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Augmentation Based Detection Model for Brain Tumor Using VGG 19

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Abstract: A brain tumour is a serious malignancy that can lead to death. Early diagnosis is, therefore, essential in the therapy procedure. Deep learning advances have made a significant contribution to medical diagnostics in the healthcare business. CNN's have been widely employed as a deep learning strategy for detecting brain cancers using MRI images. Deep learning techniques like CNNs should be upgraded to be more efficient because of the restricted dataset. As a result, data augmentation is one of the most well-known methods for improving model performance. This article details the implementation of multiple VGG-19 architectures as a foundation layer for specific models. Pre-processing, cropping, augmentation, and VGG-19 as a base layer with transfer learning-based brain tumour binary classification and extra layers of normalisation, dense, and activation layers are all part of the proposed system. On brain tumour, kaggle MRI datasets, the suggested technique obtained Cohen Kappa Score, f1-score, recall, accuracy, precision, and ROC AUC score are .9900, .9949, .9950, .9950,.9950, and 1.000, respectively. The experiments demonstrated that the proposed methodology is efficient and effective and outperformed comparable recent research in the literature on kaggle MRI datasets.

Keywords: Brain Tumor, Augmentation, Deep Learning, VGG-19, Cross Entropy Loss Function, Adam Optimizer

1. INTRODUCTION

Cancer has evolved into a highly lethal illness that affects people of all ages. In 2020, 308,102 persons worldwide were expected to be identified with a primary spinal cord or brain cord tumour [1]. Brain tumours are the tenth largest cause of mortality [2]. A tissue anomaly brings it on in the central spine or the brain. As a result, it causes problems with brain function. Although the aetiology of brain tumours is uncertain, radiation exposure and family history might increase the risk [3].Early diagnosis and identification of brain tumours are critical for successful therapy. According to a WHO assessment[1], [4] brain cancers are divided into many categories, such as glioma, meningioma, metastasis, sarcoma, and so on, as shown in figure 1. Many of the most present investigation initiatives are to divide brain tumour types into four classes. Recent developments in medical image processing, together with the use of computer-assisted diagnosis (CAD) as well as magnetic resonance imaging (MRI), make tumour portion detection much more effortless. Nonetheless, identifying and classifying brain tumour kinds and grades remains a tedious task. In this study, we describe a CAD-based augmentation-based model for brain tumour detection and prediction.

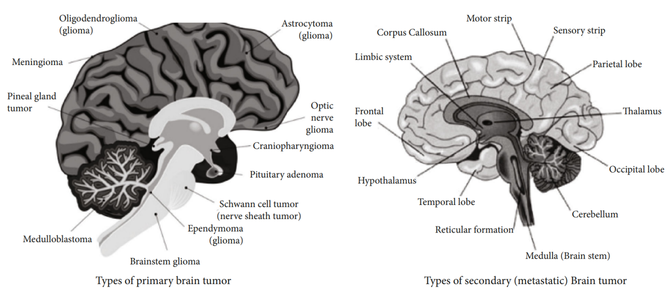

Figure 1. Category of Brain Tumor [5]

Gliomas are infiltrative tumours with fuzzy borders, making them difficult to spot in pictures of varying intensities. It tackles the difficulty of changing intensity steps due to varied magnetic resonance imaging machine setups (1.3, 5 or 7 T) [6]. Multiple MRI modalities are utilised to improve the information collected from MR pictures. T2-weighted spin-spin relaxation (T2), T1-weighted spin-lattice relaxation (T1), T1-weighted MRI with contrast improvement (T1c), and T2-weighted Magnetic Resonance Imaging with fluid attenuation inversion recovery (T2-flair) are among these modalities, each of which makes available different types of statistics about tumour pixels [7], as

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shown in figure 2.

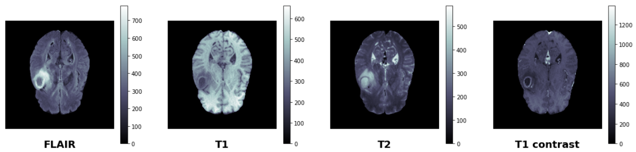


Figure 2. Four Multi-sequence MR Images

Deep Learning has recently received considerable attention from researchers in medical sciences. It has had a substantial influence on clinical research in a variety of ways, including the detection of diseases, predictions, and identification. For segmentation and classification, deep learning approaches such as CNN architecture are used. These procedures give a high level of knowledge of diagnosis, treatment, and perception in radiology [8]. This investigation attempts to solve compared to other conventional problems and achieve excellent outcome but with much less computational effort and error rate [9]. As a result, the devised approach for the automated identification of brain tumours is practical and dependable. The whole CNN model VGG19 is used in the suggested technique to detect tumours. The recommended practice uses the VGG19 transfer learning CNN model for tumour identification. Deep learning algorithms for detecting brain tumours have proven to be more successful than traditional methods [10]. In the diagnosis of cancers using MR images, the CNN-based deep learning model has shown encouraging results [11].

