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DenseNet for Brain Tumor Classification in MRI Images

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Abstract:- During the last decade, Computer Vision and Artificial Intelligence (A.I) have transformed the world in every way possible. Deep Learning is a subfield of machine learning that has shown extraordinary results in every field, particularly the biomedical field, due to its proficiency in handling huge amounts of data. Its potential and ability have also been applied and examined in detecting brain tumors' using MRI images for effective prognosis and have shown impressive performance. The main objective of this research is to present a detailed fundamental analysis of the research and findings performed to detect and classify brain tumors through MRI images in the recent past. This analysis is especially beneficial for researchers who are deep learning connoisseurs and enthusiastic about applying their expertise to brain tumor detection and classification. A brief review of the past research papers using Deep Learning for brain tumor classification and detection is carried out as a first step. Afterwards, a critical analysis of Deep Learning techniques like Transfer Learning, Classic Neural Networks, Convolution Neural Networks, etc., are proposed in these research papers and are being carried out in the form of a graph. Ultimately, the conclusion highlights the merits and demerits of deep neural networks. The outcomes formulated in this paper will deliver a thorough comparison of recent studies to future researchers and the effectiveness of numerous deep learning approaches. We are optimistic that this study would extensively assist in advancing and improving brain tumor research.

Keywords:- *Brain Tumor, Deep Learning, Transfer Learning, Magnetic Resonance Imaging (MRI).*

I. INTRODUCTION

Brain Tumor Detection is one of the most challenging tasks in medical image processing. The detection task is difficult because there is a lot of diversity in the images as brain tumors come in different shapes and textures. Brain tumors arise from other types of cells, and the cells can suggest things like the nature, severity, and rarity of cancer. Tumors can occur in other locations, and the location of tumors can indicate something about the type of cells causing cancer which can aid further diagnosis. The task of brain tumor detection can become aggravated by the problems present in almost all digital images, e.g., Illumination problems. Tumor and non-tumor images can have overlapping image intensities, making it difficult for any model to make good predictions from raw images. Different types of brain tumor can be seen in the Figure -1 below. In Our Project we have tried to classify the brain tumor into three types which are Meningioma, Glioma, and Pituitary respectively, these are the main classifications in which brain tumors are generally classified. A meningioma is a tumor that arises from the meninges. the membranes that surround the brain and spinal cord. Gliomas are malignant (cancerous), but some can be very slow-growing. They're primary brain tumors, meaning they originate in the brain tissue. Pituitary tumors usually don't grow or spread extensively. However, they can affect your health, possibly causing vision loss and permanent hormone deficiency. So basically, these are the types in which we have classified the Brain Tumors.

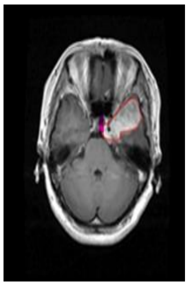
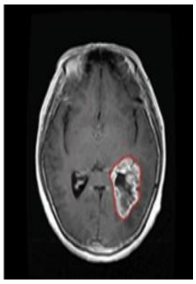
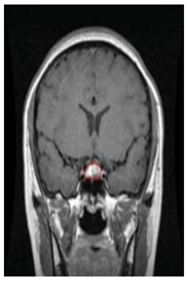
MENIGIOMA	GLIOMA	PITUITARY
		

Fig. 1: Depicts the Brain Tumor Classifications

II. LITERATURE SURVEY

In this article, to perform the review, different research articles from IEEE-Xplore, Science direct, and springer databases are selected and organized into three sections: Machine Learning approach Deep Learning approach, Transfer Learning and Automated Computer Detection System (CADs).

A. Deep Learning Approach

Deep learning algorithms had proven as the better version for classification of various medical imaging from 2015.

Different image processing frameworks like DenseNet, AlexNet, VGGNet, GoogLeNet, InceptionV3/V4, ResNet, MobileNet, U-Net, etc., being implemented in and provided better results in different medical applications.

