IV. Results and Performance Evaluation

In this case study, we have found Convolutional Neural Network (CNN) Efficient Net B-3 performed better at MRI Brain Tumor classification. CNN is very good at image pattern recognition. Other, Machine learning algorithms performed well respectively but did not produce result as good as Convolutional Neural Networks. Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF) were good in the early days of Machine Learning. But Deep Learning method Convolutional Neural Network produced much more good results than other algorithms in a short amount of time. Thus, we need to use more Deep Learning algorithms for better MRI image recognition such that, Vgg16, EfficientNet-B3, ResNet-150V2, Inception ResNetV2, TCN etc. This research is based on the analysis of the results and the accuracy we found throughout our experiment.

Performance Evaluation:

True Positive = TP, True Negative = TN

False Positive = FP, False Negative = FN

1) $\text{Accuracy} = \frac{(TP+TN)}{(TP+FN+FP+TN)}$ (6)

2) $\text{Recall} = \frac{(TP)}{(TP+FN)}$ (7)

3) $\text{Precision} = \frac{(TP)}{(TP+FP)}$ (8)

4) $F1 = 2 * \left(\frac{Precision\ x\ Recall}{Precision\ +\ Recall}\right)$ (9)

A. Using Vgg16

Epoch vs. Accuracy:

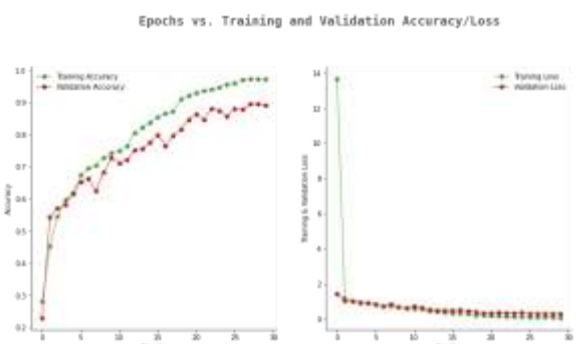

Fig. 13. Vgg16 Accuracy & Loss

Confusion Matrix:

Class	Assigned					Name
	0	1	2	3	#	
Actual	79	2	12	0	0	glioma_tumor
	1	42	6	2	1	no_tumor
	5	4	85	2	2	meningioma_tumor
	1	1	3	82	3	pituitary_tumor

Here Vgg16,

$\text{Accuracy} = \frac{(TP+TN)}{(TP+FN+FP+TN)} = 88.07\%$

$\text{Recall} = \frac{(TP)}{(TP+FN)} = 0.88$

$\text{Precision} = \frac{(TP)}{(TP+FP)} = 0.88$

$F1 = 2 * \left(\frac{Precision\ x\ Recall}{Precision\ +\ Recall}\right) = 0.88$

Also, we have used around 30 epochs in the vgg16 model and achieved 88.07% validation accuracy in average.

B. Using EfficientNet-B3

Epoch vs. Accuracy:

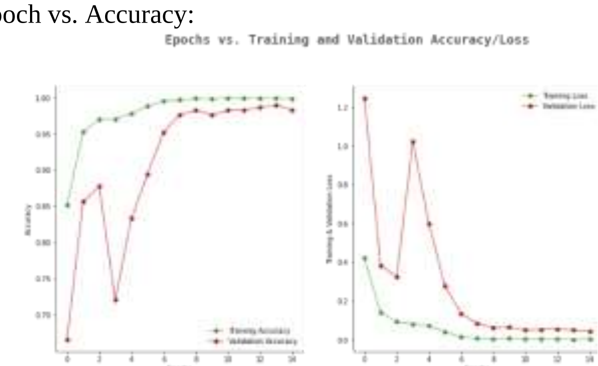

Fig. 14. EfficientNet-B3 Accuracy & Loss

Confusion Matrix:

Class	Assigned					Name
	0	1	2	3	#	
Actual	89	2	1	0	0	glioma_tumor
	0	49	0	0	1	no_tumor
	1	0	95	0	2	meningioma_tumor
	0	0	2	87	3	pituitary_tumor

Here EfficienNet-B3,

$\text{Accuracy} = \frac{(TP+TN)}{(TP+FN+FP+TN)} = 98.16\%$

$\text{Recall} = \frac{(TP)}{(TP+FN)} = 0.98$

$\text{Precision} = \frac{(TP)}{(TP+FP)} = 0.98$

$F1 = 2 * \left(\frac{Precision\ x\ Recall}{Precision\ +\ Recall}\right) = 0.98$

Well, in the EfficientNet-B3 model after 15 epochs, we have achieved validation accuracy around 98.16%.

