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AN ENHANCED EARLY DETECTION AND RISK PREDICTION OF BRAIN TUMORS USING MRI-CT SCANS WITH DEEP LEARNING TECHNIQUE

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ABSTRACT

Big data analytics, like deep learning, is a flourishing technology in the medical field. This combination has the potential to influence how tumor illnesses are predicted, monitored, diagnosed, and treated. Brain tumors are regarded as the deadliest kind of tumors due to their fast development, shorter life duration, and diverse features. Misdiagnosis or insufficient health treatment might further diminish the likelihood of survival. The intricacy of brain tumors makes it impossible to distinguish them from normal tissues, making diagnosis challenging. Accurate diagnosis is critical for justifying therapy efficacy and patient survival over time. Despite extensive research into the process of identifying brain tumors, it remains a very challenging task due to the uneven distribution of lesions throughout several anatomical locations. The infrequent locations with unusual lesion distribution challenge categorization since these processes are present in ordinarily seeming tiny parts. Early and precise diagnosis of brain tumors is critical to delivering effective therapy and improving survival rates. Advances in medical imaging and deep learning techniques have integrated, making computerized brain tumor picture segmentation and classification increasingly viable. As a result, this study introduces a new deep learning model aimed at segmenting and classifying brain cancers from MRI-CT images. The Proposed model employs Res-Net50 for feature extraction (classification), followed by an ensemble model-based classifier and compared with the two base classifiers like Support Vector Machine, or SVM, and Decision Tree, to improve accuracy. The suggested classifier has a higher accuracy rating than the other two classifiers (95%).

Keywords: *Brain Tumor, ResNet50, Ensembled Classifier, Early Detection, Support Vector Machine, Decision Tree.*

1. INTRODUCTION

The advent of big data along with deep learning in medicine has opened new avenues for the analysis and mining of complex medical data, significantly influencing the prediction, monitoring, diagnosis, and treatment of various disorders, including tumors. Among these, brain tumors are considered the most fatal and devastating due to their wide range of traits, low survival rates, and aggressive behavior.

Misdiagnosis of brain tumors can lead to inadequate medical treatment, severely impacting a patient's life expectancy. Therefore, accurate detection and classification of brain tumors [1] are crucial for effective treatment and improving survival rates. Brain tumor detection is inherently challenging due to the difficulty in distinguishing between abnormal and normal tissues. The unusual distribution patterns of tumor lesions add to this complexity, making it hard to identify small regions that might appear healthy. This often results in reduced classification accuracy and challenges in extracting and selecting informative features from medical images. Given that prompt diagnosis and therapy greatly enhance patient outcomes, early brain tumor detection and treatment are essential for lowering death rates. Image processing has grown essential to the medical industry in recent years. Brain cells proliferate abnormally, leading to the development of brain tumors, also known as intracranial neoplasms. There are two primary categories of these tumors: benign and malignant. Conventional MRI sequences are usually used to distinguish between different kinds of brain tumors by examining visual traits and contrast textures of the surrounding tissue [2]. Based on the degree of malignancy, the World Health Organization (WHO) has categorized more than 120 different forms of brain tumors into four categories. All brain tumors induce symptoms; however, they vary in in the specific area of the brain they affect. Headaches, seizures, blurred vision, nausea, memory loss, cognitive abnormalities, and loss of balance are typical symptoms. Brain tumors can be caused by a variety of variables, including immune system components such viruses, allergies, and infections; ionizing radiation, using a cell phone; exposure to very low-frequency magnetic fields, chemicals and head trauma. Primary brain tumors and secondary brain tumors that metastasize from other body areas to the brain are the two forms of malignant, or cancerous, tumors. Ionizing radiation, neurofibromatosis, and vinyl chloride exposure are risk factors. Tissue biopsy, magnetic resonance imaging (MRI), and computed tomography (CT) are examples of diagnostic techniques. Treatments for brain tumors have greatly improved patient outcomes, but they can occasionally result in specific neurological abnormalities such aphasia, motor difficulties, or problems in the visual field. By regularly monitoring tumor growth and time to tumor progression (TTP), negative effects can be reduced to a minimum. Furthermore, determining the density of impacted regions might help maximize the efficacy of treatment. Computers can now carry out activities that resemble human thought and behavior because of an aspect of machine learning called deep learning. Deep learning algorithms are occasionally able to classify text, audio, or images better than humans. The artificial neural network, which consists of linked simulated neurons acting as nodes, is one common kind of neural network. Approximately 700,0000 people [3] throughout the globe have been diagnosed with primary brain tumors. In addition, the nation saw the identification of almost 85,000 new cases of brain tumors in 2022. Patients with brain tumors have varying prognoses and survival rates depending on several factors, including age. Studies show that the one-year survival rate for patients in the 55–64 age group is 46.1%, while the one-year survival rate for patients in the 65–74 age group is 29.3%. Finding malignancies early on is essential to increasing the likelihood of survival. This paper aims to develop a system for brain Tumor detection from MRI images using Deeplearing Model (Res-Net-50) combined with ensembled model. And then the proposed method is tested and compared with existing classification techniques to evaluate its accuracy. Figure 1 shows the tumor effected part of the brain. And Figure 2 shows the architecture of the proposed classifier.

