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Enhancing Brain Tumor Diagnosis with Optimized Deep Convolutional Transfer Learning Models

Jeevan Kumar[1], Vijay Pandey[2], Rajesh Kumar Tiwari[3]

Department of CSE[1, 3], Department of ME[2]
JUT, Ranchi, Jharkhand, India[1], BIT Sindri, Jharkhand, India[2], RVSCET Jamshedpur, Jharkhand, India[3]
jeevancse01@gmail.com[1], vpandey.me@bitsindri.ac.in[2], rajeshkrtiwari@yahoo.com[3]

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Abstract: Brain tumors represent a critical and aggressive class of neurological disorders, often leading to significantly reduced life expectancy, particularly in their advanced stages. This study introduces an enhanced diagnostic approach leveraging optimized deep convolutional neural networks (CNNs) integrated with transfer learning to improve the accuracy and efficiency of brain tumor classification. Specifically, we employ a fine-tuned MobileNetV2 model to categorize brain MRI images into four classes: gliomas, meningiomas, pituitary tumors, and non-tumorous conditions. The proposed method achieves a high classification accuracy of 98.33%, with a precision of 0.98, recall of 0.97, and specificity of 0.99, under an 80:20 train-test split. Notably, our approach maintains low computational complexity while delivering superior performance compared to existing models. These results highlight the potential of our optimized transfer learning framework as a reliable and time-efficient tool for aiding clinical decision-making in brain tumor diagnosis.

Keywords: Deep Learning, Brain Tumor, Convolutional neural network, Transfer Learning, Data Training, Data Testing.

1. Introduction

An abnormal mass of cells caused by the unchecked proliferation of brain cells is called a brain tumour. Low-grade and high-grade are the two primary categories into which these tumours are typically divided. Benign tumours, another name for low-grade tumours, are non-invasive and non-cancerous, which means they don't spread to other areas of the brain. On the other hand, high-grade tumours, often known as malignant tumours, are malignant and have the ability to aggressively penetrate nearby brain tissue. Malignant tumours proliferate quickly, encroaching on neighbouring tissues without end and frequently metastasising to distant parts of the body. They are potentially fatal due to their aggressive nature, which makes them life-threatening if left untreated.

Deep learning (DL) is a subfield of machine learning that trains computers to make predictions and draw conclusions by using data representations. Medical picture categorisation is one of the many applications that use deep learning (DL), a crucial tool in artificial intelligence. A dataset size at least ten times bigger than the number of degrees of freedom is usually required to attain excellent accuracy, despite its impressive success in a variety of areas [1]. As a deep learning method, transfer learning entails first training a network on a big dataset and then using what it has learnt on a smaller dataset [2]. Fine-tuning and CNN layer freezing are the two main techniques for transfer learning. By applying the pretrained CNN to the target dataset, the fine-tuning strategy permits backpropagation through the network while preserving a portion of the initial layers. The target dataset is then categorised by the last completely linked layer.

1.1 Motivation for the Work

The primary motivation for this research is to develop a prediction model for detecting brain tumor occurrence. Additionally, the research aims to identify the most effective classification algorithm for determining the likelihood of brain tumor disease in patients. A comparative study is conducted by analyzing deep learning algorithms across various evaluation levels. These algorithms are assessed using different evaluation strategies to ensure thorough analysis. The findings will help researchers and medical practitioners establish a more accurate and reliable method for brain tumor diagnosis.

1.2 Major Contribution

The main difficulty in brain tumour diagnosis is early identification. Although there are tools for forecasting the likelihood of brain tumour disease, they are frequently either ineffective at precisely estimating the disease's risk or excessively costly. Early identification can minimize complications and drastically lower death rates. DL algorithms can be used to analyse the large volumes of data that are currently available and find hidden patterns, which will help with the faster and more accurate identification of brain tumours.

The following are the primary contributions of our proposed research:

- For the classification and automated detection of brain tumours, a unique and reliable deep learning method combining transfer learning is described. Significant and rich features are successfully extracted from the Kaggle dataset using this strategy.
- Examining the MobileNet V2 architecture with transfer learning techniques on a target dataset comprised of MRI pictures of brain tumours.
- Applying several frozen layers from a pretrained model to the deep learning model after they have been passed through brain tumour classification and detection performance is assessed through a comparative analysis based on multiple CNN architectural.

The layout of this paper is as follows: The relevant work is presented in Section 2. The materials and techniques are described in depth in Section 3. Section 4 describes the experimental setup. A comparative analysis, results, and discussion are presented in Section 5. Lastly, the conclusion provides a review of findings and suggestions for further research.

2. Related Work

This section summarizes earlier research on the classification of brain tumours. The automatic segmentation of brain tumour regions in MRI images has received a lot of attention, according to a review of previous medical imaging studies. Using MRI imaging techniques, a number of researchers have recently proposed several approaches for identifying and categorizing brain tumours. The related works are shown in Table 1.

Table 1. Related Works

Author & Reference	Year	Description
Bauer S et al [3]	2011	To simulate tumour growth, discrete and continuous approaches are used together.
Liu J et al [4]	2014	DL models are used to segment tumour locations from MRI images in a CNN-based multi-grade brain tumour classification.
Menze, B et al [5]	2015	In order to outperform the current techniques, a variety of segmentation algorithms have been combined.
Mohsen H et al. [6]	2017	A DNN is used to classify brain tumours, providing a high degree of precision.
Bakhtyar Ahmed Mohammed et al. [7]	2021	Brain tumour diagnosis is accomplished by a methodical CNN-based technique, with accuracy, sensitivity, and error rates assessed.
Emrah Irmak et al. [8]	2021	In order to facilitate early identification, this study aims to categorise brain tumours into several groups.
Md. Saikat Islam Khan et al. [9]	2022	Brain tumours classified as binary or multiclass can be identified using deep learning algorithms.
S. Shanthi et al. [10]	2022	The two stages of the suggested method are brain tumour categorization and pre-processing.
Shtwai Alsubai et al. [11]	2022	Presents a hybrid CNN-LSTM for MRI-based brain tumour classification and prediction.
Alok Sarkar et al. [12]	2023	A novel and efficient method based on the AlexNet CNN architecture for identifying brain tumours from MRIs.
Md. Alamin Talukder et al. [13]	2023	Brain tumour classification made possible by a revolutionary DP method that makes use of transfer learning.
Saeed mohsen et al. [14]	2023	To differentiate between gliomas and pituitary tumours, two types of brain tumours, ResNext10_32×8d and VGG19 are utilised.
Tahia Tazin et al. [15]	2023	The investigation of CNNs for the identification of brain tumours from X-ray imaging is covered in this publication.
Farjana Parvin et al. [16]	2023	It extracts both local and global information from brain MRI images using two parallel networks..

