



# Classification Of Brain Tumours Types Based On MRI Images Using Mobilenet

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# Introduction

- MRI helps to detect soft tissue abnormalities, including brain tumors.
- Deep learning techniques have a high role in this.
- MobileNet is a CNN model.
- It has high accuracy and computational efficiency.
- MobileNet helps to classify different types of brain tumors based on MRI images.
- This test has 94% of Accuracy.
- The version of MobileNet used for this is MobileNet V2 140×224 .

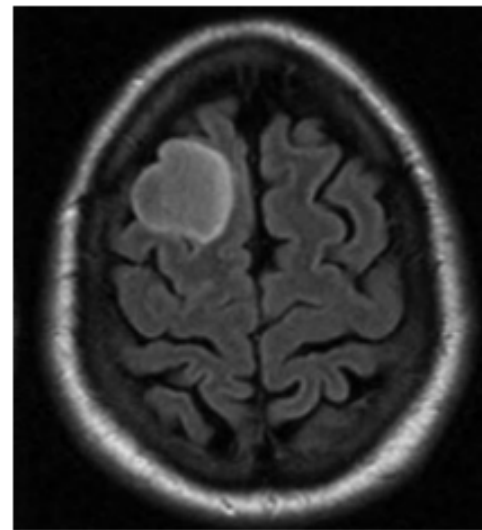
# Keywords

- Brain tumour
- MRI
- Mobilenet
- Deep Learning
- Transfer Learning
- Classification

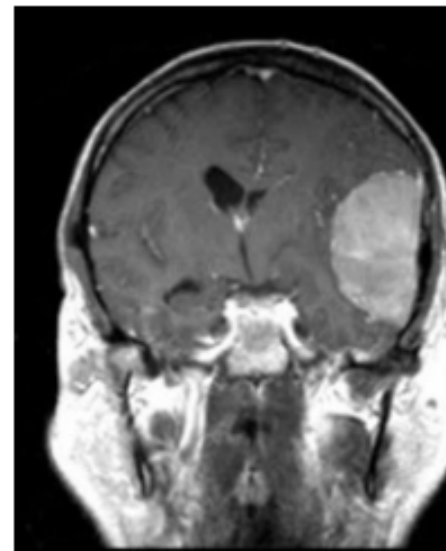


# Related works

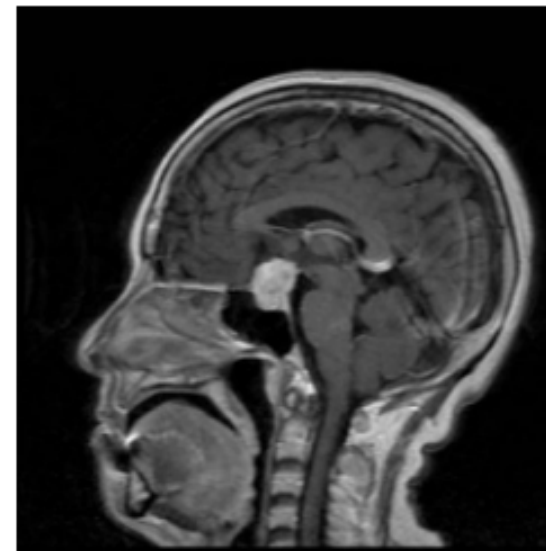
- Brain tumour.
- Deep learning and brain tumours(CNN).
- Automated brain tumour segmentation(DCNN).
- Health informatics and deep leaning (SVM,GBM) .



Glioma



Meningioma



Pituitary

Fig. 1. Sample brain tumours image MRI

# Methodology

- Dataset
- Transfer Learning
- MobileNet
- Experiment



# 1. Dataset

- Three different Brain tumour MR images are used.
- Every image is having a size of 512 x 512 pixels with 2475 images.
- We divide the dataset into 80% training, 10% validation, and 10% testing

