IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 1, February 2025, pp. 428~438
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i1.pp428-438

Detection of location-specific intra-cranial brain tumors

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Article Info

Article history:

Received Jan 25, 2024
Revised Sep 6, 2024
Accepted Sep 30, 2024

Keywords:

Brain tumor
Convolutional neural network
EfficientNet
Genes
Machine learning models
MobileNet v2

ABSTRACT

Mutations or abnormalities in genes can occasionally cause cells to grow uncontrolled, resulting in a tumor, which is very dangerous. These are the most prevalent cancer causes. They are caused by significant damage to genes in a specific cell during a person's existence. Brain tumors are increasing rapidly, majorly brain tumor cases in the US are projected to rise from 27,000 in 2020 to 31,000 in 2023 at an annual growth rate of 1.5%, all the cases are rising because of the detection of the tumors in the late phase. Thus, it needs the hour to create something which can solve this anomaly and help us detect the tumor rapidly and efficiently. While major research papers on brain tumor detection mainly focus on the detection and classification of the tumors, the presented research aims to first detect the tumor using pre-recognized photos using machine learning object detection models. Then after successful detection of the tumor, the study team plans to determine its precise coordinates and display the tumor and its location in the picture.

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1. INTRODUCTION

A tumor is a tissue formed by an accumulation of aberrant cells. These abnormal cells consume the healthy bodily cells, obliterate them, and continue to swell. Brain tumor is one of these tumors. It has an impact on the brain, neurological system, glands, and brain-surrounding membranes. Imaging and pathology can both be used to diagnose tumors. Magnetic resonance imaging (MRI), which produces cross-sectional images of the brain, is used to image brain tumors.

One of the most serious conditions involving the brain is a brain tumor, in which an uncontrolled growth of abnormal cells occurs in a group of cells. The development of various deep learning algorithms has led to a notable expansion of the field of image processing for use in biomedical applications. The focus of the research paper is to detect brain tumors along with the brain tumor location coordinate in the given MRI scan of the brain. Brain tumor cases are rising rapidly because of the late detection of brain tumors. Brain tumor case are increasing rapidly, the cases in the United State is expected to rise from 27,000 in 2020 to 31,000 in 2023 at an annual growth rate of 1.5%, all the cases are rising because of the late detection of brain tumor. So this paper aims early detection of the tumor by explicitly giving the link cation coordinates of the tumor along with a visual representation of a rectangular box encompassing the tumor for efficient detection.

Brain image processing research is currently focused on the identification of brain tumors. This study suggests a strategy for using magnetic resonance images to segment and categorize brain tumors (MRI) [1]. For tumor segmentation, a deep neural networks (DNN)-based architecture is used [2]–[4] articles validation

techniques used such as dice similarity coefficient and the Jaccard similarity index. The classification process is crucial in the diagnosis of brain cancers which aims to identify brain cancers using various categorization [5] techniques are earlier research activities [6]. However, current classification methods have substantial false alarm rates (FARs). The weighted correlation feature selection based iterative bayesian multivariate deep neural learning (WCFS-IBMDNL) [7]–[9] technique is suggested in this study to fasten the classification detection of early-stage brain tumors for faster diagnosis many automated segmentation and classification algorithms that are successful in employing multimodal MRIs to extract the key characteristics of brain tumor detection [10], [11].