Shweta Suryawanshi et al. [17]	2024	The suggested approach makes use of Deep Learning's feature extraction capabilities as well as Support Vector Machines' (SVM) classification flexibility.
Daniel Reyes et al. [18]	2024	The objective of this work is to assess CNNs' efficacy in brain tumour classification.

3. Proposed Method and Materials

This section presents different deep CNN topologies for our suggested framework, which uses the Kaggle brain tumour dataset [19] for brain tumour detection and classification. We evaluate and investigate well-known CNN designs, including MobileNet V2, using augmented MRI slices from the dataset of brain tumours. To extract rich, visually discriminative features, transfer learning techniques are applied to these pretrained CNN models. Ultimately, a log-based softmax layer handles classification. The ensuing subsections go over the main elements of the suggested framework. We also describe in detail the measurement matrices that are utilised to assess our proposed system's performance.

3.1 Dataset

We employed different CNN architectures to assess and analyse our suggested framework using a publicly accessible brain tumour dataset from Kaggle. In 2017, Cheng created this dataset, which includes 2,400 brain MRI slices from 250 different patients. The information is divided into two groups: tumours and non-tumors. In our research, we only employ image data, splitting it into training, validation, and test sets, and all CNN models take images as input. A bar graph showing the types of tumors is shown in figure 1.

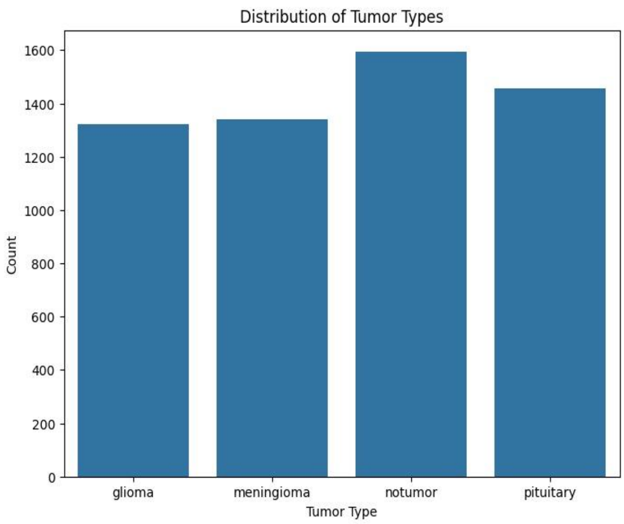

Fig.1. Types of tumors

A grid of MRI scans tumour groups is shown in figure 2. The grid consists of variety of MRI images that highlight different regions of the brain scans.

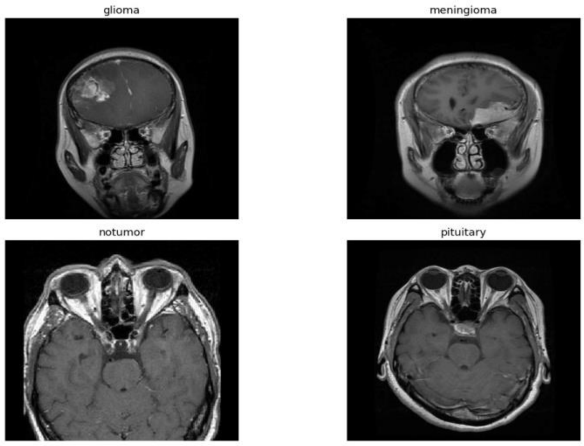

Fig.2. MRI scan brain tumour

3.2 Proposed CNN-Based Architectures

A CNN is made to automatically identify important visual patterns from unprocessed picture pixels with very little preparation. To attain greater accuracy on image datasets, the suggested deep CNN architectures add more convolutional layers and increase in complexity. These architectures, when combined with transfer learning strategies like freezing layers and fine-tuning, have greatly enhanced image classification performance. In this work, we use MRI scans from the Kaggle brain tumour dataset to investigate and use the CNN architecture with MobileNet V2 for the classification and identification of brain tumours. The figure 3 represents a deep learning-based tumor classification framework using transfer learning. The model receives tumor and non-tumor images of dimension 224×224×3 (RGB images). The images are preprocessed and input to a pre-trained MobileNetV2 model. The ImageNet-trained weights are utilized in transferring learning to this model for extracting features. Feature maps are extracted using the base model. Global Average Pooling (GAP 2D) layer is used to down-sample and produce a feature vector. The resulting feature vector goes through several dense layers (DLs): DL-1: 512 units, DL-2: 128 units, DL-3: 64 units, DL-4: 32 units. The output is passed through a softmax classifier for final classification. The classifier classified tumor such as Gliomas, Meningiomas, or Pituitary tumors and non-tumor. This model leverages transfer learning to enhance efficiency by using a pre-trained network, reducing training time while improving accuracy in medical image classification.

3.3 Mobile Net V2

In order to improve its performance and efficiency in image classification task, MobileNetV2 incorporates a number of critical improvements. These consist of squeeze-and-excitation (SE) blocks, bottleneck design, linear bottlenecks, inverted residuals, and depthwise separable convolutions. To maintain high accuracy while lowering the computing cost of the model, each of these qualities is crucial. Now that we have a firm grasp on the characteristics and architecture of MobileNetV2, as shown in figure 4, we can move on to the process of training the model.