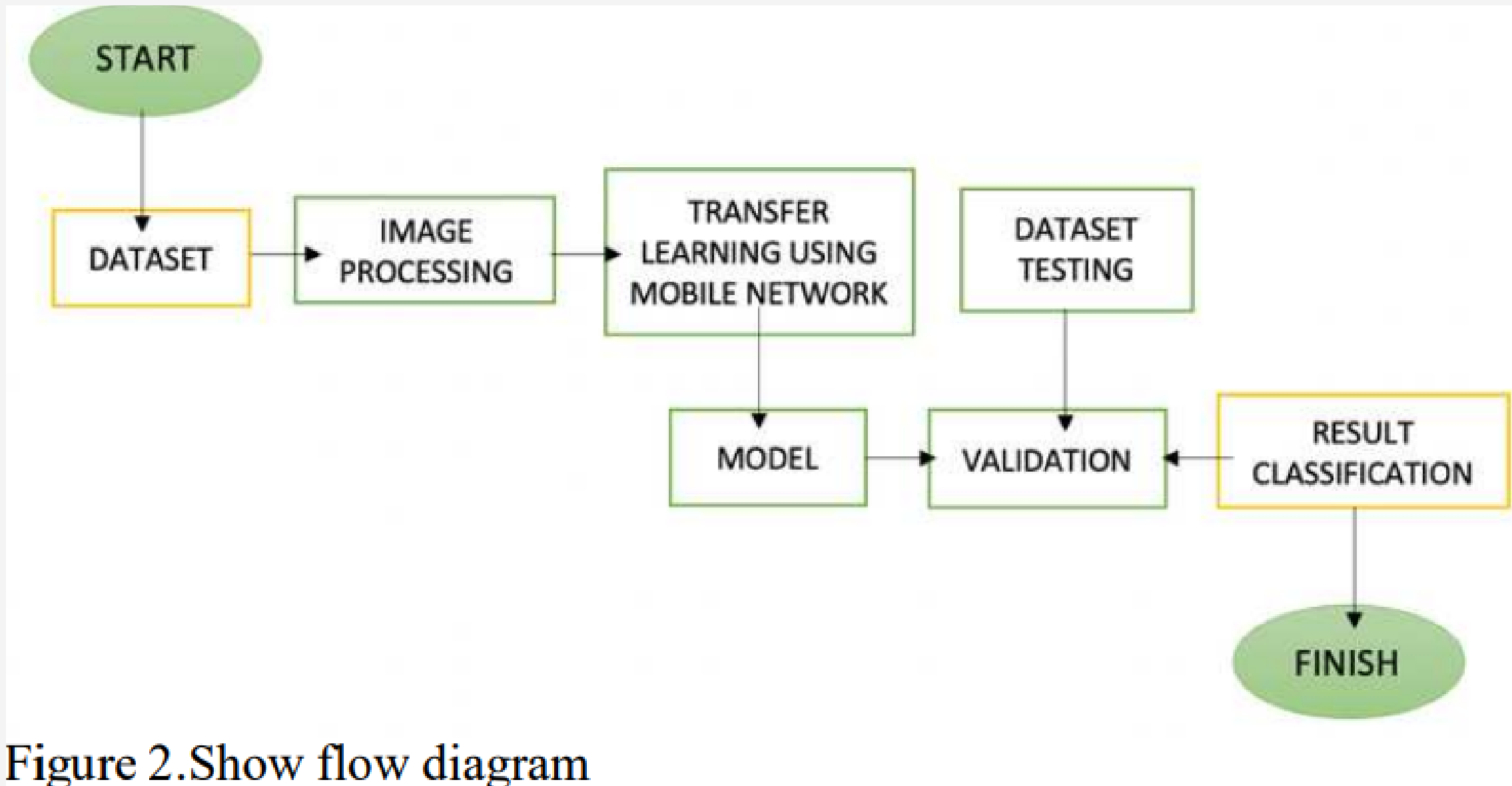


Figure 2. Show flow diagram

TABLE 1. LIST THE NUMBER OF DIVIDED DATASETS.

<b>Class</b>	<b>Total</b>	<b>Training 80%</b>	<b>Validation 10%</b>	<b>Testing 10%</b>
Glioma	826	676	75	75
Meningioma	822	674	74	74
Pituitary	827	677	75	75
<b>Sub Total</b>	<b>2475</b>	<b>2027</b>	<b>224</b>	<b>224</b>

