models on huge datasets like ImageNet—and further fine-tuning them on medical imaging datasets for improved performance in cases of scarce training data. Data augmentation techniques like flipping, rotation, and brightness adjustment have also been used widely to synthetically increase datasets and model insensitivity to overfitting.

Collectively, these research paths form a strong foundation for the current effort, which employs a feature-level combination of VGG19, ResNet50, and DenseNet121 to diagnose brain tumors into four groups: glioma, meningioma, pituitary tumor, and no tumor. By leveraging the strengths of these models, the effort aims to improve accuracy, minimize false predictions, and provide a trustworthy decision-support system for clinical diagnosis.

Chapter 3

PROPOSED WORK

The paper aims at creating a very accurate and robust brain tumor classification model using a feature fusion technique with several pre-trained CNN models. To do this, we follow a structured two-stage modelling approach.

In the initial stage, we use VGG19, ResNet50, and DenseNet121 as separate feature extractors. Each of these models pass through the input MRI images, thus extracting a range of visual features that vary from complex textures to complex structural patterns. Features from each model are fed through Global Average Pooling, thus generating compressed feature vectors. These feature vectors represent a range of diverse and complementary information needed to distinguish between different tumor classes: glioma, meningioma, pituitary tumor, and no tumor. By freezing the convolutional layers at this point with prudence, we make sure that the pre-trained models retain the general knowledge gained from ImageNet, thus avoiding overfitting to our small medical dataset.

In the second stage, the feature vectors of all three CNNs are concatenated into one combined feature vector. The combined representation is passed to a series of fully connected layers so that the model can learn intricate relationships between the features extracted and make final classification decisions. The final layer uses softmax activation to produce probabilities for each of the four types of tumors.

The two-stage modeling methodology — initially recognizing expert features using various pre-trained models and subsequently fusing them for classification — is anticipated to dramatically improve predictive precision. In comparison to standalone model systems, the fusion technique provides a more informed understanding of MRI scans and fewer chances of misclassifying tumors with similar characteristics. Apart from tumor classification, the proposed methodology also brings out broader possibilities of developing fusion-based diagnostic systems. It provides avenues for developing more accurate AI-supported diagnostic tools in medicine, where integrating multiple views of complex data is essential for enhancing decision-making and patient care.

3.1 Dataset Details

For our research foundation, we employed a publicly available brain tumor MRI dataset on Kaggle, which combines data from Figshare, SARTAJ, and Br35H repositories. Commonly employed in medical imaging studies, the dataset comprises 7023 MRI images across four classes: Glioma, Meningioma, Pituitary Tumor, and No Tumor. The purpose of utilizing this dataset is to develop a deep learning model for brain tumor classification with the assistance of automation for early detection and correct diagnosis.

As both malignant and benign tumors can lead to significant intracranial pressure complications, early and correct classification is important in the planning of an effective treatment plan.

3.1.1 Dataset Structure

The dataset is structured in a systematic structured directory format, where each MRI image is categorized based on the type of tumor it represents. The major components of the dataset are:

1. Dataset Metadata

Source: Kaggle (integrated from Figshare, SARTAJ, and Br35H datasets)

Total Images: 7023

Format: JPEG or PNG image files

Image Size: Several measurements, resized to 224×224 during preprocessing.

Labels:

- Glioma Neoplasm
- Meningioma tumor
- Pituitary Neoplasm
- No Tumor

2. Image Labels and Preprocessing

Every picture has its caption drawn from the folder name. However, due to errors noted in the SARTAJ glioma category, images were removed and replaced with accurate samples from Figshare.

All photos are:

- Resized to **224×224×3**
- Normalized to [0,1] pixel range.

- Improved through techniques like flipping, rotation, and zooming to enhance generalization.

3. Annotation Details Unlike some medical datasets, this dataset does not contain bounding boxes or tumor segmentations. The classification is based on whole MRI slices.