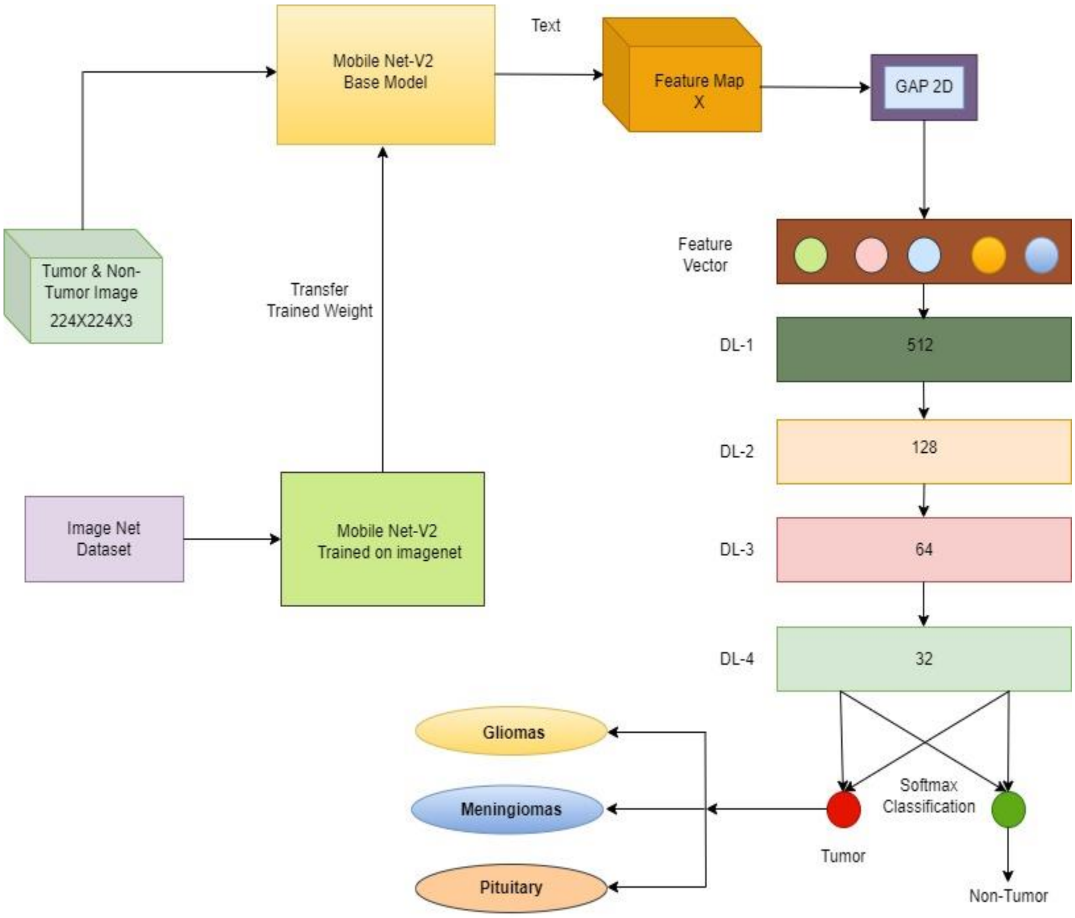

Fig.3. Proposed CNN Architecture of Mobile Net V2 with Transfer Learning

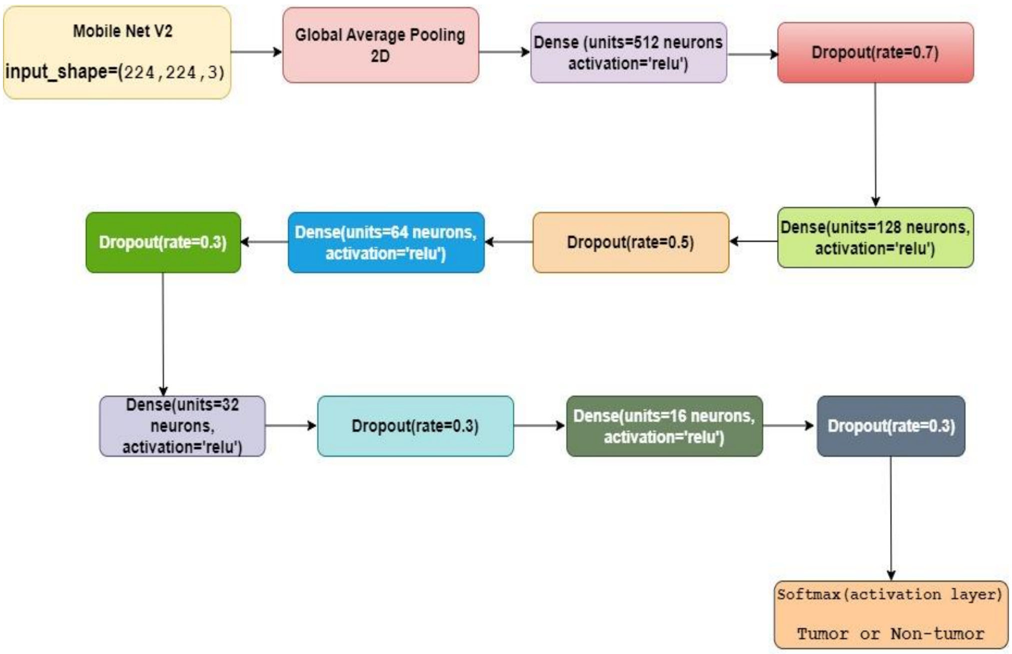

Fig.4. Architecture of MobileNetV2

3.4 Transfer learning: - A deep learning method called transfer learning uses a model that has already been trained on one task as a basis for creating a model on another, frequently related activity. This method works particularly well when there is little data for the second task. The model can learn more quickly and effectively on the second challenge by utilising the features it learnt from the previous task. Additionally, because the model has already gained generalisable properties that will probably be helpful for the new job, transfer learning helps lower the danger of overfitting. This gives a broad idea of how transfer learning operates.

