Collating Deep Learning Architectures Efficacy for Detection of Brain Tumor

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Abstract.

Brain Tumor is a medical phenomenon where differently abled cells escalate inside a Human Brain. The explication of the Tumor in an individual's Brain at a pilot stage becomes extremely prominent for diagnosing it successfully. Early scrutiny of these tumors aids the medical operations as well as effectuates the possibility of a person being cured. Diverse outlook has been consummated for the indagation of Brain Tumor inside a host encapsulating the Machine Learning and Deep Learning prospects. Detection of different types of Brain Tumors has also been imposed to aid the surgical discernment. The explications around this malady have led to the development of modular approaches with eminent efficacies. Certainly, with higher accuracy, the complexity of the modus operandi increases. For developing the automated system for Brain Tumor Detection, the elucidation has to be on Computational Complexity and the Instances utilized. In this articulation, we have subsumed diverse Deep Learning Architectures for Brain Tumor Detection engaging open-source Brain MRI Images. Specifically, we've collated algorithms which are Light-weight and Heavy-weight in terms of their architecture i.e., on the basis of Size, No. of Parameters and Depth. MobileNetV2, DenseNet121, InceptionV3, InceptionResNetV2 and ResNet50 are the selected Deep Learning Models which have been trained over Binary Class Dataset expelling the Output as 'BT' and 'NBT' for Brain Tumor Detection. The output we achieved in terms of Accuracy was phenomenal and also gave us a prominent insight over the behavioural outlook of Deep Learning Architectures over a particular Dataset. For the validation of the performance of each utilized structure we inculcated quantitative prospect as well.

Keywords— Deep Learning (DL), Brain Tumor (BT), Convolutional Neural Network (CNN), No Brain Tumor (NBT), Magnetic Resonance Imaging (MRI).

1. INTRODUCTION

Brain Tumor stands out to be one of the most complicated maladies procured by an individual. There are majorly 03 types of Brain Tumor namely: Glioma, Meningioma, and Pituitary [1]. The development of extra mass i.e., Tumor, inside a Brain causes Brain Haemorrhages [2] due to increased pressure intrinsic to the Brain. People affected by Brain Tumor in 2019 was aggregated to be 0.7M. Moreover, 0.86M people had been diagnosed in the US, where 60K were Benign and 26K were Malignant [3]. The fatality rate of Malignant Patients in the US stands at 65% with the survival approximation consummating to 35% [4]. As a result, MRI Images are utilized to detect the presence of

Brain Tumor in a particular person. Thus, radiologists, through their experience contemplates the existence of a Tumor in an individual's Brain. Plethora of Automated Systems has been formulated for Brain Tumor Detection incorporating state of the art technological prospects. But, the ignorance in terms of Computational Complexity can be visualized. Deep Learning Models surpassed Machine Learning Models in terms of accuracy, due to addition of Hidden Layers, which thereby increased the overall complexity of the model. When we're dealing with Medical Operations it's extremely important to build a system which is less complex and which is fast in producing results.

Therefore, we inculcated diverse pre-trained models such as MobileNetV2, DenseNet121, InceptionV3, InceptionResNetV2, and ResNet50 based on certain parameters such as "Size" and "Depth" for Brain Tumor Detection. We aggregated MRI Brain Tumor Images from Open-Source Platform i.e., Kaggle and pre-processed it. We initially thought of creating a Multi-Class Dataset which would give us the type of Tumor a person is possessing, but then through greater explication we thought of creating a 02-Class Dataset, as Detection of a Tumor stands out to be more prominent when compared to the Detection of type of Tumor in real-time. The inculcation of less and more complex Deep Learning Models gave us an elucidating outlook over the impact of Depth on diverse problem statements. The efficacies we got through our proposed modus operandi, stood out to be the best when compared to the pre-existing ones. We incorporated not only the Train, Validation and Test Accuracies for the juxtaposition but also different metrics based on Confusion Matrix such as F1-Score, Recall, Precision, along with AUC and Cohen Kappa Score for advance scrutiny. The proposed explication demonstrates the Brain Tumor Detection in the most efficient manner and also diminishes the orthodox modular outlook.