Some major algorithms used are deep learning methods, K-means clustering, fuzzy C-means, K-nearest neighbours, support vector machines, and decision trees [12]–[14]. The system's prognosticated delicacy for the test data was 99.12 [15]. It substantially employs the marks of perceptivity, particularity, and precision to measure network performance in addition to the delicacy criterion, while it only detects excrescences present, no visibility of excrescences is shown [16]. This study focuses on the assessable characteristics of brain tumors, like shape, signal intensity and texture, to predict higher accuracy with a lower error rate and the capacity for future work in the field [17]. The paper mainly covers convolutional neural network (CNN), watershed algorithm, and rectified linear unit (ReLU). The main advantages of this paper are high accuracy, advanced novel brain tumor identification method, while it only detects tumors present, no visibility of tumors is shown [18]. This exploration paper proposes a waterfall of CNNs to member brain excrescences with hierarchical sub-regions from multi-modal glamorous resonance images (MRI), and introduce a 2.5 D network that's a trade- off between memory consumption, model complexity and open field [19]. Algorithms covered in alternate paper are Monte Carlo simulation, structure-wise query, and voxel-wise query. The main advantages are the uses of Monte Carlo simulation to prognosticate the probability of brain excrescence segmentation possibilities in arbitrary samples, high delicacy of arbitrary samples, while it only detects excrescences present, no visibility of excrescences is shown [20]. Another research paper proposed an algorithm to segment brain tumors from 2D MRI by a CNN which is followed by traditional classifiers and deep learning methods (CNN and SVM classifier mainly) [21]. This paper's CNN method helps to detect the tumor fast helps in medical industry. In one of the explorations, deep features are uprooted from the inceptionv3 model, in which score vector is acquired from SoftMax and supplied to the amount variational classifier (QVR) for demarcation between glioma, meningioma, no excrescence, and pituitary tumor. Algorithms included are substantially fuzzy c- means, QVR classifier, and neural network [22]. The main advantages of this paper are the distinct comparison with Kaggle and BraTs standard models, classifying brain excrescence in the early stage, while it only detects excrescences present, no visibility of excrescences are observed [23].

In another study artificial neural network (ANN) and CNN (majorly used algorithms in this study) is used in the bracket of normal and excrescence brain. ANN works like a mortal brain nervous system, on this base a digital computer is connected with large quantum of interconnected elements and networking which makes the neural network to train with the use of simple processing units applied on the training set and stores the existential knowledge [24]. Major advantages include the high accuracy achieved owing to the use of CNN DNN techniques while only detects excrescences present, no visibility of excrescences is shown [25].

2. RESEARCH OBJECTIVE

Brain tumor cases are rising rapidly because of the late detection of brain tumors. The main focus of the work is to detect brain tumors along with the brain tumor location coordinate in the brain MRI scan. It aims to detect the tumor early by explicitly giving the link cation coordinates of the tumor along with a visual representation of a rectangular box encompassing the tumor for efficient detection.

The proposed work is discussed in the next section. This will elaborate the methodology and architecture model used. Then it follows with three algorithms used in the proposed model with flow chart diagrams. Finally, the next section is about results and their discussions followed by conclusions with future works.

3. PROPOSED MODEL

The current work is categorized into two sections. The first segment seeks to identify brain images, and the second section aims to enclose the tumors scan in a rectangular box with the tumor’s geographical coordinates. The two neural network models used throughout the entire work, one is mobileNet v2 and other one is efficient net lite 0. While the first model i.e. the mobile net efficient V2 model is a mobile net class TensorFlow model used for object detection, the second model i.e. the efficientNet is a different TensorFlow model that is used for bespoke object detection. Figure 1 denotes the architecture of the overall process where the first part is the feeder model for the images and detects whether the tumor is present or not. Then the images of the tumor are fed into the second part for tumor location detection. For the first section, 1000 photos with a

split of 60:20:20 of test:train:validate have been used, with images of brain tumors classified tumors classified as Yes and images of non-tumors classified as No. Following training and validation with the image, the model generates its output on test images with an accuracy rate of 98%. Following tumor detection model, which determines the tumor's coordinate detection, the data is fed into the efficient net lite 0 model. Label img has been used to annotate photos of tumors with a box around them as test and train datasets for the second model, coupled with an xml file with the tumor's coordinates. The image with the tumor efficientNet model, is then checked against the outcome is then displayed together with the coordinates and an accurate 96 percent visual depiction of the image of the brain tumor.

