Undergraduate Conference on Intelligent Computing and Systems (UCICS 2025)
26-27 February, 2025; Varendra University, Rajshahi, Bangladesh

Brain Tumor Classification with MRI Images using Deep Learning Technique

Mst Nurtaz Jahan
Computer Science and Engineering
Varendra University
Rajshahi, Bangladesh
mstnurtazjahan.99@gmail.com

Md. Rabby Ahmed
Computer Science and Engineering
Varendra University
Rajshahi, Bangladesh
mrsaifahmedrabby@gmail.com

Asif Ahamed
Computer Science and Engineering
Varendra University
Rajshahi, Bangladesh
asifahamedstudent@gmail.com

Anamika Saha
Computer Science and Engineering
Varendra University
Rajshahi, Bangladesh
anamikasaha904@gmail.com

Shourav Paul
Computer Science and Engineering
Varendra University
Rajshahi, Bangladesh
spaulchem@gmail.com

Sakib Imtiaz
Computer Science and Engineering
Varendra University
Rajshahi, Bangladesh
sakibimtiaz1998@gmail.com

***Abstract*—Brain tumors are widespread in both children and adults. According to the latest data from the World Health Organization, Asia has the highest number of brain tumors and deaths. It's a life-threatening disease. A brain tumor is an abnormal growth of brain cells inside the skull which later takes the form of brain cancer. Tumor detection is challenging due to the heterogeneity of tumor cells. Convolutional Neural Network (CNN) stands for virtual learning and is the most widely used machine learning algorithm for tumor detection. Tumors can be identified through this. This research paper has four types of MRI images. They are glioma, meningioma, pituitary, and no tumor. EfficientNet CNN architecture is widely used in brain tumor diagnostic testing and research. In the brain tumor dataset 3264 images are used.80% images are training images and 20% images are testing images. The images are resized 244-by-244 and normalized in the range of [0, 1] 255 to improve the CNN during the training period. Deep learning and machine learning techniques are used to find the Confusion Matrix, precision, recall, f1-score, support, accuracy, and AUC-ROC curve. The highlight accuracy of 99.82% is the custom classifier.**

***Index Terms*—Brain Tumor, Deep learning, Machine learning, CNN, MRI**

I. INTRODUCTION

Brain tumor is an abnormal growth of brain cells. It can occur in the brain tissue and it also occurs in the other tissue near the brain. The locations near the brain where tumors can occur are the Cerebrum, cerebellum, pituitary gland, pineal gland, optic nerve and the surface of the brain. There are many different types of brain tumors like pituitary tumors, meningioma tumors, glioma tumors etc. Brain tumors are the most common and offensive disease. The idea of brain tumors in the history of medical science is from ancient times, the existence of brain tumors was first detected in 1884 by German doctor Dr.Hugo von Ziemssen and some other neurosurgeons. The first brain tumor was successfully operated by famous British Neurosurgeon Dr.Richman Godlee in 1887. In the 20th century, the first time revolutionized the brain tumor using Magnetic Resonance Imaging(MRI) [1]. In 2024, 25400 people are affected by brain tumor(14,420 in males and 10,980 in females) and 18,760 people(10,690 in males and 8,070 in females) die around the world [2]. The brain tumor is detected by using the Deep Learning (DL) and Mechine technique. Application of ML that uses complex algorithms and deep neural nets to train the model. Deep learning(DL) is the sub-field of Machine Learning(ML).Brain tumor Classification(MRI) dataset images used to solve the problem. There are four classes of MRI images. The outline of the paper is: 1. Introduction, 2. Related work/ Literature Review, 3. Methodology, 4. Result & Discussion, 5. Future work & Conclusion.

II. RELATED WORK

Raza at al. have classified brain tumors using CNN models. They have used around 3062 MRI images of 233 different patients in their dataset. They have achieved 99.67% of accuracy in the classification of brain tumor [3] .

Mijwil at al. have classified brain tumors using MobileNetVl models. They have used around 1265 MRI images in their dataset. They have achieved 97& of accuracy in the classification of brain tumors [4].

Alanazi at al. have classified brain tumors using CNN models. They have used around 3000 MRI images of 233 different patients in their dataset. They have achieved 96.89% of accuracy in the classification of brain tumors [5].

