Brain Tumor Detection using Convolutional Neural Network Architecture VGGNet and Inception Model

SAJID IBNA MAHBUB, 20-42109-1
SAIMA SADIA RATRI, 20-43793-2
ZERIN HASAN SAHOSH, 20-43744-2
MD. SAZZAD SIDIDQUE, 20-43747-2

***Abstract*—Brain tumors are one of the dangerous kinds of tumors that need to be detected as soon as possible for an effective treatment. Using specialists for examining MRI images is both time-consuming and error-pruning. So, we have used CNN for solving this problem and getting an accuracy of 97%. We have also tried out past models for demonstrating their performance. Their highest accuracy was 95%. We then used image preprocessing techniques on their model for higher accuracy. We have used Data augmentation as our image preprocessing technique and got a significant amount of increase in overall accuracy. We then tried out a lot of model architectures for finding out which is the best model architecture for their model and we found VGGNet gave us the best accuracy. So, we have used all of the findings from this experiment for creating our own model and getting an accuracy of 97%.**

Keywords—CNN, ResNet, MobileNet, VGGNet, Inception

I. INTRODUCTION

A brain tumor is an unusual growth or mass of cells in the brain that can disrupt normal brain function. Brain tumors are commonly classified into 3 classes: Glioma, Meningioma, and Pituitary. Tumors can be detected from MRI images and a specialist will go through all the images manually and decide if the patient has a brain tumor. Though this process can be error pruned. As Tumors can be of any size and any shape. So, It will need a great deal of experience for detecting tumors. Even then they can't identify the tumor accurately. So, we can take the help of computer vision for solving this problem. We can use CNN for creating our model which we will train by using MRI images that will detect all the tumors accurately with an accuracy of around 97%. There are many works of others where they have tried to solve this problem. Everyone has used different approaches or upgrade approaches from previous work for solving this problem. We have tried a lot of possible approaches for coming up with the best approach which can solve this problem.

At first, we tried the cnn model proposed by Arkapravo et al. [5] in our bigger dataset. We have then carefully calculated the accuracy of that model with precision, recall, f1-score, and support score with different activation functions and optimizers. After that, we have taken a decision on which activation function and optimizer is best for our problem. Then we have used model architectures like ResNet, MobileNet, VGGNet for finding out which model architecture is best for our problem. After finding out the best model architecture for our problem we have created a new model with the best activation function, optimizer and model architecture we have got. We have also used the inception model on our proposed approach for demonstrating the performance of our proposed model.

II. RELATED WORKS

[1] The authors of this paper proposed a method that will use a cascade of fully convolutional neural networks to automatically part brain tumors from multi-modal MRI images. The decomposition of the multi-class segmentation problem into three discrete segmentation problems is performed here as stated by the subregion hierarchy. An anisotropic structure with multi-view fusion is used to upgrade the segmentation accuracy. The implemented process was able to accomplish a respected performance on the BraTS 2017 testing and validation data set. False positives were reduced by the application of a cascaded framework. To gain higher accuracy, multi-view fusion avails the advantage of 3D contextual information. In the paper, some of the difficulties encountered in the automated segmentation of brain tumors with varying sizes, localization of brain tumors, and ambiguity of the boundaries between nearby structures due to smooth intensity gradients, shape, etc., are discussed. The applicability and value of previous understanding about shape and location, which is frequently utilized for effective segmentation of a variety of anatomical structures, may be limited by such challenges. Furthermore, the dataset taken for this is not large enough. So, the accuracy was also not up to the mark[1].

[2] Brain tumor segmentation is a very difficult feat to achieve. The authors presented a method that uses CNN, Fuzzy C-Means clustering, and traditional classifiers to identify brain tumors from MRI images. A real-time dataset was used to train the model that had diverse images with different tumor sizes, shapes, locations, and image intensities. An introduction of the five-layer CNN model was done and the performance was compared with traditional classifiers. The results with CNN show promising accuracy of 97.87%. One drawback is that they only used a small dataset of 217 images and their model will face considerable challenges while working with a larger dataset. Additionally, they missed the opportunity to discuss the possible clinical applications for their suggested methodology and how patients with brain tumors might benefit from it [2].

[3] The most familiar and threatening brain tumor with a very less rate of survival is Gliomas. So, Accurate detection of this tumor is crucial for the survival of the patients. The authors of this paper proposed a Deep Convolutional Neural Network based automated segmentation algorithm. The algorithm is said to have a patch-based approach and preprocessing and post-processing steps are included. The research provides a CNN architecture that combines both global and local properties for segmenting brain tumors. To increase training and testing performance and lower the likelihood of over-fitting, the algorithm incorporates the utilization of max-pooling, max-out, and drop-out. The dataset, implementation specifics, and evaluation criteria are additionally addressed in the research article. The proposed neural network design functions better than state-of-the-art approaches in terms of dice score, sensitivity, and specificity, according to evaluation results. The suggested approach performs satisfactorily in identifying growing tumors and identifying tumor regions. But the proposed method starts to encounter difficulties in predicting minority classes because of lacking a large dataset for training. Too many features in fully linked layers have been found to cause over-fitting, while if features are drastically reduced, the model does not learn significantly, resulting in underfitting. Furthermore, it has been found that fully connected layers take longer to process than convolutions, therefore 2048 features in a fully associated layer are used to compromise between segmentation speed and accuracy [3].

[4] Automated tumor detection can play a fundamental role in aiding physicians and radiologists to classify brain tumor. In the paper, a deep learning-based approach for brain tumor segmentation and detection in cranial MR images is proposed. Three steps make up the suggested method: image processing techniques for preprocessing, image classification with extreme learning machines local receptive fields (ELM-LRF), and tumor region extraction. The authors offer a review of the literature on methodologies and approaches for identifying and segmenting brain tumors. With a classification accuracy of 97.18%, the suggested strategy exceeds other recent findings in the literature, including convolutional neural networks and AlexNet. The ELM-LRF approach is straightforward and effective, with quick training times, connections, and input weights that are created at random. The suggested approach can be utilized to detect brain tumors with computer assistance. Additionally, the study's dataset's sample size is slightly insignificant, which could restrict the scope to which the results can be reproduced[4].

Comparison between Arkapravo et al. [5] model and our proposed model:

1) Dataset: They have used 2020 BraTS dataset for their experiment. They have taken a total of 2892 images consisting of 2 classes for their experiment whereas we have used a bigger dataset than them. Our dataset have 7023 images classified into 4 classes.

2) Image preprocessing: They have not used any kind of image preprocessing technique for their convolutional neural network whereas we have used data augmentation and gained a huge sum of accuracy which is greater than Arkapravo et al. [5] model accuracy.

3) CNN Layer Architecture: Their network consists of 9 layers whereas in our network we have used 8 layers. Their layer architecture and our layer architecture working procedures are kinda same. As we found that it is the best-experimented architecture for our datasets which gives us the best accuracy.