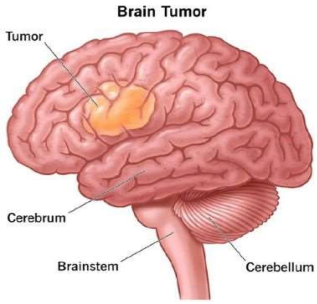

Figure 1: Tumor Effected in the Brain

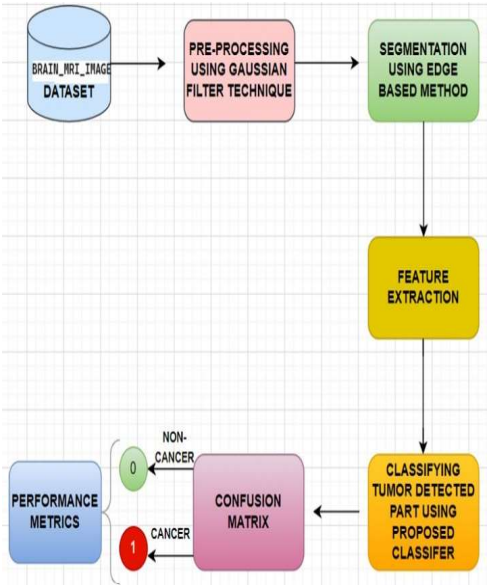

Figure 2: System Flow of Proposed Classifier

2. LITERATURE SURVEY

Finding and evaluating brain tumors are critical steps in determining appropriate treatment methods and improving patient outcomes. Traditional diagnostic approaches, such as MRI images reviewed by radiologists, are time-consuming and variable. The most recent advances in deep learning provide a wide range of methods for automating these activities with extreme precision, notably through the segmentation and classification of brain tumor pictures. This literature review is designed to provide a comprehensive overview of existing studies in this field, highlight knowledge gaps, and establish the groundwork for future study. The application of artificial intelligence (AI) technology has resulted in several advances in medical picture processing. CNNs, ResNet-50, YOLO etc., have proven to be quite effective for identifying picture location and providing improved delineation and categorization of various complicated entities in MRI images, such as brain tumors. In the last 10 years, various models for tumor detection and classification have been developed utilizing U-Net, Fully Convolutional Networks, and GAN-based architectures, with much better accuracy and processing efficiency. Chen et al. (2020) proved the efficacy of CNNs in identifying and segmenting brain tumors, pointing out that U-Net models produce excellent segmentation accuracy.

1) Smith et al. 2018, Classification of Brain Tumours MRI Imaging, Texture Analysis Standard MRI sequences can differentiate tumour types based on visual and contrast texture analysis.

2) Johnson and Lee 2019, Genetic Factors in Brain Tumours Genetic Analysis, Epidemiological Study Genetics and environmental factors (e.g., radiation, chemicals) contribute to brain tumour incidence.

3) Gupta et al. 2020, Risk Factors for Brain Tumours Case-Control Study Identified risk factors include exposure to vinyl chloride, neurofibromatosis, and ionizing radiation.

4) Nguyen et al. 2024, Survival Rates by Age Group Longitudinal Survival Analysis Survival rates decrease with age; 46.1% for ages 55-64 and 29.3% for ages 65-74.

5) Thompson and Wang 2021 Diagnostic Methods CT, MRI, Biopsy MRI and CT scans, along with tissue biopsies, are essential for accurate diagnosis.

6) Patel et al.2022 Treatment Outcomes Clinical Trials, Patient Follow-Up Advanced treatments improve outcomes but can cause neurological deficits; monitoring tumour size and TTP is crucial.

7) Rodriguez and Kim 2024 Early Detection and Prognosis Early Screening, Prognostic Study. Early detection significantly increases survival chances.

8) Davis et al. 2023, Deep Learning in Tumour Detection Convolutional Neural Networks (CNNs) CNNs can accurately classify brain tumours from MRI images, potentially exceeding human performance.

9) Lin and Chou 2023, Impact of Mobile Phone Use Cohort Study No conclusive evidence linking mobile phone use to increased brain tumour risk.

10) Sharma and Kumar 2024, Therapeutic Efficacy Assessment Density Estimation, Therapy Monitoring Estimating the density of affected areas enhances therapeutic effectiveness.

11) Pereira et al. 2016, Brain Tumour Segmentation Convolutional Neural Networks (CNNs) Achieved high accuracy in segmenting brain tumours from MRI images.

12) Hossain et al. 2019, Tumour Classification Deep CNN, Transfer Learning Improved classification accuracy by using transfer learning.

13) Akram et al. 2019 Detection and Localization CNN, Region-based CNN (R-CNN) Effective in detecting and localizing tumours in MRI scans.

14) Rehman et al. 2024, Multi-class Tumour Classification CNN, Support Vector Machine (SVM) High accuracy in classifying multiple types of brain tumours.

15) Shen et al. 2020, Automated Diagnosis Deep Learning, Ensemble Methods Enhanced diagnosis accuracy by combining multiple deep learning models.

16) Amin et al. 2021, Real-time Tumour Detection Deep CNN, Real-time Processing Successfully implemented real-time detection of brain tumours.