A related study conducted deep learning for segmentation and classification, and various pre-trained CNN models were employed to detect brain tumours. Tumour segmentation is a complex topic since tumours vary considerably in size, form, and severity. Previous research has been limited by an inability to anticipate this segmentation difficulty. Previously, tumour areas were manually segmented, which was time-consuming and invasive. The existing set of rules, and also their modifications, failed to improve performance appreciably. Additionally, previous methods had only been trained and tested on local, small datasets that did not fully reflect all tumour categories. Therefore, precise classification is challenging and problematic research that a CNN model can tackle [12]. CNN classifiers have the advantage of requiring no manual categorisation and providing automatic classification. However, the development of utterly automated brain tumour identification utilising MR imaging, which requires robust categorisation of brain cancers, is urgently needed. As a result, a wholly automated deep learning model that segments and further classifies the tumour is suggested. This research presents an augmentation-based detection approach based on the VGG19 transfer learning algorithm. VGG19 is a base layer, followed by flattening, normalisation, dense, activation, and drop layers. Transfer learning, freezing, and fine-tuning approaches minimised the parameters.

The following figure 3 are the paper's significant contributions:

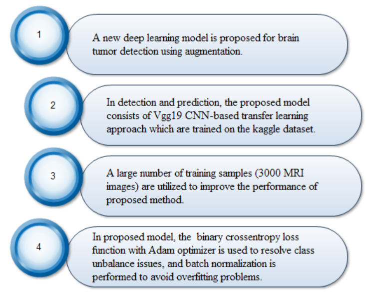


Figure 3. Key Contribution

The remainder of this research is organised as follows: Section 2 expands on the related research that looks into current models, approaches, and how prior methods function. The entire features of the proposed framework for brain tumour detection are provided in Section 3. The suggested method, which is based on CNN architecture, covers visualization, cropping, pre-processing, augmenting, classification, and detection with prediction, and is intended to address current tumour difficulties. Section 4 suggested methodology's measuring metrics, conclusions, and experiment results are defined. The proposed technique is discussed and critically discussed in Section 5. Summarising the findings and examining the domain's future prospects is the motto of Section 6.

2. RELATED WORK

This [13] paper looks at a variety of CNN architectures and emphasizes the characteristics of certain models including AlexNet, ResNet, and VGG. The author attempted to propose an efficient method for detecting brain tumors using MRI datasets by applying CNN and data augmentation techniques.

[14] present a pipeline for identifying implantable programmable cerebrospinal fluid drain vents utilizing X-ray pictures of the radiologist computer terminal displays acquired at various angles and illuminations using cell phone integrated cameras. The suggested convolutional neural network is compared against existing approaches in this study. Based on experimental proof, the author's approach outperforms currently published techniques that rely on extreme learning machines specifically fine-tuned on mobile phone images, as well as methods trained on images directly obtained from scanners and then applied to mobile phone images. The proposed model found that accuracy is .95, precision is .96, and average recall is .95.

In this study, the author proposed an automated process for identifying MRI brain images with benign or malignant tumors using a sophisticated convolutional neural network (CNN) architecture [15]. The proposed model is assessed using metrics like precision, recall, and F1 score, and the outcomes demonstrate that the proposed method surpasses currently available cutting-edge approaches.

In this study, the researchers proposed a hybrid method combining Extreme Learning Machine (ELM) and Convolutional Neural Network (CNN) for Magnetic Resonance Imaging analysis [16]. Due to its superior learning algorithm, which is faster than traditional machine learning methods, CNN was selected to replace the previous feature extraction technique. Consequently, the CNN-ELM method outperforms the CNN-ELM approach, which uses a different number of inputs and hidden neurons in the network, 8 filters in the convolution operation, and 6000 hidden nodes. This is demonstrated by the 0.915 average precision, F1-Score, and recall, as well as the 91.4 percent test accuracy.

The suggested method employs Convolutional Neural Network (CNN) and Conscience Artificial Neural Network (ANN) to detect the presence of brain tumors, and their effectiveness is assessed [17].

3. METHODOLOGY ADAPTED

Diagnosing and recognizing MRI brain tumour images is critical in locating and classifying deadly malignancies, whether benign or malignant. Brain tumours have been analyzed using medical imaging in research. The discriminativeness and descriptiveness of the retrieved features are essential for excellent classification results. Machine learning is crucial in categorization because of its extensive range of methodologies and applicability for a specific task. This study presents an end-to-end convolutional network for multi-class classification identification, adopting the VGG19 base model, with the entire visual volume as feed. The pipeline consists of four basic steps: MRI image preprocessing with threshold, erosion, and cropping; Data Augmentation using rotation, CNN-based VGG19 base model with an added layer of flattening, normalization, activation and dense; model training and evaluation using Adam and Cross-Entropy functions.

The neurons in a Convolutional Networks have weights and biases. The inputs from the anterior regions are captured by these neurons figure 4. In comparison to traditional neural networks, CNN provides a fast and accurate method that performs well in detection and characterization [13].