4) Activation functions and optimizers: They have used different activation functions and optimizers for their experiment. We have also used different activation functions and optimizers for our experiment for finding out the best-performing activation function and optimizer for our datasets.

5) Architecture Model: We have used different types of architecture models like ResNet, MobileNet, VGGNet, and Inception models whereas they have not used any kind of model for demonstrating their performance. By using the model we have found out that the accuracy of the models is really low but the most accurate model we have found is VGGNet.

6) Accuracy calculations: They have used only accuracy matric for calculating their accuracy whereas we have used precision, recall, f1-score, and support for calculating the performance of our model accurately.

III. PROPOSED MODEL

1) Dataset: We have used a dataset that contains of 7023 visuals of human brain MRI images. The images are parted into 4 classes which are glioma, meningioma, no tumor, and pituitary. Glioma has 300 images, Meningioma has 306 images, No tumor has 405 images and Pituitary has 300 images.

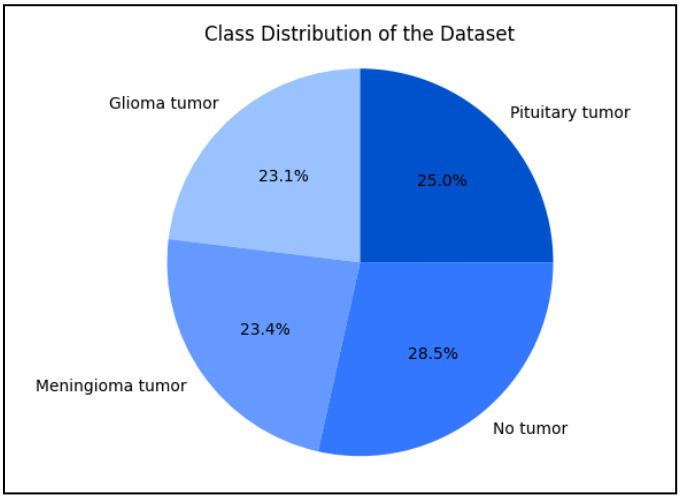

Fig. 1. Class Distribution of the dataset

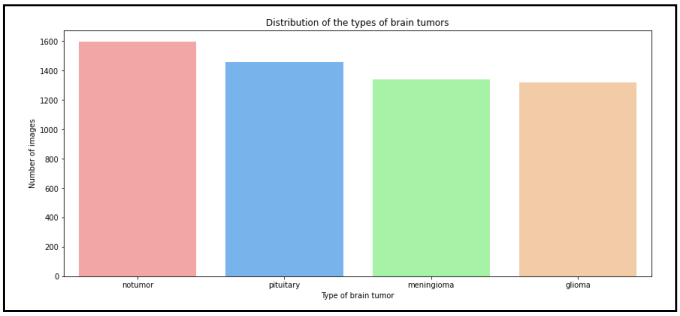

Fig. 2. Distribution of the types of brain tumours

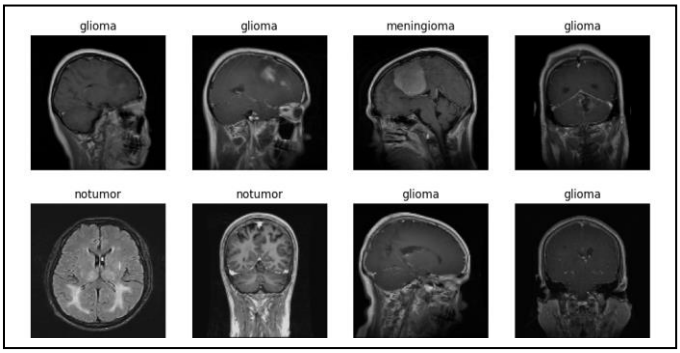

Fig. 3. Visualization of the dataset

2) Image preprocessing: We have used data augmentation for our image preprocessing. In data augmentation, we have applied random brightness from 80% to 120%, random contrast from 80% to 120%, random sharpness from 80% to 120%.

3) CNN Layer architecture: At first we have used Arkapravo et al. [5] model in our dataset for verifying their performance in other datasets where the data is not augmented.

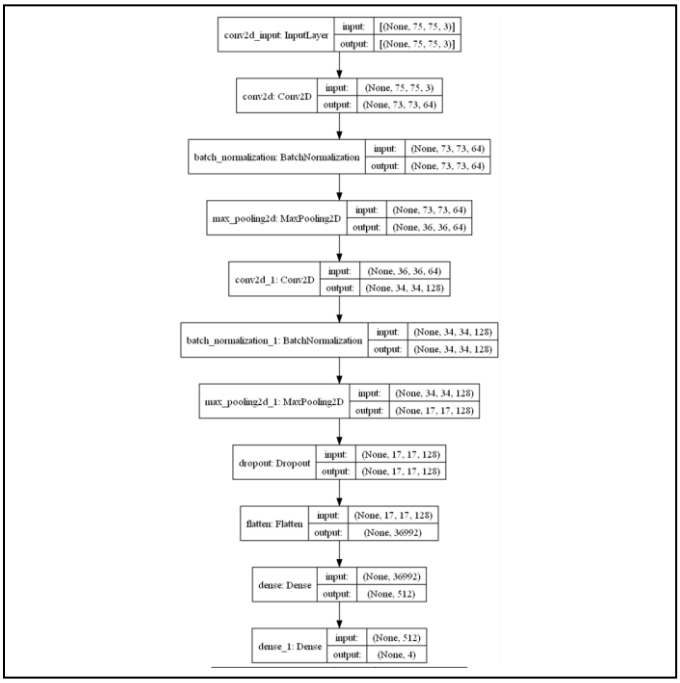

Fig. 4. Arkapavo et al. [5] proposed model

Then we created our model for better performance than Arkapravo et al. [5] model. Where -

- We have used a 8-layer convolutional Neural Network architecture. Where we have load our input dataset and slit it into 8:2 ratio.
- We have added a layer with 32 convolutional filter.
- We have added batch normalization.
- We have passed the convolutional kernel in 2*2 max pooling layer.
- We have added CNN layer with 64 convolutional filters.
- We have added batch normalization.
- We have passed the convolutional kernel in 2*2 max pooling layer.
- We have abandoned some visuals to avoid overfitting.
- We have pooled a feature map.
- We have applied dense layer with 512 nodes.
- We have usedlied softmax activation function in the final dense layer.