## 2.Transfer Learning

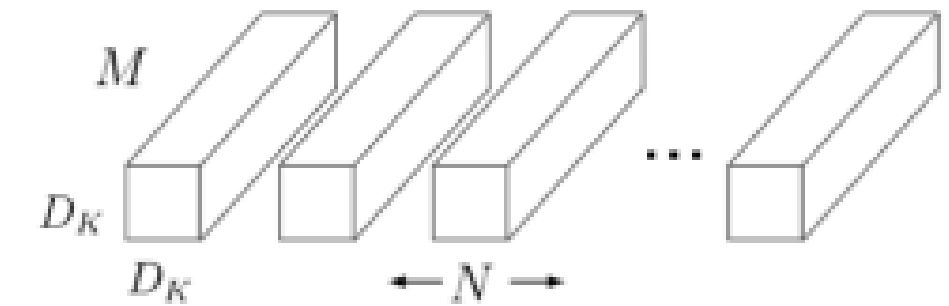
- It uses a previously trained model.
- Neural Network takes more time for training data.
- It uses small training data for studying
- One technique is to transfer knowledge of other pre-trained neural network models into a model.
- This is also know as self-taught learning.



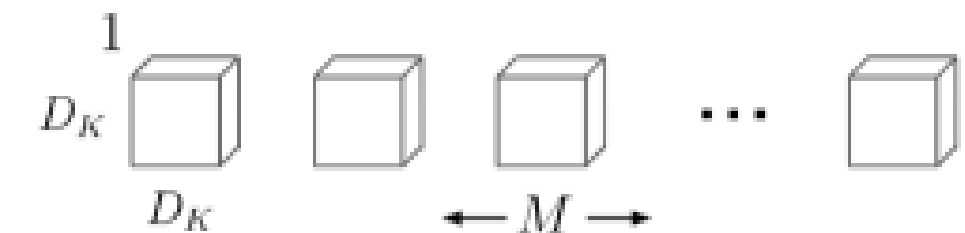


# 3.MobileNet

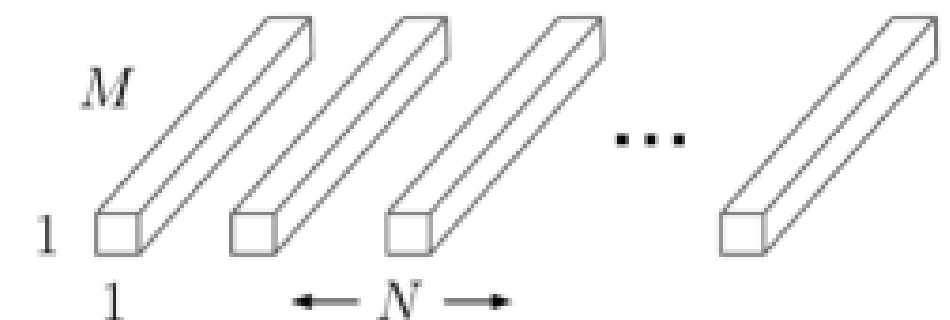
- One of the CNN architecture.
- It divides convolution into depthwise convolution and pointwise convolution.
- It utilizes Batch Normalization (BN) and Rectified-Linear units (ReLU).



Standard Convolution Filters



Depthwise Convolutional Filters



$1 \times 1$  Convolutional filters called Pointwise Convolution in the context of Depthwise Separable Convolution

Figure 3. Convolution standard

- Left side Standard convolutional layer with the batch norm and ReLU.
- The structure of MobileNet divided parts into deep separable convolutions .
- It is easy to explore the network topology to a better network.