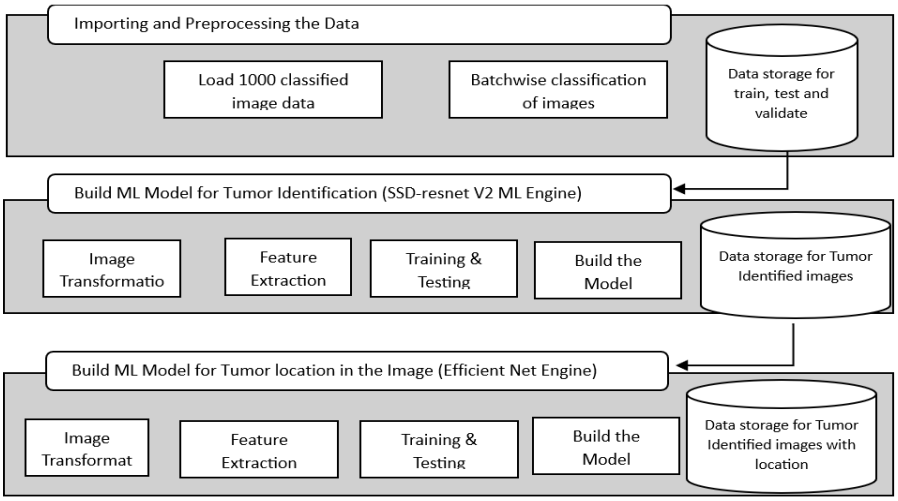


Figure 1. Architecture pipeline diagram for the proposed model

4. METHOD

The entire study was implemented in Google Colab (GUI), with the first part's dataset taken from Kaggle and the second part's sample of 100 tumor-containing images being labeled in Label-img for the test train set. The models are from the TensorFlow API, and individual tweaking has been applied to each model to improve accuracy. MobileNetV2 is an excellent feature extractor for object recognition and segmentation. For instance, the new model is approximately 35% faster for detection when used with the recently released SSD Lite while maintaining the same accuracy as MobileNetV1. This architecture mainly involves a 32-filter initial fully convolution layer as well as 19 additional bottleneck layers. As shown in Figure 2, which depicts Mobile net V2 architecture as block diagram. There are two different kinds of blocks in MobileNetV2. Block one has a stride of one. Another is a block for shrinking with a stride of two. For both varieties of blocks, there are three levels. This time, 11 convolutions with ReLU6 make up the first layer. The depth-wise convolution is the second layer. The third layer is an 11 convolution once more, but this time there is no non-linearity.

According to this architecture, neural networks only have the capacity of a linear classifier on the non-zero volume portion of the resulting domain if ReLU is applied once more. As shown in Figure 3(a) depicts the architecture for calculation in MobileNet tensor layers. Where t: expansion factor, c: number of output channels, n: repeating number, s: stride. 3×3 kernels are used for spatial convolution. Typically, the primary network (width multiplier 1, 224224) uses 3.4 million parameters and requires 300 million multiply-add operations. In MobileNetV1, a width multiplier is introduced. For input resolutions ranging from 96 to 224 and width multipliers ranging from 0.35 to 1.4, the performance trade-offs are further investigated. While model sizes range from 1.7 M to 6.9 M parameters, network computation can cost up to 585 M MAdds. Using 16 GPUs and a batch size of 96, the network is trained.

Figure 3(b) depicts efficient net architecture diagrams which is used for object-detecting models have 3 sections namely backbone, feature network, and class/box network. While the backbone is the input section that extracts the intended features of an image, the feature network represents a fused combination of the backbone extracted features, i.e., a collection of feature characteristic of the image. The box network uses fused features to predict the class assigned to the respective feature and its location. While traditional backbones like ResNet 50 and ResNeXT are suitable backbones for a feature extraction process, recent studies indicate that just by replacing the traditional backbones with Efficient Net can improve the model accuracy by 3% while

reducing computation power by 20%. While traditional feature network like top-down feature pyramid network (FPN) restricts the information flow to one way, bottom-up flow like neural architecture search (NAS)_FPN structure proved to be a lot complex. So the intended model proposed a bi directional feature network, bidirectional feature pyramid network (BiFPN) that enables both approaches discussed above as well as portrayed in Figure 3(b), which increase accuracy by 4% and reduces computational power by 50%. The efficient net lie 0 architecture has been implemented by using a mixture of new backbone and BiFPN.

