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Optimised Brain Tumor Detection Using texture-based features and deep learning Algorithm

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Abstract
Brain Tumor Detection (BTD) using Artificial Intelligence (AI) has gained major attention in the field of medical imaging and diagnostics. AI-based systems, particularly Machine Learning (ML) and Deep Learning (DL) algorithms, offer an advanced and efficient approach to identifying Brain Tumors (BTs) in medical images such as Magnetic Resonance Imaging (MRI) scans. These systems can automatically process and analyze large volumes of imaging data, detecting abnormalities with high accuracy and speed. In this study, the authors proposed 4 ML models (SVM, RF, MLP, and XG-Boost) and 4 DL (Bi-LSTM, Res-Net50, VGG-16, and Inception V3) models. This proposed approach involves data preprocessing step, feature selection, model optimization in a timely manner to improve and maximize prediction of BT. By training AI models on vast datasets, these technologies learn to recognize patterns associated with different types of BTs, including gliomas, meningiomas, and pituitary tumors. By leveraging these algorithms, the research evaluates their performance in terms of accuracy ($A_{accuracy}$), precision ($P_{precision}$), recall (R_{recall}), Specificity ($S_{specificity}$) and F1-score ($F1_{score}$). After comparison between the ML and DL model, the proposed DL methods, including Inception V3 achieved highest accuracy (99.04%), precision (98.23%), recall (98.53), $S_{specificity}$ (96.73%), and F1-score (97.95%) than the suggested ML models.

Keywords: Artificial intelligence, ML, DL, BT, Detection.

1. Introduction

Recently, computerized medical imaging has played a fundamental role in the diagnosis of many diseases. Other applications include learning and research. Digital medical imaging is becoming more important; for example, in 2002, the University Hospital of Geneva's Radiology Department generated 12,000 to 15,000 images every day [1]. Medical image research and report generation need an accurate and effective computer-aided diagnosis system. The traditional approach of manually assessing medical imaging is laborious, imprecise, and susceptible to human error [2]. Brain Tumors (BTs) are now one of the most serious health issues, and they are 10th on the list of top deaths in the US. Figure 1 illustrates the causes and symptoms of BTs.

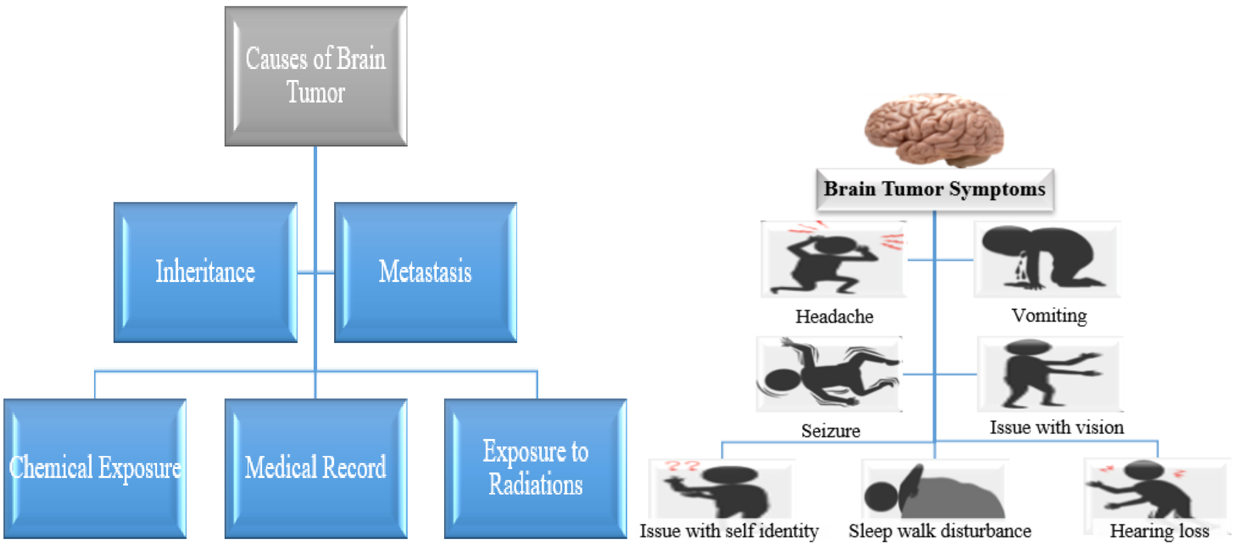


Figure 1: Causes and Symptoms of BT [3,4]

Among the estimated 700,000 people living with BTs, 80% are considered noncancerous and 20% are considered cancerous [5]. The number of newly diagnosed BTs in 2023 was 347,992 (Figure 2), with 187,491 (or 54% of the total) men and 160,501 (or 46% of the total) females receiving the diagnosis. The number of newly diagnosed BTs in 2023 was 347,992 (Figure 2), with 187,491 (or 54% of the total) men and 160,501 (or 46% of the total) females receiving the diagnosis [6]. According to research, the majority of cancer-related deaths in both children and adults worldwide are caused by BTs [7].

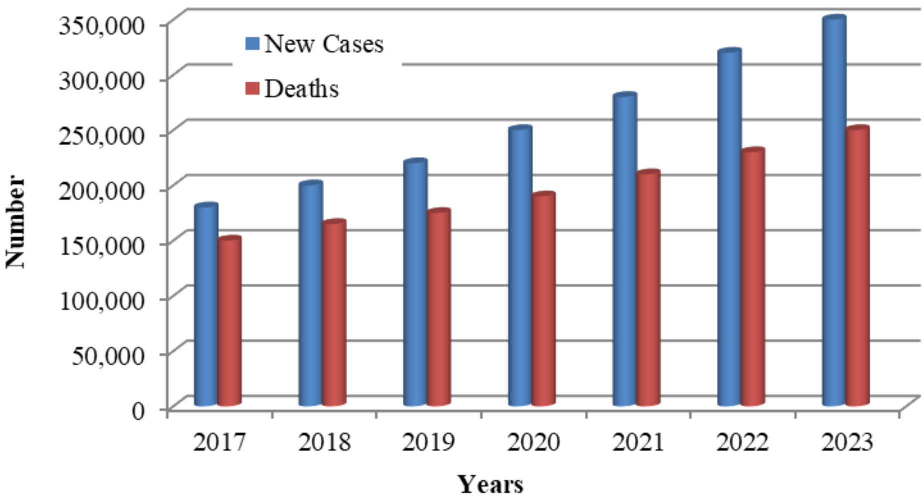


Figure 1: Global incidence of new cases and deaths due to brain cancer from 2017 to 2023 [8].

The brain is a complex organ with billions of cells, yet tumors can grow when cells divide uncontrollably, either inside or beyond the brain's normal peripheral. Its cancer rates rank first in the world, both in terms of mortality and complications for both adults and children [9]. The origin of a BT cannot be defined along with its development rate. It is often classified as a primary or secondary tumor. The former has a rate of 70% of the total of BTs originating within the inside of the brain. The most egregious of them is the main BT, which is mostly malignant. Among the most difficult primary brain cancers for doctors to discover and treat early on are gliomas (80% of all malignant BTs; of the four grades, only Grade I is benign) [10], meningiomas, and pituitary (Figure 3). The most common of these three tumor kinds is glioma, which begins in the brain's glial cells. The meningioma is a benign tumor that begins in the membrane that surrounds the brain and spinal cord and develops inside the skull [11]. Pituitary tumors are located on the pituitary gland, which primarily regulates hormone levels in the body. It could be either benign or malignant, and its imbalance can end in visual problems [12,13].