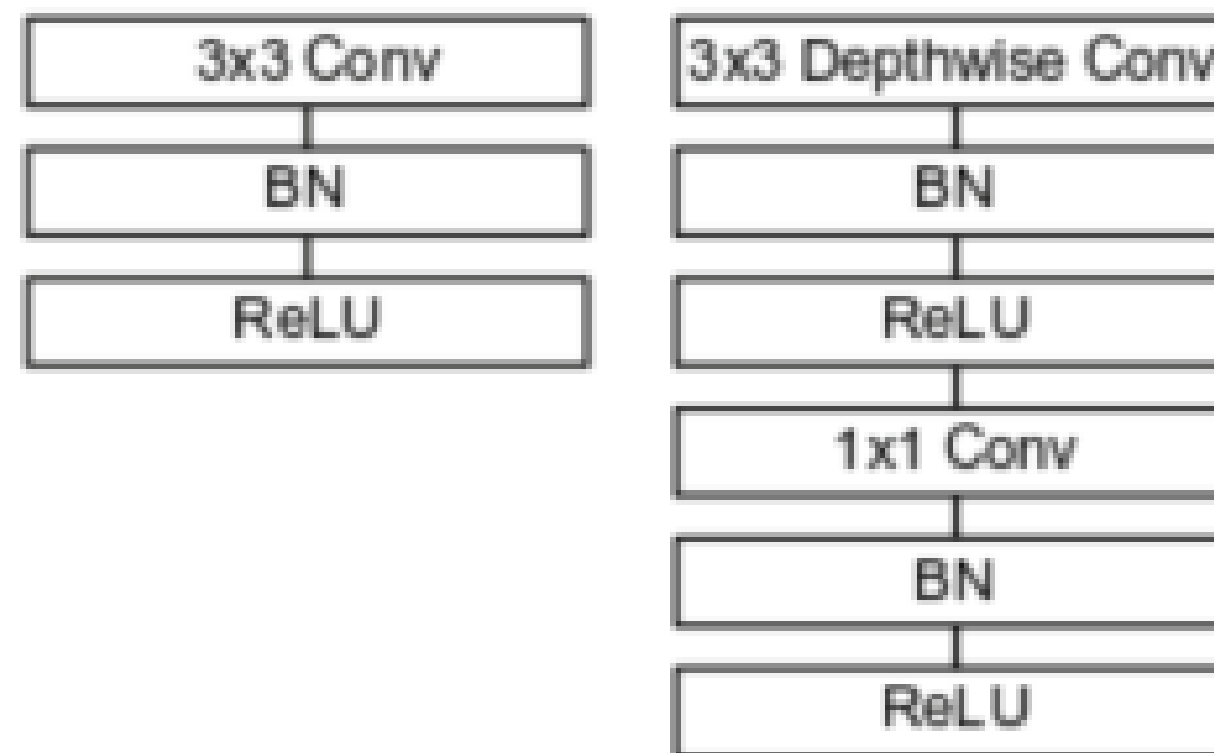


Figure 4. Convolution layer

TABLE 2. DEFAULT INPUT IMAGES OF MOBILENETV2.

Model	Input size
Mobilenet V2	100 x 224
Mobilenet V2	130 x 224
Mobilenet V2	140 x 224

- MobileNetV2 still uses depthwise and pointwise convolution.
- MobileNetV2 adds two new features:
  - linear bottlenecks and
  - shortcut connections between bottlenecks

# MobileNetV2

- Inverted Residual Structure.
- Depthwise Separable Convolutions.
- Bottleneck Design.
- Linear Bottlenecks.



# 4.Experiment

- It is compiled using the Python programming language.

- Use transfer learning with the latest CNN model, r Mobilenet.

- Use mobilenet\_v2\_140\_224 with a batch\_size of 32

- This experiment uses 25 training epochs and momentum with a learning rate of 0,01.

- 80% training data, 10% validation and 10% testing

TABLE 3.MOBILENETV2 ARCHITECTURE

Input	Operator	<i>t</i>	<i>c</i>	<i>n</i>	<i>s</i>
$224^2 \times 3$	Conv2d	-	32	1	2
$112^2 \times 32$	Bottleneck	1	16	1	1
$112^2 \times 16$	Bottleneck	6	24	2	2
$56^2 \times 24$	Bottleneck	6	32	3	2
$28^2 \times 32$	Bottleneck	6	64	4	2
$14^2 \times 64$	Bottleneck	6	96	3	1
$14^2 \times 96$	Bottleneck	6	160	3	2
$7^2 \times 160$	Bottleneck	6	320	1	1
$7^2 \times 320$	Conv2d 1x1	-	1280	1	1
$7^2 \times 1280$	Avgpool 7 x 7	-	-	1	-
$1 \times 1 \times 1280$	Conv2d 1x1	-	k	-	-

# Result and Descussion

- It test the medical image classification network using the Mobilenet model.
- Encountered an error while we were fine-tuning the model.
- get maximum accuracy results on Mobilenet\_v2\_140\_224.

TABLE 4. COMPARISON OF TRAINING ACCURACY AND TESTING ACCURACY

Model	Fine Tuning	Accuracy Testing (%)	Accuracy Training (%)
Mobilenetv2 100 x 224	True	90	98.60
Mobilenetv2 100 x 224	False	82	79.45
Mobilenetv2 130 x 224	True	91	100
Mobilenetv2 130 x 224	False	86	83.91
<b>Mobilenetv2 140 x 224</b>	<b>True</b>	<b>94</b>	<b>100</b>
Mobilenetv2 140 x 224	False	81	76.44

TABLE 5. SHOWS CONFUSION MATRIX OF THE CLASS DATASET.