2. LITERATURE SURVEY

Before initiating with the proposed modus operandi, we scrutinized the pre-existing methodologies induced for Brain Tumor Detection which gave us an overview about the possible outlooks. Image Segmentation technique had been imposed for extracting dominant features for Brain Tumor Detection aggregating 96% accuracy with the limitation of the Dataset exhibited [5]. Utilization of Variational Model for analysing Glio-Blastoma affected patients got an efficacy of 85.7% which is extremely less when analogized with other modus operandi's [6]. An efficacy of 95% was procured through the collation of Convolutional Neural Network (CNN) with K-Means for Brain Tumor Detection with shortcoming of increased model complexity [7]. A minimum and maximum correctness i.e., 88% and 96% respectively was obtained through inculcation of Fully Convolution Network (FCN), but had issues with the real-time actuation [8]. 03-Class Dataset was formulated for classification of different types of Brain Tumors i.e., Glioma, Meningioma and Pituitary through Convolutional Neural Networks (CNN) which gained an efficacy of 96% [9].

The amalgamation of R-CNN and Support Vector Machine (SVM) Classifier was also formulated for Brain Tumor Detection utilizing high-resolution Brain MRI Images which was able to procure an efficacy of 95% [10]. Moreover, CNN surpassed Discrete Wavelet Transform (DWT) when imposed over MRI and Positron Emission Tomography (PET) Instances [11]. A comparative analysis between CNN Model (which was built from scratch) and VGG16 (a pre-trained Model) was also carried out where the CNN gave an accuracy of 91.6% whereas VGG16 gave an accuracy of 91.9% [12]. 98% F1-Score was achieved when Xception Model (a heavy-weight model) was incorporated and 97.25% was achieved when MobileNet (a light-weight model) was utilized [13]. A Binary Classification CNN Model was formulated with the Outputs as "Tumor Detected" and "Tumor Not Detected" gaining an accuracy of 96.08% and F1-Score of 97.3% [14]. Brain MRI Images of 150 Patients were collated and were imposed over Deep Convolutional Neural Network (D-CNN) contemplating Cohen Kappa Score of 0.91 and AUC of 0.95 [15]. Automated Heterogenous Segmentation inducing Support Vector Machine (SVM) was also formulated for Brain Tumor Detection through Image Segmentation colligating an efficacy of 98% [16].

The Literature Review gave us an elucidation of the shortcomings of the already executed architectures. Thus, hovering over all the technological modus operandi's, there were some loopholes which we observed and rectified and induced it in our proposed approach.

3. Methodology Used For Analysis

We instantiated with our methodological workflow through colligating the Dataset. Rather going in for the "Type of Brain Tumor" Classification, we stuck upon the "Actuality of a Tumor" Classification in a Human Brain. Thus, we dissected our Instances into a 02-Class Dataset namely 'BT' and 'NBT'. The Data Balancing has been elucidated in Figure.1.

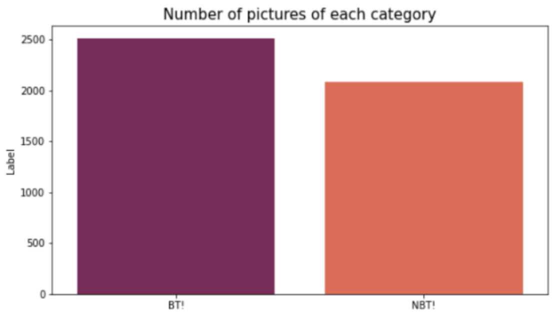

Fig.1. Data Balancing Overview for a 02-Class Dataset.

Moreover, we encapsulated varied Deep Learning Architectures for amalgamating it with the Dataset but inhibited building a model from scratch as it would increase the overall complexity of the modus operandi. There are certain prominent prospects which affects the operation of a model and makes it more complex which are as follows: 1] More Parameters (Exceeding Millions of Parameters). 2] More Recurrent Units (Consisting of more Convolutional Operations). 3] Complex Activation Functions (Not selecting Activation Functions as per the Problem Statement) 4] Deep Networks (With Increased Depth in terms of Layers). Commemorating the above elucidation, we constricted ourselves to specified models exhibited in Table-1. Table-1 demonstrates the parameters over which the models were selected i.e., Size of the Models (In Mega-Bytes), No. of Parameters in a Model (In Millions), and Depth of the Model (Number of Layers). We tried to collate the Light-weight as well as Heavy-weight Systems for greater insights.