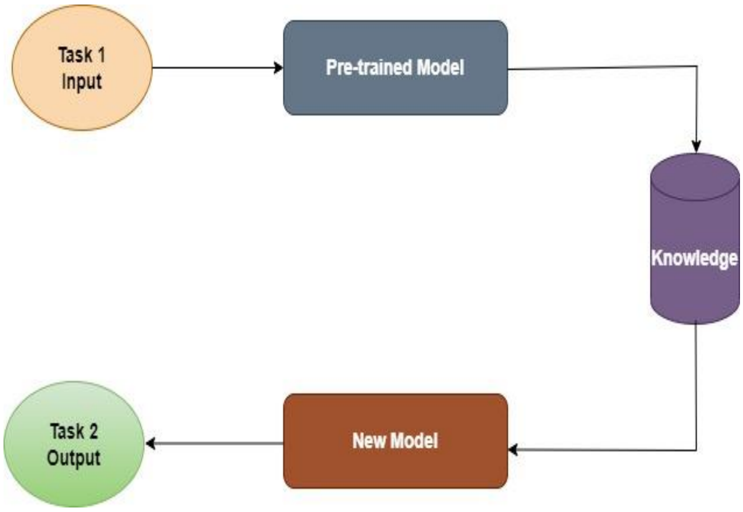

Fig.5. Process of transfer learning

The transfer learning process, which involves applying knowledge from a pre-trained model to a new model for a different task, seems to be illustrated in figure 5.

4. Experimental Setting

This section presents a comprehensive evaluation process for our proposed automated method of identifying and classifying brain tumors using 2,400 images.

4.1 Workframe of the Proposed Model

MobileNetV2 is one of the two pretrained CNN architectures used in the suggested framework. Three primary steps comprise the model's workflow: preprocessing, feature extraction, and classification/detection. Using a contrast stretching approach, MRI pictures are improved in the first phase. In the second stage, the target brain tumour dataset from Kaggle is used to train pretrained CNN architectures based on MobileNetV2 in order to extract distinctive visual characteristics from the MRI pictures. At the last stage, MobileNetV2 is used to apply the transfer learning techniques of freezing layers and fine-tuning them. While utilising the freeze layers technique, automated features are classified using a linear classifier; while utilising the fine-tuned layers strategy, the log-softmax layer is used. Figure 6 is an illustration of the suggested model's framework.

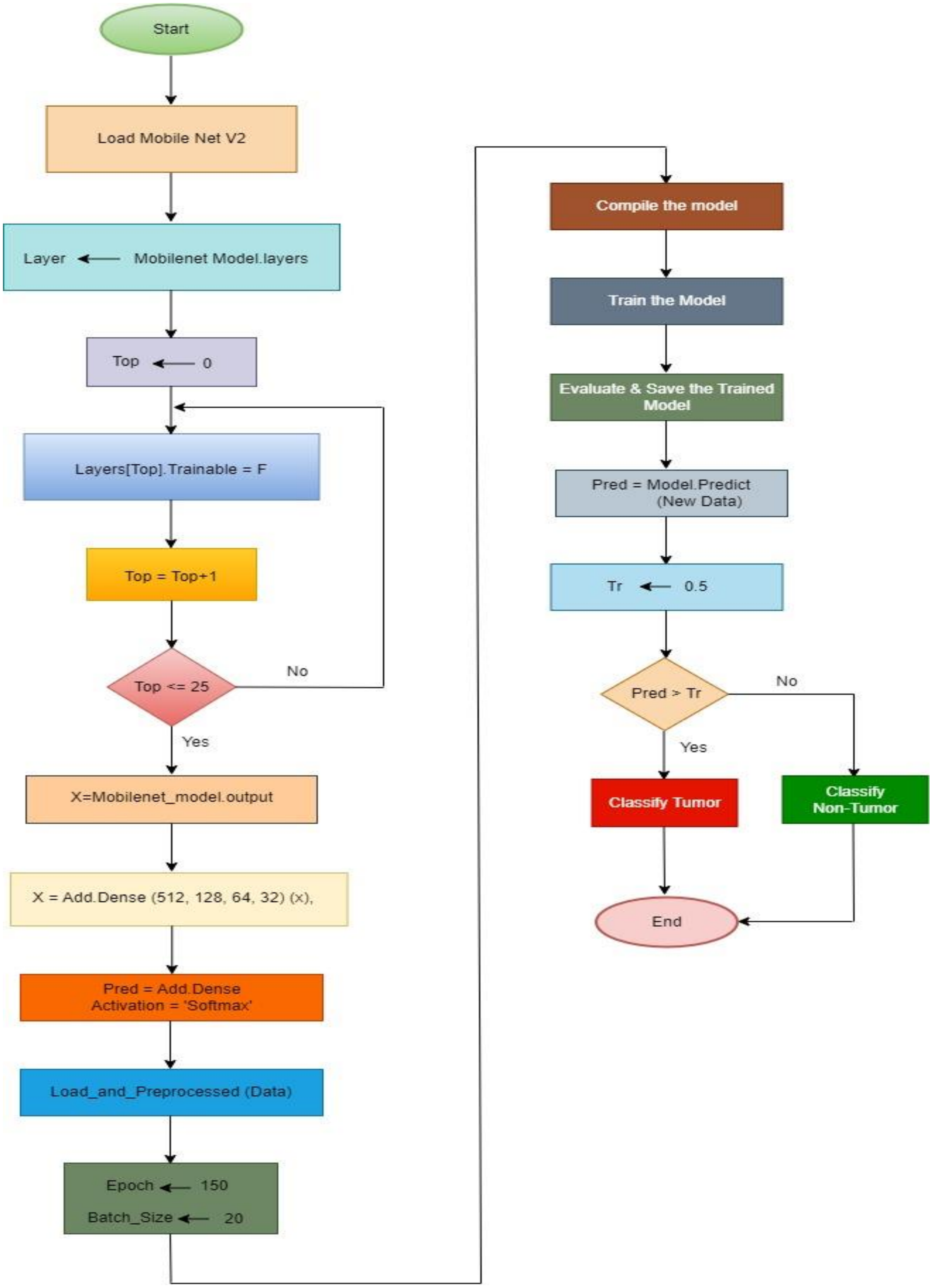

Fig.6. Work Flow of proposed model

4.2 Algorithms for Proposed Model: - Two algorithms are design for the proposed model, which are mention below.

Algorithm 1: Tumor and Non-Tumor Classification using MobileNetV2

Begin:

Step-1: // Load MobileNetV2 pre-trained weights

mobilenet_model ← mobileNetV2.load_pretrained_model ()

Step-2: //Modify the top layers for binary classification (tumor type and non-tumor)

model ← modify_top_layers (mobilenet_model)