Class	Precision	Recall	F1-Score
Glioma	91%	95%	93%
Meningioma	93%	89%	91%
Pituitary	99%	99%	99%

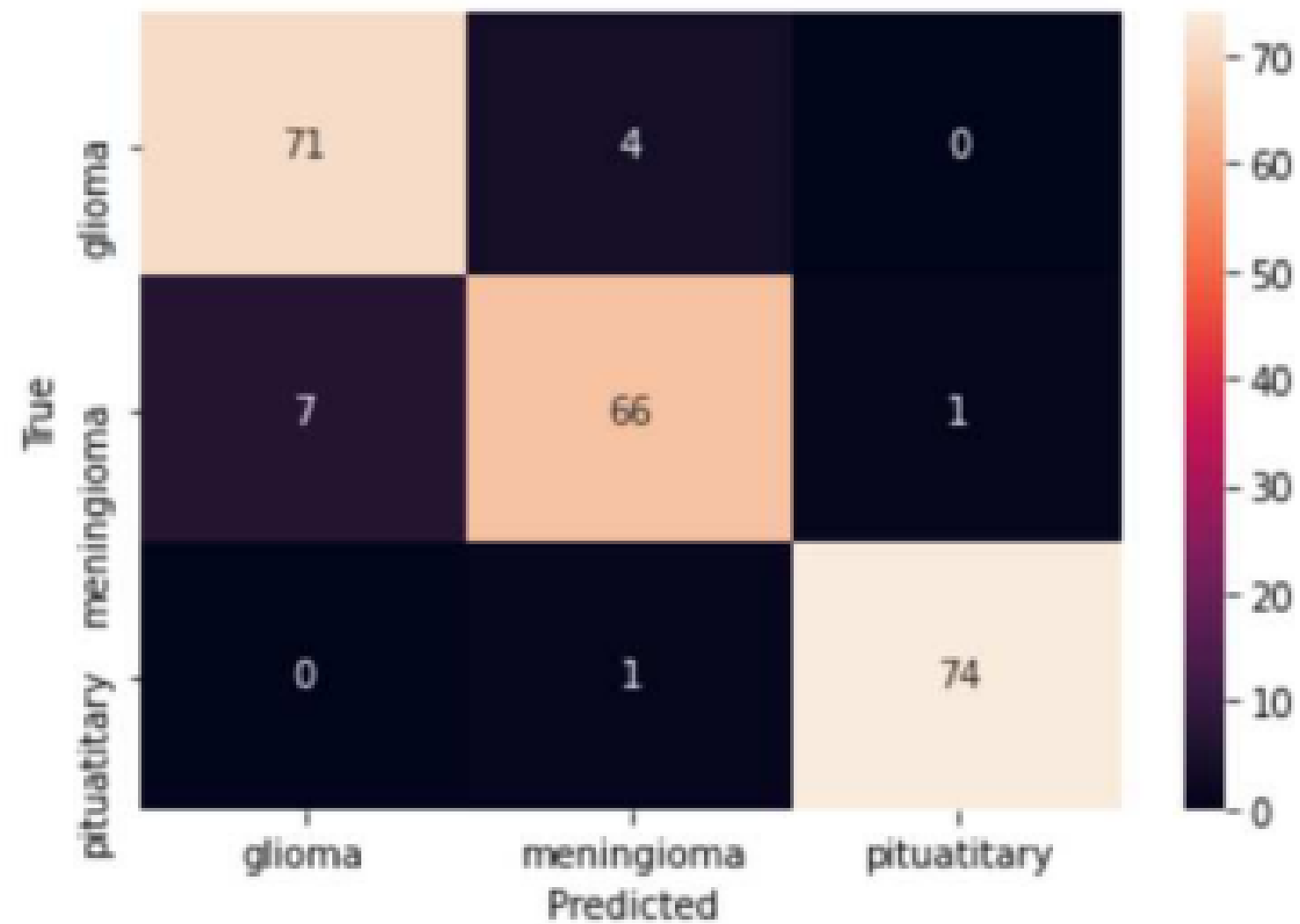