TABLE I. MODEL SELECTION DEMONSTRATION

S.No.	Pre-Trained Models	Size (In MB)	No. of Models Parameters (in M)	No. of Layers
1.	MobileNetV2	14	3.5	88
2.	DenseNet121	33	8	121
3.	InceptionV3	92	23.8	159
4.	ResNet50	99	25.6	168
5.	InceptionResNetV2	215	55.8	572

Representation of Structure of each utilized Model:

A. MobileNetV2: MobileNetV2 possesses 88 Layers into its architecture along with 3.5 million Parameters. The Size of the Model is 14 MB and stands into Light-weight System category. Figure.2. demonstrates MobileNetV2 Architecture.

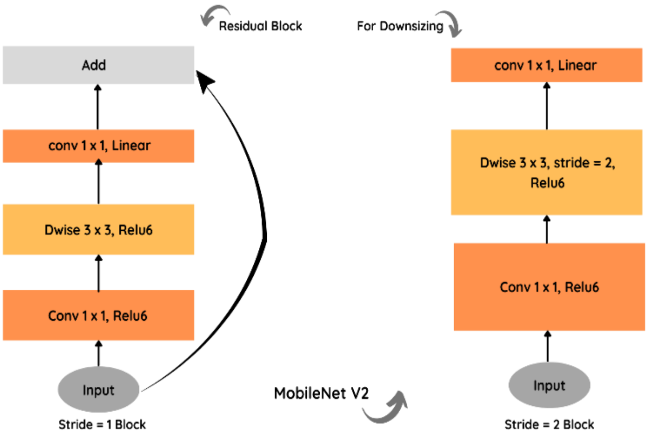

Fig.2. Architecture of MobileNetV2.

B. DenseNet121: DenseNet121 possesses 121 Layers into its architecture along with 08 million Parameters. The Size of the Model is 33 MB and stands into Light-weight System category. Figure.3. demonstrates DenseNet121 Architecture.

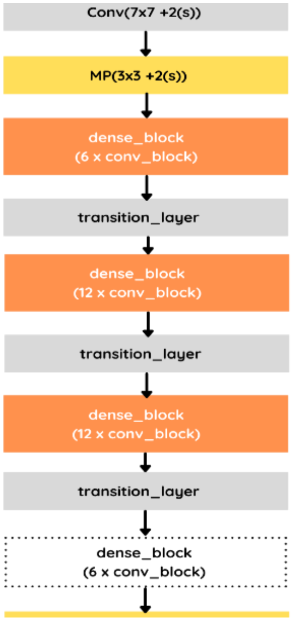

Fig.3. Architecture of DenseNet121.

C. InceptionV3: InceptionV3 possesses 159 Layers into its architecture along with 23.8 million Parameters. The Size of the Model is 92 MB and stands into Heavy-weight System category. Figure.4. demonstrates InceptionV3 Architecture.

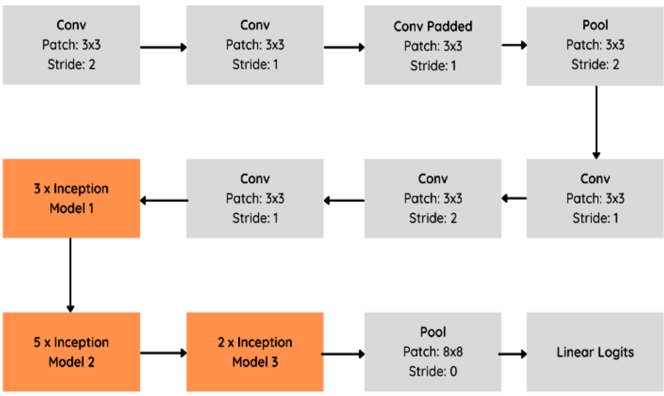

Fig.4. Architecture of InceptionV3.

D. ResNet50: ResNet50 possesses 168 Layers into its architecture along with 25.6 million Parameters. The Size of the Model is 99 MB and stands into Heavy-weight System category. Figure.5. demonstrates ResNet50 Architecture and Figure.6. demonstrates Residual Identity Mapping Structure.