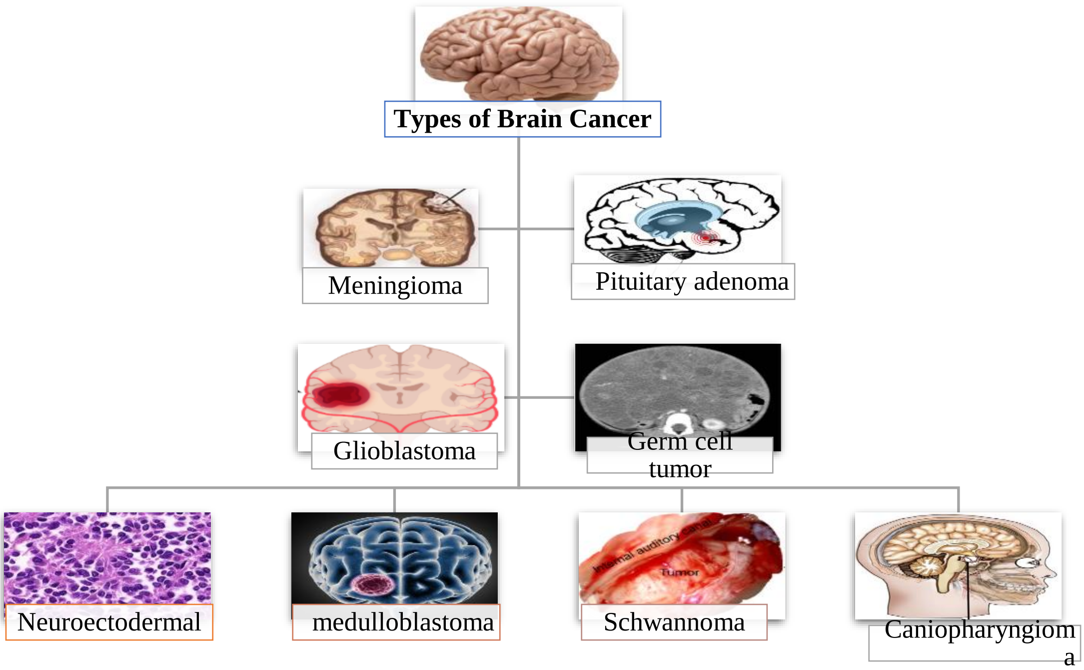


Figure 2: Types of BTs [14,15].

BT surgery is infamously challenging, but Artificial Intelligence (AI) plays a key role in both the diagnosis and detection of BTs. AI subfields such as Deep Learning (DL) and Machine Learning (ML) have completely altered neuro-pathological procedures [16]. These approaches enhance the accuracy and speed of differentiating the location of BTs from medical images such as MRI or CT. Advanced computational systems can work with huge numbers of inputs, learn patterns in the data, and find patterns that could not be observed by skilled practitioners. Preliminary operations to improve image quality and segmentation methods for tumor area extraction are typically used in the implementation of these systems. Computerized systems facilitate the accurate differentiation of cancer subtypes and their features. This technology also helps in diagnosing and planning the treatment of patients, thus acting as a tool that helps to minimize errors as it deals with patients. In general, the use of intelligent algorithms for the detection of BTs is a revolutionary concept that has embedded computational proficiency with medical knowledge. Here the potential research objectives are:

i. Collect and preprocess brain imaging datasets (e.g., MRI, CT scans) to create a robust dataset for training and testing.
ii. Develop a system to classify BTs into different types (e.g., benign, malignant, gliomas, meningiomas).
iii. Identify and extract relevant features from medical images, such as texture, shape, intensity, and edge-based features.
iv. Design and implement ML models (e.g., SVM, DT, rf) and DL architectures (e.g., CNNs, transformers) for BTD.
v. Estimate the performance of the proposed simulations using metrics like $A_{accuracy}$, $P_{precision}$, R_{recall}, $S_{specificity}$, *and* $F1_{score}$.

2. Literature Review

This section presents the authors' prior work based on BTD using DL and ML algorithms. The previous authors provided their outcomes based on the $A_{accuracy}$, $P_{precision}$, R_{recall}, and $F1_{score}$. Modern development in the traditional methods ML and DL have vast enhancement in the identification and categorization of BTs. Anantharajan et al. (2024) [17] developed the Ensemble Deep Neural Support Vector Machine (EDN-SVM) classifier which aimed at claim, accuracy of 97.93%, sensitivity of 92%, and specificity of 98%; for BTD using MRI images. Khan et al. (2024) [18] used DenseNet169 as a feature extractor and collaborated with RF, SVM, and XG-Boost classifiers to classify five different types of BT with 95.10% accuracy to develop the tumor detection model more accurately using ML.

Along the same line of thought, different deep transfer learning (TL) structures such as ResNet152, VGG19, DenseNet169 and MobileNetv3 were used by Mathivanan et al., (2024) [19] with MobileNetv3 yielding the highest accuracy of 99.75% on Kaggle data sets. Similarly, in [20], the authors include TL and merge the VGG16 design with the suggested "23 layers CNN" architecture. The models were able to get classification accuracy of up to 97.8% and 100% for the datasets that were used in the experiments, respectively. To categorize brain MRI into normal or tumor instances, researchers in study [21] used TL-based models along to a CNN named BRAIN-TUMOR-net that was trained from scratch. The suggested BRAIN-TUMOR-net is compared against the pre-trained InceptionResNetv2, Inceptionv3, and ResNet50 models. It achieves accuracy values of 100%, 97%, and 84.78% for three distinct MRI datasets.

However, apart from these methods, hybrid models and ensemble methods have also been seen to be highly effective. Finally, Ibrahim et al. (2023) [22] proposed a novel Physical and PSO initialized CNNs, with accuracies of 98.50%, 98.83%, 97.12%, Alzheimer's as well as BT databases. Venmathi et al. (2023) [23] also aimed to classify malignant and benign tumors and applied an enhanced DCNN classifier with accuracy higher than 99.65%. In the same year, Rasheed et al., [24] recommended an algorithm based on CNN for classification of glioma, meningioma, and pituitary tumor with accuracy of 98.04%, the best $P_{precision}$, R_{recall} and $F1_{score}$. For the purpose of MRI-based BT classification and prediction, the authors of research [25] suggest a CNN-LSTM hybrid DL model. Researchers examine a collection of MRI brain images. The suggested model correctly predicts the BT 99.1% of the $A_{accuracy}$, with 98.8% $P_{precision}$, 98.9% R_{recall}, and 99.0% $F1_{score}$.

Regarding the segmentation, Pedada et al. (2023) [26] introduced U-Net with residual networks and sub-pixel convolution to gain 93.40% and 92.20% of accuracies on BraTS datasets. To improve the ensemble techniques, Jain et al. (2023) [27] proposed the Ensemble Deep Learning- Brain Tumor Classification (EDL-BTC) using MobileNetV2, InceptionV3, and ResNet50, achieving better overall accuracy (98.6%) than prior models for five cross-validation folds. Similarly [28], developed a method for classifying BTs using hierarchical DL (HDL2BT) and CNN. In comparison to previous approaches, the recommended model outperforms them in terms of $A_{accuracy}$ (92.13%) and miss rate (7.87%) when it comes to identifying and segmenting BTs. Woźniak et al. (2023) [29] have proposed a new correlation learning mechanism (CLM) that incorporates CNNs and classical approaches obtaining around 96% of accuracy and 95% of precision.