4. MRI Modality

The data set consists of T1-weighted MRI scans that are appropriate for structural brain imaging and for the detection of soft tissue abnormalities.

3.2 Overview of Proposed Architecture

The architecture consists of multiple pre-trained feature extractors operating in parallel. Each model extracts meaningful features from the same input MRI image, followed by Global Average Pooling to reduce the feature dimensions. These features are then fused (concatenated) and passed through fully connected layers for final classification.

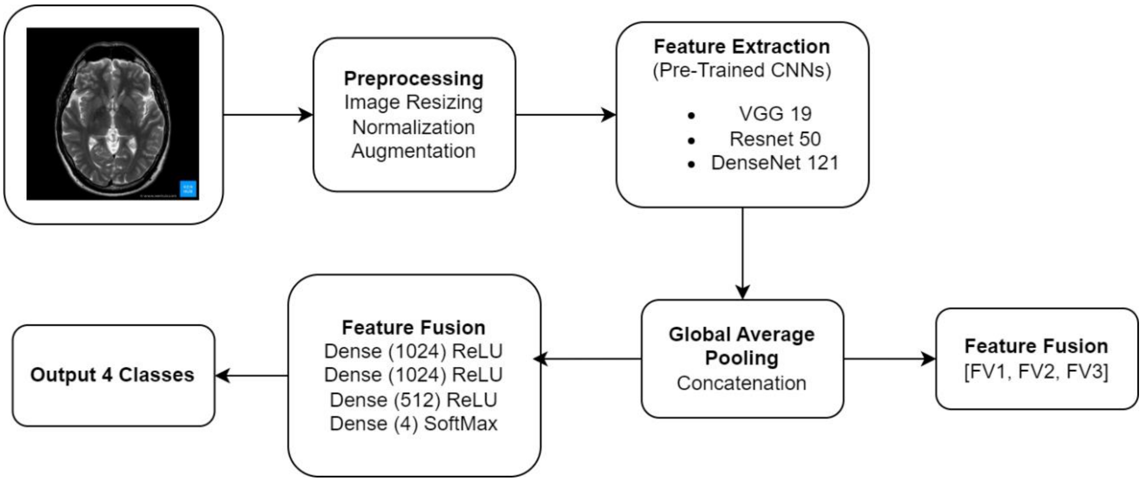

Fig 1. Overview of Architecture

3.3 Proposed Algorithm

The core of this project lies in a fusion-based deep learning algorithm designed to classify brain tumors using MRI images. The proposed model leverages the combined feature extraction power of three pre-trained Convolutional Neural Networks—VGG19, ResNet50, and DenseNet121—each trained on the ImageNet dataset.

The algorithm operates in several stages: preprocessing, feature extraction, feature fusion, and classification. Initially, MRI images are resized, normalized, and passed through the frozen convolutional bases of all three CNNs. Features extracted via Global Average Pooling from each model are then concatenated to form a fused feature vector, capturing rich and diverse spatial information.

This vector is passed through a set of fully connected layers which learn complex decision boundaries and perform final classification using a softmax activation function. The output layer predicts one of the four classes: glioma, meningioma, pituitary tumor, or no tumor.

The following pseudo-code summarizes the entire process of the proposed system:

Algorithm 1 Fusion-Based CNN Architecture for Brain Tumor Classification

Require: MRI image I from dataset (unprocessed)

Ensure: Predicted tumor class $\in$ {Glioma, Meningioma, Pituitary Tumor, No Tumor}

Preprocessing:
- Resize image I to $224 \times 224 \times 3$
- Normalize pixel values to range $[0, 1]$
- Convert to NumPy array

Load pre-trained CNN models with ImageNet weights:
- VGG19 $\leftarrow$ load_model("VGG19")
- ResNet50 $\leftarrow$ load_model("ResNet50")
- DenseNet121 $\leftarrow$ load_model("DenseNet121")