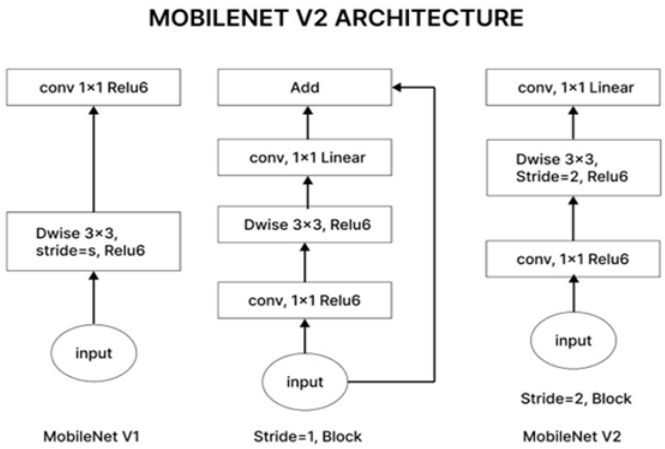
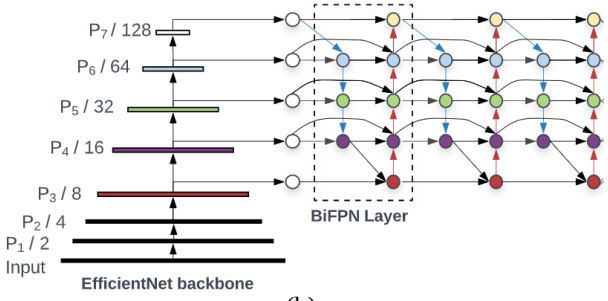


Figure 2. Block diagram for MobileNetV2 architecture

Input	Operator	t	c	n	s
224^2 x 3	conv2d	-	32	1	2
112^2 x 32	bottleneck	1	16	1	1
112^2 x 16	bottleneck	6	24	2	2
56^2 x 24	bottleneck	6	32	3	2
28^2 x 32	bottleneck	6	64	4	2
14^2 x 64	bottleneck	6	96	3	1
14^2 x 96	bottleneck	6	160	3	2
7^2 x 160	bottleneck	6	320	1	1
7^2 x 320	conv2d 1 x 1	-	1280	1	1
7^2 x 1280	avgpool 7 x 7	-	-	1	-
1 x 1 x 1280	conv2d 1 x 1	-	k	-	

(a)



(b)

Figure 3. Architecture model for (a) MobileNet tensors in MobileNet [24] and (b) EfficientNet lite diagram [9]

3.1. Proposed algorithm for detection of brain tumor

Figure 4(a) denotes the flow chart pipeline which detects whether the tumor is present or not, its related steps for identification of tumor is given in the Algorithm 1. It basically collects the sample MRI image classified data set. It checks its training data set and testing data set for validating its accuracy.

Algorithm 1: Steps for detection of brain tumor
Input: Sample data set having yes and no tumor in image
Output: Predicted tumor images on test data set
1. Start Collection Phase
2. Read Sample test images having yes tumor and no tumor in MRI scan as train, test and validation data set
3. Train and validate data with mobile net_v2 tesorflow model
4. if accuracy>.95 then
5. Call model. predict with test images to test the model with sample data set
6. else
7. while accuracy< .95 /* Hyper Tune model features */
8. accuracy=True Positive (Images having tumor predicted as tumor) /(True Positive+True Negative(Images having no tumor predicted no tumor))
9. end
10. end
11. end

3.2. Proposed working flow for detection of brain tumor

The annotation of location coordinates for brain tumors is indispensable for detecting location-specific intra-cranial tumors. It enhances precision in treatment planning, facilitates surgical navigation and targeting, integrates with advanced imaging technologies, fosters multidisciplinary collaboration, and supports longitudinal monitoring and follow-up, ultimately improving patient outcomes and quality of care. Figure 4(b) denotes the flow chart pipeline to annotate the brain tumor from the image. Label Img is used for annotating the tumors present in the image and the xml coordinates of the tumor get stored along with the image for the next model training process. The XML coordinates are crucial since they act as a feeder set in the next algorithm along with the detected tumor images. Its related steps are given as an Algorithm 2.