The net input for the neural network - based conceptual model above may be computed as follows:

$$y_i n = (x_1 w_1 \ + \ x_2 w_2 \ + \ x_3 w_3 \ .... \ + \ x_n w_n) \ + \ b \quad (1)$$

i.e., Net input $y_{in} = \sum_{i=1}^{n} \ x_i w_i \ + \ b$

The activation function may be applied to the net input to calculate the output.

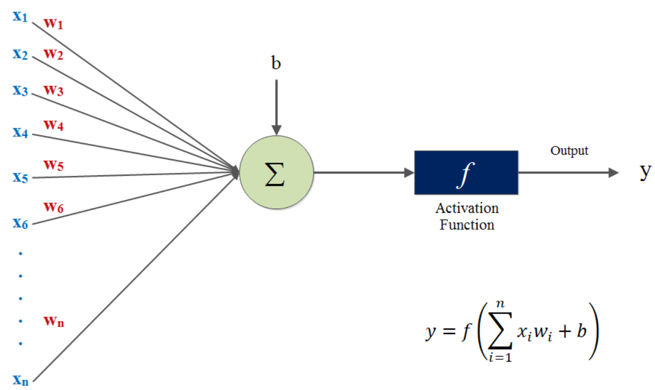


Figure 4. Concept of Artificial Neural Network [13]

$$Y = f(\sum_{i=1}^{n} \ x_i w_i \ + \ b) \quad (2)$$

A. Dataset Description

The image data that was used for this research is Brain MRI Images from Kaggle. It consists of MRI scans of two classes figure 5 and figure 6:

$$DatasetEncode = \left\{ \begin{array}{ll} 0, & for\ Tumor - No \\ 1, & for\ Tumor - Yes \end{array} \right\} \quad (3)$$

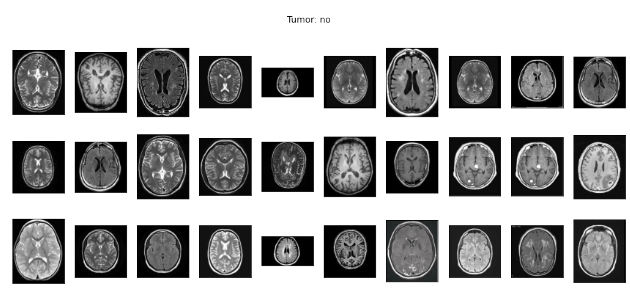


Figure 5. Brain MRI images Kaggle Dataset (Tumor No)

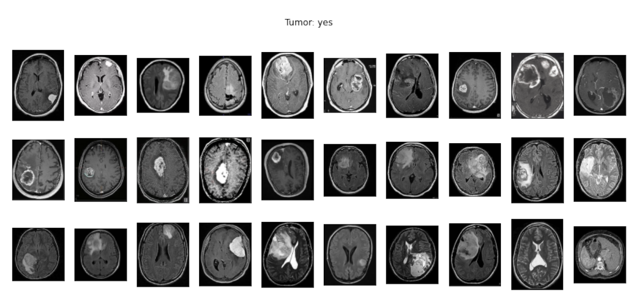


Figure 6. Brain MRI images Kaggle Dataset (Tumor Yes)

Adapted dataset has been divided in training, testing and validation sets. figure 7 is visualization of the distribution of images as selected dataset for the study.

The next visualization figure 8 graph is represented as the image count ratio wise in the adapted brain MRI dataset.

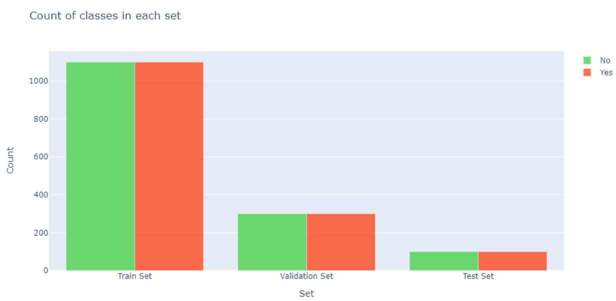


Figure 7. Brain MRI images Kaggle Dataset (Training, Testing and Validation Distribution)

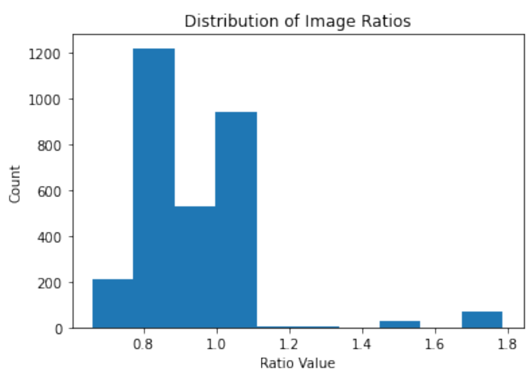


Figure 8. Brain MRI images Kaggle Dataset (Distribution graph with different ratio)

B. Pre-Processing

The objective of the preprocessing phase is to improve image quality, eliminate irrelevant data, and enhance the contrast of MR images. First, perform the thresholding in the input images. It's an image analysis approach that involves changing the pixels in a picture to make it easier to analyse. It is the conversion of a colour or grayscale image to an image in the form of binary, which is noted as black and white. Thresholding is widely used to choose regions of interest in an image while ignoring the portions we don't care about. Erosion is one of two essential processes in morphological preprocessing that all other morphological operations rely on after the thresholding application sequence. It was first proposed for binary pictures, but it was later expanded to images that are in grayscale mode and then to entire lattices.