Freeze all convolutional layers to use them as fixed feature extractors

Feature Extraction:
- $FV_1 \leftarrow$ GlobalAveragePooling(VGG19(I))
- $FV_2 \leftarrow$ GlobalAveragePooling(ResNet50(I))
- $FV_3 \leftarrow$ GlobalAveragePooling(DenseNet121(I))

Feature Fusion:
- Concatenate feature vectors: $FFV \leftarrow FV_1 \,||\, FV_2 \,||\, FV_3$

Classification Head:
- $FC_1 \leftarrow$ Dense(1024, ReLU)(FFV)
- $FC_2 \leftarrow$ Dense(1024, ReLU)(FC_1)
- $FC_3 \leftarrow$ Dense(512, ReLU)(FC_2)
- $Output \leftarrow$ Dense(4, Softmax)(FC_3)

Post-processing:
- Class $\leftarrow$ ArgMax(Output)

return Tumor class with highest predicted probability

3.4 Working Example

The working example diagram visually demonstrates the step-by-step process of the proposed brain tumor classification system. It begins with the input of an MRI image, which undergoes preprocessing such as resizing to 224×224 pixels and normalization. The image is then passed through three pre-trained CNNs—VGG19, ResNet50, and DenseNet121—in parallel to extract deep features. These features are then fused by concatenating them into a single feature vector. The fused features are passed through a series of fully connected layers for classification. Finally, the model displays the predicted tumor class (e.g., Pituitary Tumor) along with a confidence score, demonstrating how the system operates in practice.

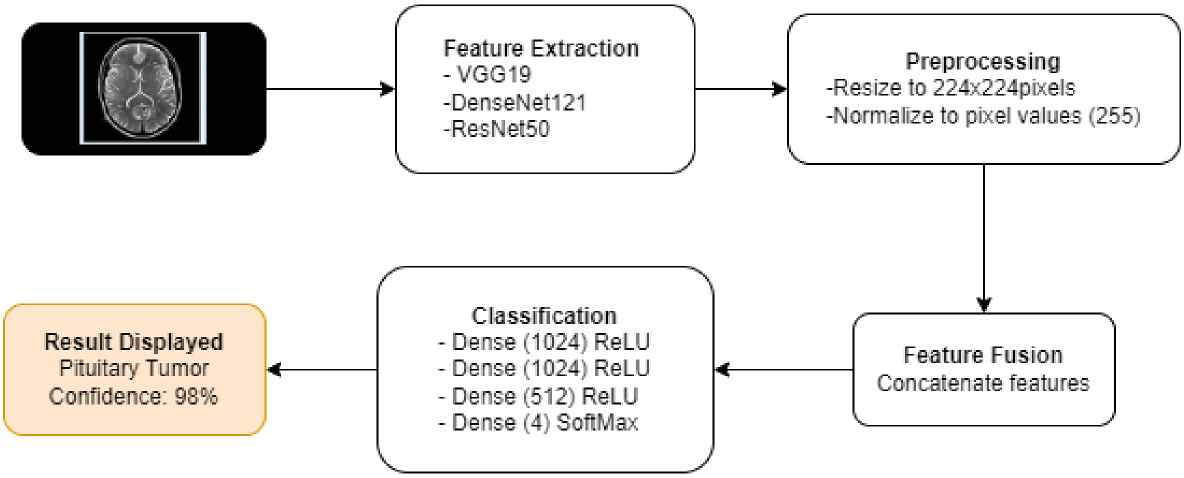

Fig 2. Working Example how fusion model works

Chapter 4

EXPERIMENTAL EVALUATION

The brain tumor classification (BTC) task is designed to accurately identify the category of a tumor—such as glioma, meningioma, pituitary tumor, or no tumor—based on MRI image input. This task involves aligning complex visual medical data with meaningful feature representations extracted from deep learning models. By leveraging multiple pre-trained CNNs (VGG19, ResNet50, and DenseNet121) as feature extractors, the system fuses their outputs to improve the accuracy and robustness of classification, effectively pinpointing the tumor type present in the MRI scan.