Our model –

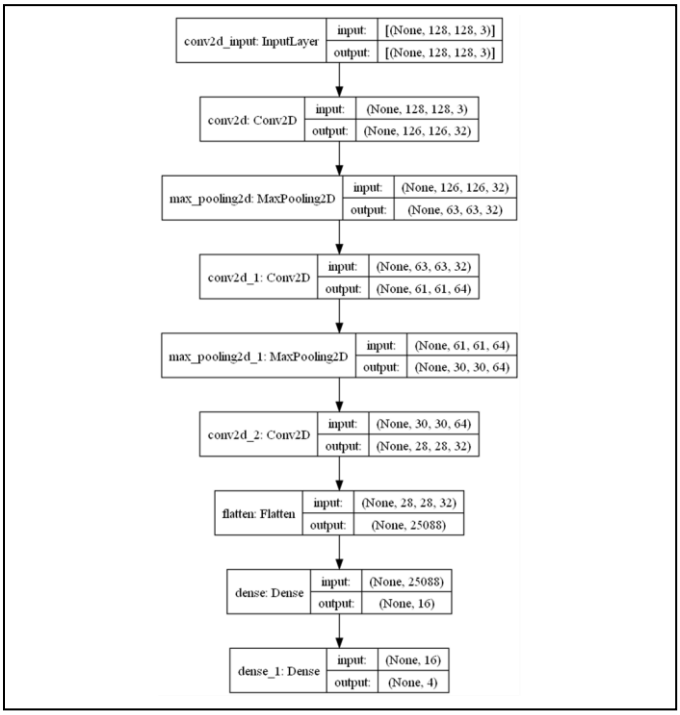

Fig. 5. Our proposed model

4) Activation functions and Optimizers: We have at first used all the activation functions and optimizers used by Arkapravo et al. [5]. We have verified their model accuracy in our dataset by using those activation functions and optimizers. We have used softmax activation function and Adam optimizer for our model.

5) CNN Model Architecture:

a) ResNet: We have used ResNet on Arkapravo et al. [5] model for finding out how well it will perform on our dataset.

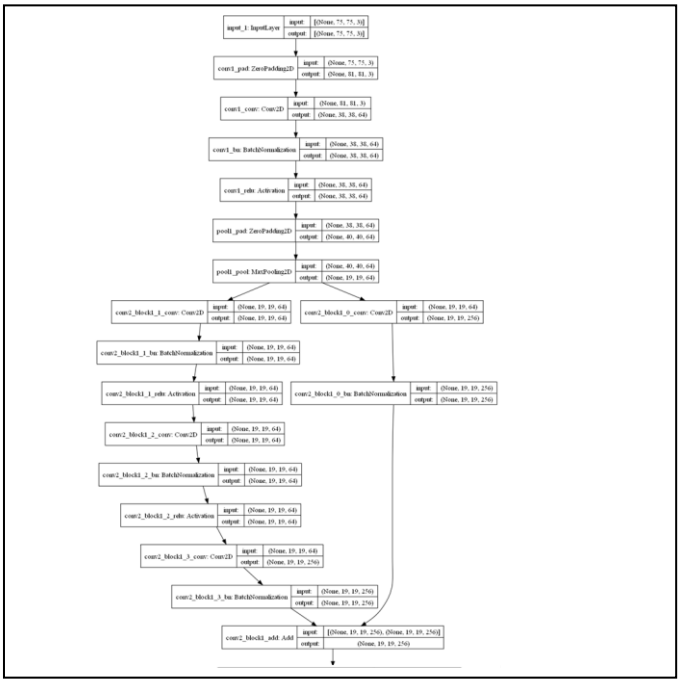

Fig. 6. ResNet model architecture on Arkapavo et al. [5] proposed model

b) MobileNet: We have used MobileNet on Arkapravo et al. [5] model for finding out how well it will perform on our dataset.

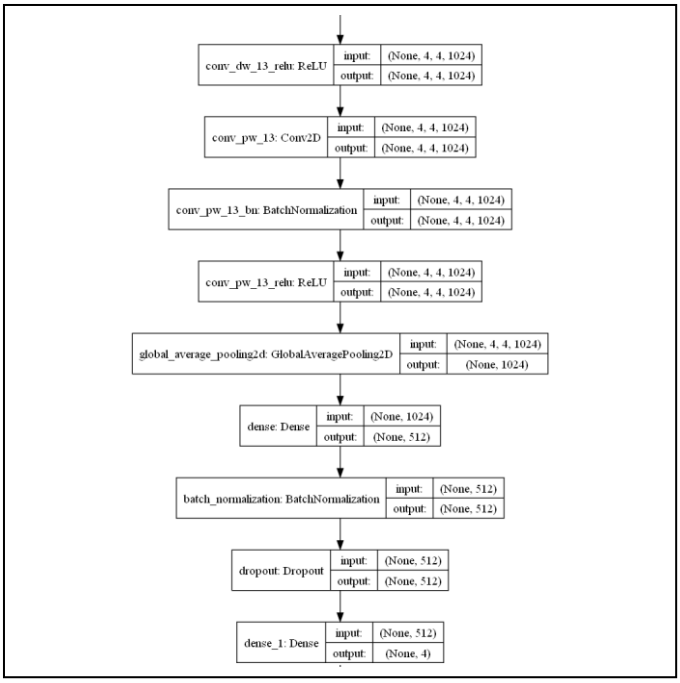

Fig. 7. MobileNet model architecture on Arkapavo et al. [5] proposed model

c) VGGNet: We have used MobileNet on Arkapravo et al. [5] model for finding out how well it will perform on our dataset.

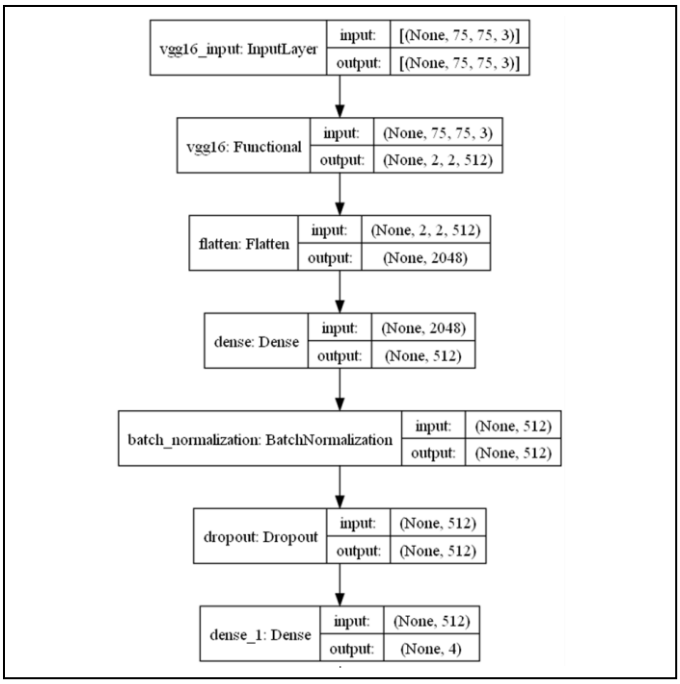

Fig. 8. VGGNet model architecture on Arkapavo et al. [5] proposed model

We have also used VGGnet in our proposed model as it was performing best in the Arkapravo et al. [5].