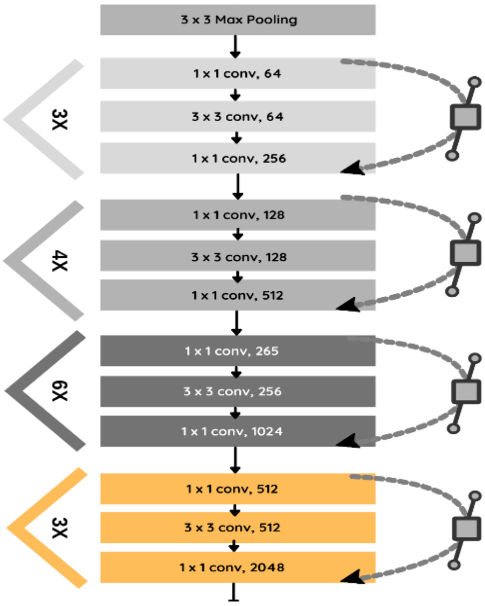

Fig .5. Architecture of ResNet50.

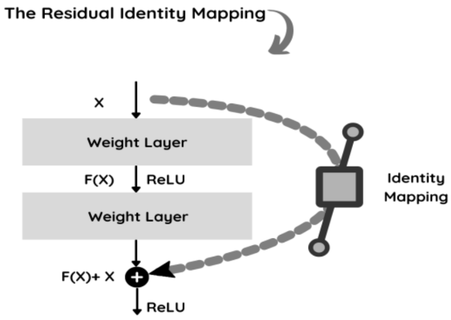

Fig .6. Architecture of Residual Identity Mapping.

D. InceptionResNetV2: InceptionResNetV2 possesses 572 Layers into its architecture along with 55.8 million Parameters. The Size of the Model is 215 MB and stands into Heavy-weight System category. Figure.7. demonstrates InceptionResNetV2 Architecture.

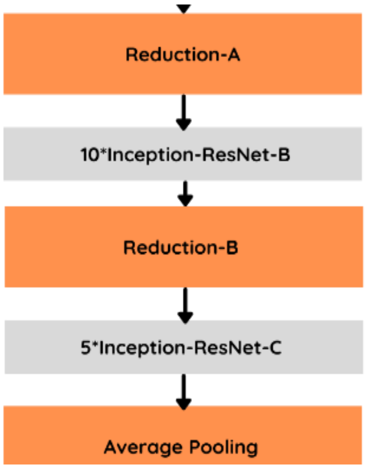

Fig.7. InceptionResNetV2 Basic Architecture.

4. Implementation and Tools

After explicating the Deep Learning Architectures, we initiated the implementation workflow for obtaining potent outlook.

A. About the Dataset: We collated authentic Brain MRI Images [17], from the open-source platform i.e., Kaggle. To increase the number of Instances we infused varied Brain MRI Images into a Primary Folder. As the resolution were different for different datasets, we resized it to 224x224, as we utilized the pre-trained models [18].

There was total 2513 Images of Brain Tumor Positive and 2087 Images of Brain Tumor Negative giving us a sum of 4600 Image Samples. For increasing the training size of the Dataset, we also used Data Augmentation [19] through which our total dataset value increased to 55,200 Instances. Figure.8. demonstrates the visual aspect of the Dataset.

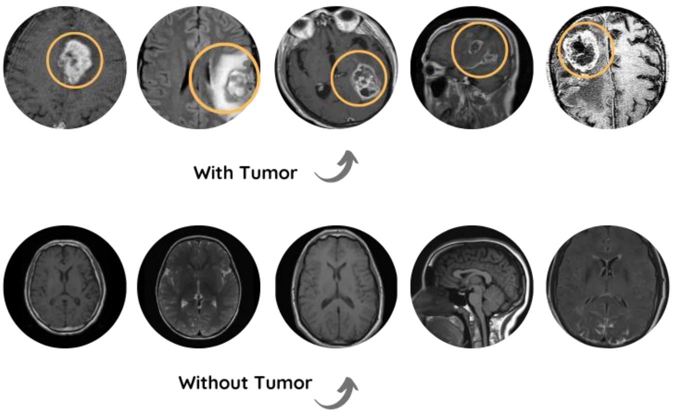

Fig .8. Visual Representation of Collated and Processed Brain MRI Images.