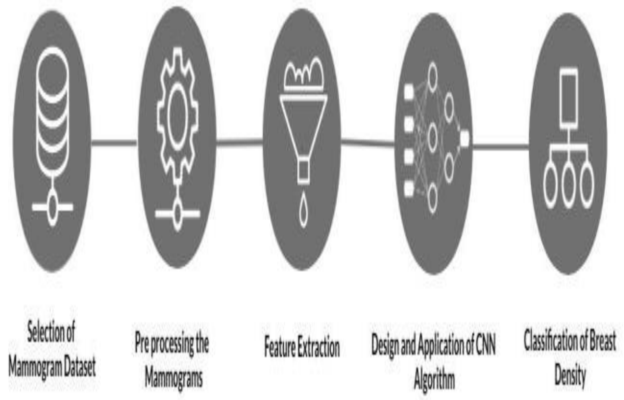


Fig. 2: depicts the Deep Learning Approach

Some of the state-of-art algorithms are provided in this section. Many previous state-of-the-art articles provide detailed and lucid explanations of the various techniques used by other researchers in image processing and deep learning algorithms. Some of them are explained in this article.(Khairandish et al., 2021) proposed the excellence of CNN on a public dataset to classify Benign and Malignant tumors on brain MRI images. In this approach, deep learning (DL) is used to extract the features without handcrafted models and eventually improve classification accuracy. The proposed hybrid model combined CNN and support vector machine (SVM) in terms of classification and threshold-based segmentation in detection. The different approaches provide different classification accuracies like Rough Extreme Learning Machine (RELM)-94.233%, Deep CNN (DCNN)-95%, Deep Neural Network (DNN), and Discrete Wavelet Auto encoder (DWA)-96%, k-nearest neighbors (kNN)-96.6%, CNN-97.5%. The overall accuracy of the hybrid CNN-SVM is obtained as 98.4959%.(Qodri et al., 2021) proposed comparing and performing six CNN models to classify brain tumors. In this approach, the author used the Xception, VGG19, VGG16, NASNetLarge, and Dense Net) for detecting brain tumors using brain MRI using a dataset. The proposed method consisted of 253 images and was divided into 98 tumor-free brain images and 155 tumor images. In this approach, the first step is to prepare the image and in the second stage, select the biggest contour. The third stage is used to find the extreme points based on the most extensive contour and then crop the image corresponding to the outer ends. After cropping, data augmentation is used, and then data is spitted 80% for training, 10% for validation, and 10% for testing. The ResNet50 and VGG16 obtain high accuracy results; the Xception model gets high results for sensitivity, precision, and specification.(Kokila et al., 2021) proposed a deep learning approach for MRI images taken from the Kaggle dataset repositories and Cancer Imaging Archive. In this approach, 233, 3064 T1-weighted contrast MRI images were used to test and validate the proposed model. These images consist of three different types of tumors such as meningioma, Glioma, and pituitary. The proposed method used a CNN-based multi-task classification model, which depends upon Residual Network (ResNet34). Furthermore, the CNN-based U-Net architecture is used for the segmentation of tumors. The proposed model achieved an overall classification accuracy of 92%. The tumors identification module is evaluated in terms of the Dice coefficient. An average Dice score of 89% is obtained.(Tandel et al., 2021) proposed the non-invasive brain tumor grading system using MRI. In this study, the opinion of five deep learning (DL) and five machine learning (ML) models was considered in the proposed DL and ML-based majority voting (MajVot) ensemble algorithm, respectively, to optimize the classification performance of four clinically relevant brain tumors datasets. Although many brain tumor grading methods were already studied on single or multiple models, the highest-performing model was highlighted, and other models were unutilized. The proposed study helps identify the significant concern of brain tumor classification and decide the future path towards classifying brain tumors.