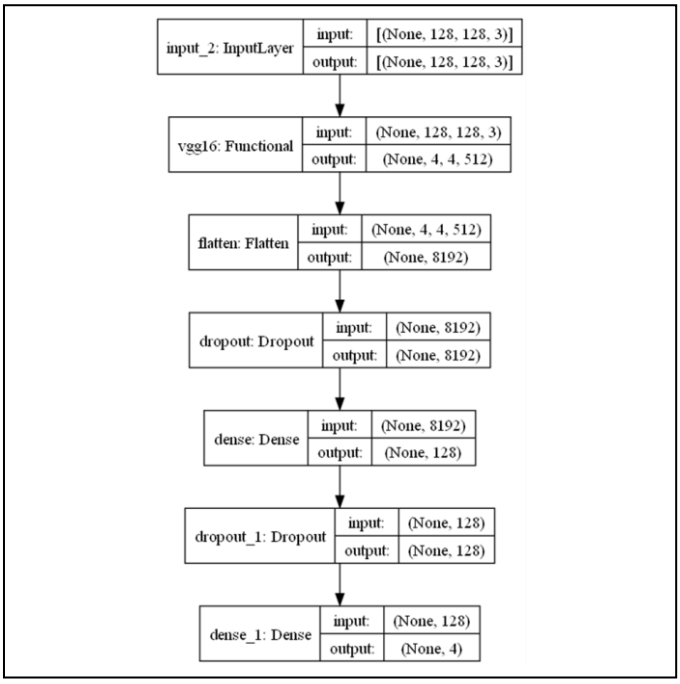

Fig. 9. VGGNet model architecture on our proposed model

d) Inception Model: We have also used Inception model in our proposed model for demonstrating how well it performs in our dataset.

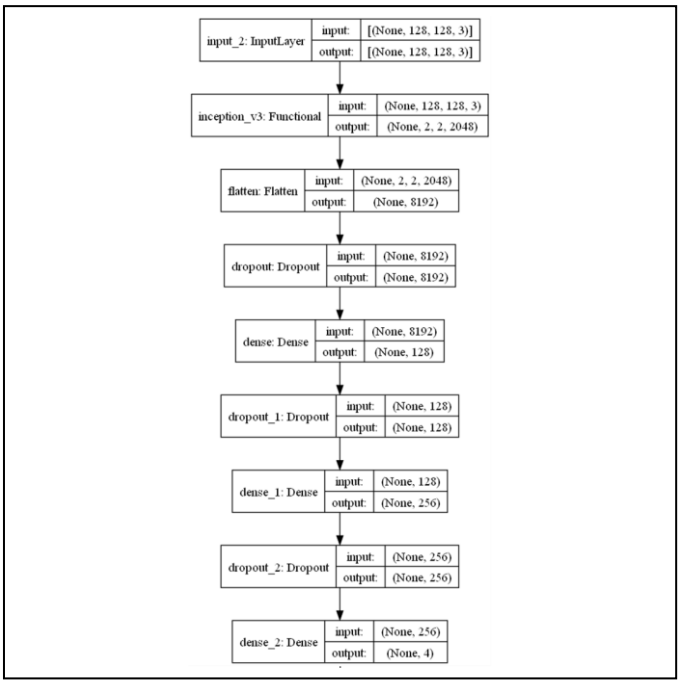

Fig. 10. Inception model architecture on our proposed model

6) Training and testing split: We have used 8:2 for testing Arkapravo et al. [5] model and also our proposed model.

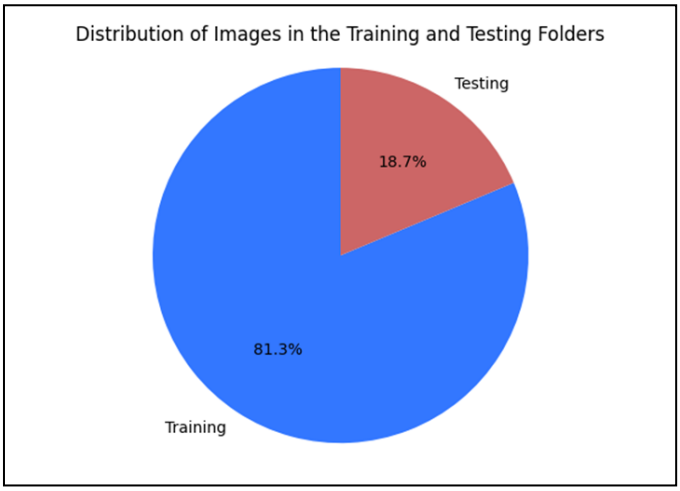

Fig. 11. Distribution of images in the Training and testing split

IV. RESULTS

Arkapravo et al. [5] has used different activation functions and different optimizers in their paper for demonstrating the performance of their proposed model where they got the best accuracy by using Softmax activation function and RMSprop optimizer. They used this model on their dataset for deriving a result of 99.74% accuracy.

Table 1
Comparison of different models.

Final Layer Activation Method	Optimizer	Accuracy (%)	Testing Accuracy (%)	Evaluation of the Model (%)
SVM	N/A	15.17	20.83	24.17
Sigmoid	RMSProp	97.63	58.33	68.72
Softmax	AdaMax	98.10	75	82.40
Softmax	RMSProp	**99.74**	93.78	97.71

Fig. 12. Comparison of different models of Arkapravo et al. [5].

We also have used the same model with same activation function and optimizers that was used by Arkapravo et al. [5]. But we didn't get the accuracy that was achieved by them but it was close. Then we have used architecture model like ResNet, MobileNet and VGGNet to see how well it performs. But it was really disappointing to see the results.

1) For Sigmoid Activation function and RMSprop Optimizer using Arkapravo et al. [5] model:

	precision	recall	f1-score	support
glioma	0.90	0.98	0.94	300
meningioma	0.92	0.83	0.87	306
notumor	0.97	0.95	0.96	405
pituitary	0.96	0.99	0.98	300
accuracy			0.94	1311
macro avg	0.94	0.94	0.94	1311
weighted avg	0.94	0.94	0.94	1311

Fig. 13. Accuracy of Arkapravo et al. [5] model for Sigmoid function and RMSprop optimizer on our used dataset.

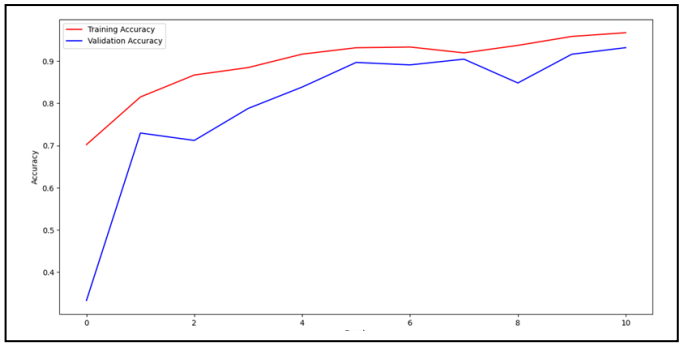

Fig. 14. Training Accuracy and Validaion Accuracy of Arkapravo et al. [5] model for Sigmoid function and RMSprop optimizer on our used dataset.