Hashemzehi at al. have classified brain tumors using CNN models. They have used around 3064 MRI images of 233 different patients in their dataset. They have achieved 95% of accuracy in the classification of brain tumors [6].

Nayak, D.R. at al. have classified brain tumors using CNN models. They have used around 3062 MRI images of 233 different patients in their dataset. They have achieved 99.97% of accuracy in the classification of brain tumors [7].

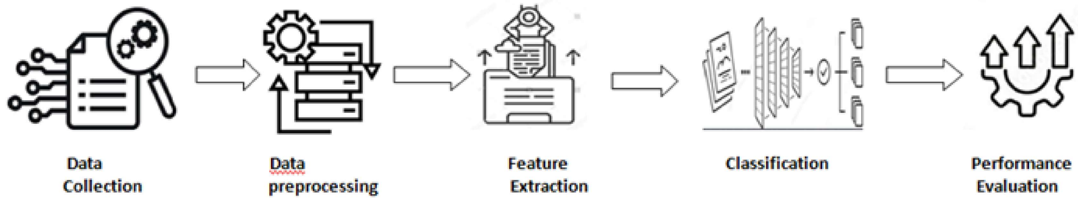


Fig. 1. Methodology

III. Methodology

This section describes and highlights the research proposer methodology for the brain tumor classification. Describe the data collection, data preprocessing, Feature extraction, classification, and performance evaluation. It elaborates on the process of deep learning it detects and classifies.

A. Data Collection

The datasets used for the study are publicly available. The dataset is Brain Tumor Classification(MRI) images and is classified into 4 classes. This dataset contains 3 types of tumor images and some healthy images. The images are inside the train and test file. The training file has 2870 images and the test file has 394 images. The brain tumor consists of a total of 3264 images. The non-tumor class has 500 images, the pituitary class has 901 images, the meningioma class has 937 images, and the glioma class has 926 images [8].

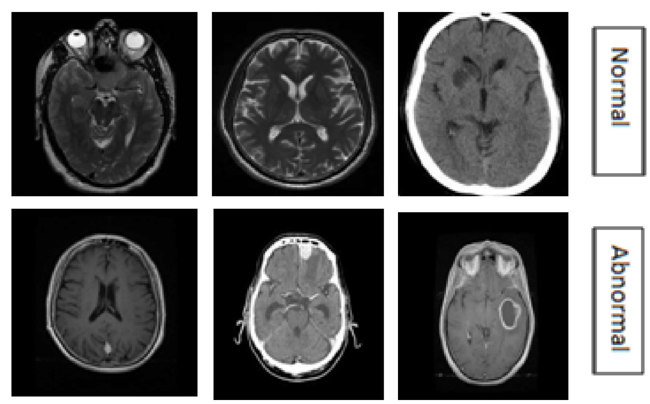
The dataset used to study and solve the problem is brain-tumor-classification-mri-binary-dataset(MRI) images are classified into two classes. Class 0 consists of 500 normal and class 1 consists of 2764 abnormal images.

TABLE I
Data collection table

Brain tumor classification	**class 0**	**pituitary tumor**	**menin-gioma tumor**	**glioma tumor**	**class 1**	**Total**
Train data	395	827	822	826	2475	2870
Test data	105	74	115	100	289	394
Total	500	901	937	926	2764	3264

B. Data preprocessing

The preprocessing techniques I use are CLAHE (Contrast Limited Adaptive Histogram Equalization) and the Laplacian filter. These methods enhance the image data from the dataset and improve its quality for analysis. We are working with mixed MRI scan images of brain tumors from classes 0 and 1. The input dataset consists of images of varying dimensions and aspect ratios.To standardize the dataset, we resize the images to a preset format and utilize a well-known technique CNN. This type of Artificial Neural Network is specifically designed for image recognition and processing. The images are resized to 244 x 244 pixels to meet the input size requirement of the model. Normalization is applied to all pixel values, scaling them to the range [0, 1]. Both the training and test images are normalized by dividing the pixel values by 255. This normalization helps improve the performance of the CNN during the training phase.