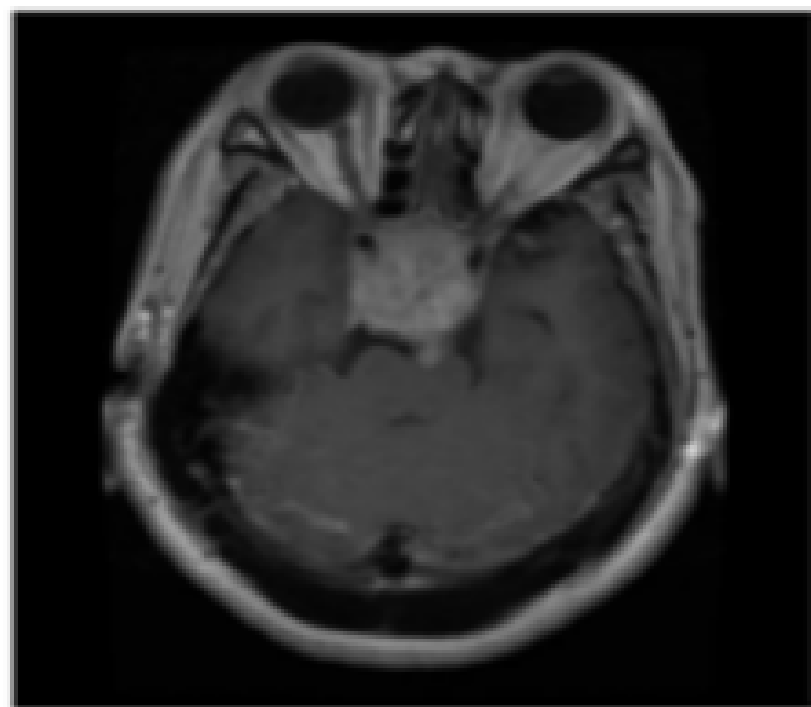
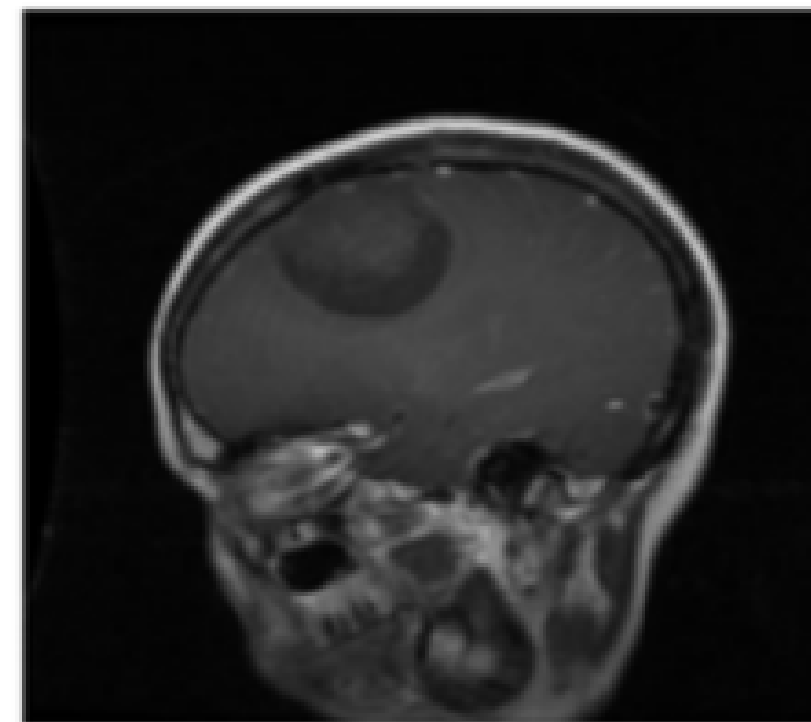


Figure 5. Show maps of confusion matrix.