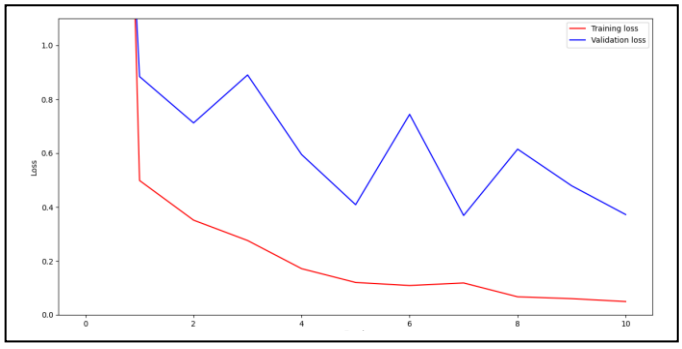

Fig. 15. Training Loss and Validation Loss of Arkapravo et al. [5] model for Sigmoid function and RMSprop optimizer on our used dataset.

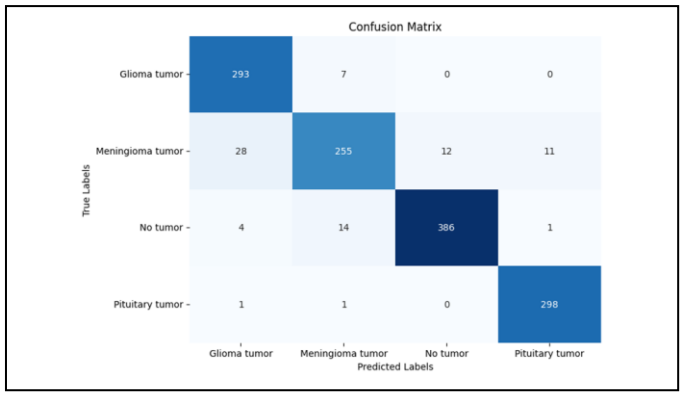

Fig. 16. Confusion Matrix Arkapravo et al. [5] model for Sigmoid function and RMSprop optimizer on our used dataset.

So, we can see it derived an accuracy of 94% whereas Arkapravo et al. [5] showed it will derive 97.63%.

2) For Softmax Activation function and Adam Optimizer using Arkapravo et al. [5] model:

	precision	recall	f1-score	support
glioma	0.99	0.79	0.88	300
meningioma	0.75	0.96	0.84	306
notumor	0.98	0.95	0.97	405
pituitary	0.98	0.93	0.96	300
accuracy			0.91	1311
macro avg	0.92	0.91	0.91	1311
weighted avg	0.93	0.91	0.91	1311

Fig. 17. Accuracy of Arkapravo et al. [5] model for Softmax function and Adam optimizer on our used dataset.

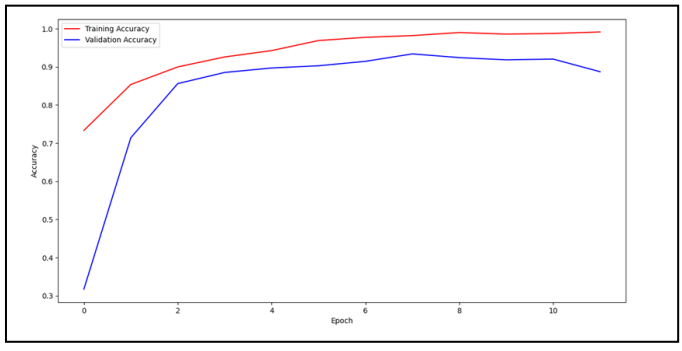

Fig. 18. Training Accuracy and Validaion Accuracy of Arkapravo et al. [5] model for Softmax function and Adam optimizer on our used dataset.

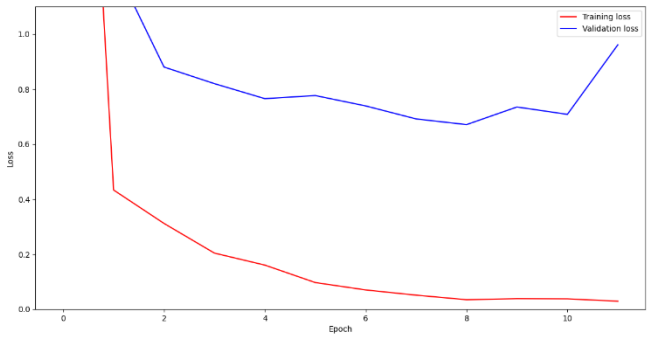

Fig. 19. Training Loss and Validation Loss of Arkapravo et al. [5] model for Softmax function and Adam optimizer on our used dataset.

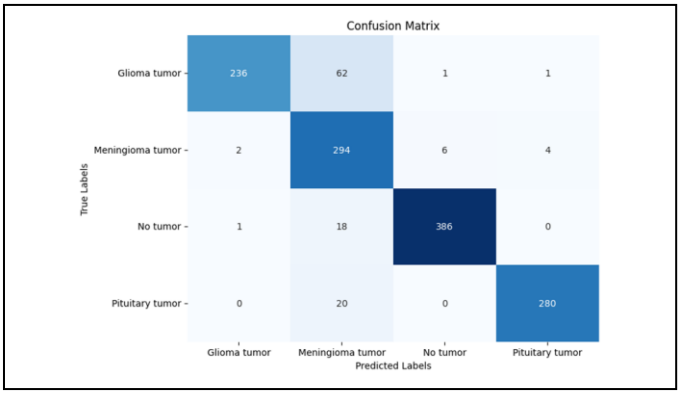

Fig. 20. Confusion Matrix Arkapravo et al. [5] model for Softmax function and Adam optimizer on our used dataset.

So, we can see it derived a accuracy of 91% whereas Arkapravo et al. [5] showed it will derive 98.10%.

3) For Softmax Activation function and RMSprop Optimizer using Arkapravo et al. [5] model r:

	precision	recall	f1-score	support
glioma	0.94	0.95	0.95	300
meningioma	0.94	0.86	0.90	306
notumor	0.95	0.99	0.97	405
pituitary	0.98	0.99	0.99	300
accuracy			0.95	1311
macro avg	0.95	0.95	0.95	1311
weighted avg	0.95	0.95	0.95	1311

Fig. 21. Accuracy of Arkapravo et al. [5] model for Softmax function and RMSprop optimizer on our used dataset.

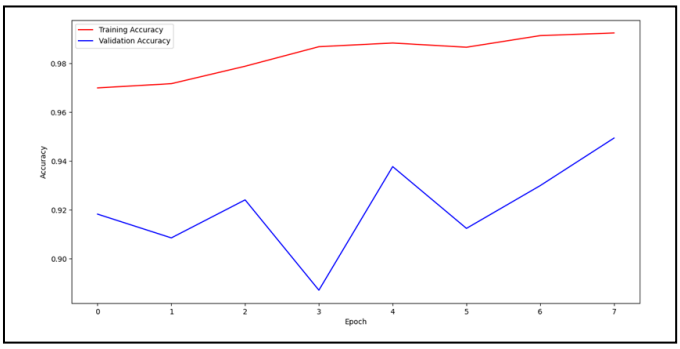

Fig. 22. Training Accuracy and Validation Accuracy of Arkapravo et al. [5] model for Softmax function and RMSprop optimizer on our used dataset.