Archana et al. (2023) [30] put forward the Bagging Ensemble with K-Nearest Neighbor (BKNN) method for brain malignancy detection, and by using U-Net based segmentation it yields 97.7% classification accuracy, thus proceeded the idea of ensemble and deep learning methods to classify and detect the BTs. In order to classify tumors as benign or malignant, and to extract features from synthetic data accessible on the internet from sources like OASIS and ADNI, they show the study of several state-of-the-art ML algorithms, including LR, MLP, DT, NB, and SVM [31]. A further finding from the study is that the LR and MLP achieve a maximum accuracy of 90%.

The study Lamrani et al., (2022) [32] used CNN as a feature of ML to perform BTD and classification. Precisions of the pre-trained architecture model after training and testing are of 96% in both classification accuracy rates. While comparing both the techniques for the given dataset, it concludes that CNN is a better classifier in terms of presence of BTs. Similarly, in [33], they using ML and CNN to analyze MRI based BTs. The study relied on an open dataset. The study shows that CNN model has a better classification accuracy of handling new data with an accuracy of 98.21% compared to the ML algorithms. Last for BTD, several experiments are conducted using a combination of the DL and conventional ML techniques [34]. In the work, for BTD purposes AlexNet and ResNet-18 architectures are employed; these are combined with the SVM algorithm. Regarding the diagnosis accuracy, AlexNet+SVM hybrid technique has the best $A_{accuracy}$ of 95.10%, sensitivity of 95.25%, and specificity of 98.50%.

Altogether, these works demonstrate the importance of combining multiple DL and ML techniques to obtain high accuracy and reduced error rates in detecting BTs from medical imagery.

The detection of BTs is a critical challenge in medical diagnostics, traditionally requiring manual analysis of imaging data such as MRI scans by radiologists. This process can be time-consuming, prone to human error, and affected by inter-observer variability, which emphasizes the need for automated solutions. ML and DL provide an innovative approach to address these limitations by leveraging algorithms to detect and classify BTs accurately from medical images. The problem involves developing a model that takes MRI scans as input and predicts the presence and type of BT, such as benign, malignant, or no tumor. Key challenges include ensuring the availability of high-quality, annotated datasets, preprocessing the data to handle artifacts and normalizing imaging conditions, and extracting relevant features to differentiate tumors from normal tissue. Additionally, the model must generalize well to new, unseen data and provide interpretable results to support medical decision-making. Evaluating the model's performance through metrics like $A_{accuracy}$, $P_{precision}$, R_{recall}, $S_{specificity}$, $and\ F1_{score}$ ensures its reliability and effectiveness. A successful ML and DL system for BTD can enhance diagnostic speed and accuracy, reduce the workload on healthcare professionals, and improve patient outcomes.

3. Research Methodology

Figure 6 illustrates a comprehensive workflow for BTD using AI, specifically leveraging ML and DL approaches. The process begins with the selection of a dataset comprising MRI images that classify brain conditions into four categories: glioma tumor, meningioma tumor, pituitary tumor, and no tumor. The first step is data preprocessing, which involves resizing the MRI images for uniformity, removing noise to enhance image clarity, and normalizing the data to ensure consistency across the dataset. Preprocessed images then undergo feature extraction, where shape-based, intensity-based, and texture-based features are computed to highlight relevant characteristics crucial for classification.

Following feature extraction, the dataset is divided into training (80%) and testing (20%) subsets. The training data is fed into various models, categorized under ML and DL. The ML models explored include SVM, RF, MLP, and XG-Boost. On the other hand, DL models such as VGG-16, ResNet-50, Inception-V3, and Bi-LSTM are utilized for more sophisticated feature learning and classification. Once the models are trained, they are validated using the testing dataset. Model performance is evaluated using metrics like $\mathrm{A_{accuracy}}$, $\mathrm{P_{precision}}$, $\mathrm{R_{recall}}$, $\mathrm{S_{specificity}}$, and $\mathrm{F1_{score}}$. The ultimate goal of this process is to determine the most effective model for classifying MRI images into the respective tumor categories. This automated approach enables accurate and efficient BTD, aiding medical professionals in diagnosis and treatment planning.

3.1 Dataset

A total of 2470 MRI scans of the human brain were carefully categorized into four groups: glioma, meningioma, no tumor, and pituitary [35]. There are many different kinds of tumors, and Figure 2 shows instances of them on several planes [36]. Table 1 shows how the labelled photos were distributed across these four categories.

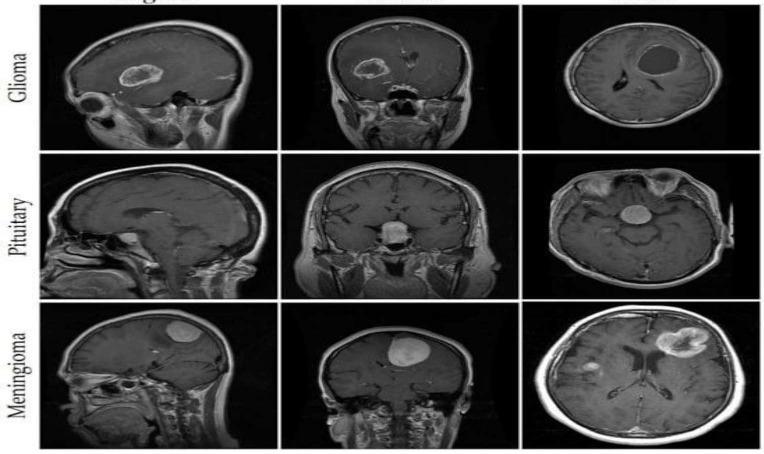


Figure 4: The description of normalized MRI pictures showing various types of tumors on a distinct plane

Glioma is the main category of malignant BT, mostly arising in glial cells inside the brain and spinal cord. Meningioma is a benign BT that can transform into a malignant form if not properly treated. These classifications are designated by doctors. The dimensions of the input photos are 64×64 pixels. Table 1 presents the discriminations of the training, test, and validation sets by class. Figure 5 shows the bar graph of distribution data.