(Irmak, 2021) proposed the multiclassification of brain tumors for early diagnosis using a convolutional neural network (CNN). Three diverse CNN models are proposed for three different classification tasks. Brain tumor discovery is achieved with 99.33% accuracy using the first CNN model. Magnetic Resonance Image (MRI) scan analysis is a powerful tool in recent technology that effectively detects abnormal tissues from the brain. It is a difficult task to diagnose and classify cancer from numerous images for radiologists. The proposed study is the first study for multi-classification of brain tumor MRI images using CNN, whose grid search optimizer tunes almost all hyperparameters to the best of the author's knowledge. The proposed CNN models are compared with other traditional state-of-the-art CNN models such as AlexNet, Inceptionv3, ResNet-50, VGG-16, and GoogleNet. Magnetic Resonance Image (MRI) scan analysis is a powerful tool in recent technology that effectively detects abnormal tissues from the brain. In the case of the brain image, the size of a tumor can be varied for several patients, along with the instant features of cancer. It is a difficult task to diagnose and classify cancer from numerous images for radiologists.(Shanmuga et al., 2020) proposed a deep learning algorithm for brain tumor detection. In this approach, a total input dataset of 256 images is used, in which 152 images consist of normal brain MRI and 94 images of the tumor. Each image resolution is 128 x 128. Brain MRI is converted to a grayscale image. In the grayscale image, red, green, and blue are equally spread. It contains only luminance information and not color information. Luminance is more critical in distinguishing visual features. Features extracted in these papers are GLCM + Haralick texture features. After the features are extracted and selected, the classification step is performed on the resulting feature vector of corresponding images given as input to the classifiers SVM, MLP. Classification is performed by using a tenfold cross-validation technique. Also, for evaluating the performance of the selected classifier, WEKA is used to import other machine learning classification algorithms. SMO-SVM and MLP are the classification algorithm we used here with tenfold cross-validation. The proposed architecture has provided classification. The proposed algorithm has delivered 76.12% classification accuracy and 82.18%.(S & Ameer, 2020) proposed neural network models for classifying brain tumors into three classes. The proposed models consist of two transfer learned Google Net models for feature representation and an SNN (with feed-forward sub-networks) for feature dimension reduction and metric learning. The ranking of similar images