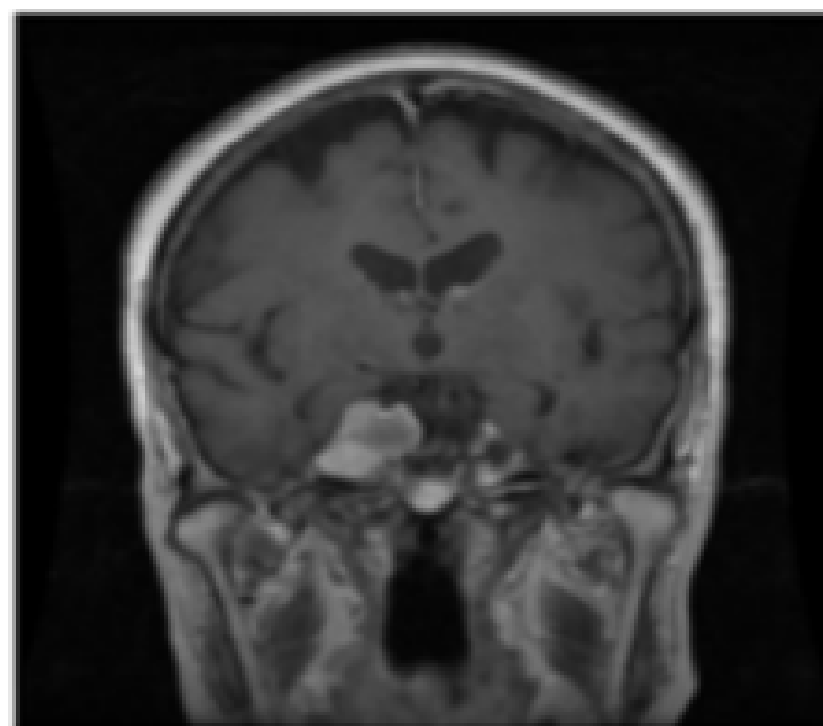
True label : Pituitary

Predicted label : Pituitary



True label : Glioma

Predicted label : Glioma

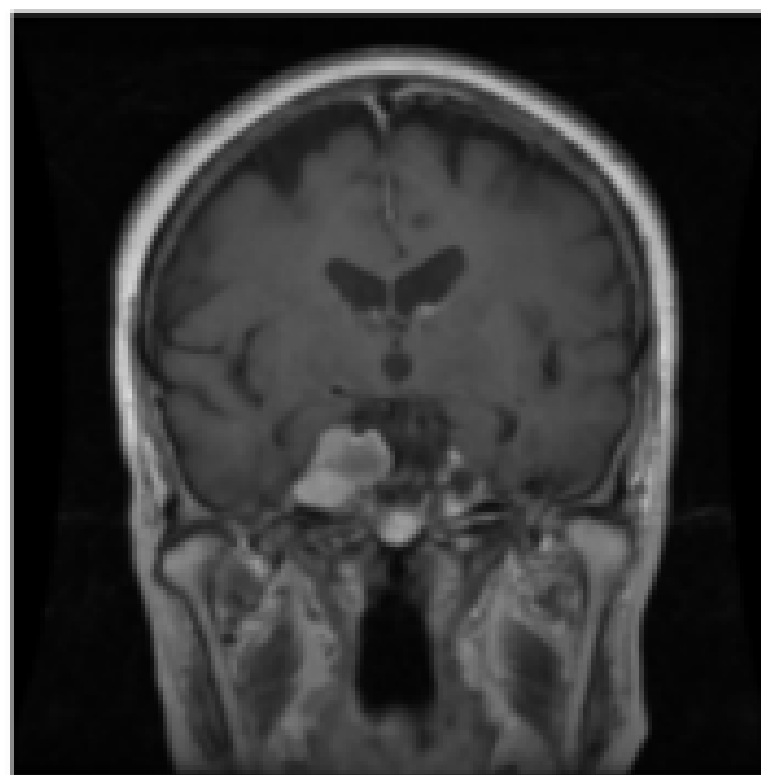


True label : Meningioma

Predicted label : Meningioma

Figure 6. Show training accuracy data testing





True label: meningioma  
Predicted label: pituitary

Figure 7. Prediction model error test

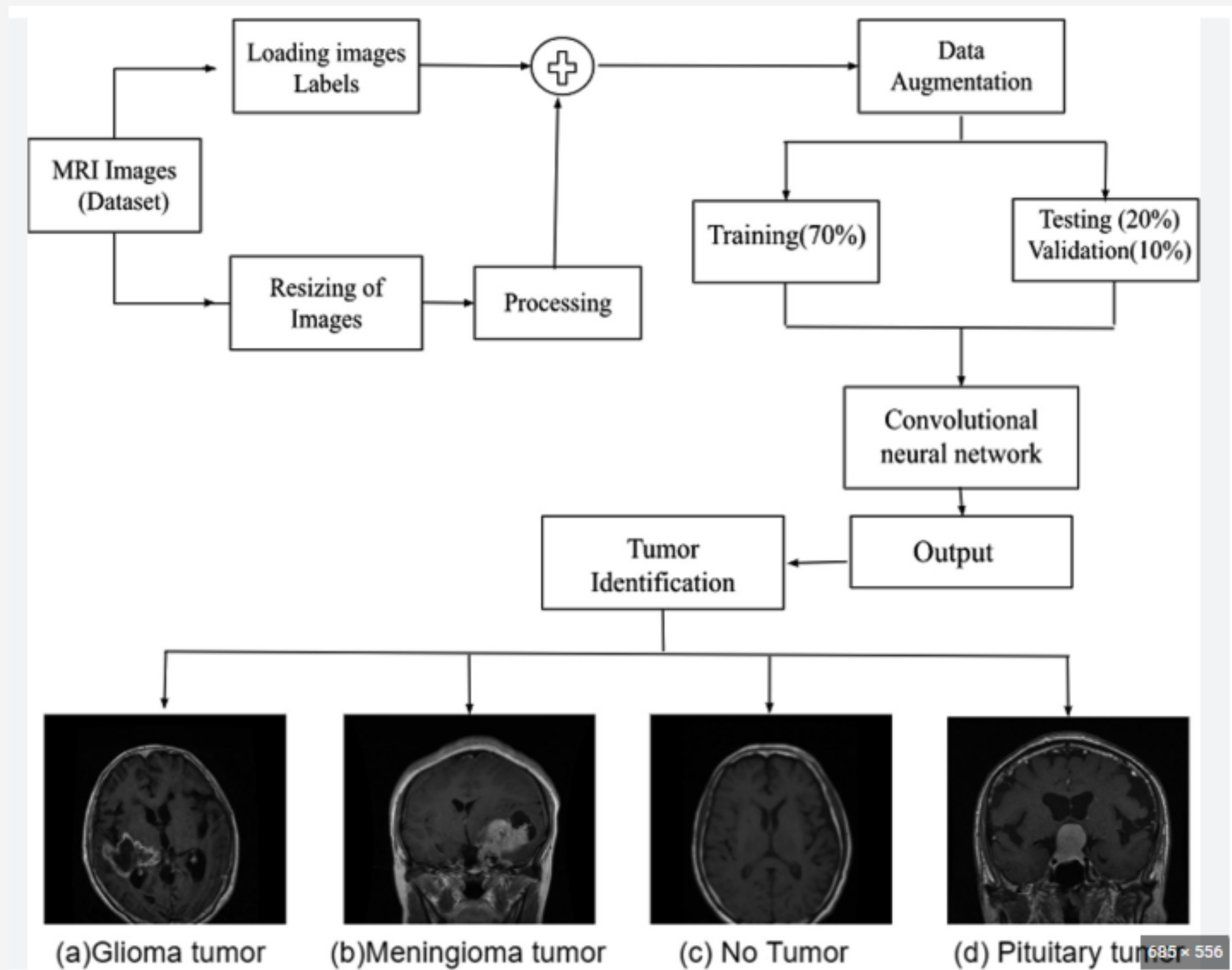


Figure. 8 [https://link.springer.com/chapter/10.1007/978-981-99-0969-8\\_388](https://link.springer.com/chapter/10.1007/978-981-99-0969-8_388)  
Brain tumour recognition and classification using CNN Model.

# Advantages

- Use of Mobilenet for brain tumor classification resulted in high accuracy.
- CNN architecture that can overcome the need for excess computing resources.
- The use of transfer learning was beneficial for improving performance in the deep learning area.



# Disadvantages

- Encountered an error while fine-tuning the Mobilenet\_v2\_100\_224 model.
- The size of the input from the efficient network causes different time consumption in training.
- Some images that the model could not detect.



# Conclusion

- MobilenetV2 140 x 224 architecture to improve classification accuracy.
- It improves the overall prediction of accuracy.
- It achieved high accuracy of 94%.
- Transfer learning helpful for the classification to improve better performance in the deep learning area.



**Thank you!**