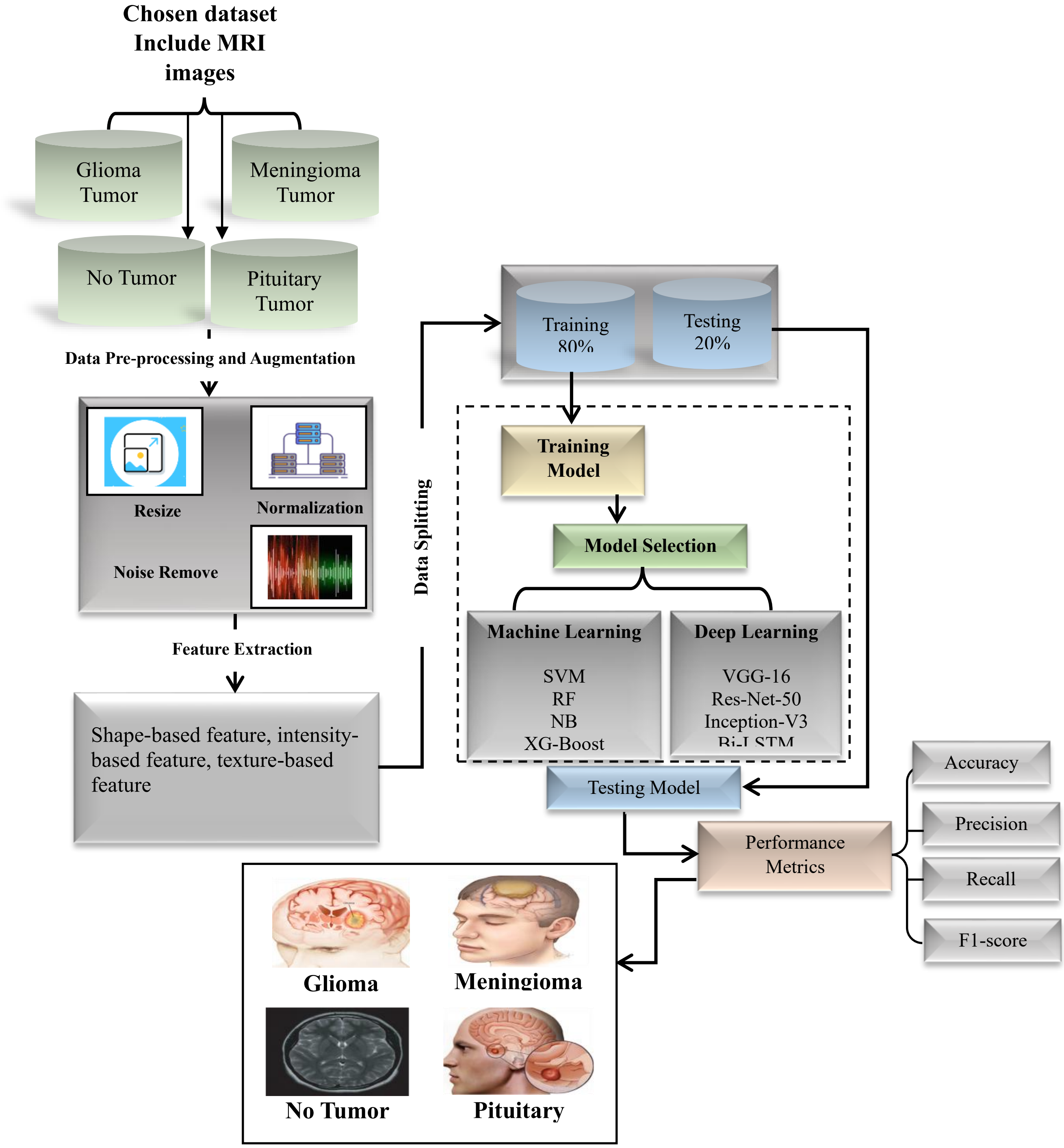


Figure 6: Flowchart of Proposed Work

Table 1: Distribution of data

Data	Glioma	Meningioma	No tumor	Pituitary	Total
Training Data	694	723	317	682	2416
Testing Data	94	95	50	92	331
Validation Data	140	142	78	136	496

3.2 Data Pre-processing and augmentation

It is the most important phase in which data is transformed into suitable form for the training purpose. Basically, the collected MR pictures which are from the patient database depicted low contrast and quality images. At this level, we normalized the photos to make further adjustments on them. The authors also reduced the picture to blur with the aid of Gaussian and Laplacian filters to enhance the quality of the pictures taken by the camera. As a limited dataset, the data set consisted of MRI pictures. There were a total of 2470 MRI pictures in our dataset; training comprised 80% of the data, while testing and validation each utilized 10% of the remaining images. The training could be made better if the quantity of original data is enhanced by augmentation. This also improves the model's ability to learn. Thus, they augmented the data by applying rotation, width and height shifting, and zooming to the mirrored MRI pictures. The next step was to apply the holdout validation procedure to the datasets.

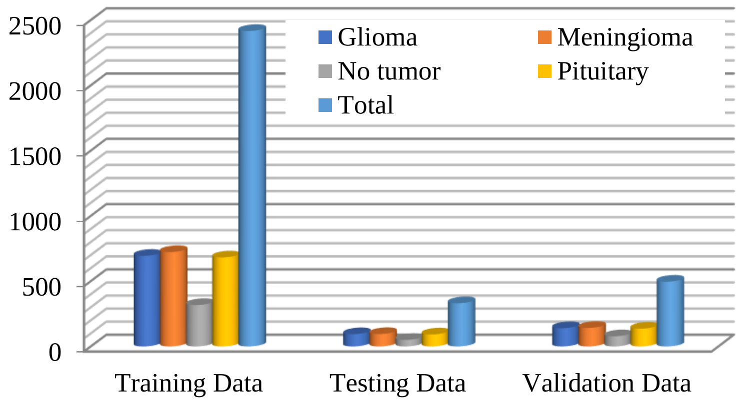


Figure 5: Bar graph of distribution data

3.3 Feature Extraction

Feature extraction is essential for categorization. This research extracts the shapes, textures, and colors significant for depicting BT pictures. The extraction of optimum characteristics from brain pictures is a complex task [37]. In feature extraction process actual data is converted into numeric data with an aim to maintain the originality of the data as well. Features can be extracted by either a fully automated process or manually. Automated feature extraction extracts only significant features relevant to the issues while manual feature extraction extracts whole lot of significant features. Texture features used in the present study include gray-level co-occurrence matrix (GLCM) features. Features are obtained from the GLCM functions of the BT image texture. Matrix dimensions determine the proportionating of the pixels within a BT image. The features give four outcomes defined as homogeneity and dissimilarity, energy, and contrast.

3.4 Classify Models

In this section, the author provides the classification methods such as ML and Dl for BTD.

3.4.1 Machine Learning (ML)

ML methods are used globally to identify any illness, and classification is a crucial part of these strategies. They define the best-suited classification model among SVM, RF, MLP, and XG-Boost classifiers and provide a short overview of their respective methods.

a) Support Vector Machine (SVM)

The SVM provides an alternate method for binary classifier problems and has several kernel applications [38]. The hyperplane's dimension is affected by the number of characteristics. It is definitely challenging to identify the plane that divides the data points into the model because there are many viable configurations for a hyperplane in an N-dimensional space. The goal is to identify the data point that separates the two groups with the biggest disparity. It is possible to express the cost function for the SVM model mathematically using Equation (1).

$$(\theta) = \frac{1}{2}\sum_{j=1}^{n} \theta^2 j \qquad (1)$$

b) Random Forest (RF)

RF methods are used in both classification and regression analyses. Predictions are generated via a tree-based model of the data [39]. Using the RF method on big datasets could still provide the same outcomes even if a huge number of records are missing. A variety of data sets could benefit from the decision tree's analysis and study after it has been preserved. There are two parts to a RF: first, making the RF itself; and second, making a prediction based on the classifications generated in the first part.

$$Gini = 1 - \sum_{i=1}^{n} (p_i)^2 \qquad (2)$$

Equation (2) uses the value of p_i to represent the object's classification probability according to a given class or characteristic.

c) Multilayer perceptron neural networks (MLP)

An ANN model often known as a "multilayer perceptron" (MLP) has an input layer, a pooling layer (or layers), and convolution layers. It is one of the most famous approaches in the ML sector due to its consistent performance beatings of other strategies. Researchers have enhanced this methodology by using diverse factors and adjusting the number of layers to develop optimal forecasting models, despite the simplicity of having all three layers. A simple multilayered perceptron model could be described using one hidden layer, as shown in the function below [40]:

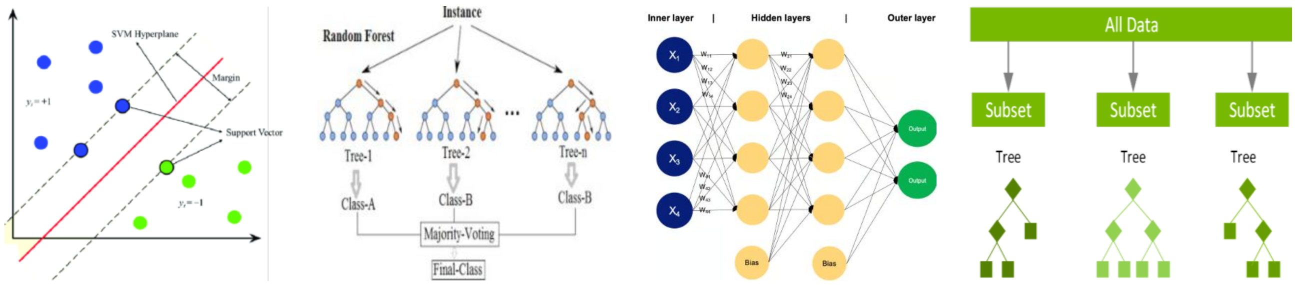
$$f(x) = g\left(b^{(2)}\right) + w^{(2)}\left(S^{b^{(1)}} + W^{(1)}x\right) \qquad (3)$$

In this case, they have the activation functions g and s, the weight matrices $W^{(1)}$ and $W^{(2)}$ the bias vectors $b^{(1)}$ and $b^{(2)}$, and the matrices W.

d) eXtreme gradient boost (XG-Boost)

This gradient boost variant is partially more manageable. While it employs more complex smoothing techniques (L1 and L2), its performance is noticeably superior to gradient boost methods [41]. Its execution speed is rapid. XG-Boost utilizes a distinctive method for tree construction, whereby the ideal node splits are ascertained using similarity scores and gains, in contrast to conventional gradient boosting.

$$The\ similarity\ Score = \frac{(\sum_{i=1}^{n} Residual_i)^2}{\sum_{i=0}^{n}[Previous\ Probability_i^{*}(1 - Previous\ Probability_i)] + \lambda} \qquad (4)$$



SVM **RF** **MLP** **XG-Boost**

Figure 7: ML proposed Methods

3.4.2 Deep Learning (DL)

DL is a subdivision of ML concerned with teaching ANNs to carry out complicated tasks by acquiring representations and patterns in data via direct observation and analysis. DL algorithms automatically generate robust and reliable models by extracting hierarchical features from data, in contrast to conventional ML methods that dictate human feature engineering [42,43] In this study, a Bi-LSTM model is used.

a) Bi-directional Long Short-Term Memory

Bi-LSTM is a developed architecture from regular LSTM that could be used to improve sequence classification difficulties [44]. As shown in Figure 8, an LSTM cell consists of three essential components: an input gate, a forget gate, and an output gate. One of the main roles of input gates is to control the flow of fresh data into memory. The forget gate is responsible for storing items in memory for a certain duration. The quantity of memory needed to activate the block is finally controlled by the output gate [45, 46]. The computation for the gates is:

$$G_i^t = \sigma(w_i x^t + U_i h^{t-1} + b_i) \qquad (5)$$

$$G_f^t = \sigma(w_f x^t + U_f h^{t-1} + b_f \qquad (6)$$

$$G_o^t = \sigma(w_o x^t + U_o h^{t-1} + b_o) \qquad (7)$$

$$C^t = G_f^t \times C^{t-1} + G_f^t \times \tanh\,(W_c x^t + U_c h^{t-1} + b_c) \qquad (8)$$

$$h^t = G_o^t \times \tanh\,(C^t)$$

U and W denote the weight matrices of each gate, while the bias is provided by b. The activation functions are σ and tanh.

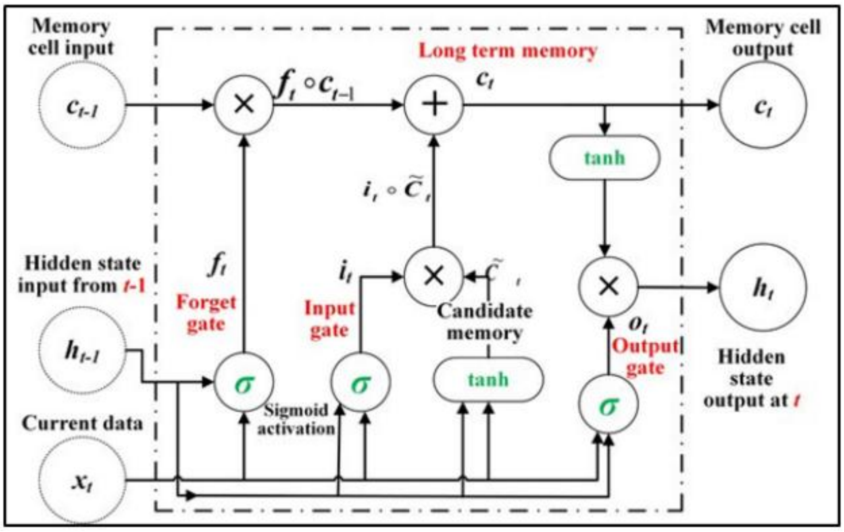


Figure 8: An LSTM network [47].

3.4.3 Transfer Learning

Machine learning technique known as transfer learning are often used with neural networks that have already been trained [48,49]. Significant instances of transfer learning models used for image classification and detection include Inception V3, ResNet-50, and VGG16 [50-52].

a) Res-Net 50

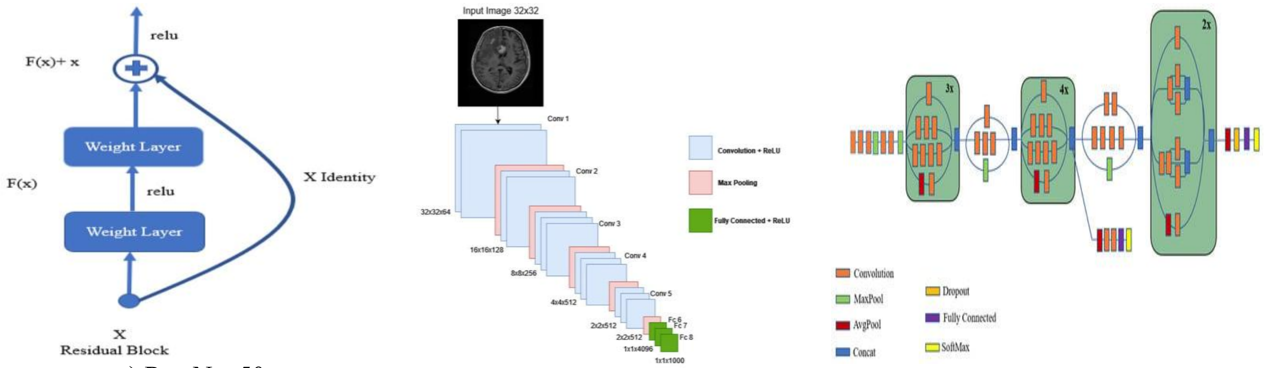
ResNet-50 is a deep CNN architecture that is part of the ResNet (Residual Networks) family, presented by Microsoft Research in 2015. ResNet-50 is a connected architecture of Res-Net containing 50 deep layers in its structure and the minimum ImageNet sample of one million for training purposes [53]. The structure of ResNet-50 contains a series of average pooling convolutional units [54]. For all the layers in a usual neural network, one layer or layer connection connects to successive layers but the output layer's result links with the successive layer input layer [55]. Figure 9 depicts the residual block of the transfer learning model [56].