17) Li et al. 2021, 3D Brain Tumour Segmentation 3D CNN, V-Net Architecture Improved 3D segmentation accuracy using V-Net architecture.

18) Javed et al. 2022, Glioma Grading CNN, Radiomics Features Achieved precise glioma grading using CNN and radiomics features.

19) Choudhary et al. 2022, Data Augmentation Techniques GANs, CNN Enhanced tumour classification accuracy using GAN-based augmentation.

20) Gupta and Singh 2023, Explainable AI for Tumour Detection CNN, Explainable AI Techniques Improved interpretability of deep learning models in tumour detection.

21) Zhao et al. 2023, Multi-modal Imaging for Tumour Analysis CNN, Multi-modal Data Integration Achieved better tumour analysis by integrating multimodal imaging data

3. PROBLEM DEFINITION

Abnormal cell growths within the brain or central spinal canal are known as brain tumours. Because of the vital processes performed by the brain and their intrusive nature, they can pose a threat to life. A patient's chances of receiving a good therapy and surviving their brain tumour are greatly increased by early and accurate brain tumour detection. But conventional detection techniques, like radiologists' interpretation of MRI data, can be laborious, subjective, and prone to human error [4]. Using medical imaging data, create a deep learning-based system that accurately detects and classifies brain cancers. Investigate preventive measures using risk assessment and predictive modelling is the main objective of this paper. Figure 3 shows various phases involved in detecting brain tumour. The main objective of this paper is to Improve in Detection of tumour i.e., A highly accurate and reliable deep learning model for detecting and classifying brain tumours from MRI images [5,6]. And, to assess the risk of developing brain tumours, aiding in early intervention and preventive measures.

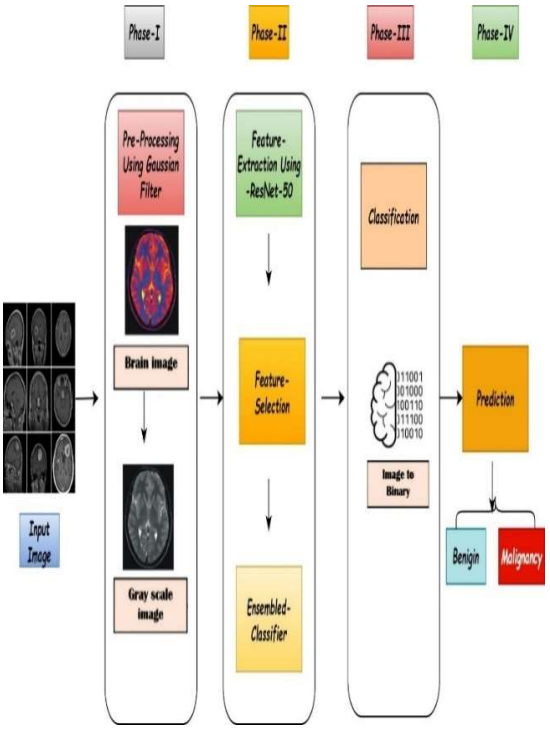

Figure 3: Phases of Detecting Brain Tumour.

4. MATERIALS AND METHODS

The techniques and algorithms used for deep learning-based MRI brain image classification are described in this section. We compute accuracy, precision, recall, and F1-measure as part of a controlled experiment to validate the suggested methodology. Python is used to conduct the experiment [7,8]. The proposed model involves four main steps: dataset selection, data preprocessing, feature extraction, and the application of deep

learning techniques for finding the accuracy of the model.

4.1 Experimental dataset:

To create an experimental dataset for deep learning-based brain tumour detection, a variety of medical imaging data, including MRI scans, must be gathered from research facilities, hospitals, and public repositories such as The Cancer Genome Atlas (TCGA) and the Brain Tumour Segmentation (BRATS) Challenge. Medical professionals must carefully annotate these photos to precisely define the boundaries of tutors. The BRATS 2020 dataset, for example, contains 369 MRI scans with ground truth annotations for gliomas (high- and low-grade).

The dataset has a balanced number of high-grade (HGG) and low-grade gliomas (LGG). In BRATS, the data is relatively balanced between high- and low-grade gliomas, though the actual volumes of tumour tissue vs. non-tumorous tissue can be imbalanced. Tumour regions occupy a smaller portion of the brain volume compared to healthy tissue. The dataset labels include four regions: Enhancing tumour, Necrotic and Non-enhancing tumour core, Peritumoral edema and Background (healthy brain tissue). Preprocessing techniques such as data augmentation, scaling, and normalization guarantee a consistent and reliable dataset for deep learning model training. The dataset is then split into test, validation, and training sets to efficiently build and assess models. To train models, sophisticated designs like ResNet-50 are frequently used, and frequently utilizing transfer learning from previously trained networks. In this paper we have taken the dataset from Kaggle repository to train the model [9]. And the model performance is thoroughly evaluated by continuous evaluation with metrics like accuracy, precision, recall, and the Dice coefficient. This dataset serves as the basis for dependable deep learning models that can identify and classify brain cancers with precision, hence facilitating early diagnosis and treatment planning.