•

Fig. 2. Healthy & Unhealthy images

C. Feature extraction

When the datasets are processed through resizing normalisation, intensity standardization data argumentation, the data is pre-trained. Feature extractor are used to utilized [h]the architecture for DenseNet121, VGG19, InceptionV3, InceptionResNetV2 pre-trained model. The 80% images are train images and 20% images are test images. Pre-trainea technique architecture is utilized for feature extraction.Feature extractor are already effective by low-level (texture, shape) MRI images.It optimize the MRI images in a specfic task.

D. Classification

In this dataset model, I used Custom classifier, SVM, XGBoost, and Random Forest classifier. The classifier is held in this model.

- The custom layers in this architecture include: 1. GlobalAveragePooling2D(): This layer simplifies the model by reducing the dimensionality of the feature maps. It calculates the average of each feature map, effectively replacing the traditional flattening process, which can be beneficial in reducing overfitting.

TABLE II
PERFORMANCE METRICS FOR DIFFERENT FEATURE EXTRACTORS AND CLASSIFIERS

Feature Extractors	Classifier	Accuracy	Precision				Recall				F1 Score				AUC
			Class 1	Class 2	Mac. Avg	Wtd Avg	Class 1	Class 2	Mac. Avg	Wtd Avg	Class 1	Class 2	Mac. Avg	Wtd Avg	
DenseNet121	Custom Classifier	0.9982	0.9982	0.9982	0.9982	0.9982	0.9982	0.9982	0.9982	0.9982	0.9982	0.9982	0.9982	0.9982	0.9999
	SVM	0.9928	0.9928	0.9928	0.9928	0.9928	0.9928	0.9928	0.9928	0.9928	0.9928	0.9928	0.9928	0.9928	0.9998
	XGBoost	0.9892	0.9874	0.9909	0.9892	0.9892	0.9910	0.9873	0.9892	0.9892	0.9892	0.9891	0.9892	0.9892	0.9996
	Random Forest	0.9819	0.9785	0.9854	0.9819	0.9819	0.9855	0.9783	0.9819	0.9819	0.9820	0.9819	0.9819	0.9819	0.9994
VGG19	Custom Classifier	0.9919	0.9857	0.9982	0.9919	0.9919	0.9982	0.9855	0.9919	0.9919	0.9919	0.9918	0.9919	0.9919	0.9999
	SVM	0.9910	0.9874	0.9945	0.9910	0.9910	0.9946	0.9873	0.9910	0.9910	0.9910	0.9909	0.9910	0.9910	0.9983
	XGBoost	0.9873	0.9856	0.9891	0.9873	0.9873	0.9892	0.9855	0.9873	0.9873	0.9874	0.9873	0.9873	0.9873	0.9991
	Random Forest	0.9855	0.9855	0.9855	0.9855	0.9855	0.9855	0.9855	0.9855	0.9855	0.9855	0.9855	0.9855	0.9855	0.9994
InceptionV3	Custom Classifier	0.9991	1.0000	0.9982	0.9991	0.9991	0.9982	1.0000	0.9991	0.9991	0.9991	0.9991	0.9991	0.9991	0.9991
	SVM	0.9892	0.9874	0.9909	0.9892	0.9892	0.9910	0.9873	0.9892	0.9892	0.9892	0.9891	0.9892	0.9892	0.9996
	XGBoost	0.9882	0.9891	0.9874	0.9882	0.9882	0.9873	0.9892	0.9882	0.9882	0.9882	0.9883	0.9882	0.9882	0.9881
	Random Forest	0.9819	0.9785	0.9854	0.9819	0.9819	0.9855	0.9783	0.9819	0.9819	0.9820	0.9819	0.9819	0.9819	0.9994
InceptionResNetV2	Custom Classifier	0.9973	0.9946	1.0000	0.9973	0.9973	1.0000	0.9946	0.9973	0.9973	0.9973	0.9973	0.9973	0.9973	0.9999
	SVM	0.9864	0.9891	0.9838	0.9865	0.9865	0.9837	0.9892	0.9864	0.9864	0.9864	0.9865	0.9864	0.9864	0.9997
	XGBoost	0.9882	0.9927	0.9839	0.9883	0.9883	0.9837	0.9928	0.9882	0.9882	0.9882	0.9883	0.9882	0.9882	0.9991
	Random Forest	0.9819	0.9785	0.9854	0.9819	0.9819	0.9855	0.9783	0.9819	0.9819	0.9820	0.9819	0.9819	0.9819	0.9994