The main idea behind binary morphology is to look at a picture with a pre-defined shape, basic and how it misses or fits the forms in the image. A binary picture works as a basic "probe" for the structural element.

Let Euclidean plane E or a grid of integer, let A be a binary picture in E. The structural element B causes the binary picture A to erode as follows:

$$A \Theta B = \{z \in E \mid B_z \subsetneq A\} \tag{4}$$

Where B_z *is the vector* z'*s translation of* B., *i.e.*,

$$B_z = \{b + Z \mid b \in B\}, \forall z \in E \tag{5}$$

If the structural element B is positioned at the origin of E, the erosion of A by B can be visualized as the collection of locations reached by the center of B as it moves inside A. For instance, a 10x10 square at the origin is eroded by a disc with a radius of 2 positioned at the origin, resulting in a 6x6 square centered at the origin. Let A and B be matrices with dimensions 13x13 and 3x3, respectively. (figure 9):

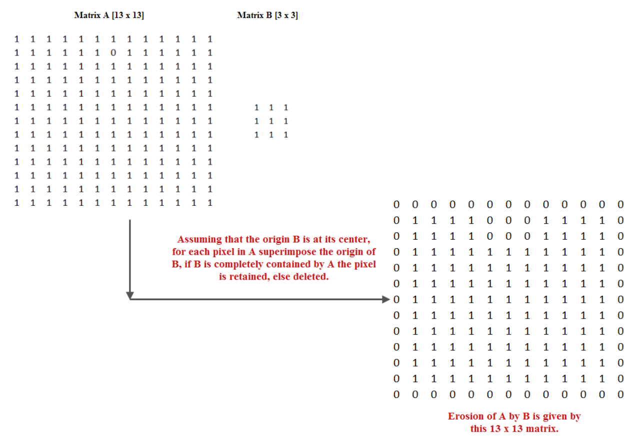


Figure 9. 13 × 13 matrix represents the erosion of A by B

This indicates that the pixels values are maintained only when B is totally enclosed within A; otherwise, they are destroyed or eroded.

In the next step of methodology is used to increase the likelihood of detecting a suspicious region in an MRI image. Finer features of the image are increased and noise is eliminated from the relevant photographs. The accuracy of MRI scans is reduced when they are contaminated with noise. The first step in the normalisation method is to crop out the brain from the images by locating the contours' extreme points figure 10.

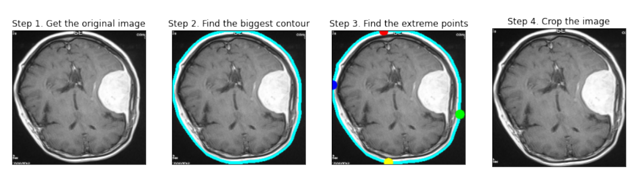


Figure 10. Steps to find the contour and extreme point

To improve framing or composition, crop an image by removing or adjusting the outside corners of an MRI brain image figure 11 and figure 12.

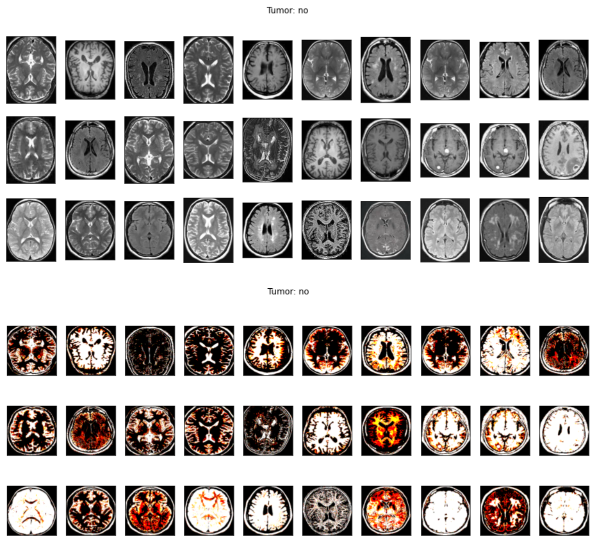


Figure 11. Visualization of Brain MRI in Grayscale and RGB form after cropping (No Tumor)