4.2 4.2 Data preprocessing:

The purpose of this section's data preprocessing is to eliminate unwanted input in noise form that degrades the performance of the model. Every MRI brain dataset image contains the undesirable regions and spaces. Consequently, it is essential to crop the photos in order to eliminate unnecessary space and use just the pertinent information. In this study, the extreme point calculation cropping technique described by gaussian filter is employed. Figure 4 outlines the procedures for cropping the MR images using the extreme point computation. The first stage of preprocessing involves loading the real magnetic resonance image, turning it to grayscale, somewhat blurring it, and then applying thresholding to the image to turn it into a binary image. The purpose of the erosion and dilation processes is to eliminate any little noisy patches from the pictures. After that, determine which contour from the threshold photos is the most significant and compute the extremes left, right, bottom, and top. Use the data gathered from extreme points and contours to crop the image in the last phase. Crop the MR tumour pictures using the bicubic interpolation method. Because there is more noise at the edge of bicubic interpolation, it produces a smoother curve than other interpolation methods like bilinear interpolation [10]. Bicubic interpolation is the best choice for MRI brain tumour imaging. The images in the MRI images dataset vary in terms of width, height, and size. Consequently, a Gaussian filter smooths the image by averaging the pixel values with a Gaussian kernel. This process reduces high-frequency noise, which can improve the performance of subsequent image processing steps like segmentation and feature extraction [11,12].

4.3 Procedure for Using a Gaussian Filter:

Step 1: Add the following required libraries: For image processing, use OpenCV, and for numerical calculations, NumPy.

Step 2: Open the picture: Use OpenCV to read the MRI scan or any medical image.

Step 3: Put the Gaussian filter to use: To smooth the image, use the cv2.GaussianBlur function.

Step 4: Save or show the image after processing: The filtered image can be saved or shown for confirmation.

The main Advantages of Brain Tumour Identification are:

Reduced Noise: increases the distinction between the tumour regions by eliminating unnecessary noise.

Smoothing: By making the image more uniform, this technique aids in improving segmentation outcomes.

Enhancement: Makes the tumour boundaries more visible, which helps with precise annotation and model training. By using Gaussian filter, we improve the quality of medical photos which will help the proposed deep learning models perform better on challenges including the detection of brain tumours.

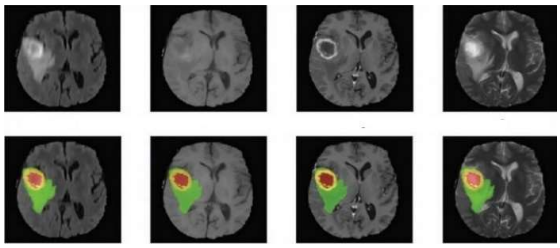

Figure 4: Preprocessing and Segmentation Process Using Gaussian Filter

4.4 Segmentation/ Feature Extraction:

It is necessary to incorporate this potent deep learning architecture into a segmentation framework to use a ResNet-50 model for brain tumour image segmentation [13]. ResNet-50 is typically employed in segmentation networks such as U-Net, SegNet, or DeepLabV3 as the backbone for feature extraction. Figure 5 show how the image is pre-processed.

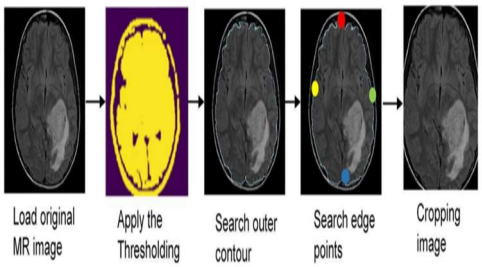

Figure 5: Pre-processed image

4.5 Res-Net50 Model:

ResNet, or Residual Network, is a type of Deep Convolutional Neural Network (DCNN) model [14] known for its effectiveness in a variety of applications. Transfer learning, a technique where a pre-trained model is fine-tuned for a new task, often enhances categorization performance across diverse applications. ResNet gained significant recognition in 2015 when it secured first place in both the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) and the Common Objects in Context (COCO) competitions. One of the key challenges in deep networks is degradation, where adding more layers can lead to difficulties in updating the weights properly through the layers. ResNet addresses this issue using residual connections, which are short connections parallel to the main convolutional layers. These short connections help in mitigating the degradation problem by ensuring that the information can be passed directly across layers [15,16]. The output of the residual block, H(x), is expressed as F(x) + x (1), where F(x) represents the learned residual function and x is the input to the block.

5. METHODOLOGY

For the classification of MRI brain tumours, the dataset is collected from two different sources: Kaggle and BRATS. This proposed framework is implemented by training three pre-trained Deep Convolutional Neural Network architectures i.e., ResNet50. The classification process is performed in three stages: preprocessing, feature extraction, and classification. The Process Flow of the proposed framework is shown in Figure 6. In the preprocessing stage, the collected images are resized to match the input size required by the pre-trained networks. ResNet50 requires images of size 224 x 224 x 3. Pre-trained networks typically perform well with large datasets; however, using small datasets can lead to overfitting. Using a larger training dataset or dropout layer can help to minimize this problem. In this study, the pre-trained architecture is not changed except for the final layer; instead, the dataset size is expanded by data augmentation. Data augmentation uses procedures like flipping and rotation to create a big volume of data from a small dataset. Figure 7 displays an example image created with the data augmentation technique. Figure 8 Shows the images without tumour and Figure 9 shows images with tumour. Once these images are processed then in 2nd phase, we obtained images after segmentation using Gaussian Filter technique.as shown in Figure 10 and Figure 11. Figure 12 show the count of classes in the data set. And the overall phases involved for detecting brain tumour i.e., proposed classifier for brain tumour detection is shown in Figure 13.