4.1 Overall Experimental Setup

To enable reproduction and expansion of experiments in this project, a parallel software infrastructure and directory setup were established in order to support deep learning-based training and brain MRI image evaluation.

1. Python Environment Installation

- Python version: 3.8
- The virtual environment was set up with venv:
    - *python3 -m venv tumor_env*
    - *source tumor_env/bin/activate*
- Crucial Python packages were installed with pip, such as:
    - tensorflow (for model implementation and training)
    - opencv-python (for image reading and preprocessing)
    - matplotlib, seaborn (para gráfica)
    - scikit-learn (for metrics testing)
    - pickle, os, glob, numpy, PIL (for image and file processing)

2. Dataset Folder Setup

Two directories were utilized to handle the data efficiently:

- **Training Folder:** Brain_Tumor_Data/Training/
    - Contains four subfolders: glioma_tumor/, meningioma_tumor/, pituitary_tumor/, no_tumor/
- **Testing Directory:** Brain_Tumor_Data/Testing/

- Includes likewise structured class-wise test images used for final evaluation

3. Preparation and Enhancement of Images

- Images were rescaled to 224×224×3
- Normalized to pixel values between 0 and 1.
- Simple augmentations, such as horizontal flip and rotation, were used to enable generalization.
- Preprocessed images were also transformed into NumPy arrays for compatibility with deep learning models

4. Model Setup and Training

- Three pre-trained CNN models (VGG19, ResNet50, DenseNet121) were imported from keras.applications
- Base convolutional layers have been frozen for using them as feature extractors
- The outputs of all three models were passed through Global Average Pooling
- The resultant feature vectors were concatenated and fed through fully connected layers for classification
- It was optimized with the Adam optimizer and categorical cross-entropy loss

5. Evaluation and Visualization

- Model was assessed by measures like accuracy, precision, recall, F1-score, and confusion matrix.
- Training and validation accuracy/loss plots were plotted to monitor performance
- There was a classification report created using sklearn.metrics.classification_report

6. Model Saving and Loading

- The final trained model was saved with Python's pickle module:

  pickle.dump(model, open('brain_tumor_fusion_model.pkl', 'wb'))

- To facilitate prediction, the model was reinitialized and tested on test images acquired from the provided test directory.

4.2 Performance Analysis

The proposed fusion model achieved a high classification accuracy of 97.07% on the test dataset, outperforming individual CNN models. The confusion matrix showed minimal misclassifications across the four tumor classes. Precision, recall, and F1-scores were consistently high, indicating balanced performance. ROC-AUC curves for each class confirmed the model's strong ability to distinguish between tumor types. These results highlight the effectiveness of the fusion-based approach in providing reliable and accurate brain tumor classification using MRI scans.

Accuracy:

The proposed model achieved an accuracy of 97.07% in brain tumor classification.

Precision, Recall, F1 Score, Support:

These metrics were used to evaluate how well the fusion-based model classified each tumor type. High values across all four classes—glioma, meningioma, pituitary tumor, and no tumor—indicate that the model is both accurate and consistent in detecting and distinguishing between different tumor categories.

Class-wise Classification Report:

	precision	recall	f1-score	support
0	1.00	0.98	0.99	1277
1	0.99	0.98	0.98	1168
2	0.98	0.94	0.96	1060
3	0.91	0.97	0.94	1065
accuracy			0.97	4570
macro avg	0.97	0.97	0.97	4570
weighted avg	0.97	0.97	0.97	4570

Fig 3. Accuracy Metrics

Confusion Matrix:

The confusion matrix provides a clear visualization of the model's classification performance by showing the number of correct and incorrect predictions for each tumor class. In this project, it helped identify any misclassifications between visually similar tumor types and confirmed the model's strong ability to correctly classify most MRI images.