2. Dense(512, activation='relu'): This fully connected layer has 512 units and employs the ReLU (Rectified Linear Unit) activation function. Increasing the size of the dense layer allows the model to learn more complex representations of the data.
3. BatchNormalization(): This layer normalizes the output of the previous layer, which helps stabilize and accelerate the training process. By scaling and shifting the inputs to maintain a consistent distribution, Batch Normalization can improve the overall performance of the network.
4. Dropout(0.25): This regularization technique randomly sets 25% of the neurons to zero during training. Dropout helps prevent overfitting by ensuring the model does not rely too heavily on any individual neuron.

- SVM is a supervised algorithm used for classification. It achieves data accuracy and performs classification using the kernel method. SVM is highly memory efficient; however, it is sensitive to noise and performs well on large datasets.
- XGBoost is a gradient-boosting algorithm designed for speed and improved performance. This classifier reduces overfitting and efficiently handles disorganized values faster. However, it requires complex parameter tuning, especially for large datasets.
- Random Forest is an ensemble learning method that organizes data in decision trees. It combines multiple trees, handles large datasets, and reduces overfitting.

E. Performance evaluation

The system's performance is evaluated using a Confusion Matrix, precision, recall, F1-score, support, accuracy, and the AUC-ROC curve.

$$1.\ \text{Acc} = \frac{\text{T Positives} + \text{T Negatives}}{\text{T Positives} + \text{T Negatives} + \text{F Positives} + \text{F Negatives}}$$

$$2.\ \text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$3.\ \text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

$$4.\ \text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

AUC-ROC curve represents a plot of the true position rate versus the false position rate for the different points.ROC curve (AUC) under area measures the distinguishing model between different classes [9].

IV. RESULT & DISCUSSION

This dataset contains four different types of classifiers for brain tumor (MRI) images. The MRI dataset was classified using deep learning with pre-trained models, consisting of 80% training data and 20% testing data. In this model, I utilized four feature extractors.

- **DenseNet121** The feature extractor DenseNet121 uses thus four classifiers. That has a group of information and logical order. In the custom classifier, all performs are well.The average accuracy of 99.82%, the precision, recall, f1 Score of 99.82% the average of auc of 99.99%. In the SVM classifier, all performs well the precision, recall, f1 Score, auc of 99.28% and the average of auc of 99.98%. For the XGBoost classifier, all performances are well. The average accuracy is 98.92%.In the Random Forest classifier the average accuracy of 98.19%. The denseNet121 model proposed the highest-ever accuracy of 99.82% in the custom classifier.
- **VGG19** is a Convolutional Neural Network(CNN) that is 19 layers deep. It has 1000 object categories. This network has a learned rich network with an image input size of 244-by-244 [10]. The custom classifier has an average accuracy of 99.19%. The SVM classifier has an average accuracy of 99.10%. The XGBoost classifier has an average accuracy of 98.73 %. The Random Forest average accuracy is 98.55%. VGG19 model proposed highest ever accuracy of 99.19% in the custom classifier.

- **InceptionV3** is the CNN model used to classify images. It is the third version inception of CNN. It has 48 layers. The custom classifier has an average accuracy of 99.91%. The SVM classifier has an average accuracy of 98.92%. The XGBoost classifier has an average accuracy of 98.82 %. The Random Forest average accuracy is 98.19%. InceptionV3 model the custom classifier has the best accuracy.
- **InceptionResNetV2** is the Convolutional Neural Network(CNN) model used to classify images.It has 164 layers. The custom classifier has an average accuracy of 99.73 %. The SVM classifier has an average accuracy of 98.64 %. The XGBoost classifier has an average accuracy of 98.82 %. The Random Forest average accuracy is 98.19%. InceptionV3 model the custom classifier has the best accuracy.

The custom classifier's accuracy is better than other classifiers. In DenseNet121 model data accuracy of 99.82%, VGG-19 model accuracy of 99.19%, InceptionV3 model accuracy of 99.91% or InceptionResNetV2 model accuracy of 99.73%.