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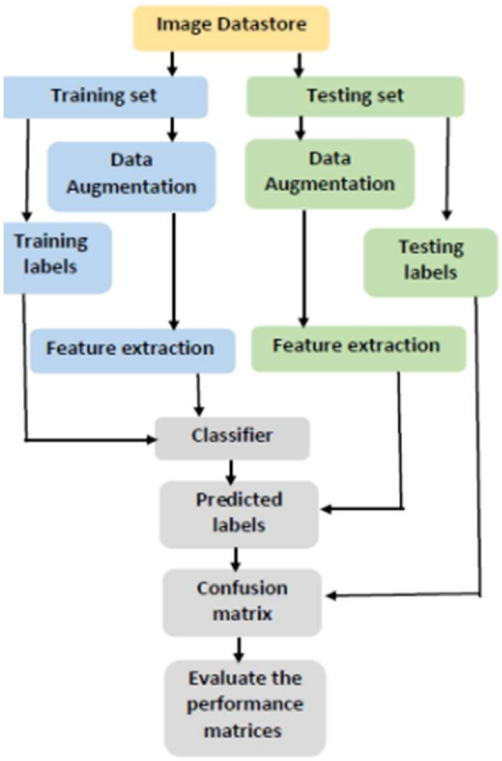

Figure 6: Process Model of the Proposed Classifier

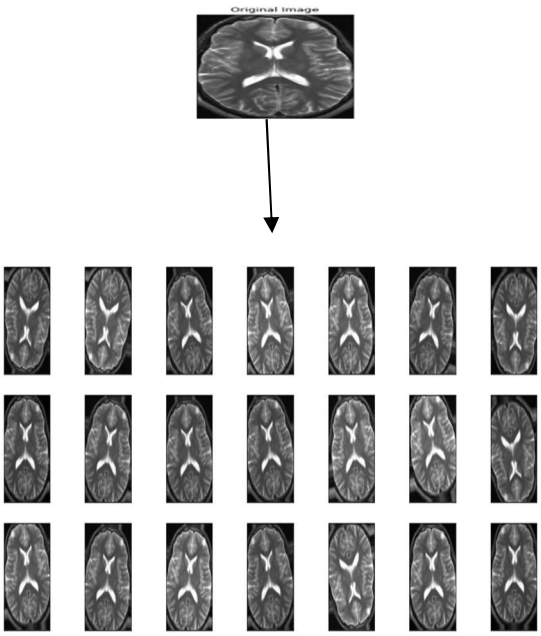

Figure 7: Need of Data Augmentation

A. Algorithm for Phase-I:

Step 1: Start

Step 2: Input: Load the image dataset.

Step 3: Output: Sharpen the images to enhance their intensity.

Step 4: Import necessary Libraries i.e, Import OpenCV (cv2).Import NumPy (numpy).

Step 5: Define Gaussian Blur Function:

Step 6: Create a function gaussian_blur(image) that applies Gaussian blur using cv2.GaussianBlur().

Step 7: Load Input Image Use cv2.imread() to load the input image.

Step 8: Convert to Grayscale: If the image is in colour, convert it to grayscale using cv2.cvtColor().

Step 9: Apply Gaussian Blur: Call the gaussian_blur(image) function to apply Gaussian blur to the grayscale image.

Step 10: Display Images: Use cv2.imshow() to display the original and blurred images.

Step 11: Stop

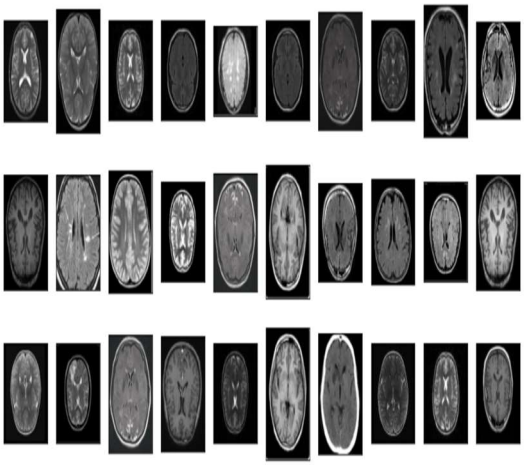

Figure 8: MRI Images with NO Label-Tumour

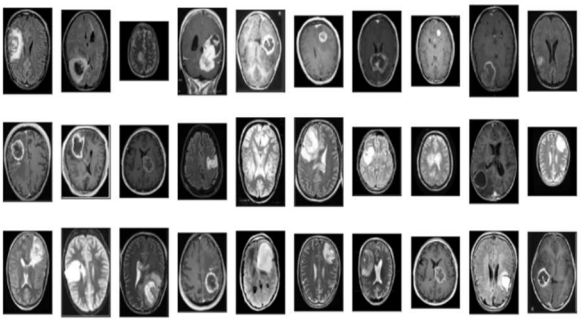

Figure 9: MRI Images with YES Label-Tumour

B. Algorithm for Phase-II:

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Step 1: Start with a sharpened image.