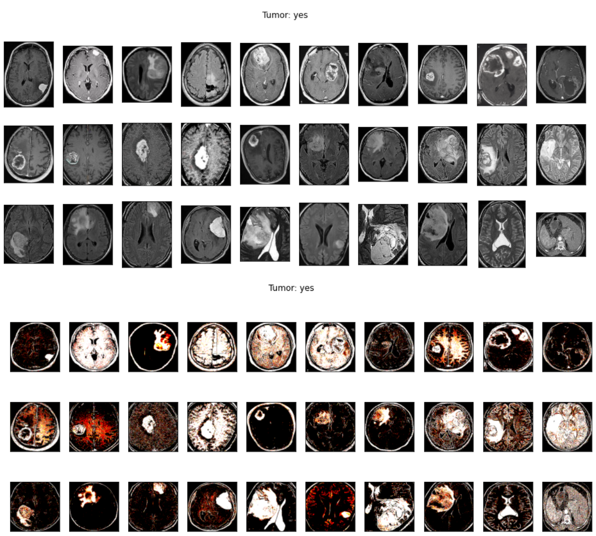


Figure 12. Visualization of Brain MRI in Grayscale and RGB form after cropping (Tumor)

C. Augmentation

A vast amount of data is necessary to increase the efficacy of a Deep Learning CNN model. However, accessing these databases is frequently accompanied by a slew of limitations [18]. To solve these challenges, data augmentation methods are instigated to upsurge the quantity of sample images in the sample dataset [19]. Data augmentation methods have been used to boost the extent of training cliques to let inventors utilise significantly more relevant training information. The fundamental idea is to artificially intensification the quantity of training instances figure 13.

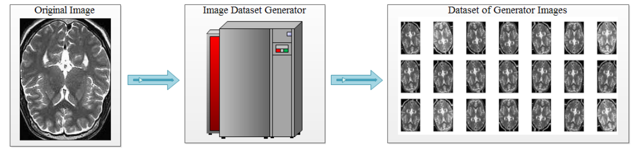


Figure 13. Generation of dataset and intensifying an existing dataset

Three types of data augmentation strategies have been identified in the literature:

- Dataset creation and expansion
- Augmenting data on-the-fly/ in-place
- Dataset creation as well as in augmentation combined

The most well-known methods are

- Rotation: spinning a picture around the centre pixel at an angle
- Flipping: produces a mirror copy of the unique.
- Translation entails shifting a picture in either the X or Y axes, or both.

D. Model Building

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning method for assigning significance (learnable biases and weights) to distinct components in a picture and discriminating between them. ConvNet requires far less preprocessing than other classification algorithms. ConvNets can learn these filters/characteristics with appropriate training, whereas simple techniques need the hand-engineering of filters. A ConvNet may capture an image's temporal and spatial correlations by using appropriate filters. The design performs better adaptation to the image dataset due to decreased amount of features and weight durability.

In the presented study, VGG 19 is used as a base model and followed by flatten, normalisation, dense, activation, and drop layers in that order. A 224 x 224 RGB picture serves as the foundation for such VGG-based convNet. The foundation layer takes away the RGB picture with adjacent pixels ranging from 0 to 255 from the mean representation values generated for the whole ImageNet training dataset. The input photographs are delivered via these weight layers after pre-treatment. A layer of convolutional layers is used to process the training pictures. The VGG19 architecture has 16 convolutional layers as well as three fully linked layers. VGG employs smaller (3*3) filters with deeper depth and the same 5 pooling layers as large filters. VGG19 features two 4096-channel fully connected layers, succeeded by a 1000-channel fully connected layer that predicts 1000 labels. Architecture Walkthrough is like that:

- The vector was of shape when this structure was provided a fixed length (224 x 224) RGB image as input (224,224,3).

- The sole pre-processing was to remove out of each pixel the mean RGB value was calculated throughout the whole training set.
- To cover the complete visual notion, they employed kernels of size (3 * 3) and stride sizes of 1 pixel.
- Spatial padding was used to maintain the image's spatial resolution.
- With sride 2, maximum pooling was achieved over a 2 * 2 pixel window.
- To improve classification and processing speed, the Rectified linear unit (ReLu) was used to infuse non-linearity into to the framework. Previous versions had relied on tanh or sigmoid processes, but this one much outperformed them.
- Three completely linked layers were accomplished: the first two were 4096 layers, followed by a 1000-channel layer for 1000-way ILSVRC classification, and lastly a softmax function.

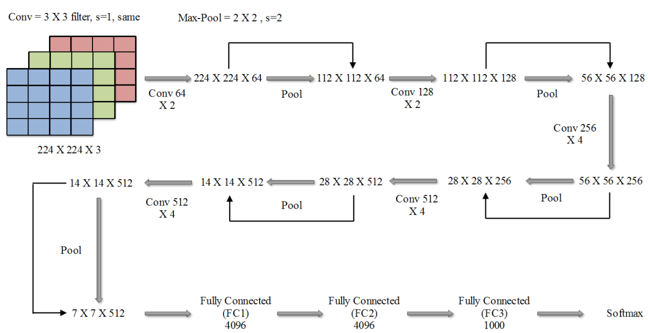


Figure 14. VGG 19 Architecture Walkthrough

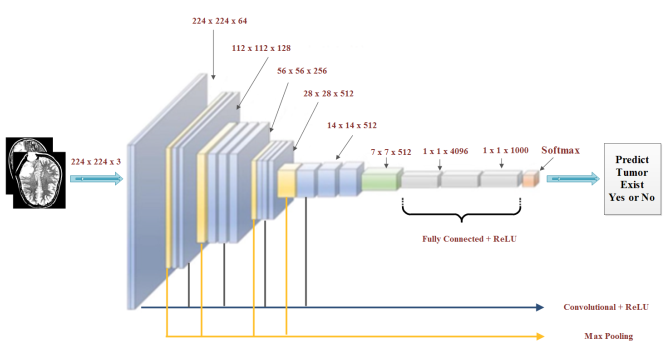


Figure 15. VGG19 used base layer model

Several convolutional layers, along with pooling and fully linked layers, are included in a VGG19 basic design. The convolutional layer's purpose is to recognise and extract data. To get the highlighted areas, we repeat the technique, starting with the input image and computing the dot product while accounting for the weights and biases. The technique for getting a single output vector is described by equation.