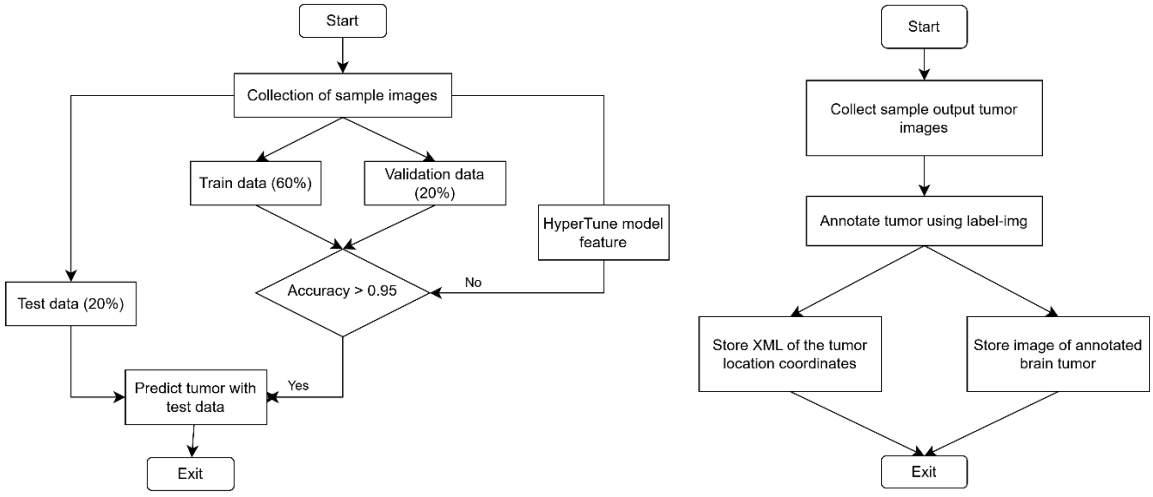


Figure 4. Flowchart for (a) detection of brain tumor and (b) annotating of detection brain tumor

Algorithm 2: Steps for annotating the locations of brain tumor
Input: Sample data set having yes and no tumor in image
Output: Location coordinate of tumor in image in xml format
1. Start collection phase /* From previous algorithm output*/
2. Read sample test images from previous model results
3. do
4. if tumor present then
5. annotate tumor with a rectangular box using labelimg
6. Loc(tumor)= (xleft,yleft),(xleft,yright),(xright,yleft),(xright,yright)

7. store Loc(tumor) in xml format
8. end
9. till images are present
10. end
11. Prepare the annotated images and xml file containing location coordinates of tumor as test,train and validation set for next algorithm
12. End

3.3. Proposed algorithm for finding the location coordinates of brain tumor

Accurate location coordinates provide precise information about the tumor's position within the brain. This precision is crucial for treatment planning, enabling healthcare providers to determine the optimal approach for surgery, radiation therapy, or other interventions. It allows for the development of customized treatment strategies tailored to the tumor's specific location, minimizing the risk of damage to critical brain structures and improving treatment outcomes. Figure 5 denotes the architecture pipeline that processes the annotated tumor images along with XML coordinates into an efficient net lite 0 TensorFlow model. This step is the most crucial one for the research purpose since it introduces an innovative way of locating the brain tumors in the image with increased accuracy. The inputs are further split into test train and validate set and the model is hyperparameter tuned till the target accuracy is reached after which it gives the desired output images having tumor locations as coordinates in the picture itself along with a rectangular annotation.

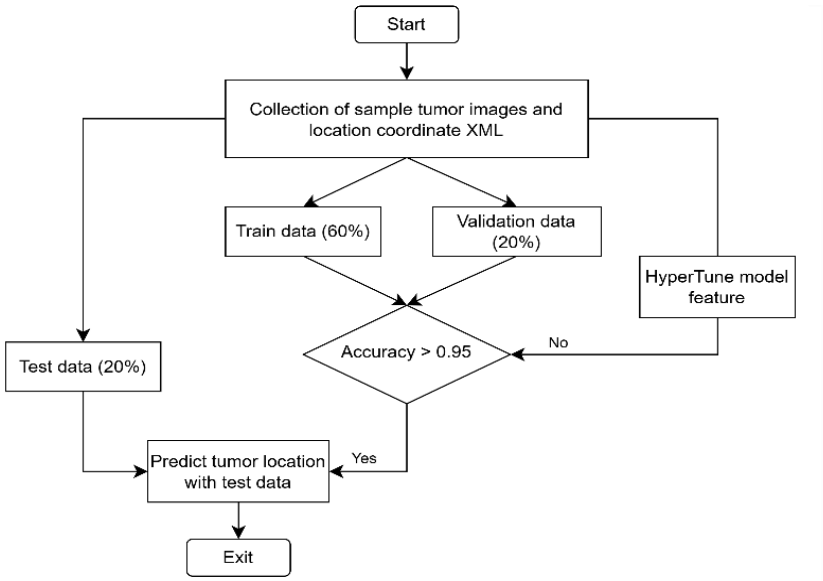


Figure 5. Flowchart for annotating and storing images

Algorithm 3: Steps for detection of location coordinates of brain tumor
Input: Sample brain mri image having tumor
Output: Predicted location coordinates of tumor image