b) VGG-16

It is also a CNN architecture that was introduced by the Visual Geometry Group (VGG) at the University of Oxford [57]. The kind of architecture known as VGG16 is deeper network for detection and classification of images [58]. The dataset could be represented with better precision in image identification and segmentation using VGG16 model. Besides, the key strength of VGG16 lies in larger datasets and challenging context recognition abilities [59,60]. Part of the structure of Convolutional neural networks, the VGG16 has 16 convolutional layers and employs the 3x3 receptive field. The architecture of VGG16 is shown in Figure 9.

c) Inception V3

It is a DL architecture that is mainly applied for image classification and detection [61]. Training Inception V3 is a tough task with a basic computer; often, it takes several days to train the model. Inception V3 is improvement to Inception V1, which has been introduced by GoogLeNet in 2014 [62]. In 2015 another version of inception was proposed, Inception V3 with 42 layers and described to have lesser error rate than the previous versions. Inception method outlined convolution, pooling, dropout, fully linked layers, and softmax activation method. Architecture of Inception V3 is depicted in figure 9 [63].



a) Res-Net 50 b) VGG-16 c) Inception V3

Figure 9: DL proposed methods

3.5 Performance Metrics

The evaluation model consists of four parts: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The model's performance was evaluated using Equations (9)–(12), where $A_{accuracy}$, $F1_{score}$, $P_{precision}$, and R_{recall} are the relevant variables.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

$$Recall = Sensitivity = \frac{TP}{TP+FN} \quad (10)$$

$$Precision = \frac{TP}{TP+FP} \quad (11)$$

$$F1-score = \frac{2*Precision*Recall}{Precision+Recall} \quad (12)$$

4. Result and Analysis

Herein, we report the findings of training and validating the proposed fine-tuned ML and DL model based on MRI images along with general evaluation. Different medical preprocessing and data augmentation methods were adopted in order to enhance the quality and size of the dataset. Several hyperparameters were applied to train the proposed model aimed at the best performance. The ML and DL model was trained on the author's personal computer with 8 cores 3.70 GHz Intel processor, Nvidia GeForce 1080Ti Graphic Cards and 32 RAM in each computer [64].

4.1 Machine Learning

The SVM, RF, MLP, and XG-Boost methods (Table 2) were applied and discussed in terms of the BTD model's $A_{accuracy}$, $P_{precision}$, R_{recall}, $S_{specificity}$, and $F1_{score}$. Among these, the MLP showed the highest level of performance. For the non-tumor samples, the highest accuracy (96.48%) and the highest precision (96.04%) and recall (96.16%) were obtained by the MLP system along with competitive values of metrics for the tumor-present cases, with a precision of 96.83% and an F1-score of 95.83%. Thiss suggests that MLP is very good at differentiating tumor and non-tumor cases as proven by the test done. Figure 10 shows the Confusion Matrix of Proposed ML methods.

SVM also proved satisfactory with its accuracy greater than 92% for both cases with tumour and without tumour. They achieved high sensitivity and virtually equal performance of all the essential parameters, making it a suitable substitute for MLP. From the results acquired in Table 2 it could be deduced that RF gave satisfactory results, but its precision and recall, though satisfactory were marginally lower than MLP and SVM. Despite the high efficiency, XG-Boost possessed the lowest separating ability or sensitivity which do not allow identifying the presence of tumors adequately. Comparing the results of all models MLP was concluded as the most precise and accurate model. Hence, these results evidenced that MLP has higher diagnostic probable and suitable for clinical applications in terms of better tumor detection.\

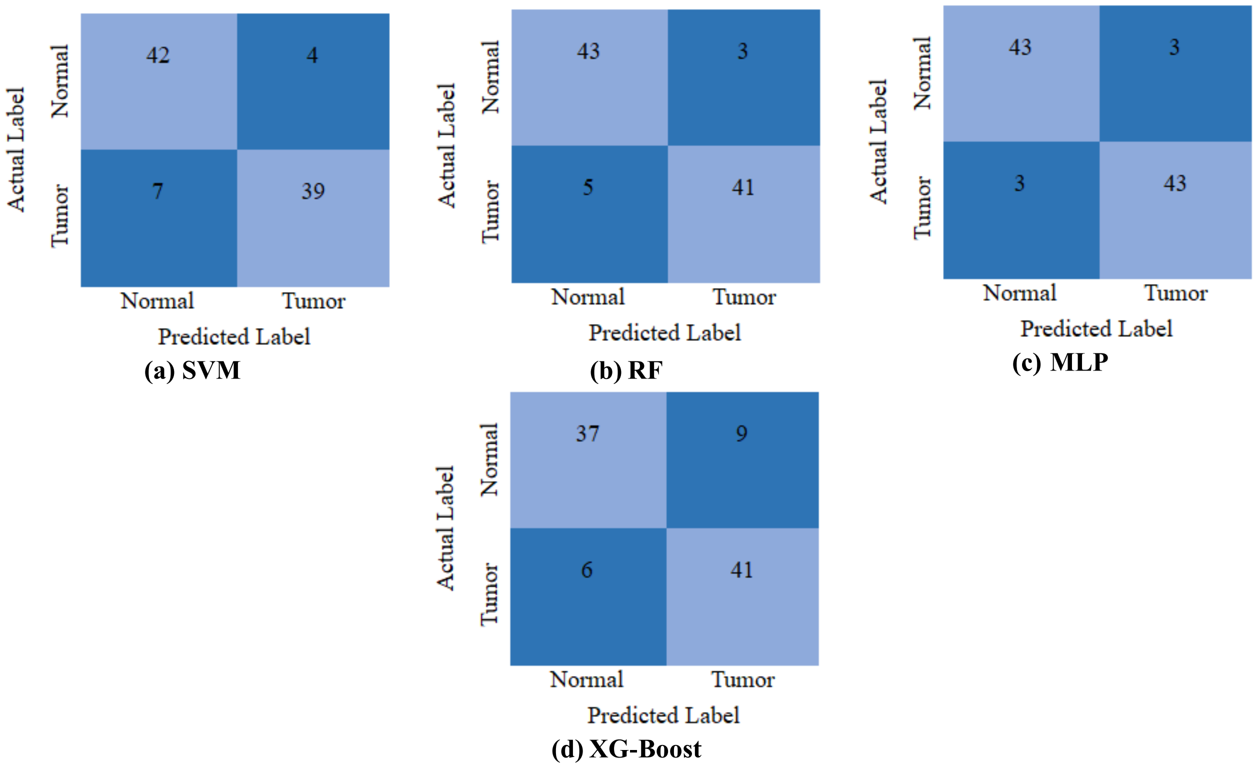


Figure 10: Confusion Matrix of Proposed ML methods

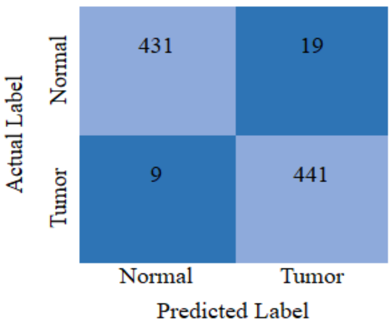
Table 2: Evaluation of Proposed ML Methods