$$A_j = f\left(\sum_{i=1}^{N} I_i \; x \; K_{i,j} \; + \; B_j\right) \tag{6}$$

Where I = Input Vector, K = Convolutional Kernel, N =Input size, $B_j = Bias\ value\ and\ f = Non-linear\ activation\ function.$

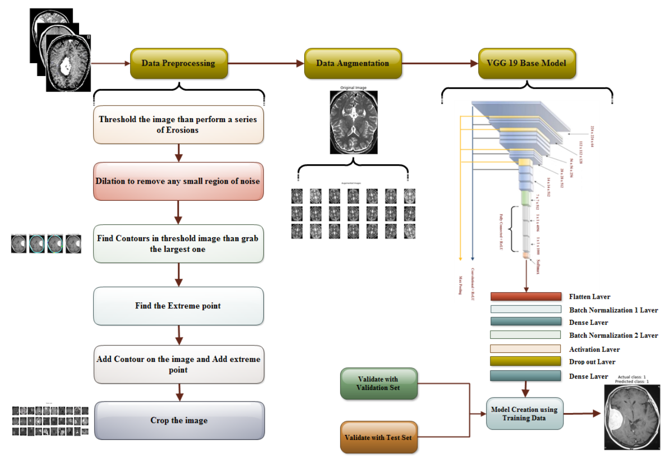


Figure 16. Adapted Methodology in this study

Figure 16 presented that the following layer have been added

- Flatten Layer: Flattening refers to the procedure of transforming data into a one-dimensional set for subsequent analysis. In this research, the output of the convolution layers is flattened to create a long feature representation, which is then connected to the final classification model, also known as a fully-connected layer.
- Batch Normalization Layer: Batch normalization is a deep learning training approach that rationalises each bunch of mini-contributions to a layer. This slows down the learning process and substantially reduces the number of training set needed to build deep convolution neural networks.
- Dense Layer: The dense layer is a basic layer of neurons in which each neuron gets input from all other activation in the previous layer, thus the name. Based on the output of convolution layers, dense layers are utilised to detect features.
- Activation Layer: A Neural Network's activation function can be defined that is inserted at the end or in the middle. They help determine whether the neuron will fire or not. The activation function modifies the input signal in a nonlinear way. This modified output is sent into the next layer of neurons as input.
- The Drop Out Layer is a technique used to eliminate

neurons from a neural network or exclude them during training. In simpler terms, certain neurons are temporarily deactivated within the network.

4. Model Performance and Evaluation Metrics

A. Adam Optimizer

The Adam optimizer, an enhanced form of stochastic gradient descent, might be used in a variety of computer vision algorithms such as computer vision applications processing. The Adam optimizer produce the best accuracy of .995 in enhancing the model using VGG 19 as a base model in the proposed system.Momentum and RMSP are two gradient descent algorithms that Adam combines.

- Momentum: The Momentum approach is an optimization method that accelerates gradient descent by incorporating an "exponentially weighted average." It is a variant of the gradient descent optimization method [20]. The Momentum algorithm consists of two phases. The first phase computes the change in position, while the second phase updates the previous position. The following factors influence the shift in position:

$$update = \alpha \ x \ m_t \tag{7}$$

The updated weight or position at time t is agreed by

$$w_t \ + \ 1 = w_t \ - \ update \tag{8}$$

Where

$$m_t \ = \beta_1 \ x \ m_t \ + \ (1 \ - \ \beta_1) \ x \ (\delta L \delta w_t) \tag{9}$$

m_t *and* m_{t-1} *are the average of gradients at period* t *and average of gradients at period* $t-1$, *respectively, in the preceding equation.*

To every point location in the solution space, momentum dampens the modification in the gradient and, as a result, the phase size.