C. Using Inception-ResNet-v2

Epoch vs. Accuracy:

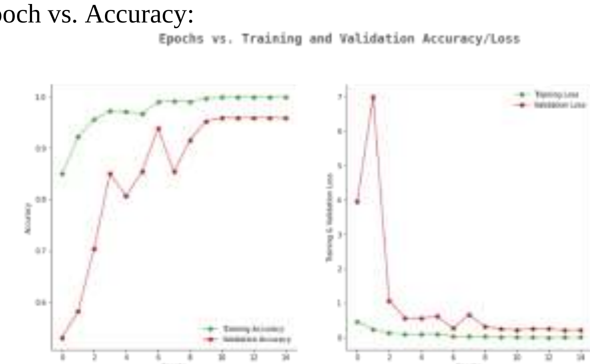

Fig. 15. Inception-Resnet-V2 Accuracy & Loss

Confusion Matrix:

Class	Assigned					Name
	0	1	2	3	#	
Actual	90	2	1	0	0	glioma_tumor
	0	48	0	3	1	no_tumor
	2	0	93	1	2	meningioma_tumor
	0	0	2	87	3	pituitary_tumor

Here Inception-Resnet-v2,

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+FN+FP+TN)} = 96.66\%$$

$$\text{Recall} = \frac{(TP)}{(TP+FN)} = 0.97$$

$$\text{Precision} = \frac{(TP)}{(TP+FP)} = 0.97$$

$$\text{F1} = 2 * \left(\frac{Precision\ x\ Recall}{Precision\ +Recall}\right) = 0.97$$

Moreover, Inception-Resnet-v2 got an accuracy of 96.66% with a number of 15 epoch.

D. Using Resnet-150-v2

Epoch vs. Accuracy:

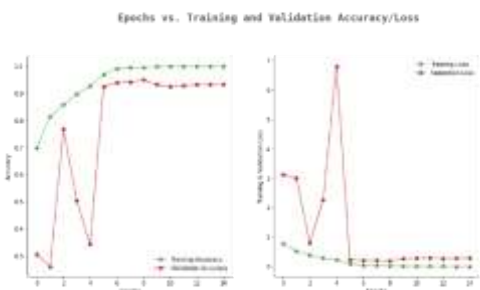

Fig. 16. Resnet-150v2 Accuracy & Loss

Confusion Matrix:

Class	Assigned					Name
	0	1	2	3	#	
Actual	87	3	3	0	0	glioma_tumor
	0	50	1	0	1	no_tumor
	1	1	92	2	2	meningioma_tumor
	1	0	0	86	3	pituitary_tumor

Here Resnet-150v2,

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+FN+FP+TN)} = 95.74\%$$

$$\text{Recall} = \frac{(TP)}{(TP+FN)} = 0.96$$

$$\text{Precision} = \frac{(TP)}{(TP+FP)} = 0.96$$

$$\text{F1} = 2 * \left(\frac{Precision\ x\ Recall}{Precision\ +Recall}\right) = 0.96$$

After 15 epochs, Resnet-150v2 models validation accuracy is gone flat and therefore stopped the model for further training. At this point, Resnet-150v2 the model got 95.74% accuracy in average.

E. Using TCN

Epoch vs. Accuracy:

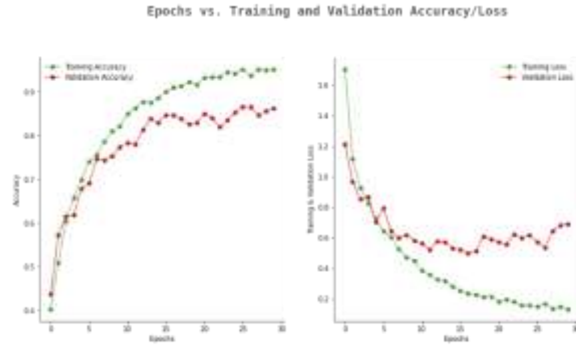

Fig. 17. TCN Accuracy & Loss

Confusion Matrix:

Class	Assigned					Name
	0	1	2	3	#	
Actual	83	0	13	1	0	glioma_tumor
	2	37	7	2	1	no_tumor
	11	4	85	1	2	meningioma_tumor
	1	0	3	77	3	pituitary_tumor

Here TCN,

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+FN+FP+TN)} = 85.46\%$$

$$\text{Recall} = \frac{(TP)}{(TP+FN)} = 0.86$$

$$\text{Precision} = \frac{(TP)}{(TP+FP)} = 0.86$$

$$\text{F1} = 2 * \left(\frac{Precision\ x\ Recall}{Precision\ +Recall}\right) = 0.86$$

TCN network ran for 30 epoch and achieved 85.46% accuracy which is still better than some of the machine learning algorithms.

TABLE 1. Performance Metrics

Algorithms	Labels	Precision	Recall	F1	Accuracy (%)
SVM [1]	Glioma	85	85	87	79.9%
	Meningioma	76	64	69	
	Pituitary	97	94	92	
KNN [1]	Glioma	91	93	92	91.83%
	Meningioma	88	83	85	
	Pituitary	97	97	98	
RF [1]	Glioma	86	83	85	77.87%
	Meningioma	80	55	66	
	Pituitary	95	88	91	
EFFICIENT NET-B3	Glioma	99	96	97	98.16%

	Meningioma	98	99	98	
	Pituitary	98	100	99	
RESNET-150v2	Glioma	98	94	96	95.74%
	Meningioma	96	96	96	
	Pituitary	98	99	98	
INCEPTION-RESNETV2	Glioma	98	97	97	96.66%
	Meningioma	99	97	98	
	Pituitary	96	100	98	
VGG16	Glioma	92	85	88	88.07%
	Meningioma	80	89	84	
	Pituitary	95	94	95	
TCN	Glioma	86	86	86	85.46%
	Meningioma	79	84	81	
	Pituitary	95	95	95	

Precision, recall & F1: macro-averaged (equally weighted avg. of 4 classes).

From Table. 1, we have perceived the accuracy of Support Vector Machine (SVM) is 79.9%, K-Nearest Neighbor (KNN) is 91.83%, and Random Forest (RF) is 77.87% from recent studies [1]. In our pre-trained model, we acquired accuracy level of 98.16% in EfficientNet-B3, 96.66% in Inception-ResNet-v2, 95.74% in ResNet-150v2, 88.07% in VGG16 and 85.46% in Temporal Convolutional Network (TCN) [26]. Besides, individual score for precision, recall and F1 is calculated for each classes like Glioma, Meningioma and Pituitary Tumor. We can clearly see that Deep Learning models like EfficientNet-B3 [23], Inception-Resnetv2 [24, 25] and Resnet150v2 [24] is clearly better than other models introduced in the paper. Above all, EfficientNet-B3 classifier achieved higher accuracy amongst all other models.

V. Discussion

To figure out the early stage of brain tumor, we need an efficient MRI brain tumor classification for our medical therapy. So, considering our current medical tools, we can treat individuals before it's too late. The main research is to discover a brain tumor classifier with high accuracy and performance. In the traditional image recognition of the brain, classification is carried out by using image segmentation. The complexity is lower than the other networks. Computation time is high, and the accuracy seems too low. The model's accuracy development is leading to a very demanding compensated sector. From SVM, RF, DT, KNN, and CNN algorithms convolutional neural networks model EfficientNet-B3 [23] performed well in the image feature recognition of Brain Tumor Detection. So, we can utilize the use of tumor identification using these Convolutional Neural Networks to get high accuracy in less amount of time. Thus, we prefer selecting convolutional neural networks like EfficientNetB3 for brain tumor identification.

VI. Conclusion

Brain is vital portion of human body which controls the overall activity of human body and maintain all the functionality. So, it is very much important to keep brain away from any harm. That is why tumor detection is very much important and has to be detected as soon as possible. By the grace of technology, we can improve the detection process by using different machine and deep learning algorithms. In this paper, different algorithms are introduced and studied for finding the better classification process. At the end, CNN is found most suitable deep learning method. Through Convolutional Layer and Max Pooling, feature maps are being extracted and get trained with a fully connected dense neural network. After training, we can classify MRI images with given labels attached to them. Whether the brain has Benign and Malignant tumors, we can detect with given MRI images. At this point, we found that the Deep Learning method CNN model EfficientNet-B3 performed very well at large-scale image pattern recognition.

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