Step-3: // Load and preprocess the dataset

train_data, test_data ← load_and_preprocess_data ()

Step-4: //Define training parameters

epochs ← 150

batch_size ←20

Step-5: // Compile the model

model.compile (optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

Step-6: // Train the model using transfer learning

model.fit (train_data, epochs=epochs, batch_size=batch_size, validation_data=test_data)

Step-7: //Evaluate the model on the test set

accuracy = model.evaluate(test_data)

Step-8: // Save the trained model

model.save ('tumor_classification_model.h5')

Step-9: Make predictions on new data

new_data = preprocess_new_data(new_data)

predictions = model.predict (new_data)

// Set Threshold (Tr)← 0.5

If predictions > Tr Then

  classify as tumor (Gliomas, Meningiomas, & Pituitary)

else

  classify as Non-Tumor

end if

end

Algorithm 2: modify_top_layers (MobileNet V2_model)

```
{
//Extract all the layers from mobilenet_model
layers← mobilenet_model.layers
// Freeze 25 layers
top ← 0
do
{
layers[top].trainable = False
top=top+1
}
while (top ≤ 25)
// x is the output feature map from mobilenet_model
x = mobilenet_model.output
x = layers.GlobalAveragePooling2D()(x)
x = Dense(units=512, activation='relu')(x)
x = Dense (units=128, activation='relu')(x)
x = Dense (units=64, activation='relu')(x)
x = Dense (units=32, activation='relu')(x)
Predictions = layers.Dense (2, activation='softmax')(x)
model = Model(mobilenet_model.input, predictions)
return (model)
}
```

4.3 Preprocessing and Data Augmentation

Data cleaning is a step in preprocessing that aims to improve and refine the input data for task that come after. Cleaning MRI images is the main goal of medical image analysis. These images can include artefacts and inaccurate intensity levels because they were obtained using different modalities. Different DL algorithms are used to improve the contrast of MRI images in order to address this. Our method produced high-resolution, contrast-enhanced images by preprocessing using the contrast stretching algorithm. Various image variations were created utilising conventional data augmentation techniques, which help reduce overfitting during CNN training. Rotations and flipping were two of the augmentation techniques we used to expand the training dataset and provide the CNNs a bigger input area. Rotation is a basic augmentation technique that involves rotating input images at various angles, including 90°, 180°, and 270°. Furthermore, images were flipped, or mirrored along both the vertical and horizontal axes.

4.4 CNN-Based Feature Extraction

The process of extracting discriminative and visual features to describe the qualities of the data is the next stage after data augmentation, which generates a huge set of image samples for the training dataset. One significant development in CNNs' feature extraction techniques is transfer learning, which is especially helpful in situations like this one where there aren't as many dataset samples available. For feature extraction in this study, we used the MobileNet V2 pretrained CNN architecture. Two scenarios of transfer learning were used to extract the discriminative visual features: freezing and fine-tuning.

4.5 Classification and Detection of Brain Tumors

Classification and detection on the target dataset are the next steps to take after employing transfer learning algorithms to successfully extract significant visual features and patterns. In the first case, a softmax layer is used to classify brain tumours, and the number of neurones is set up for two classes. Each CNN architecture's acquired visual features are adjusted to match the target dataset. In order to improve performance, the network does not automatically set the fine-tuning parameters; instead, the parameters must be explicitly configured and optimised based on the training outcomes. Based on validation criteria, the ideal number of epochs was modified, with a 50-iteration validation frequency. With MobileNet V2, the top-performing network attained a maximum accuracy of 97.00%. The pretrained networks' frozen layers were fed into a softmax classifier in the second classification case. This method established a validation frequency of every 50 iterations, frozen 25 layers, and varied the number of epochs according to validation requirements. This method produced 98.33% accuracy, which is a much higher result.

5. Comparative Result Analysis, and Discussion

A publicly accessible dataset of 2,400 images related to brain tumours was used for the experimental investigation on Kaggle. The CNN design makes use of different numbers of features and parameters were changed to fine-tune the pretrained MobileNetV2 model. During these research, the maximum accuracy attained was 98.33%. We employed a cross-validation strategy to record training and validation accuracy with split ratios of 70:30, 80:20, and 90:10.

5.1 Cross-validation strategy: - A statistical method called cross-validation divides the dataset into several subgroups in order to assess how well deep learning models perform. By ensuring that the model is evaluated on unknown data, it helps to mitigate overfitting and underfitting problems and evaluate the model's capacity for generalisation.

(a) **Split Ratio 70:30-** "Model Accuracy," a line graph that shows the accuracy of training and validation data over 50 epochs, is the image that was uploaded as shown in figure 7. The y-axis indicates accuracy, and the x-axis shows the number of epochs.

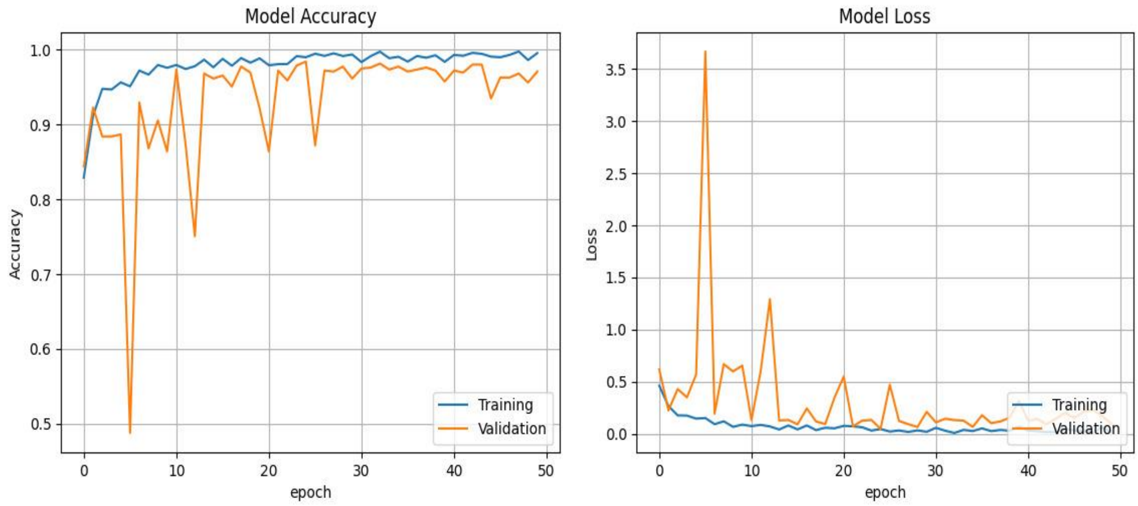

Fig.7. Shows the model accuracy and loss over 50 epochs with split ratio 70:30

(b) Split Ratio 80:20:- The graph depicts the model's accuracy during training and validation over 50 epochs as shown in figure 8.