1. Start Collection Phase /* Stored xml and the images from the last algorithm*/
2. Read Sample test images having annotated images and location coordinates of tumor in xml as train,test and validation data set
3. Train and validate data with efficient net lite 0 tensorflow model
4. if accuracy>.95 then
5. Call model.predict with test images to test the model with sample data set to predict tumor location in visual representation
6. else
7. while accuracy< .95 /* Hyper Tune model features */
8. accuracy=True Positive(Images having tumor predicted as tumor) /(True Positive+True Negative(Images having no tumor predicted no tumor)
9. end
10. end
11. end

3.4. Equations used

Equations for computational costs of conventional convolution C_{normal} and depth wise separable convolution $C_{separable}$ as used in Algorithms 1 and 3 and has used training and test set respectively.

$$C_{normal} = h_i * w_i * d_i * d_j * k^2 \quad (1)$$

$$C_{separable} = h_i * w_i * d_i * (d_j + k^2) \quad (2)$$

Where $C_{separable}$: cost of depth wise separable convolution, C_{normal}: cost of conventional convolution, i: index of input layer , j: index of output layer, h_i: input feature maps height, w_i: input feature maps width, d_i: input feature maps number, d_j: output feature maps number, and K: filter size.

True positive rates equation as used in metric scores of model evaluation which takes into training, test, and validation dataset into account:

$$M = \begin{bmatrix} m_{1,1} & \cdots & m_{1,4} \\ \vdots & \ddots & \vdots \\ m_{4,1} & \cdots & m_{4,4} \end{bmatrix} \quad (3)$$

$$\mathrm{tpr_i} = \frac{\mathrm{m_{i,i}}}{\sum_{\mathrm{j=1}}^{4} \mathrm{m_{i,j}}} \quad (4)$$

Where $m_{i,j}$: counts elements labeled with class I, but predicted as class j, M matrix: confusion matrix with diagonal elements as true positives and rest as misclassifications, and $\mathrm{tpr_i}$: true positive rate for class i.

Error rate for epoch and class as used in metric scores of model evaluation which takes into training, test, and validation dataset into account:

$$e_{t,i} = 1 - TPR_{t,i} \quad (5)$$

Where $e_{t,i}$: error rate for epoch t and class I, $tpr_{t,i}$: true positive rate for epoch t and class i

Default boundary box width and height of efficient net lite 0 as used in Algorithm 3 model build phase for training, test, and validation dataset.

$$\mathrm{w1} = \mathrm{scale} * \sqrt{\mathrm{aspect\ ratio}} \quad (6)$$

$$\mathrm{h1} = \frac{\mathrm{scale}}{\sqrt{\mathrm{aspect\ ratio}}} \quad (7)$$

Efficient net adds an extra default scale box:

$$\mathrm{scale} = \sqrt{\mathrm{scale} * \mathrm{scale\ at\ next\ level}} \text{ (aspect ratio=1)} \quad (8)$$

Where w1: width of boundary box, h1: height of boundary box. Skipping connection in resnet as used in Algorithm 1 model architecture:

Linear layer 1: $z^{l+1} = W^{l+1} * a^l + b^{l+1}$

ReLu operation on layer 1: $a^{l+1} = g(z^{l+1})$

Linear layer 1: $z^{l+2} = W^{l+2} * a^l + b^{l+2}$

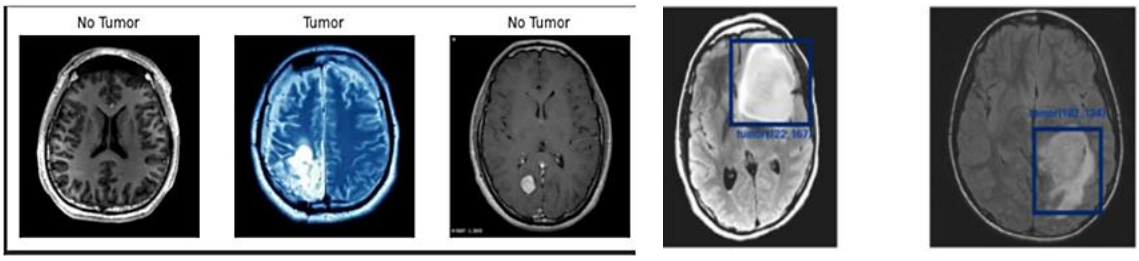
ReLu operation on layer 1: $a^{l+2} = g(z^{l+2} + a^l) = g(W^{l+2} * a^l + b^{l+2} + a^l)$ (W^{l+2} and b^{l+2}=0 where, since L2 regularization is used). $= g(a^l) = a^l$ (Skipping a^{l+1} layer) (12)

where a: incoming residual network, l : level of layer, W, b: weight decay, and g(z^l):relu function

5. RESULTS AND DISCUSSION

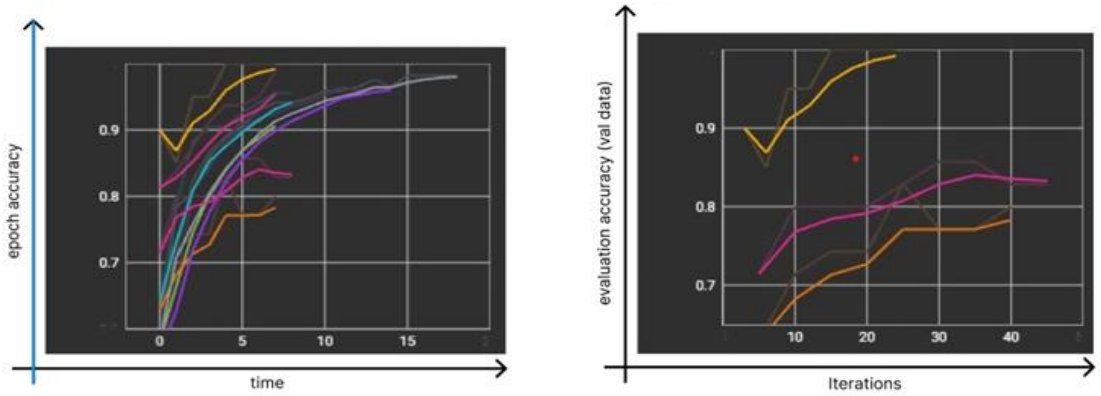
While earlier studies have explored the detection of tumor, the proposed model tends to detect the tumor location coordinates as per the given methodology discussed in previous sections and derive the final results as discussed in this section. Figure 6(a) (brain having tumor) is the output of the mobile net model with

98 percent accuracy. The figure was acceptable as a test data set input into the machine learning model which produced the classification result of yes or no based on the presence of tumor in the picture, showing how the following result yielded the following results. Figure 6(b) is the output of the rectangular box encompassing the tumor which particularly was mostly yielded by efficient net lite 0 model with 96 percent accuracy.The output also incorporated the given xml coordinates of the tumor location in the picture. Figures 7(a) and 7(b) describe the model accuracy of test and validate data set respectively with time how the model tested on the test data set and validate data set and how its accuracy increased in a major way. Figures 8(a) and 8(b) describe the epoch loss decrease with time for the model with time for the test and validation data set respectively.



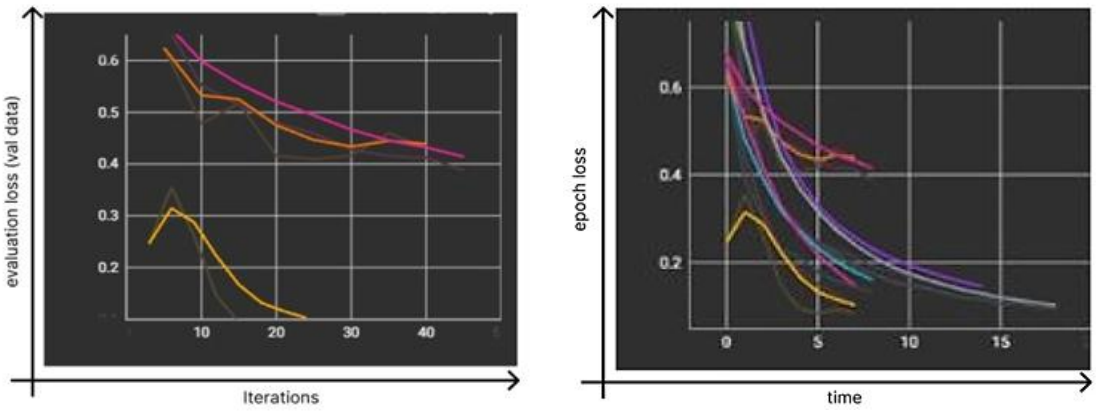
(a) (b)