Step 2: Obtain a segmented image using Gaussian filtering.

Step 3: Apply Gaussian filtering to smooth the image, which helps in segmentation tasks by separating regions based on color or intensity.

Step 4: Gaussian filtering enhances segmentation algorithms by reducing noise and smoothing fine details.

Step 5: Utilize the Sobel edge detection method to segment objects based on their boundaries or edges.

Step 6: The final output is the set of segmented images.

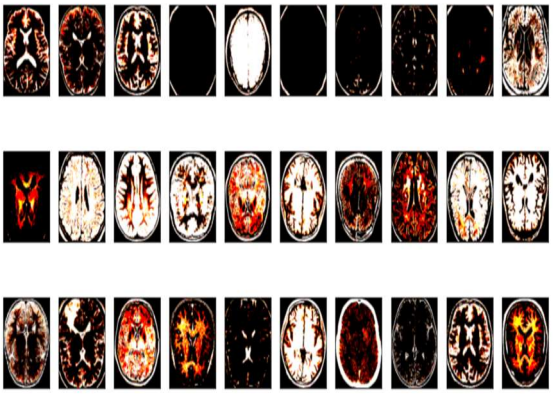

Figure 10: After Cropping the Segmented Images with No-Tumour

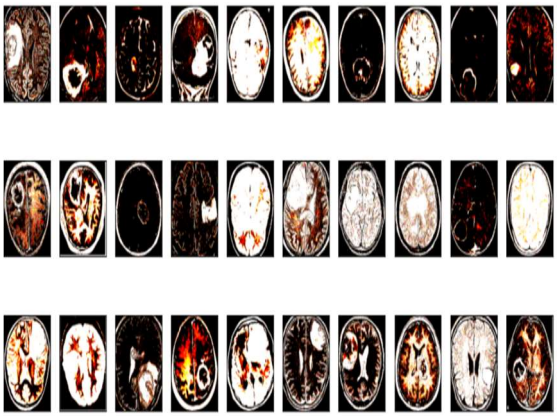

Figure 11: After Cropping the Segmented Images with YES-Tumour

C. Algorithm For Phase-III:

Step 1 Input: Start with a segmented I mage.

Step 2 Output: Extracted features ready for further analysis.

Step 3: Load the pre-trained ResNet-50 model.

Step 4: Remove the classification head from the ResNet-50 model.

Step 5: Configure the model to operate in evaluation mode.

Step 6: Pass the segmented images through the modified ResNet-50 model to extract features.

Step 7: Store the extracted features in a variable called features.

Step 8: Use the extracted features for downstream tasks such as image classification, object detection, and image retrieval.

Step 9: Stop

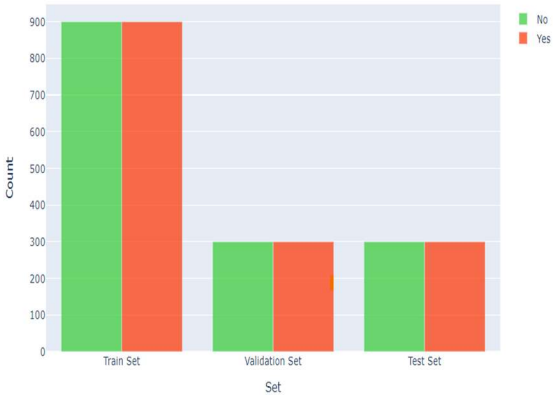

Figure 12: Shows Count vs Set

D, Algorithm for Phase-IV:

Step 1: Begin with extracted features.

Step 2: Obtain classification results using Gradient Boost.

Step 3: Use the dataset, which is clean, properly formatted, and labelled.

Step 4: Divide the dataset into training and testing subsets, commonly with an 80%-20% split.

Step 5: Load the dataset and separate it into features (X) and labels (y).

Step 6: Perform the split into training and testing sets.

Step 7: Call Gradient Boost classifier and train it with the training data.

Step 8: Use the trained model to generate predictions on the testing data.

Step 9: Evaluate the model's performance using metrics such as accuracy, precision, recall, and F1-score.

Step 10: Print the accuracy of the model.