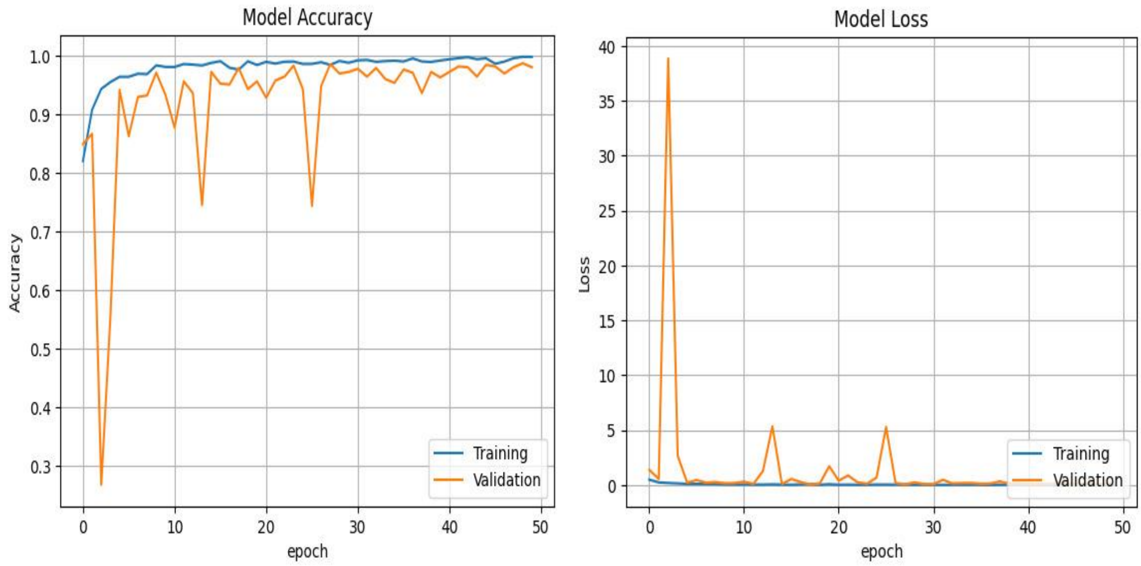

Fig.8. shows the model accuracy and loss over 50 epochs with split ratio 80:20

(c) Split Ratio 90:10:- This graph depicts the accuracy of a deep learning model over 50 epochs, showing both the training and validation accuracies as shown in figure 9.

5.2 Comparative Results: - This table 2 presents the training and testing accuracy, along with loss values, for various CNN models using a 70:30 train-test split. MobileNetV2 with freeze layer achieves the highest training (98.14%) and test accuracy (98.09%), while maintaining low training (0.0160) and testing loss (0.0370). MobileNetV2 without freeze layer follows closely, with 98.09% training accuracy and 98.06% test accuracy, having the lowest training loss (0.0157). ResNet-50 and Inception also perform well, with training accuracy of 97.51% and 97.88%, and test accuracy of 97.10% and 96.90%, respectively. Meanwhile, VGG-19 and VGG-16 show slightly lower test accuracy (95.65% and 95.35%), with VGG-16 exhibiting the highest test loss (0.0701), indicating potential overfitting.

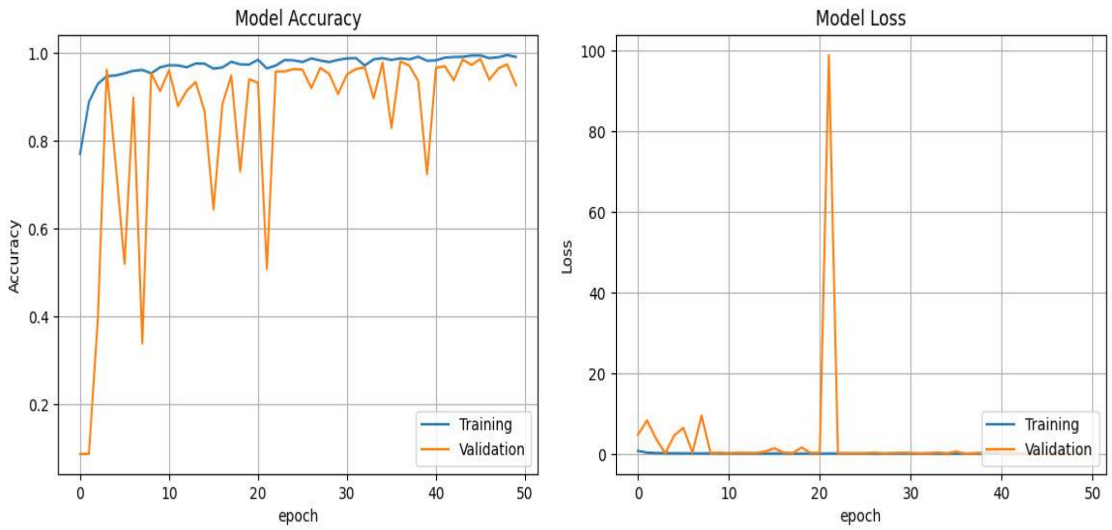

Fig.9. shows the model accuracy and loss over 50 epochs with split ratio 90:10

Table2. Results of different models with split ratio 70:30

Model	Split ratios	Acc(Train)	loss(Train)	Acc(Test)	loss(Test)
VGG-19	70:30	96.82	0.0311	95.65	0.0430
VGG-16		96.96	0.0364	95.35	0.0701
ResNet 50		97.51	0.0349	97.10	0.1200
Inception		97.88	0.0415	96.90	0.1117
MobileNet V2		98.09	0.0157	98.06	0.0368
MobileNetV2 with freeze layer		98.14	0.0160	98.09	0.0370

The table 3 presents the classification performance metrics (Precision, Recall, and Specificity) for different tumor types (Gliomas, Meningiomas, and Pituitary) using a 70:30 train-test split ratio. Key insights:

- **Gliomas** achieve a precision of 96.2%, recall of 97.8%, and specificity of 97.5%, indicating strong detection capability with minimal false negatives.
- **Meningiomas** demonstrate high accuracy, with a precision of 97.8%, recall of 98.1%, and specificity of 98.2%, ensuring reliable classification.