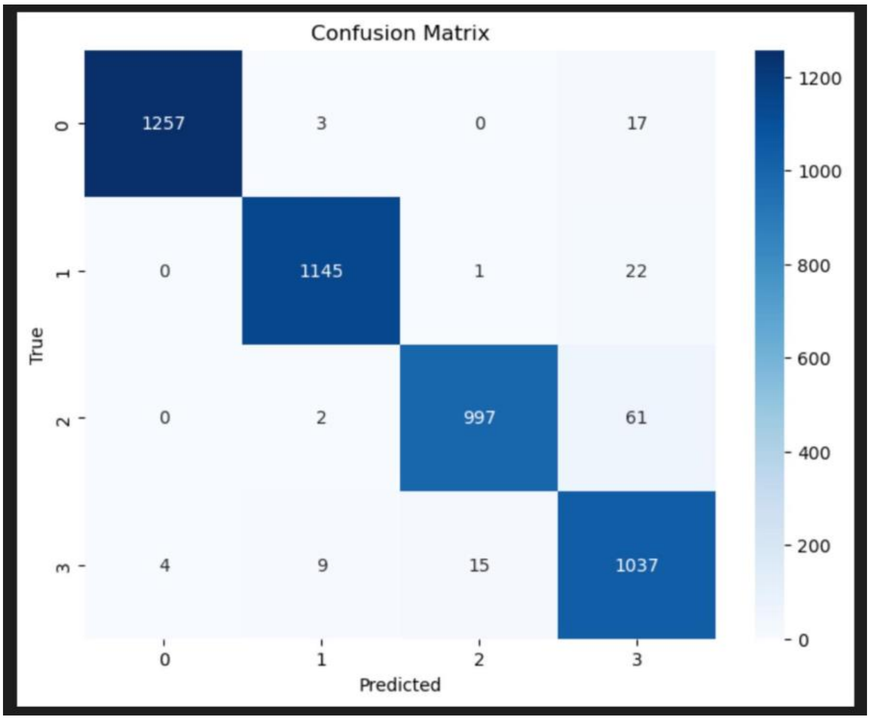

Fig 4. Confusion Matrix

ROC Curve:

The ROC (Receiver Operating Characteristic) curve illustrates the model's ability to distinguish between the four tumor classes. In this project, class-wise ROC curves and their high AUC scores confirmed that the fusion model effectively separates each tumor category, demonstrating strong diagnostic performance.