Step 11: Stop

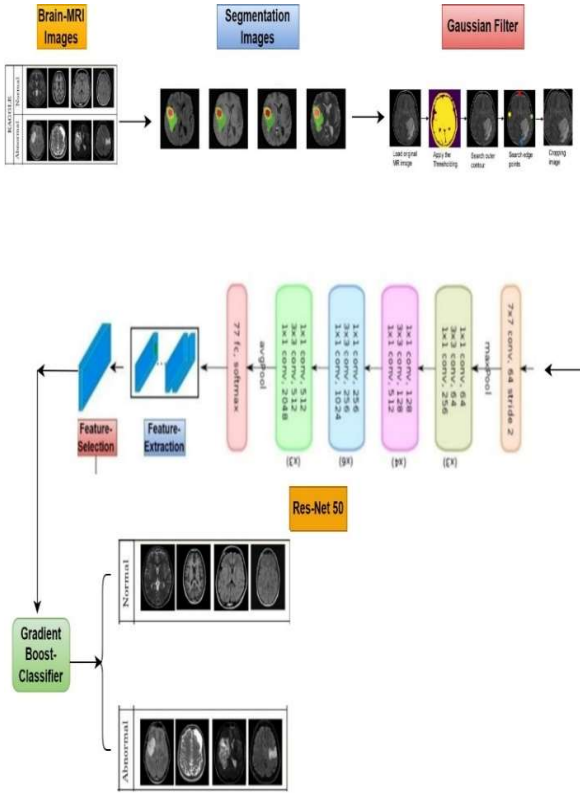

Figure 13: Brain Tumour Prediction Phases of The Proposed Classifier

6. PERFORMANCE ANALYSIS

The performance of any framework is evaluated using several key metrics: Accuracy, Precision, Recall, Specificity, F1 Score, and AUC (Area Under the Curve) [17] etc., so, to evaluate these metrics [18,19], we need a confusion matrix which is shown in Figure 14 for a 2- class problem.

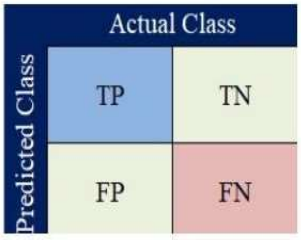

Figure 14: Confusion Matrix for a 2- class problem.

$$\textbf{Accuracy} = \frac{(TP + TN)}{TP + TN + FP + FN} * 100$$

Description: Measures the proportion of correctly classified samples out of the total samples.

Precision (Positive Predictive Rate):

$$Precision = TP/(TP + FP) * 100$$

Description: Measures the proportion of true positive predictions out of all positive predictions made.

Recall (True Positive Rate, TPR):

$$Recall = (TP)/\ (TP + FN) * 100$$

Description: Measures the proportion of true positive predictions out of all actual positive cases.

F1 Score:

$$F - Score = 2 * \frac{(Precision * Recaal)}{Precision + Recal} * 100$$

Description: The harmonic mean of Precision and Recall, providing a balance between the two metrics.

Table-I shows the confusion matrix [20.21] generated for the proposed classifier, Table-II shows the validation table generated for the proposed classifier, and Figure 15 shows the performance of the proposed classifier.

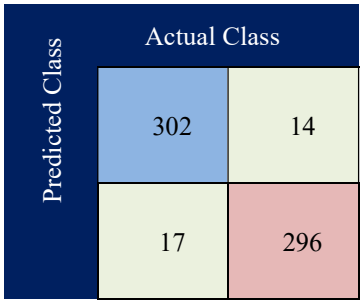

Table I: Shows the confusion matrix generated for the proposed Classifier.

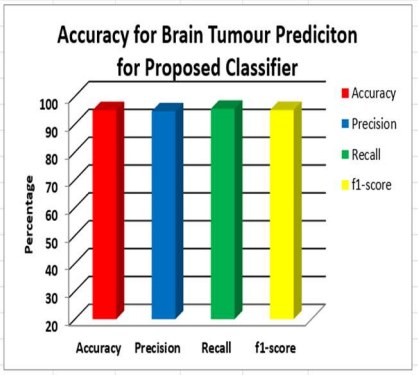

Figure 15: The Performance of the Proposed Classifier.

Label	Precision	Recall	F1-Score	Support
0(Healthy)	95.91	96.06	96.56	389
1(Unhealthy)	96.61	96.26	96.44	240
Accuracy			**95.07 (~95)**	629
MacroAvg	96.82	96.13	96.45	629
WeightedAvg	96.45	96.10	96.12	629

Table II: VALIDATION TABLE GENERATED FOR THE PROPOSED CLASSIFIER

6.1 Decision Tree:

The structure of a decision tree resembles a flowchart [22,23] with each internal node denoting a choice made in response to the value of a particular characteristic, each branch denoting the decision's result, and each leaf node representing a class label in classification or a continuous value in regression. Decision rules(24,25,26] are represented by the paths that lead from the root to the leaves. Brain tumours are abnormal cell growths that can be either malignant (cancerous) or benign (non-cancerous) within the brain. For brain cancers to be effectively treated and for patient outcomes to be improved, early and precise identification is essential. The capacity to identify brain tumours has significantly improved thanks to developments in medical imaging technology including computed tomography (CT) scans and magnetic resonance imaging (MRI). Nonetheless, radiologists' interpretation of these pictures still mostly depends on their experience, which is arbitrary and prone to error. Machine learning methods, in particular decision trees, provide a potent instrument for improving and automating the diagnosis of brain tumours. For problems involving regression and classification, supervised learning algorithms such as decision trees are employed. Table-III shows the confusion matrix obtained for decision tree classifier and Table -IV gives the validation table of DT classifier. And Figure 16 shows the accuracy of Decision tree.