- **Pituitary tumors** exhibit balanced and excellent performance, with precision, recall, and specificity all at 98.1.

Overall, the high classification accuracy across all tumor types, making it highly effective for tumor detection and diagnosis

Table 3. Class-specific evaluation of brain tumor classifier

Tumor Type	Split ratios	Precision	Recall	Specificity
Gliomas	70:30	96.2	97.8	97.5
Meningiomas		97.8	98.1	98.2
Pituitary		98.1	98.1	98.1

This table 4 presents the training and testing accuracy, along with loss values, for various CNN models using an 80:20 train-test split. MobileNetV2 with a freeze layer achieves the highest test accuracy (98.33%), slightly surpassing MobileNetV2 without a freeze layer (98.07%). VGG-19 also performs well, with a test accuracy of 97.25% and a low test loss (0.0142); however, its high training accuracy (98.80%) suggests some overfitting. VGG-16 and ResNet-50 follow with test accuracies of 96.55% and 97.30%, respectively, though ResNet-50 exhibits a significantly high test loss (0.1210), indicating overfitting. Inception shows the largest accuracy drop, from 98.10% (train) to 94.97% (test), highlighting poor generalization.

Table 4. Results of different models with split ratio 80:20

Model	Split ratios	Acc(Train)	loss(Train)	Acc(Test)	loss(Test)
VGG-19	80:20	98.80	0.0364	97.25	0.0142
VGG-16		97.98	0.0212	96.55	0.0331
ResNet 50		98.00	0.0140	97.30	0.1210
Inception		98.10	0.0312	94.97	0.0126
MobileNet V2		98.20	0.0360	98.07	0.0205
MobileNetV2 with freeze layer		98.33	0.0365	98.16	0.0208

The table 5 presents classification performance metrics (Precision, Recall, and Specificity) for different tumor types (Gliomas, Meningiomas, and Pituitary) using an 80:20 train-test split ratio. Key insights:

- **Gliomas** achieve a precision of 98.1%, recall of 97.2%, and specificity of 96.5%, ensuring strong detection with minimal false positives.
- **Meningiomas** demonstrate reliable classification, with a precision of 96.9%, recall of 97.5%, and specificity of 97.5%.
- **Pituitary tumors** exhibit the highest performance, with precision at 98.1%, recall at 98.3%, and specificity at 98.1%, reflecting a well-balanced and highly accurate classification.

Overall, the model maintains high classification accuracy across all tumor types, making it effective for precise tumor detection and diagnosis.

Table 5. Class-specific evaluation of brain tumor classifier

Tumor Type	Split ratios	Precision	Recall	Specificity
Gliomas	80:20	98.1	97.2	96.5
Meningiomas		96.9	97.5	97.5
Pituitary		98.1	98.3	98.1

This table 6 presents the training and testing accuracy, along with loss values, for various CNN models using a 90:10 train-test split. MobileNetV2 with a freeze layer achieves the highest test accuracy (98.08%), making it the top-performing model for this split. MobileNetV2 without a freeze layer follows closely with 97.07% test accuracy and a lower test loss (0.0203). ResNet-50 attains 97.20% test accuracy but exhibits a high test loss (0.1210), indicating potential overfitting. VGG-16 (96.54%) and VGG-19 (96.20%) perform reasonably well but have higher test losses than the MobileNetV2 models. Inception shows the lowest test accuracy (94.90%) but also the lowest test loss (0.0116), suggesting possible underfitting or suboptimal learning.

Table 6. Results of different models with split ratio 90:10

Model	Split ratios	Acc(Train)	loss(Train)	Acc(Test)	loss(Test)
VGG-19	90:10	97.81	0.0362	96.20	0.0241
VGG-16		97.93	0.0215	96.54	0.0333
ResNet 50		97.98	0.0249	97.20	0.1210
Inception		97.54	0.0313	94.90	0.0116
MobileNet V2		98.01	0.0360	97.07	0.0203
MobileNetV2 with freeze layer		98.17	0.0363	98.08	0.0304

The table 7 presents classification performance metrics (Precision, Recall, and Specificity) for different tumor types (Gliomas, Meningiomas, and Pituitary) using a 90:10 train-test split ratio. Key observations:

- **Gliomas** achieve a precision of 98.1%, recall of 97.3%, and specificity of 97.5%, ensuring strong classification accuracy with minimal false negatives.
- **Meningiomas** demonstrate reliable detection with a precision of 97.9%, recall of 97.1%, and specificity of 96.5%, indicating balanced performance.
- **Pituitary tumors** exhibit the highest classification accuracy, with precision at 98.1%, recall at 98.3%, and specificity at 98.1%, ensuring minimal misclassification.

Overall, the model maintains high performance across all tumor types, making it well-suited for precise tumor detection and diagnosis.

Table 7. Class-specific evaluation of brain tumor classifier

Tumor Type	Split ratios	Precision	Recall	Specificity
Gliomas	90:10	98.1	97.3	97.5
Meningiomas		97.9	97.1	96.5
Pituitary		98.1	98.3	98.1

Based on the comparative analysis of the split ratio, the 80:20 strategies outperformed the other approaches. Consequently, we proceeded with the 80:20 split for further analysis.