- Root Mean Square Propagation (RMSP): RMSP is an upgraded variant of AdaGrad, an adaptive optimization method. RMSP addresses momentum issues and performs effectively in online environments [21].

$$w_t \ + \ 1 = w_t \ - \ (\alpha_t / \sqrt{(v_t)} + e) \ x \ (\delta L / \delta w_t) \tag{10}$$

Where

$$v_t \ = \beta \ x \ v_t \ + \ (1 \ - \ \beta) \ x \ (\delta L \delta w_t)^2 \tag{11}$$

Here,
$m_t - 1$ = *Aggregate of gradient at t*
m_t = *Aggregate of gradient at t*
w_t = *Weights at time*
$w_t + 1$ = *Weights at time* $t+1$
α_t = *rate of learning*
δL = *loss function derivative*
β = *Average parameter*
δ_{w_t} = *derivative of weights at t*
e = constant

B. Cross Entropy Loss Function

Cross-entropy loss, often known as log loss, is an indicator of the success of a binary classifier whose output is a probability number between 0 and 1. As the projected likelihood differs from the actual label, cross-entropy loss grows. When the exact observation tag is 1, forecasting a chance of.012 is low and results in a big loss value. In a perfect model, the log loss would be 0. Cross-entropy may be determined in classification model when the number of categories M equals 2:

$$-(ylog(p) \ + \ (1-y)log(1-p)) \tag{12}$$

If M¿2 (multi-class categorization), that estimate a loss with each target class per observation separately and add the results.

$$-\sum c = 1My_{0,c}log(P_{0,c}) \tag{13}$$

To improve the loss function, the suggested model uses the loss of a soft Fixed dice.

C. Accuracy

The effectiveness of a model is gauged by its ability to identify connections and patterns between variables in a dataset through the use of input or training data.

$$ACC = \frac{TP \ + \ TN}{TP \ + \ TN \ + \ FP \ + \ FN} \tag{14}$$

D. Precision

To assess the accuracy, the number of correctly diagnosed positive samples is divided by the sum of true positive and false positive data (both correctly and incorrectly identified). The performance of the model in identifying a sample as positive is measured.

$$Precision = \frac{TP}{TP \ + \ FP} \tag{15}$$

E. Recall

The recall is obtained by dividing the total number of significant samples by the number of successful samples accurately classified as positive. The recall of the model determines its ability to identify positive samples. A higher recall indicates a greater number of positive samples discovered.

$$Recall = \frac{TP}{TP \ + \ FN} \tag{16}$$

F. F1 Score

The F1-score or F1-measure is employed to assess the accuracy of a test. It is calculated based on the test's accuracy and recall.

$$Recall = \frac{2TP}{2TP \ + \ FP + \ FN} \tag{17}$$

G. AUC ROC Curve

A classification model issue evaluation measure is the Receiver Operator Characteristic (ROC) graph. It's a probability - based curve that compares the TPR to the FPR at different thresholds, allowing the 'signal' to be distinguished from the 'noise.' The AUC is a graphical depiction of the ROC curve that shows how well a classifier can discriminate amongst classes.

H. Cohen Kappa Score

Cohen's Kappa is a statistical metric that is being used to determine how frequently two evaluators who are evaluating the same amount agree.

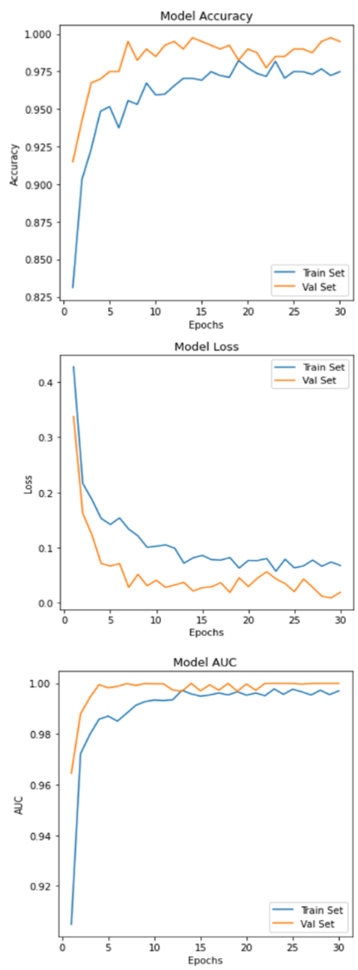
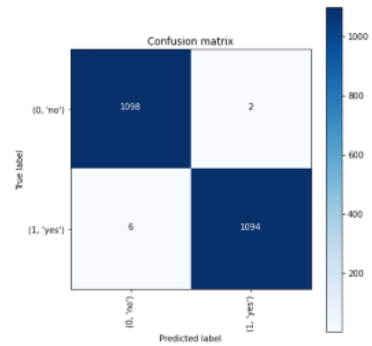


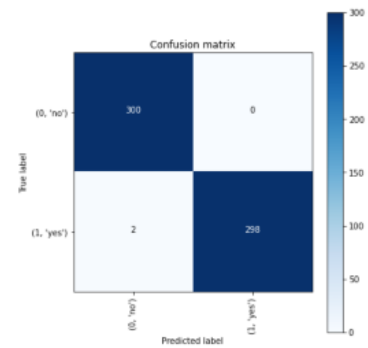
Figure 17. Model Performance in term of Accuracy, Loss and AUC (Area Under Curve)

The data utilised here is a set of MRI pictures of a brain tumour that has been separated into three data sets: train, validate, and test. Overfitting is checked using the Validate dataset. It is used to change hyper parameters throughout model development. Convolution neural network is used with the assistance of the testing dataset to produce the desired performance of the model. figure figure 17 and figure 18 are showing the results of the model.