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and similarity analysis of images are directed in the lower dimensional feature space. The proposed two neural network models work self-reliantly, and there is no sharing of factors between them. The proposed models use the T1-weighted CE-MRI dataset consisting of images with three types of brain tumors: meningioma, glioma, and pituitary tumors. Each image in the dataset is of size 512x512. Out of two models, the SNN model has provided the maximum accuracy of 98.1%. The fundamental limitations of this model are the used concept of transfer learning, which can give different accuracy on different data sets. (Bodapati et al., 2020) proposed different machine learning approaches for the classification of brain tumors. In the proposed method, Support Vector Machine (SVM) gives better accuracy than other models for the classification of brain tumors. In the proposed method, prominent features of the tumor images are collected by passing them through a pre-trained Convolutional Network, VGG16. Even though this model has achieved 84% accuracy that is the performance is not satisfactory. The idea for the poor performance of any machine learning model could be improper bias and variance. One way to avoid model over-fitting is by reducing the number of dimensions of the data. The proposed model heads to an accuracy of 100% as deep features extract important data characteristics, and further LDA projects the data onto the most discriminant directions. During this phase, pre-trained model VGG16 is used to get 4096 in-depth features. The principal component analysis (LDA) is one of the feature transformation methods, where the features are projected to some other space without loss. In PCA, the data is projected onto directions of maximum variance. LDA addresses this issue by projecting the data onto the directions of max separability. The proposed model provides 100% classification accuracy by all the models hence required minor revision to use in clinical practices.(Raut et al., 2020) Auto encoders and K-Means algorithm algorithms for classification of brain tumor images from the dataset from Kaggle. This dataset contains 253 brain MRI images in total. 155 of them are images containing tumor (tumorous images) and 98 images are normal (without tumor). The proposed system is trained with pre-processed MRI brain images that classifies newly input image as Tumorous or normal based on features extracted during training. Back propagation is used while training to minimize the error and generate more accurate results. Auto encoders are used to generate image which removes irrelevant features and further tumor region is segmented using K-Means algorithm which is an unsupervised learning method. The proposed method provides classification accuracy 95.66 %.(Naser &Deen, 2020) proposed brain tumor segmentation and grading of lower-grade Glioma using deep learning in MRI images. In this proposed method, a total of 110 patients' MRI data is used to classify the tumor. The proposed method uses the U-net architecture for tumor segmentation. Then, for the tumor's grading, a densely connected neural network classifier is used on top of the Vgg16 convolution base. The proposed method provides the classification results of accuracy, sensitivity, and specificity 0.92 over all the images. (Khan et al., 2019) proposed a new approach for brain tumor image classification based on transfer learning and fine-tuning. The proposed strategy of transfer learning with block-wise fine-tuning suggests an alternative approach. This approach is different from using pre-trained CNN as an off-the-shelf feature extractor (without training) that trains the particular method for classification (such as k-nearest-neighbors, Support Vector Machines, Boosted Trees, Decision Trees, and Random Forests). It also demonstrates the transferability of learning from natural images to medical brain MR images. The proposed approach may develop a classification system for other body organ MRI images and other medical imaging domains, such as X-rays, PET, and CT. The proposed method is more generic because it requires minimum preprocessing for 2D MR images and does not use handcrafted features.(Pathak et al., 2019) proposed a novel approach for the classification with the segmentation of tumor part with the help of convolutional neural network and Watershed Algorithm. In this proposed algorithm, the input to the system is considered as brain scanned MRI image. CNN will classify the image for the presence of Tumor, and if Tumor is present, it will be processed by watershed segmentation (MARKER BASED) and morphological operation. A watershed algorithm and Thresholding is one of the most mundane segmentation algorithms utilized in processing medical and material science images. The median filter effectively removes any salt and pepper noise present in the image. Then its output is given to a segmentation algorithm that segments the tumor part accurately. Erosion is applied to the segmented result for removing any holes present in the segmentation output. The Calculated area of the Tumor using the equation shown above is 16.56mm2. The total no of white pixels is 10046. The proposed method is applied across 240 images and provides the classification accuracy during training is 98% and validation 100%. A brain tumor is detected and classified by biopsy that is conducted after the brain surgery. Advancements in technology and machine learning techniques could help radiologists diagnose tumors without any invasive measures. (Siar&Teshnehlab, 2019) A Convolutional Neural Network (CNN) was proposed to detect a tumor through brain Magnetic Resonance Imaging (MRI) images. The input images were first applied to the CNN. The accuracy of the SoftMax in the Fully Connected layer used to classify images obtained 98.67%. Also, the accuracy of the CNN is obtained with the Radial Basis Function (RBF) classifier 97.34% and the Decision Tree (DT) classifier, which is 94.24%. In addition to the accuracy criterion, this model uses the benchmarks of Sensitivity, specificity, and precision to evaluate network performance. According to the results obtained from the categorizers, the SoftMax classifier has the best accuracy in the CNN according to the results obtained from network accuracy on the image testing. The proposed method is based on feature extraction techniques with CNN for tumor detection from brain images. The method offered an accuracy of 99.12% on the test data.(Mohsen et al., 2018) proposed four different models named CNN, DNN, DWT, and Fuzzy C-Means to classify brain tumors. The proposed model uses the dataset consists of 66 real human brain MRIs with 22 average and 44 abnormal images: glioblastoma, sarcoma, and metastatic bronchogenic carcinoma tumors. The proposedmethodology utilizes a 3-levels decomposition of Haar wavelet to extract 32X 32 = 1024 features for each brain MRI. However, this number is not so significant compared to the number of feature maps resulted from the convolution filters of CNNs. Still, the proposed method used the principal components analysis (PCA) to approximate the originally extracted features with lower-dimensional feature vectors. The proposed CNN, KNN, and LDA algorithms provided 96.67%, 95.45%, and 93.94%, respectively.