B. Tools Utilized: The frameworks we utilized were TensorFlow and Keras. We also used Image Data Generator for Data Augmentation. We trained our model over free GPU provided by Kaggle Notebook IDE.

C. Metrics Utilized: The Train, Validation and Test Accuracy had been elucidated for gaining certain insights. But, for greater validation we inculcated some more metrics based on Confusion Matrix such as F1-Score, Recall, Precision.

Also, we infused Cohen Kappa Score which gives the agreement rate between the evaluators along with Area Under Curve (AUC) Score which gives Degree of Separability Score.

Both the Scores range between 0 to 1, i.e., score near to ‘0’ stands to be least effective and score near to ‘1’ stands to be most effective. Figure.9. demonstrates the Metrics Overview.

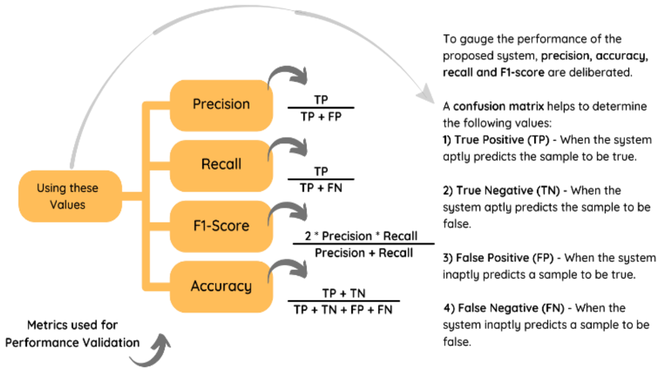

Fig .9. Overview of the Metrics Utilized.

D. Proposed Modus Operandi: Illustrated in Figure.10.

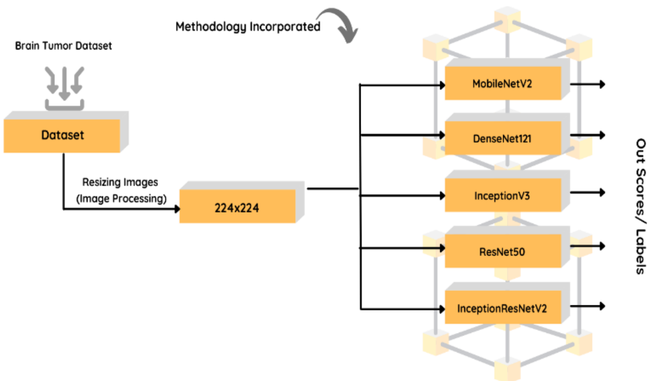

Fig .10. Implementation Structure with Full Process.

5. RESULTS THROUGH EXPERIMENT & ITS ANALYSIS

After the Actuation, the results we procured were overwhelming which is illustrated in Figure.11, Figure.12, Figure.13 and Figure.14.

Prowess of our modus operandi reflected in our Graphical Outlook.

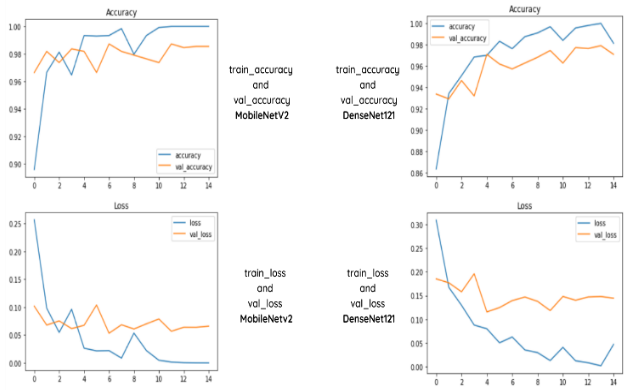

Fig .11. MobileNetV2 and DenseNet121 Graphical Results.