Methods	$A_{accuracy}$	$P_{precision}$	R_{recall}	$F1_{score}$	$S_{specificity}$	Labels
SVM	92.30	91.58	90.13	92.49	94.48	No Tumor (0)
		90.43	92.05	92.75	95.47	Tumor Present (1)
RF	89.04	88.71	85.78	89.42	92.30	No Tumor (0)
		86.45	86.35	90.21	93.4	Tumor Present (1)
MLP	**96.48**	**96.04**	**96.16**	**93.51**	**95.27**	No Tumor (0)
		95.35	**96.83**	**94.11**	**95.83**	Tumor Present (1)
XG-Boost	85.78	87.10	90.13	85.09	81.43	No Tumor (0)
		89.22	91.04	86.23	82.64	Tumor Present (1)

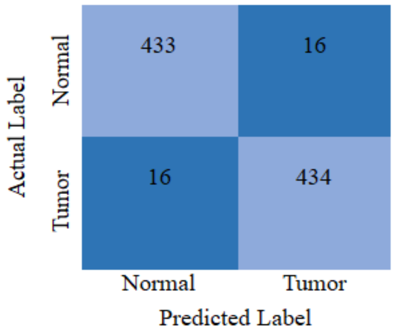
4.2 Deep Learning

The performance summary of different DL models such as Bi-LSTM, ResNet-50, VGG-16, and Inception V3 has been presented in Table 3 predicting evaluation of BTs. Bi-LSTM has a higher $A_{accuracy}$ of 98.89%, and more specific over the No Tumor cases with a precision of 98.95%% and R_{recall} of 98.02%. Even for Tumor Present, the model retrieves high $P_{precision}$ (98.56%) and $F1_{score}$ (98.63%), which is a sign of model credibility. For Tumor Present cases, ResNet-50 show good detection capability with a predictive $A_{accuracy}$ of 97.33% and R_{recall} of 98.37%, and $F1_{score}$ of 97.84% for the same class. However, its recall for No Tumor cases is slightly lower than that of Tumor cases and amounts to 95.89%. Figure 11 shows the Confusion Matrix of Proposed DL methods.

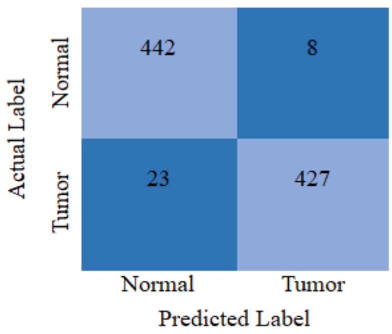
VGG-16 reports the accuracy of 97.56%. The result of No Tumor is slightly poor precision with 96.06 % while promising high recall value, 98.35 % and F1 score of 97.61%. However, for Tumor Present, the F1-score achieves 98.00%, which indicates that the proposed model has equivalent precision and recall capacity. Inceptio nV3 is leading in overall performance with an accuracy of 99.04 %, high precision of 98.23% for No Tumor and high recall of 98.53%. It performs a little lower for Tumor Present but still it is highly effective value. Finally, Inception V3 is the most accurate model of the five while the Bi-LSTM model is excellent in detecting tumor cases thus proving the ability of DL on BTD.



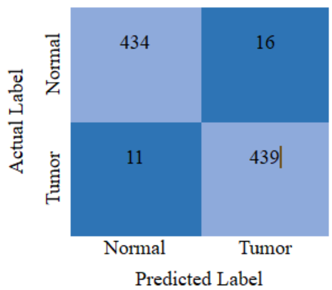
(a)



(b)



(c)



(d)

Figure 11: Confusion Matrix of Proposed DL methods

Table 3: Evaluation of Proposed ML Methods

Methods	$A_{accuracy}$	$P_{precision}$	R_{recall}	$F1_{score}$	$S_{specificity}$	Labels
Bi-LSTM	98.89	98.95	98.02	97.85	98.14	No Tumor (0)
		97.45	98.56	98.05	98,63	Tumor Present (1)
Res-Net50	97.33	97.44	95.89	97.33	97.22	No Tumor (0)
		96.53	96.73	98.37	97.84	Tumor Present (1)
VGG-16	97.56	96.06	95.89	97.61	98.35	No Tumor (0)
		96.74	96.34	96.52	98.00	Tumor Present (1)
Inception V3	**99.04**	**98.23**	**98.53**	**97.95**	**97.44**	No Tumor (0)
		97.45	**97.03**	**96.52**	**96.73**	Tumor Present (1)

4.3 Comparison Analysis

They do comparative analysis in this section, which is divided into two parts. The first part is an evaluation of the suggested ML and DL methods. In the second part, a comparative analysis of the best model with the State-of-the-Art (SOTA) methods.

4.3.1 Comparison of suggested Methods

Table 4 illustrates a systematic approach to identifying the best predictive technique using both ML and DL methods. The process begins with a dataset, which forms the foundation of the analysis. This dataset undergoes processing and is subsequently analyzed using two distinct categories of techniques: ML and DL Techniques. ML approaches leverage algorithms such as SVM, RF, MLP, and XG-Boost, while DL methods rely on complex neural networks for pattern recognition and prediction.

The performance of these techniques is evaluated using a performance evaluation matrix, where accuracy is highlighted as the key metric. By comparing the accuracy of predictions across the various techniques, the most effective approach is identified and selected as the best technique. Figure 12 demonstrates a structured methodology for optimizing prediction outcomes in data-driven tasks, ensuring the selection of the most appropriate model for the given dataset.

Table 4: Comparative Examination of proposed ML and DL Techniques

Algorithm	ML				DL			
	SVM	RF	MLP	XG-Boost	Bi-LSTM	Res-Net50	VGG-16	Inception V3
Accuracy	92.30	89.04	**96.48**	85.78	98.89	97.33	97.56	**99.04**
Precision	90.43	86.45	**95.35**	89.22	97.45	96.53	96.74	**97.45**
Recall	92.05	86.35	**96.83**	91.04	98.56	96.73	96.34	**97.03**
F1-score	92.75	90.21	**94.11**	86.23	98.05	98.37	96.52	**96.52**
Specificity	95.47	93.4	**95.83**	82.64	98.63	97.84	98.00	**96.73**