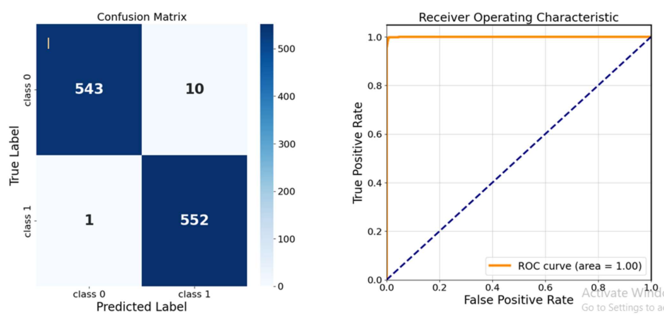


Fig. 3. Confusion Matrix and ROC Curve.

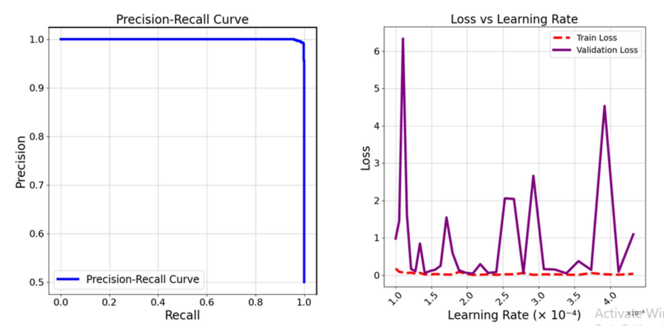


Fig. 4. Precision vs Recall and Loss vs Learning Rate.

V. Limitation& Future work

The preprocessing techniques I use are CLAHE (Contrast Limited Adaptive Histogram Equalization) and the Laplacian filter. These methods' limitations on this dataset are there on multi-class and hybrid models. Here the Images are classified into two classes. testing on larger or more diverse datasets In the future, brain tumor images distinguish which is the tumor and identify using a hybrid model. Images are classified into indifferent classes. Reduce the data limitations and increase the data size and diversity. Increasing the model performance. I am used to testing on larger or more diverse datasets.

VI. Conclusion & Future work

Brain tumors are a serious health issue, affecting many people around the world and often resulting in death. They are challenging to detect because they are located inside the brain, which can lead to brain cancer. One way to identify brain tumors is through classification using advanced techniques. This paper discusses various CNNs and introduces a new hybrid model for brain tumor classification. The custom classifier achieved a remarkable accuracy of 99.82%. The EfficientNet CNN architecture is particularly prominent in brain tumor diagnostic testing and research, making it a valuable tool for detection and analysis.

References

[1] Rengachary, S.S. and Ellenbogen, R.G. (2005) Principles of neurosurgery. Elsevier Mosby.

[2] 72 must-know brain tumor statistics (2024) Aaron CG.

[3] Raza, A. et al. (2022) "A hybrid deep learning-based approach for brain tumor classification," Electronics, 11(7), p. 1146.

[4] Mijwil, M.M. et al. (2023) "MobileNetV1-based deep learning model for accurate brain tumor classification," Mesopotamian Journal of Computer Science, 2023, pp. 32–41.

[5] Alanazi, M.F. et al. (2022) "Brain tumor/mass classification framework using magnetic-resonance-imaging-based isolated and developed transfer deep-learning model," Sensors (Basel, Switzerland), 22(1), p. 372.

[6] Hashemzehi, R. et al. (2020) "Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE," Biocybernetics and biomedical engineering, 40(3), pp. 1225–1232. Available at

[7] Nayak, D.R. et al. (2022) "Brain tumor classification using dense efficient-net," Axioms, 11(1), p. 34. Available at: https://doi.org/10.3390/axioms11010034.

[8] https://www.kaggle.com/datasets/sartajbhuvaji/brain-tumor-classification-mri

[9] https://www.researchgate.net /publication/338077321-Brain-Tumor-Classification-Using-Convolutional-Neural-Network

[10] Mathworks.com. Available at: https://www.mathworks.com/help/deeplearning/ref/vgg19.html