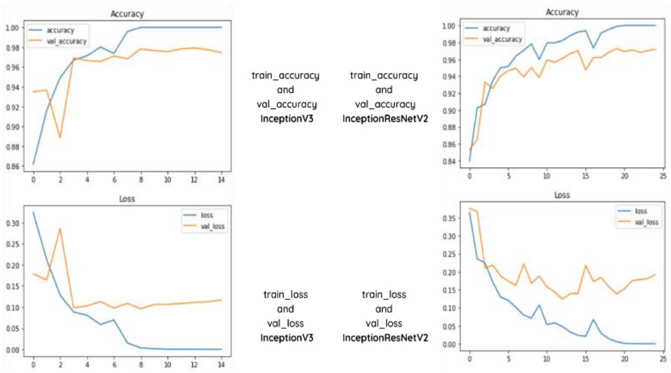

Fig .12. InceptionV3 and InceptionResNetV2 Graphical Results.

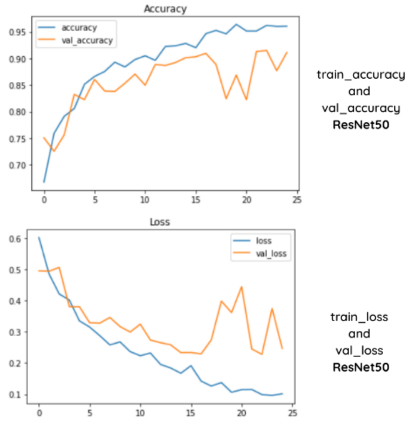

Fig .13. ResNet50 Graphical Result.

TABLE II. TRAIN, VALIDATION AND TEST ACCURACIES

Model	Train-Accuracy	Validation-Accuracy	Test-Accuracy
MobileNetV2	99.60%	98.64%	99.30%
DenseNet121	99.42%	98.11%	98.45%
Inception V3	98.30%	97.44%	97.36%
ResNet50	96.55%	94.72%	96.06%
InceptionResNetV2	98.46%	97.44%	97.55%

TABLE III. COMPARATIVE ANALYSIS OF DIFFERENT MODELS BASED ON CONFUSION MATRIX

Model	AUC	Precision	Recall	F1-Score	Cohen Kappa Score
MobileNetV2	0.9987	0.9935	0.9934	0.9934	0.9866
DenseNet121	0.9965	0.9871	0.9842	0.9842	0.9729
InceptionV3	0.9945	0.9737	0.9738	0.9738	0.9674
ResNet50	0.9877	0.9611	0.9609	0.9609	0.9491
Inception-ResNetV2	0.9956	0.9739	0.9745	0.9745	0.9650

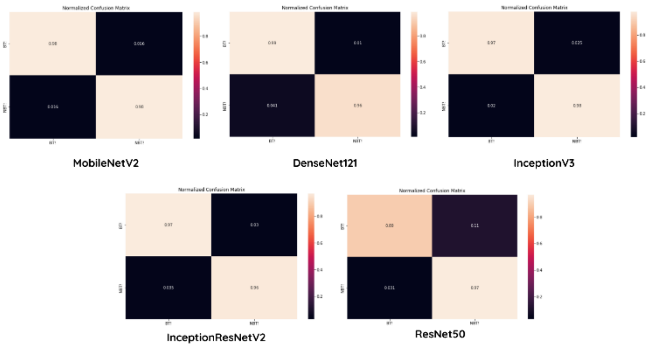

Fig .16. Illustration of Confusion Matrix for each Utilized Model.

6. Conclusion and Future Scope

The Experimental Results depicted the domination of Light-weight Systems in terms of Accuracies. MobileNetV2 and DenseNet121 exhibited the phenomenal outlook for the real-time exegesis. ResNet50, InceptionV3 and InceptionResNetV2 contemplated potent results but was not as per the expectations as these models were greater in Depth.

Thus, through this explication we got an ideation that the efficacy of any modus operandi doesn’t depends upon the depth of the model. To be more precise, the pre-conceived notion of a Deep Learning prospect of “More the Depth, More the Extracted Features” isn’t true all the time.

Thus, the performance related to MobileNetV2 was extremely high when compared to already existing workflows. As a result, for the real-time implementation we selected MobileNetV2 as our good-to-go Model. Moreover, more dataset can be contemplated for more potent results. Also, the pre-processing outlook has to be encapsulated when training any model, as it impacts the overall performance of a system in any situation.

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