Authors	Techniques used	Accuracy%	Accuracy Description
(Cheng et al., 2015)	GLCM	80.78	Model Accuracy
(Sajjad et al., 2019)	Deep CNN	96.12	Model Accuracy
(S & Ameer, 2019)	GoogLeNet+new FC layer+softmaxlayer+cross-entropy+KNN/SVM	97.90	Avg Model Accuracy
(Toğaçar et al., 2020)	BrainMRNet	96.05	Model Accuracy
(Pathak et al., 2019).	CNN+Watershed Algorithm	100.0	Validation Accuracy
(Khan et al., 2019)	Fine-tuned VGG19	94.82	92.2
(Srikanth & Venkata Suryanarayana, 2021)	Convolution Layer+ReLU+Softmax	98.00%	Model Accuracy
(Naser &Deen, 2020)	Unet+VGG16	92.00	Tumor Detection Accuracy
(Jia & Chen, 2020)	FAHS-SVM	98.51	Accuracy
(S & Ameer, 2020)	GoogLeNet+SNN	97.64	Model Accuracy
(Sadad et al., 2021)	NASNet	99.60	Model Accuracy
(Huang et al., 2020)	Modified CNNBCN-ER Modified CNNBCN-WS Modified CNNBCN-BA	95.49% 95.17% 95.01%	Test Accuracy
(Soumik& Hossain, 2020)	InceptionV3 Modified	99.45	Validation Accuracy
Mehrotra et al., 2020)	PT-CNN(AlexNet)	99.04	Model accuracy
(Harish & Baskar, 2020)	CLAHE+R-CNN+AlexNet	99.25	Model Accuracy
(Kokila et al., 2021)	ResNet34+Unet	92.00	Model Accuracy
(Methil, 2021)	ResNet101v2+ReLU+Sigmoid+Adam	95.00	Test Accuracy
(Siva Raja & Rani, 2020)	Bayesian fuzzy clustering+GLCM+SoftmaxRegression+Deep autoencoder network	98.50	Model Accuracy
(Shanmuga et al., 2020)	GLCM+Haralick+SVM/MLP+WEKA+SMO-SVM	76.12 82.18	SVM Accuracy MLP Accuracy
(Abbood et al., 2021)	AlexNet VGG16 GoogleNet RestNet50	82.70 86.40 91.00 95.80	Model Accuracy
(Qodri et al., 2021)	ResNet50 Xception VGG19 VGG16 NASNetLarge DenseNet	85.00 69.00 81.00 85.00 69.00 81.00	Test Accuracy
(Raut et al., 2020)	Autoencoders+K-Means	95.55	Model Accuracy
(Tandel et al., 2021)	AlexNet VGGNet ResNet GoogleNet	96.18 97.07 97.14 95.54	Modal Accuracy
(Kader et al., 2021)	Differential Deep CNN	99.25	Model Accuracy
(Irmak, 2021)	CNN+ReLU+ Softmax	98.14	Model Accuracy
(Kesav&Jibukumar, 2021)	RCNN+Two Channel CNN+K means clustering+ReLU+SVM	98.21	Model Accuracy