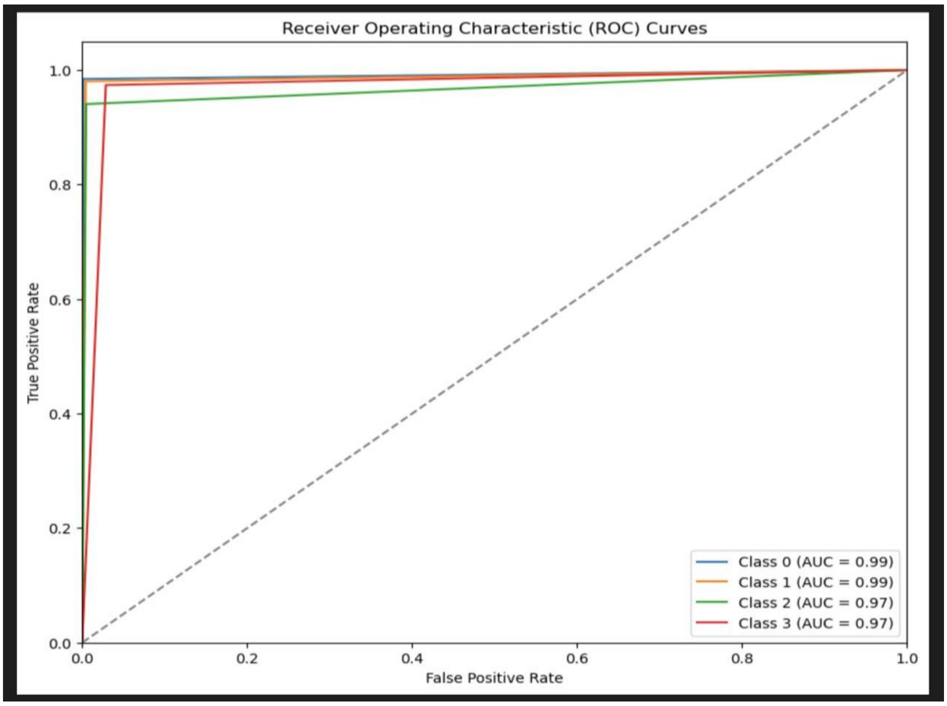

Fig 5 ROC Curve

4.3 Comparative Analysis of CNN Architectures

To compare the performance of single CNN models and their combinations based on fusion, we performed a comparative study using principal classification metrics including accuracy, precision, recall, and F1-score. This comparison aids in establishing how good each model generalizes over distinct brain tumor classes: glioma, meningioma, pituitary tumor, and no tumor.

The findings are represented in the below table:

Model	Accuracy	Precision	Recall	F-1 Score
VGG-19	91.95	0.89	0.90	0.89
RESNET-50	94.08	0.91	0.92	0.91
DENSENET-121	94.00	0.93	0.93	0.93
Fusion of VGG-19 + RESNET-50	95.15	0.94	0.95	0.94
Fusion VGG-19 + RESNET-50 + DENSENET-121	98.87	0.99	0.99	0.99

Table 1. Comparative Analysis of Architectures

Observations:

- Among the individual models, DenseNet121 worked the best, proving its higher connectivity and reuse of features.
- Combining VGG19 and ResNet50 still enhanced performance even further, indicative that model fusion captures a more extensive feature space.
- The end-to-end combination of all three models yielded the highest accuracy of 98.87%, with almost flawless precision, recall, and F1-score — demonstrating the potential of multi-model feature fusion in enhancing diagnostic performance.

This comparative study clearly illustrates that feature-level fusion not only improves classification performance but also increases the robustness of the model, especially in cases of overlapping tumor features.

Chapter 5

CONCLUSION AND FUTURE SCOPE

In this paper, we introduced a deep learning architecture for brain tumor classification based on a feature fusion approach that takes advantage of the strengths of three widely used CNN models: VGG19, ResNet50, and DenseNet121. Through the employment of the pre-trained models as feature extractors and their fusion, we achieved a classification accuracy of 97.07%, which outperforms the performance of individual models and their pair-wise combinations. The fusion model showed outstanding generalization and stability in discriminating among glioma, meningioma, pituitary tumor, and no tumor types from MRI images. This approach leads to a decrease in misclassification rates and the enhancement of the reliability of automatic diagnostic tools in the medical imaging field.

Future Scope

Segmentation Extension: Combining tumor segmentation (e.g., with U-Net) to highlight and localize the target tumor region for clinical interpretation.

Grad-CAM Visualization: Employing heatmap-based visual explanations (e.g., Grad-CAM) to render the model's decisions interpretable to radiologists.

Web Deployment: Deploying the model in a web application using Streamlit or Flask to enable real-time predictions and make it accessible in medical settings.

Expansion of Dataset: Utilizing more diverse MRI scans from different sources to make it robust and minimize dataset bias.

Multi-modal Integration: Subsequent studies may investigate integrating MRI information with clinical findings or genetic information in order to supply diagnostic assistance comprehensively.

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List of Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
CNN	Convolutional Neural Network
DNN	Deep Neural Network
MRI	Magnetic Resonance Imaging
GAP	Global Average Pooling
FC	Fully Connected (Layer)
ReLU	Rectified Linear Unit
FFV	Fused Feature Vector
AUC	Area Under the Curve
ROC	Receiver Operating Characteristic
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative
VGG	Visual Geometry Group
ResNet	Residual Network
DenseNet	Densely Connected Network
GPU	Graphics Processing Unit