5.3. Comparative Classification report: The table 8 presents the performance metrics (Precision, Recall, and Specificity) of different CNN models across three train-tests split ratios (70:30, 80:20, and 90:10). Key observations:

- **VGG-19** shows fluctuating performance, achieving its highest precision (0.93) in the 80:20 split, while recall peaks at 0.93 in the 90:10 split.
- **VGG-16** maintains high recall across splits, with precision ranging between 0.88 and 0.92, and specificity remaining above 0.94.
- **ResNet-50** delivers stable performance, with precision and recall consistently above 0.92 and specificity peaking at 0.96 in the 90:10 split.
- **Inception** achieves strong results, with the highest recall (0.97) in the 70:30 split and specificity reaching 0.98 in the 90:10 split.
- **MobileNetV2** demonstrates robust classification, with precision reaching 0.97 in the 70:30 split and recall peaking at 0.97 in both the 80:20 and 90:10 splits.

- **MobileNetV2 with a frozen layer** outperforms other models, maintaining the highest precision (0.98) in the 70:30 and 80:20 splits, with specificity reaching 0.99 in the 80:20 split.

Table 8. Comparative Classification report for Cross-validation strategy ratio 70:30, 80:20, and 90:10

CNN Model	Split ratios								
	70:30			80:20			90:10		
	Precision	Recall	Specificity	Precision	Recall	Specificity	Precision	Recall	Specificity
VGG-19	0.80	0.78	0.91	0.93	0.91	0.92	0.82	0.93	0.93
VGG-16	0.91	0.95	0.96	0.88	0.93	0.95	0.92	0.94	0.94
ResNet 50	0.92	0.94	0.95	0.92	0.95	0.95	0.93	0.94	0.96
Inception	0.96	0.97	0.97	0.93	0.96	0.96	0.95	0.96	0.98
MobileNet V2	0.97	0.90	0.96	0.95	0.97	0.97	0.96	0.97	0.97
Mobile NetV2 with freeze layer	0.98	0.96	0.97	0.98	0.97	0.99	0.97	0.97	0.96

Overall, MobileNetV2 with a frozen layer exhibits the most consistent and superior performance across all splits, making it the most effective model for classification tasks.

5.4. Confusion Matrix: - The figure 10 presents a confusion matrix that compares the actual and predicted labels, providing an evaluation of the classification model's performance in detecting four types of brain tumors: Glioma, Meningioma, Notumor, and Pituitary. In this matrix, rows correspond to the actual classes, while columns represent the predicted classes. The model demonstrates strong performance in accurately identifying Notumor and Pituitary cases. However, the highest level of misclassification occurs between Meningioma and Notumor, with 35 Meningioma instances incorrectly predicted as Notumor. Despite this, the prominent values along the diagonal indicate that the model generally achieves good classification accuracy. The accompanying image shows the confusion matrix that generated by the analysis of our approach utilising brain tumour test datasets. The accurate and incorrect classifications for each form of tumour are broken down in detail in the following table 9.

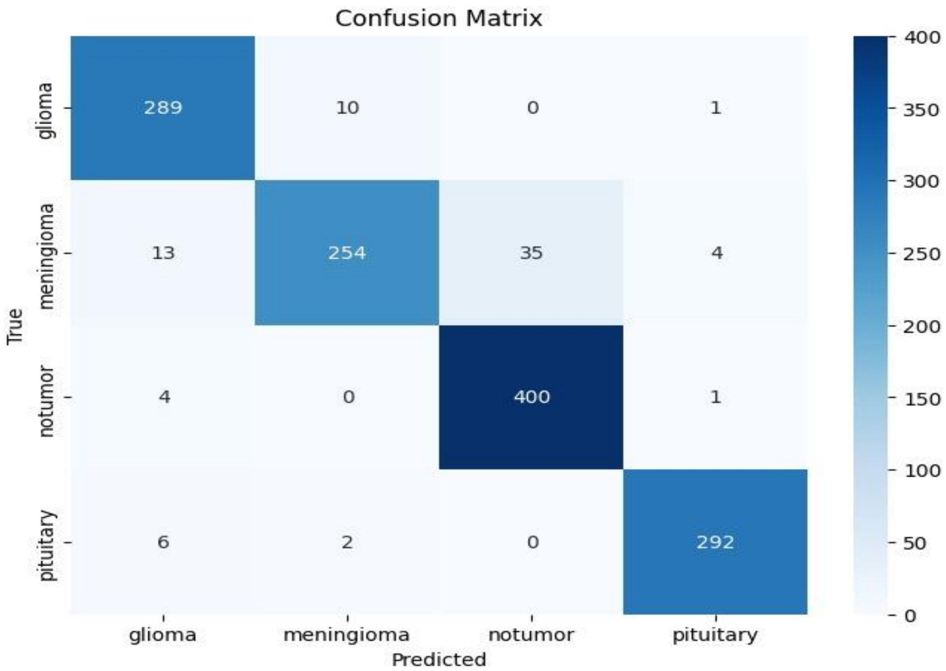

Fig.10. Confusion Matrix

Table 10. Classification and Misclassification

Sl No	Tumour types	Classification Type	Misclassification Type
01	Gliomas	289	23
02	Meningiomas	254	12
03	Notumor	400	35
04	Pituitary	292	06

5.5 Comparison with existing models: - The proposed approach is contrasted with other models, and table 11 shows a comparison of the suggested strategy with the current approaches.

Table 11. Comparative Study of existing methods with proposed method

Sl.no	Author	Methodology adopted	Overall accuracy (in %)
01	Tonmoy Hossain et.al [20]	CNN	97.87
02	Francisco Javier Díaz-Pernas et.al [21]	MCCN	97.30
03	Maad M. Mijwil et.al [22]	MobileNetV1	97.00

04	Marco Antonio Gómez-Guzmán et.al [23]	Inception V3	97.12
05	Lu Xu et.al [24]	MN-V2/CFO	97.32
06	Narayanan Krishanasamy et.al [25]	FCNs and ResNets	93.90
07	**Proposed Method**	**MobileNetV2**	**98.33**

6. Conclusion

This research paper introduces a novel method for classifying brain tumours using transfer learning and the MobileNetV2 architecture. Using a dataset of brain MRI images, we successfully differentiated between tumour (gliomas, meningiomas, & pituitary) and non-tumor classes by utilising powerful features. Discriminative visual features and patterns were extracted from MRI slices using transfer learning, which allowed the suggested model to reach a maximum accuracy of 98.33%. The future direction will investigate sophisticated deep neural network designs for brain tumour classification.

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