Table 1: Comparative analysis of different Deep Learning approaches (2016-2021)

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III. DISCUSSION

We can see that over the time various new deep learning methods as well as SVM and other ML techniques are being developed aregetting implemented with improved results throughout and thus deep learning can be implemented for further research use rather than any other technology as it is very vast and yet to be explored completely. Further we will see how different techniques helps us in constructing the model and why it plays an important role in building the proper architecture. Deep learning algorithms and Machine Learning methods had proven as the better version for classification of various medical imaging. Also, with the inclusion of Transfer Learning architectures which have also helped us to minimize the resources and also improve the efficiency while training new models. The Transfer Learning architecture also helps us to eliminate the urge of bid dataset of labelled training data for every model.This also helps in improving the efficiency of machine learning developments for numerous models. Transfer Learning helps to take a more blended approach from various models to tune to a detailed problem. This Transfer Learning approach plays a key element in machine learning processes which includes simulated training. The selection of algorithms is done based upon what type of data we have and what type of task we are trying to automateDifferent image processing frameworks like DenseNet161, AlexNet, VGGNet, GoogLeNet, InceptionV3/V4, U-Net, etc., being implemented in and provided better results in different medical applications.

IV. IMPLEMENTATION

Considering all the different methods to implement this given problem statement of Brain Tumor classification, we have designed a workflow that takes into account all the pre-mentioned research papers, information journals and articles on this topic. This section lists the steps with which we implemented this project. The first step in any Classification project is to accumulate enough data that can help train the model and make sure that the model isn't under-fitted or over-fitted. The second step is cleaning the accumulated data hence making it fit to be used and analyzed. Once the data is cleaned, we implement exploratory data analysis. EDA gives us some important insights about the various factors that may have a high influence on the Deep Learning Model. Once we are done with preprocessing the dataset, we move on to data augmentation of the brain tumor images in the dataset and then specific dimension which will help in providing unbiased training dataset to the model. Then we move on to the deep learning model which is a pre-trained model DenseNet161. After the training of model, we will design a web-application and deploy our model.

A. Dataset

The dataset that we used has a total of around 3064 T1-weighted contrast-enhanced images from 233 patients with three kinds of brain tumor. The images consist of Meningioma, Glioma and Pituitary tumors. First, we will see about the first classification that is Meningiomas. Meningioma is a tumor that forms in your meninges, the layers of tissue covering your brain and spinal cord. They're usually not cancerous (benign) but can sometimes be cancerous. Meningiomas are curable. Now moving towards further classification, we have Gliomas. Gliomas are malignant (cancerous), but some can grow gradually. They're primary brain tumors, meaning they develop in the brain tissue. Gliomas don't usually spread out of the brain or spine but are life-threatening because they can be challenging to reach and treat with surgery. Finally, the last classification that we will perform is Pituitary tumor. A pituitary tumor is a tumor that initiates in the pituitary gland close to the brain that can cause changes in hormone levels in the body. Pituitary tumors that make multiple hormones will force other glands to make more hormones. That will cause symptoms related to each of the specific hormones. Many pituitary tumors will also press against the nearby optic nerves. It can also cause vision problems. About 25% of people may have small pituitary tumors without knowing it.As cited earlier, the dataset contains 3064 T1-weighted contrast-enhanced images, which contain Meningioma (708 slices), Glioma (1426 slices), and Pituitary tumor (930 slices).

B. Preprocessing

Image preprocessing is the process used to format images and make them easy to implement in a model. Image preprocessing includes but isn't limited to resizing images, color correcting them and applying suitable orientation to them that will ultimately increase the model's accuracy.The general meaning of preprocessing is to further develop the picture information by smothering bends that might frustrate the picture quality or improve the highlights of the picture that are significant for additional handling or processing of the dataset. Rotating, scaling and transformation of images are some pre-processing techniques. Using the CV2 library we adjust the exposure of the brain tumor images in the dataset and rescale the intensity of the individual pixel by applying a threshold to it. Once the image's exposure is adjusted the image is normalized using the 'cv2.normalize' function. The final preprocessed image is a 150 x 150 pixel (RGB), is ready to be fed to the model as a training set. The below figure shows the preprocessed images.

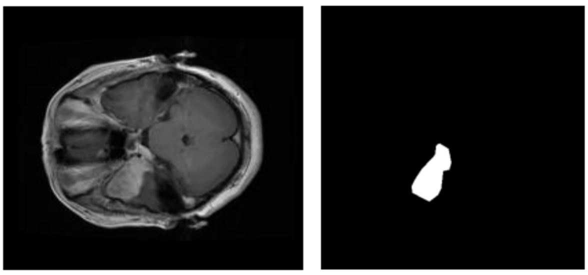

Fig. 3: Brain Tumors after basic preprocessing

C. Modeling

Modeling is the stage where the deep learning model is created, and its layers are defined along with their parameters, but first, we need to prepare the dataset for modeling and split it into training and testing segments. We load the pickled dataset using the 'pickle.load' function. Then we import the 'train_test_split' from the sklearn package. Using this predefined function, we split the 3064 brain tumor images dataset into training, validation, and testing sets. The dataset is split into 70%, 15%, and 15%. The training set consists of a total of 2144 images (70%), the validation set consists of a total of 460 images (15%), and the testing set consists of 460 images (15%). The split is given the shuffle parameter to increase the model's versatility and reduce any possible bias towards different classes. The testing set will be fed to the model as an input and it will be used to obtain the accuracy as well as the performance of the model.