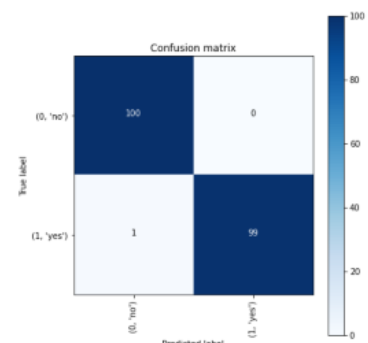
The graphs depicting model accuracy, model loss, and model AUC are shown in the images above. On the training dataset, the system attained an accuracy of around .9749 on training dataset, 1.0 validating on the validation dataset, and .995 validating on the testing dataset.



(a) Validation with Training Set



(b) Validation with Validating Set



(c) Validation with Testing Set

Figure 18. Confusion Matrix for proposed model

The following Table I and Table II is showing the performance of the model.

5. DISCUSSION

Afterwards, the proposed model's performance is compared to other existing methods in the literature, and the results are presented in a Table III. The results indicate that the customized VGG19 model performs better and produces clinical-level images compared to the conventional methods.

TABLE I. Performance metrics on test dataset

S. No.	Performance Matrices	Results
1	Accuracy	.9950
2	Precision	.9950
3	Recall	.9950
4	F1 Score	.9949
5	ROC AUC Score	1.000
6	Cohen Kappa Score	.9900

TABLE II. Classification Report

	Precision	Recall	F1 Score
0	.99	1.0	1.0
1	1.0	.99	.99
Accuracy	-	-	.99
Micro Avg	1.0	.99	.99
Weighted Avg	1.0	.99	.99

TABLE III. Comparison with existing methodologies

Ref. No.	Model Adapted	Accuracy	Precision	F1 Score	Recall
[13]	VGG 16	0.96	0.93	1.0	0.97
[14]	DCNN	0.97	0.98	0.95	0.96
[15]	CNN	0.96	0.96	0.98	0.95
[16]	CNN-ELM	0.79	0.76	0.86	0.81
[17]	ANN-CNN	0.96	0.97	0.80	0.88
Proposed Model	VGG 19 used as Base Layer	0.995	0.995	0.994	0.995

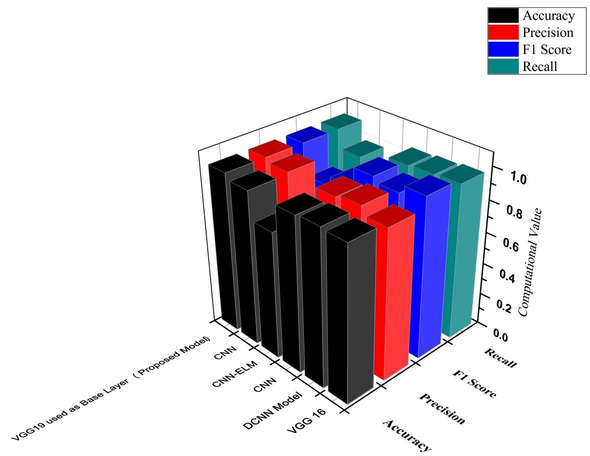


Figure 19. Comparison with existing methodologies

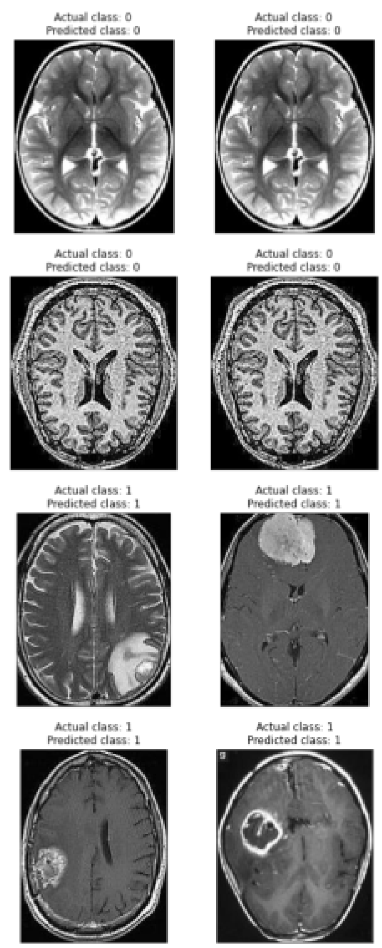


Figure 20. Prediction Tumor Yes (1) or No (0)

6. Conclusions and Future Work

The VGG19as a basis layer and data augmentation approach were used to create a brain tumour detection and prediction with classification in this research. The literature component of the study included a comprehensive assessment of several CNN designs and their limitations. Then, using data augmentation, we demonstrated how we may increase performance on restricted brain tumour datasets. The model's capacity and accuracy in identifying images were shown to be extremely motivating in experimental findings. Even in an MRI dataset, our data augmentation-based method demonstrated great detection efficiency and strong assessment metrics value. We intend to investigate more complicated architecture, a wider range of datasets, and additional data augmentation approaches in the future.

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