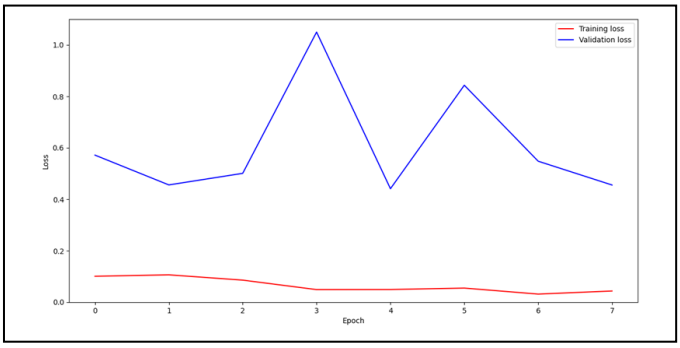

Fig. 23. Training Loss and Validaion Loss of Arkapravo et al. [5] model for Softmax function and RMSprop optimizer on our used dataset.

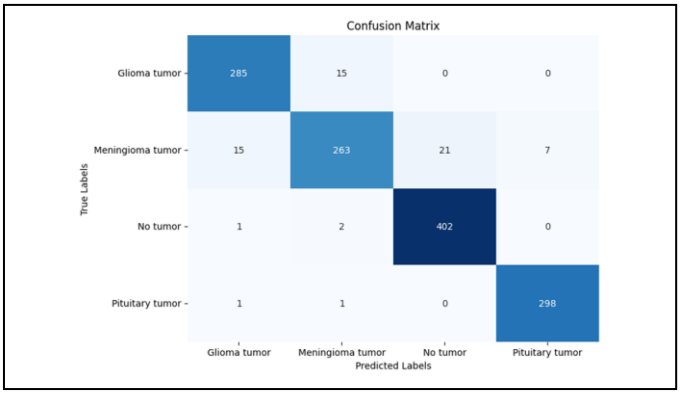

Fig. 24. Confusion Matrix Arkapravo et al. [5] model for Softmax function and RMSprop optimizer on our used dataset.

So, we can see it derived a accuracy of 95% whereas Arkapravo et al. [5] showed it will derive 99.74%.

4) For ResNet using Arkapravo et al. [5] model:

	precision	recall	f1-score	support
glioma	0.92	0.78	0.84	300
meningioma	0.80	0.84	0.82	306
notumor	0.96	0.98	0.97	405
pituitary	0.92	0.98	0.95	300
accuracy			0.90	1311
macro avg	0.90	0.89	0.89	1311
weighted avg	0.90	0.90	0.90	1311

Fig. 25. Accuracy of Arkapravo et al. [5] model for ResNet on our used dataset.

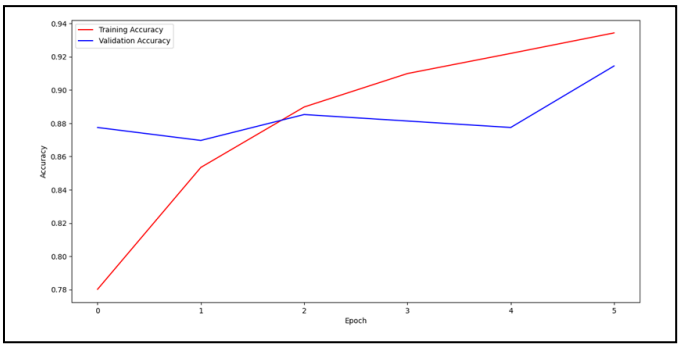

Fig. 26. Training Accuracy and Validaion Accuracy of Arkapravo et al. [5] model for ResNet on our used dataset.

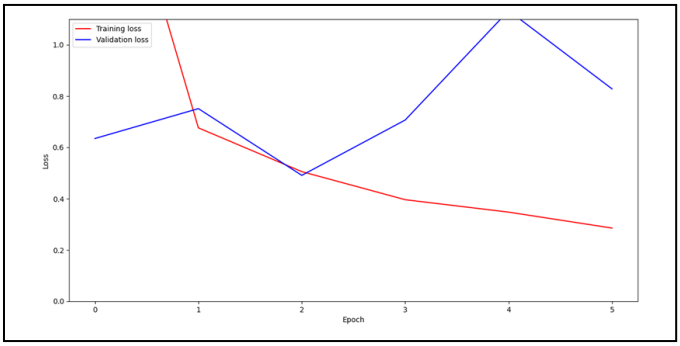

Fig. 27. Training Loss and Validaion Loss of Arkapravo et al. [5] model for ResNet on our used dataset.

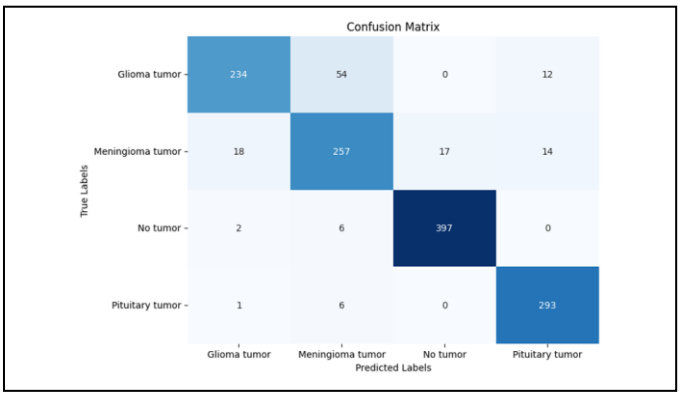

Fig. 28. Confusion Matrix Arkapravo et al. [5] model for Resnet on our used dataset.

We have derived an accuracy of 90% by using ResNet in Arkapravo et al. [5] model.

5) For MobileNet using Arkapravo et al. [5] model:

	precision	recall	f1-score	support
glioma	0.98	0.64	0.77	300
meningioma	0.70	0.80	0.75	306
notumor	0.92	1.00	0.95	405
pituitary	0.89	0.97	0.93	300
accuracy			0.86	1311
macro avg	0.87	0.85	0.85	1311
weighted avg	0.88	0.86	0.86	1311

Fig. 29. Accuracy of Arkapravo et al. [5] model for MobileNet on our used dataset.