After splitting the dataset, we carried out data augmentation as it increases the number of images in dataset. For this we augmented the images at various degrees like 0, 45, 90, 120, 180, 270, 300 and 300 degrees. After data augmentation, the training set consisted of 17152 images, the validation set consisted of 3680 images, and the testing set consisted of 3680 images. The testing set and validation sets will be fed to the model as input, and the testing set will be used to test the accuracy and performance of the model. Now we come to the stage where we build the model. For training and testing purpose we used PyTorch which is one of the libraries of Python. After that Firstly, we define our model as a Sequential model. It is designed as follows. The base layer is a convolution layer based on DenseNet161. The size of this model is 110MB. Then set all parameters as trainable. Then we redefine the fully connected layer of the model for our classification problem. We set the input shape to (256,256,3). The activation function is set to 'SELU' and dropout to 0.4. The final layer is a fully connected layer with a LogSigmoid activation function. After adding the layers in the sequential layer, we compile the model with the "Stochastic Gradient Descent" (SGD) optimizer with a momentum of 0.9 and learning rate of 3e-4 (0.0003) and use Cross Entropy as the loss function. After proper training of the model on 25 epochs with a batch of 2144. We achieved an Accuracy of 99.25% with a Loss of 0.0006 and recorded Validation Accuracy of 98.79 with Validation Loss 0.0015.

D. Results

After proper training of the model at 25 epochs we further calculated various other parameters. First, we plotted down the graphs of Accuracy Metric graph and Loss Metric graph. Moving on further we calculated. Just after carrying out the classification report, we managed to calculate the Confusion Matrix and the Jaccard Index. Below are all the results that we achieved during working on our model.

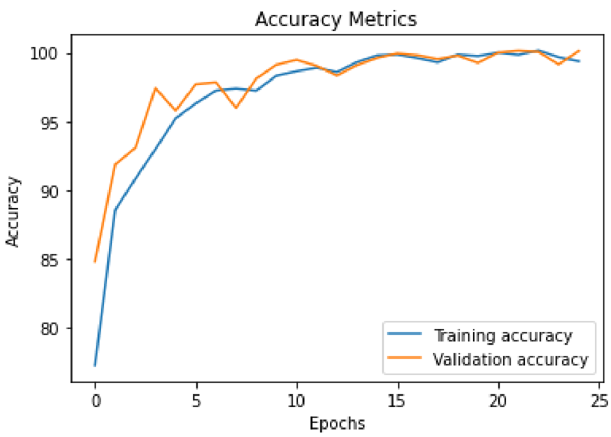

Fig. 4: Accuracy Metrics

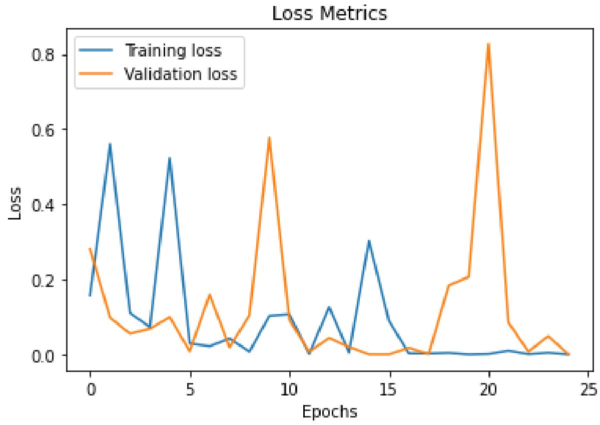

Fig. 5: Loss Metrics

Clasification Report

	precision	recall	f1-score	support
1	1.00	0.95	0.97	925
2	0.97	1.00	0.99	1754
3	1.00	1.00	1.00	1001
accuracy			0.99	3680
macro avg	0.99	0.98	0.99	3680
weighted avg	0.99	0.99	0.99	3680