Figure 6. Detection of tumor (a) output by MobileNet V2 and (b) output by EfficientNet model



(a) (b)

Figure 7. Evalation of accuracy based on (a) time and (b) iterations



(a) (b)

Figure 8. Evaluation of loss based on (a) iteration and (b) time

The proposed model was then compared with CNN, MLPNN, RCNN, and PF models from the literature survey mentioned in an earlier section. A comparative study for the above algorithms with the proposed algorithm of the paper was done as mentioned in Figure 9 and Table 1. Figure 9 denotes the model metrics in bar chart comparison format and Table 1 in tabular format with accuracy and average precision as metrics to compare. Which it is evident that EfficientNet lite 0 obtained the highest accuracy than other models, while it failed to achieve the highest average precision and mean average precision since it's a custom-tailored object detection model. Hence the given research work finally concludes on the selection of EfficientNet lite 0 as the suitable model for coordinate locations detection based on the findings above. It also concludes SSD ResNet being a just selection for the tumor detection process based on the metrics discussed above.

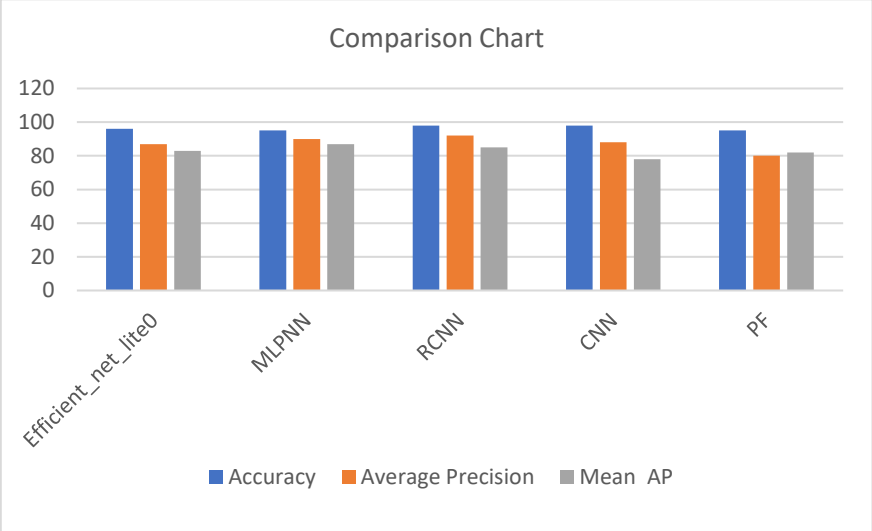


Figure 9. Comparison chart between different CNN models

Table 1. Comparison table

Model	Average precision	Accuracy	Mean average precision
Efficient_net_lite 0	87	96	83
MLPNN	90	95	87
RCNNN	92	98	85
CNN	88	98	78
PF	80	95	82

However, the emergence of more efficient neural network models in the near future could lead to an improved custom object detection algorithm. While the proposed model is recommended for achieving the research paper's objectives. Its potential benefits to the medical industry may expand further with the integration of more effective models in the future.

6. CONCLUSION

The objective of this study is to identify the coordinates of intra-cranial brain tumors using two machine learning models. These models analyze X-ray data to pinpoint tumor regions. Initially, the mobile net-v model successfully detects tumor presence, followed by the application of the efficientNet lite 0 model, which identifies annotation boxes, pinpointing tumor location coordinates through image labeling. Ultimately, this research presents a brain tumor detection model poised to benefit the medical community by enabling early tumor detection. Moving forward, the aim is to enhance the proposed model by integrating brain size dimensions to expedite tumor detection and increase accuracy in early-stage diagnosis.

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