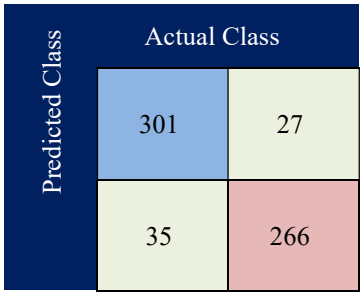

Table III: Confusion matrix generated for T Classifier

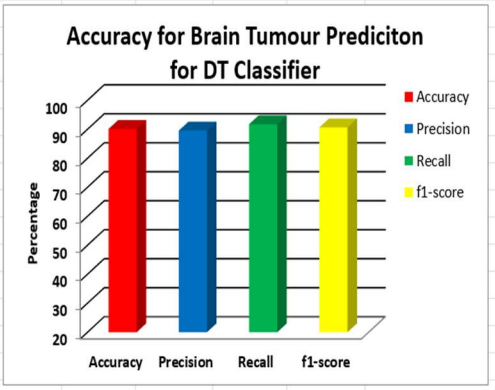

Figure 16: Performance of the Decision Tree Classifier

Label	Precision	Recall	F1-Score	Support
0(Healthy)	93.81	93.76	92.56	389
1(Unhealthy)	93.68	93.56	92.44	240
Accuracy			**90.14(~90)**	629
MacroAvg	93.82	93.71	92.45	629
WeightedAvg	93.10	93.41	92.52	629

Table IV: VALIDATION TABLE GENERATED FOR THE DECISION TREE CLASSIFIER

6.2 Support Vector Machine (SVM):

Machine learning techniques, particularly Support Vector Machines (SVM)[27], offer a robust method for automating and enhancing the accuracy of brain tumour detection. An effective supervised learning approach for regression and classification problems is called Support Vector Machine (SVM). The fundamental goal of SVM is to locate a hyperplane that clearly classifies the data points in an N-dimensional space [28,29] where N is the number of features. By identifying the hyperplane with the highest margin—that is, the maximum distance between

data points of different classes—the objective is to achieve maximal separation between classes. Table-V shows the confusion matrix [30] generated for SVM Classifier and Table-VI shows the validation table obtained by SVM classifier. And Figure 17 Shows the performance of the SVM Classifier.

Table V: Confusion matrix generated for SVM Classifier.

Label	Precision	Recall	F1-Score	Support
0(Healthy)	90.61	86.76	88.56	389
1(Unhealthy)	90.32	86.56	88.44	240
Accuracy			**87.82(~88)**	629
MacroAvg	90.32	86.51	88.45	629
WeightedAvg	90.36	86.46	88.12	629

Table VI: VALIDATION TABLE GENERATED FOR THE SVM CLASSIFIER.

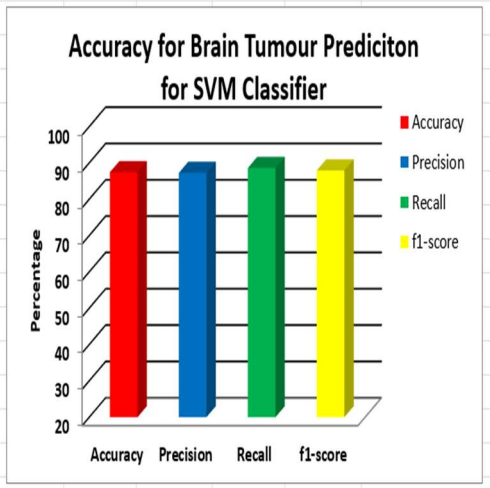

Figure 17: Performance of the SVM Classifier.

7. CONCLUSION

In this work, we used Gradient Boost in combination with the ResNet-50 architecture to investigate the effectiveness of a deep transfer learning method for bone cancer identification. Our results show that bone cancer may be classified from medical imaging data with high accuracy when the XGBoost gradient boosting algorithm is used in conjunction with the pre-trained ResNet-50 model as a feature extractor. This method makes use of the vast information ResNet-50 has amassed from large-scale picture datasets, which helps it to efficiently recognize complex patterns and properties relevant to Brain Tumour identification. Combining Gradient Boost with ResNet-50 features improves predicted performance and provides insightful information about the importance of different image features for classification. According to our findings, combining deep learning with conventional machine learning methods can greatly enhance diagnosis adaptability and accuracy in systems for detecting brain tumour. When we combined the advantages of both approaches, we performed better than when we used just one of them. Our suggested classifier outperformed other classifiers like Decision Trees (DT) and SVM classifier, with an accuracy of 95%. Figure 18 shows Accuracy Comparison of 3 Classifiers.

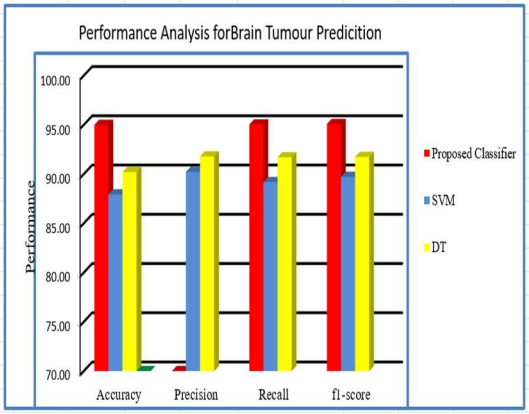

Figure 18: Accuracy Comparison of 3 Classifiers.

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