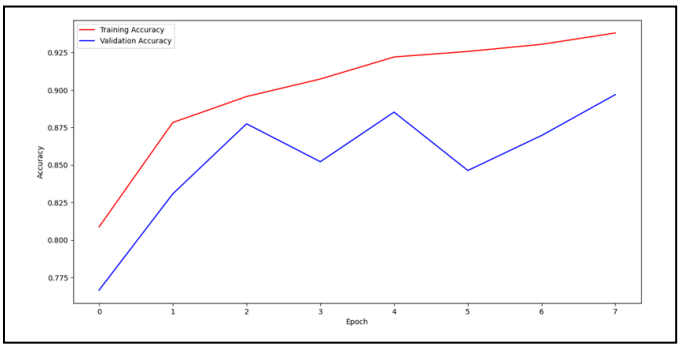

Fig. 30. Training Accuracy and Validaion Accuracy of Arkapravo et al. [5] model for MobileNet on our used dataset.

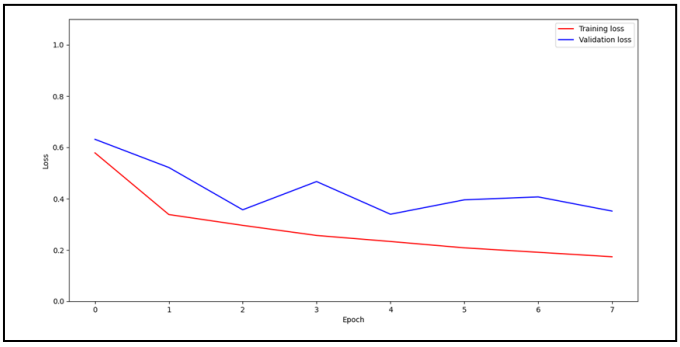

Fig. 31. Training Loss and Validaion Loss of Arkapravo et al. [5] model for MobileNet on our used dataset.

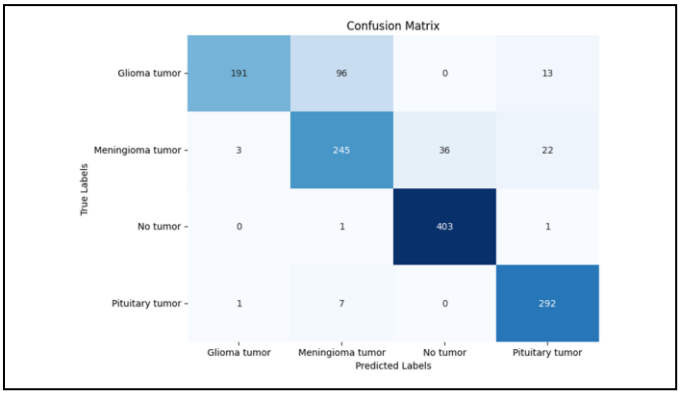

Fig. 32. Confusion Matrix Arkapravo et al. [5] model for MobileNet on our used dataset.

We have derived an accuracy of 86% by using MobileNet in Arkapravo et al. [5] model.

6) For VGGNet using Arkapravo et al. [5] model:

	precision	recall	f1-score	support
glioma	0.94	0.83	0.88	300
meningioma	0.86	0.86	0.86	306
notumor	0.97	1.00	0.98	405
pituitary	0.92	0.99	0.95	300
accuracy			0.93	1311
macro avg	0.92	0.92	0.92	1311
weighted avg	0.93	0.93	0.92	1311

Fig. 33. Accuracy of Arkapravo et al. [5] model for VGGNet on our used dataset.

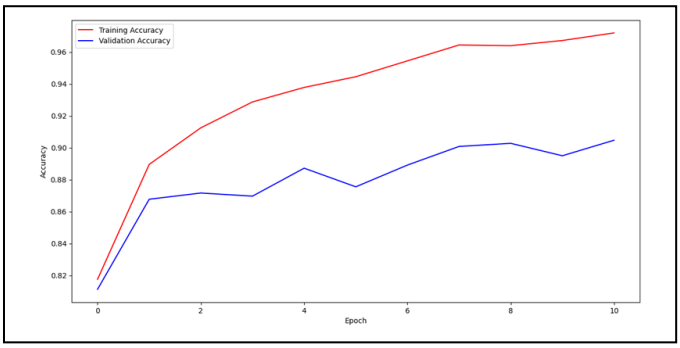

Fig. 34. Training Accuracy and Validaion Accuracy of Arkapravo et al. [5] model for VGGNet on our used dataset.

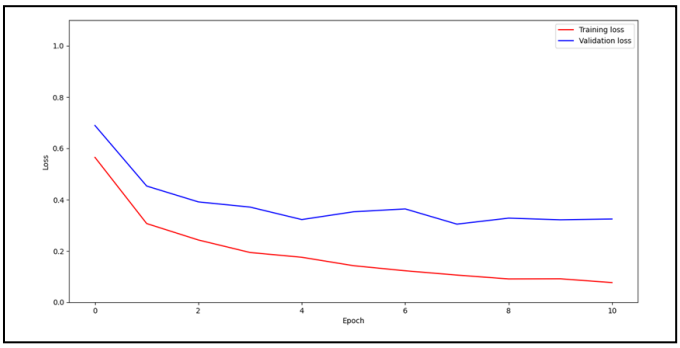

Fig. 35. Training Loss and Validaion Loss of Arkapravo et al. [5] model for VGGNet on our used dataset.

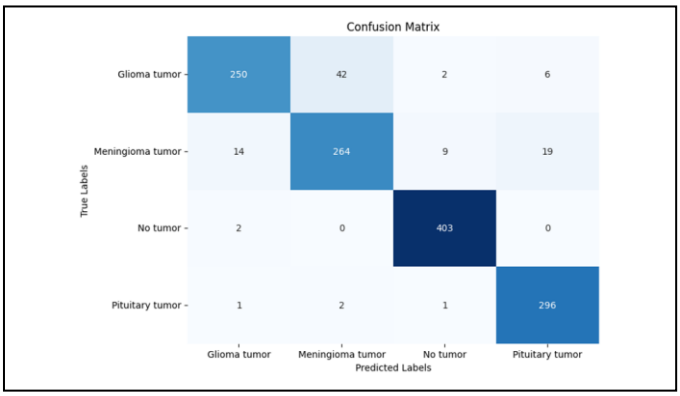

Fig. 36. Confusion Matrix Arkapravo et al. [5] model for VGGNet on our used dataset.

We have derived an accuracy of 95% by using VGGNet in Arkapravo et al. [5] model.

7) Using Softmax activation function and Adam optimizer in our proposed model:

	precision	recall	f1-score	support
glioma	0.90	0.97	0.93	300
meningioma	0.96	0.85	0.90	306
notumor	0.99	1.00	1.00	405
pituitary	0.96	0.98	0.97	300
accuracy			0.95	1311
macro avg	0.95	0.95	0.95	1311
weighted avg	0.95	0.95	0.95	1311

Fig. 37. Accuracy of our proposed model for Softmax function and Adam optimizer on our used dataset.

So, we have achieved an accuracy of 95% for using our model in our used dataset with data augmentation.