Fig. 6: Classification Report

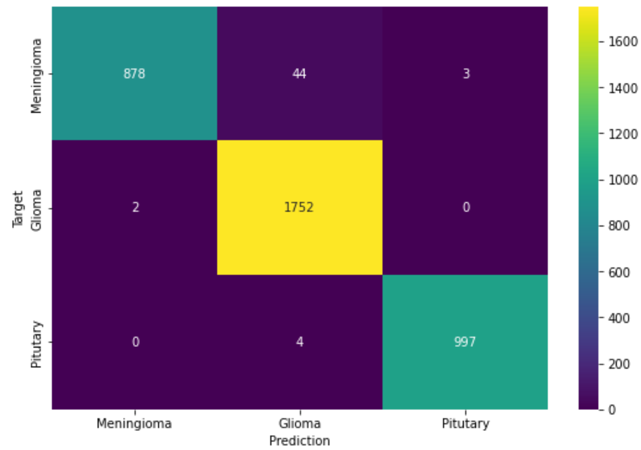

Fig. 7: Confusion Matrix

Jaccard Index

0.97

Fig. 8: Jaccard Index

E. Deployment

Now the most important part of all Deployment. It is a process of integrating our trained model into real use. For this, we have made a web-application with a simple Graphic User Interface that is user-friendly. With our web-based application which we have made using python, users can easily select the images of brain tumors and then get the results immediately. For the deployment purpose, we have used Flask which is a Python Web Framework that provides useful features and tools for creating web applications. Flask is a lightweight, small, and easy-to-use web framework. Due to its flexibility and accessibility which is easy to handle we decided to opt for Flask for deployment. Below you can see the snapshots of our web-based application.

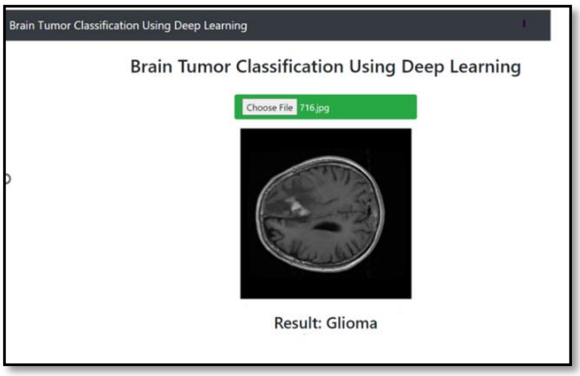

Fig. 9: Web-based Application(1)

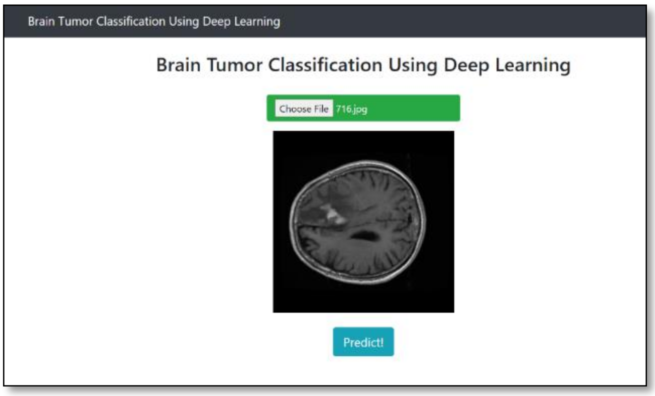

Fig. 10: Web-based Application(2)

V. CONCLUSION

This paper acknowledges all the different methods which can be implemented to the collective objective of Brain Tumor classification, ranging from CNN, ML to fully-fledged software built. In addition, the paper offers a thorough evaluation of the research work on detecting and classifying brain tumor MRI images into the tumor and non-tumor classes using Deep Learning, presented over time. Many significant and efficient algorithms have evolved thus far; however, each algorithm still lacks in one way or the other because of the lack of standardization. A significant analysis of the pros and cons of each methodology is provided in detail in this study. Some performance degrading factors and their solutions are also listed to provide an idea to potential researchers for developing some optimized CAD systems. From comparative analysis, it is clear that Deep Learning techniques and algorithms have great power and capacity to handle huge amounts of data. Still, their benefits are not exploited completely in studying brain tumors. From the above-mentioned detailed review, it can be concluded that there is a strong need for a fully automatic unified framework that could effectively locate and classify the brain tumors into multiple classes with less sophistication. The Future Scope of our Model is quite useful as it can be used to develop Mobile based applications for the classification of the tumors.

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