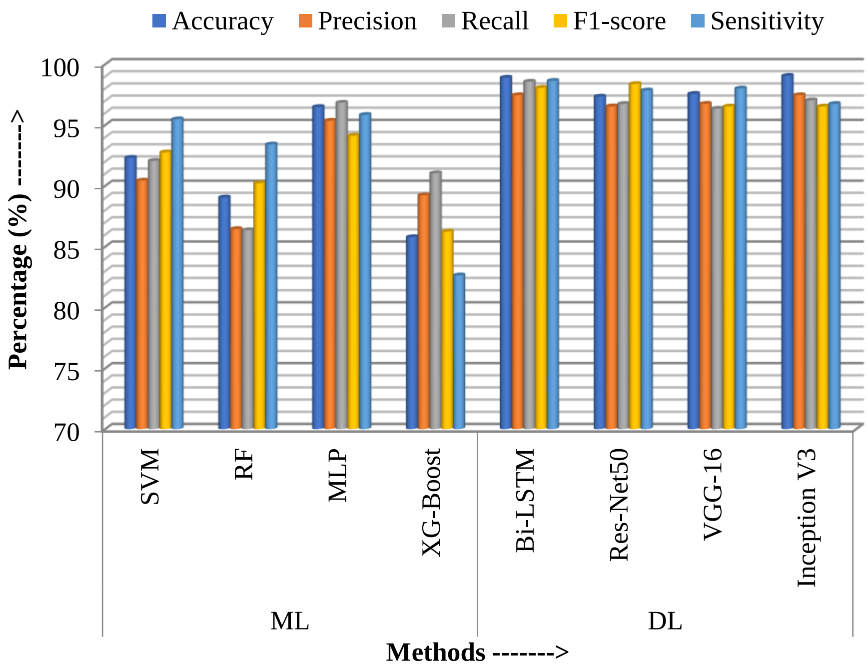


Figure 12: Graph of ML vs. DL methods

4.3.2 Comparison of proposed method with existing work

Table 5 depicts a comparison of algorithms utilizing AI for detection of brain tumours with emphasis on their accuracy. In the present study, the highest accuracy of 99.04% was reached by the proposed model based on the DL approach with Inception V3, which confirms the high specificity of this approach to the successful detection of BTs with a high degree of accuracy. YOLOv8s+U-net hybrid was applied very effectively in the image-based analysis by the researchers Zafar et al. (2024), they got the 98.6% accuracy. Sumithra et al. (2024) used the ESV-LC method and got a good, slightly lower, though accuracy of 98.3%. Al-Johani et al. (2024) studied by Mobile-Net V2 and Cinar et al. (2024) using CNN yielded accuracies of 97.03% and 96.67% respectively that too demonstrated highly better but slightly lesser accurate outcome than the other techniques. The proposed model employing ML with MLP achieved a comparable accuracy of 96.48%. However, Dandil et al. (2020) with LSTM has obtained comparatively low accuracy of 86 percent while Virupakshappa et al. (2024) with ANN has given lowest accuracy of 72%. This highlights the advancements in DL models like Inception-V3 in achieving SOTA method performance in BTD compared to earlier or simpler methods (Figure 13 and 14).

Table 5: Comparative Examination of Existing Techniques with the suggested work in BTD

Authors [Reference]	**Methodology Used**	$\mathbf{A_{accuracy}}$	$\mathbf{P_{precision}}$	$\mathbf{R_{recall}}$	$\mathbf{F1_{score}}$	$\mathbf{S_{specificity}}$
Zafar et al., (2024) [65]	YOLOv8s+U-net	98.6	97.8	98	89.1	89.1
Aljohani et al., (2024) [66]	Mobile-Net V2	97.03	97.22	98.64	96.95	98.64
Cinar et al., (2024) [67]	CNN	96.67	96.97	98.34	96.66	97.43
Sumithra et al., (2024) [68]	ESV-LC	98.3	97.7	98.1	96.7	97.6
Dandil et al., (2020) [69]	LSTM	86	97	82	95	95
Virupakshappa et al., (2024) [70]	ANN	72	95	89	73	93
Proposed Model	**ML (MLP)**	**96.48**	**95.35**	**96.83**	**94.11**	**95.83**
	DL (Inception V3)	**99.04**	**98.23**	**98.53**	**97.95**	**96.73**

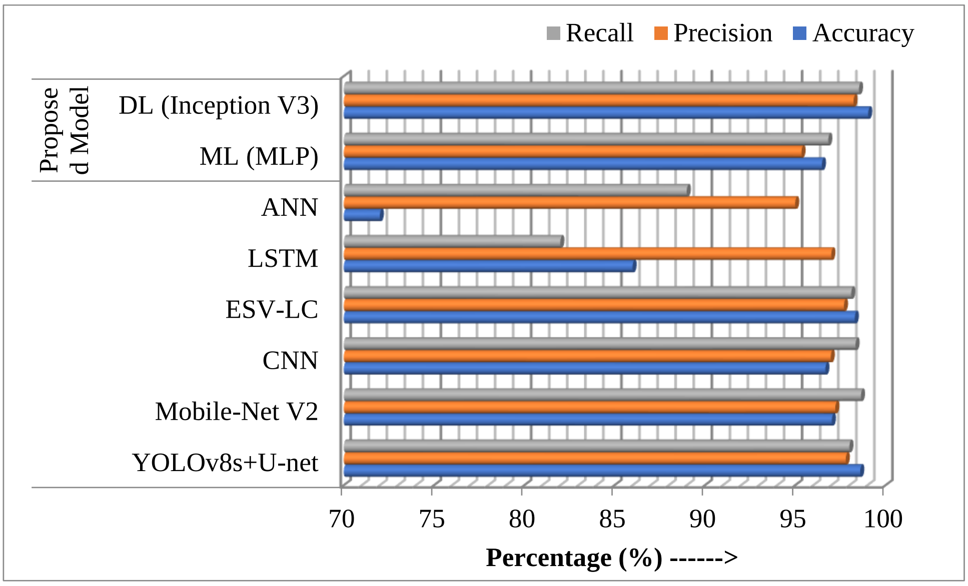


Figure 13: Bar graph of existing Techniques with the suggested work

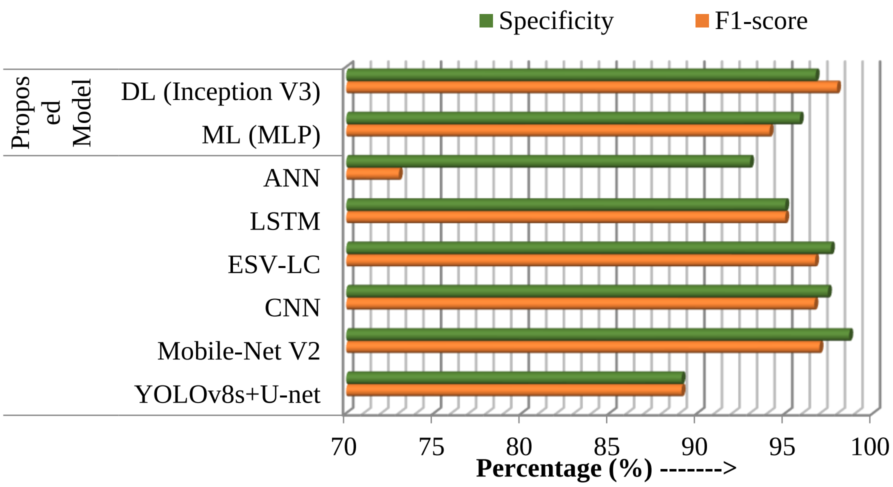


Figure 14: Bar graph of existing Techniques with the suggested work

5. Conclusion

The integration of AI in BTD has demonstrated significant advancements in improving diagnostic accuracy and efficiency. By leveraging ML and DL algorithms, AI systems can analyze medical imaging data such as MRIs with remarkable precision, detecting tumors at earlier stages and offering potential for personalized treatment plans. In this work, the researchers compare the suggested ML and DL models. By training AI models on vast datasets, these technologies learn to recognize patterns associated with different types of BTs. By leveraging these algorithms, the research evaluates their performance in terms of $A_{accuracy}$, $P_{precision}$, R_{recall}, $S_{specificity}$, and $F1_{score}$. After comparison between the ML and DL model, the proposed DL methods, including Inception V3 achieved highest $A_{accuracy}$ (99.04%), $P_{precision}$ (98.23%), R_{recall} (98.53), $S_{specificity}$ (96.73%), and $F1_{score}$ (97.95%) than the suggested ML models.

The future of BTD using AI holds great promise. Advancements in AI algorithms and the continuous accumulation of medical data will likely enhance the precision of these systems, making them even more reliable for clinical use. Additionally, AI-powered tools could potentially assist in the development of targeted therapies, leading to more effective treatments. Collaboration between AI researchers and healthcare professionals will be pivotal in realizing the full potential of this technology in oncology.

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