8) Using VGGNet in our Proposed model:

	precision	recall	f1-score	support
glioma	0.94	0.96	0.95	300
meningioma	0.95	0.95	0.95	306
notumor	0.99	1.00	0.99	405
pituitary	0.99	0.97	0.98	300
accuracy			0.97	1311
macro avg	0.97	0.97	0.97	1311
weighted avg	0.97	0.97	0.97	1311

Fig. 38. Accuracy of our proposed model for VGGNet on our used dataset.

Fig. 39. Training Accuracy and Validaion Accuracy of our proposed model for VGGNet on our used dataset.

We have achieved an accuracy of 97% by using VGGNet in our proposed model which is greater than any other model we have used until now.

9) Using Inception model in our Proposed model:

	precision	recall	f1-score	support
glioma	0.88	0.84	0.86	300
meningioma	0.82	0.77	0.80	306
notumor	0.96	0.97	0.97	405
pituitary	0.88	0.96	0.91	300
accuracy			0.89	1311
macro avg	0.89	0.89	0.89	1311
weighted avg	0.89	0.89	0.89	1311

Fig. 40. Accuracy of our proposed model for Inception on our used dataset.

Fig. 41. Training Accuracy and Validaion Accuracy of our proposed model for Inception Model on our used dataset.

We have achieved an accuracy of 89% by using inception model in our proposed model.

TABLE I. OVERALL RESULTS FROM ALL THE MODELS

Model	***Last Layer Activaiton Function***	***Optimizer***	***Architecture***	***Accuracy***
Arkapravo et al. [5]	Sigmoid	RMSprop		94%
Arkapravo et al. [5]	Softmax	Adam		91%
Arkapravo et al. [5]	Softmax	RMSprop		95%
Arkapravo et al. [5]	Softmax	RMSprop	ResNet	90%
Arkapravo et al. [5]	Softmax	RMSprop	MobileNet	86%
Arkapravo et al. [5]	Softmax	RMSprop	VGGNet	95%
Our proposed model	Softmax	Adam		95%
Our proposed model	Softmax	Adam	VGGNet	97%
Our proposed model	Softmax	Adam	Inception	89%

V. CODE

All the codes are uploaded in the https://github.com/MDSAZZADSIDDIQUE/Brain-Cancer-Detection repository.

VI. DISCUSSION

We have at first demonstrated the performance of Arkapravo et al. [5] model in our used dataset. Then we used our own model with the help of VGGNet to demonstrate the result in the used dataset. As the dataset used by Arkapravo et al. [5] was not that big, so when we used their model in our dataset we can see a great change in the accuracy also there was no image preprocessing for Arkapravo et al. [5] model. So, we can't get a state-of-the-art accuracy from their model.

The best result we got from using the Arkapravo et al. [5] model was where we used the softmax activation function and RMSprop optimizer in the last layer where we got 95% overall accuracy. Using model architecture like ResNet, MobileNet was pretty underwhelming. As the datasets are not so big so there is no need for skipping connection or there is no need for the problem of vanishing gradient. We also don't need to optimize our model because it's too big. So, we don't need to also use MobileNet.

But when we used VGGNet with our proposed model we get the best result. VGGNet consists of small 3x3 filters and the deeper the network, there is more the number of filters which helps us reduce the spatial dimensionality. We have gotten an accuracy of 97% by using VGGNet with our proposed model which is the best result so far.

Using the Inception model in our proposed model was also underwhelming. It was a network which are small, parallel convolutional neural networks that perform different types of convolutions on the same input. So, it's better when we have a huge network. As we don't have a huge network so it performed really underwhelmingly.

VII. CONCLUSION

Brain tumor is one of the lethal condition which needs to be detected in the earlier stages for effective treatments. When MRI images are examined by the specialist it can be error pruned. So, using computer vision to solve this problem will be a great help for detecting brain cancer accurately and quickly. We have tried to find the best way to detect brain tumors by taking inspiration from previous works. We have tried to come up with the best activation function or best optimizer which can give us the best result. We have also tried to find out the best model architecture which can help us get the best possible accuracy and we have succeeded. We have used Softmax function in the last layer and Adam optimizer with VGGNet for getting an accuracy of 97% which is more than any other model we have tried in this paper.

There was some limitation of our work. For the scarcity of MRI brain images what we have taken as a dataset was not big enough. We can apply our model on a bigger dataset in the future. The network was not big enough to detect complex features. We can make our network more complex and big which can detect more complex features and extract them for more accuracy. So, There is a lot of room to improve in this problem. But it is still great to get an accuracy of 97%, but it can be improved more in the future.

REFERENCES

[1] G. Wang, W. Li, S. Ourselin, and T. Vercauteren, "Automatic brain tumor segmentation using cascaded anisotropic convolutional neural networks," in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer Verlag, 2018, pp. 178–190. doi: 10.1007/978-3-319-75238-9_16.

[2] T. Hossain, F. S. Shishir, M. Ashraf, M. A. Al Nasim, and F. Muhammad Shah, "Brain Tumor Detection Using Convolutional Neural Network," in 1st International Conference on Advances in Science, Engineering and Robotics Technology 2019, ICASERT 2019, 2019. doi: 10.1109/ICASERT.2019.8934561.

[3] S. Hussain, S. Anwar, and M. Majid, Brain Tumor Segmentation Using Cascaded Deep Convolutional Neural Network. 2017. doi: 10.0/Linux-x86_64.

[4] A. Ari and D. Hanbay, "Deep learning based brain tumor classification and detection system," Turkish Journal of Electrical Engineering and Computer Sciences, vol. 26, no. 5, pp. 2275–2286, 2018, doi:

[5] Chattopadhyay, A. and Maitra, M., 2022. MRI-based brain tumor image detection using CNN based deep learning method. *Neuroscience Informatics*, p.100060.

Contribution

Name	ID	Contribution (%)	Contribution Parts
SAJID IBNA MAHBUB	20-42109-1	25%	➢ Related Works: • Described summary of the papers • Found out the advantages and limitations of the papers. • Compared their model and our model. ➢ Results: • Attached all the experimental results are on this paper. • Described those results. • Compared between those results.
SAIMA SADIA RATRI	20-43793-2	25%	➢ Proposed model: • Described the dataset used by this paper. • Contributed to the convolutional neural network architecture design. • Described the proposed model architecture. • Described all the models with different activation functions and optimizers. • Described all the models with different model architecture. • Described the image preprocessing techniques in our model. • Described the training and testing split of our experiment
ZERIN HASAN SAHOSH	20-43744-2	25%	➢ Abstract: Described what can be learned from the paper ➢ Introduction: Described what has done in the paper ➢ Discussion: Described what we have learned from our experiment ➢ Conclusion: Described our limitations and future works ➢ References
MD. SAZZAD SIDIDQUE	20-43747-2	25%	➢ Code • Have visualized the dataset with code. • Have coded the Arkapravo et al. [5] with different activation functions and optimizers. • Have coded the Arkapravo et al. [5] with different model architecture. • Have coded the proposed model described in this paper with VGGNet and Inception model.