Enhancing Brain Tumor Detection: A Machine Vision-Based Multiclass Classification Approach

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Abstract- Bioinformatics, especially clinical imaging, has become a hot topic thanks to advances in artificial intelligence, particularly deep learning. It has been quite effective in assisting Computer-Aided Diagnosis (CAD) in achieving accurate outcomes. The detection of brain tumor Magnetic Resonance imaging, despite this, is still regarded as a major challenge. The brain tumor is a life-threatening threat that is only going to get worse. Detection at an early stage could minimize the risk of mortality. To detect brain tumors, researchers are now employing a variety of machine vision-based approaches. This work focuses on a combination technique for brain tumor detection that incorporates machine learning and deep learning. The research initiate with feature extraction employing a convolutional neural network (Alex Net) and continued with classification by introducing an ensemble classifier. Early detection and diagnosis of brain tumors employing a non-invasive, contactless machine vision system are being proposed. To develop a multiclass ensemble classification model, many statistical analyses were employed and conducted. Upon Comparison with other methods, the results show that the proposed method is 96 % efficient.

Index Terms- Glioma, Meningioma, Benign, Malignant, AlexNet, Ensemble classifier, Machine vision and Clinical image processing.

I. Introduction

The brain is one of the most complex organs in the body, containing around 100 billion neurons. When the cells in the brain begin to divide uncontrollably, they can form an abnormal mass of cells in or around the brain, which is referred to as a brain tumor. Employing artificial intelligence and machine learning in biomedical research has recently become a hot topic, particularly in the field of anomaly detection. The increasing effect and death rate it has on humans of all ages make the brain tumor one of the world's worst diseases [1]. The third-largest cause of cancer in the country, according to [2,] is asbestos exposure. According to the American Cancer Society's recent publication, Cancer Statistics 2020, around 24000 people would be infected with brain tumors and approximately 19000 humans would die in the United States in 2020 [3]. Due to the complexity of the brain's anatomy, detecting tumors can be challenging, especially since there are over 120 different types of brain tumors known to date. Medical imaging has come a long way in detecting brain abnormalities, and a range of techniques such as CT scans, PET scans, MEG, and MRI are now available. MRI is particularly useful in detecting brain cancers due to its superior ability to differentiate between different tissues and structures based on contrast levels. Detecting brain tumors at an early stage is crucial because early detection often results in better treatment outcomes and higher chances of survival. Brain tumors can grow and spread rapidly, causing damage to the surrounding brain tissue, and leading to life-threatening conditions. However, identifying a brain tumor can be challenging because symptoms can vary widely, and some people may not show any symptoms until the later stages of the disease. This is where Artificial Intelligence (AI) can play a significant role in identifying tumors at an early stage, helping doctors to diagnose and treat the disease more effectively. Employing AI in brain tumor detection can help doctors to analyze images from various medical tests, such as Magnetic Resonance Imaging (MRI) scans and Computed Tomography (CT) scans, and highlight areas of concern, such as a tumor or other abnormalities. AI algorithms can analyze vast amounts of data from medical tests, identifying subtle changes in brain structure or function that may indicate the presence of a tumor. In addition, AI can help doctors to monitor the progression of a tumor and track the effectiveness of treatment, making adjustments as necessary to ensure the best possible outcome. Without early detection and treatment, brain tumors can lead to a range of physical and cognitive impairments, including vision problems, seizures, and memory loss. In more severe cases, it can lead to death. Therefore, early detection using AI can provide better chances of survival and improve the quality of life for those who are diagnosed with a brain tumor. As a result, MRI multimodality imaging has become the go-to method for identifying brain tumors. By gathering relevant clinical data, such as the location, type, and presence of tumors, computer-aided equipment can also be employed to aid in the diagnosis and treatment of brain tumors. Analyzing their shape and volume, borders and tumor identification, size and segmentation are still very difficult. Furthermore, the severity of a brain tumor differs from person to person. High variability and inherent MRI characteristics, such as tumor size or form variability; tumor identification; area calculation; segmentation; classification; and discovery ambiguity in the segmented region are all factors that contribute to tough work in Brain Tumors. When it comes to real-world applications, segmentation is the most important part of image interpretation because it aids in the extraction of features, area calculation, and significance. Tumor volume estimate, tissue classification, blood cell delineation and tumor localization, atlas matching, surgical planning, and image registration are a few examples. The precise and morphological quantification of tumors is essential for the monitoring of brain metastases therapy. Despite the fact that large-scale research has been performed in this area, clinical experts must rely on manual tumor detection. According to feature selection and learning mechanisms, ML and DL algorithms have been developed for automatic brain tumor classification in the last few years. The selection and extraction of features are critical for classification in ML techniques. DL methods, on the other hand, begin with an image and begin extracting and learning its features from there. Recent DL techniques, such as CNN (Alex Net), are commonly employed in medical image analysis because of their high level of accuracy. The limitations of these approaches (ML) include the necessity for large training datasets, time computation lower accuracy for applications with readily available small datasets, and the requirement for expensive GPUs, all of which raise the final cost to consumers. Choosing the appropriate deep-learning tools is a challenging task because it requires an understanding of many parameters, training methodologies, and topology. As an alternative to traditional methods, machine learning has played a critical role in medical imaging technology development. Support vector machine (SVM), artificial neural network (ANN), sequential minimal optimization (SMO), fuzzy C means (FCM), Naive Bayes, Random Forest, Decision Tree, and K-Nearest Neighbour have all been employed for the classification and diagnosis of brain cancers (KNN). KNN implementation is fairly simple and requires less processing and storage complexity than other algorithms. It performs well on a huge dataset, which provides accurate, precise, and other metrics for evaluation. All in all, these classifiers have attracted a lot of attention because they require only a small amount of data to be trained and have a low computational time complexity and low cost to the users. For this problem, a model that could effectively evaluate and diagnose various brain tumors is required. The computerized diagnostic interpretation of image data is a potential source of revenue for the health sector's development. Machine learning and deep learning would be employed to develop a structure that could automatically look for and detect various types of human brain tumors. The main aim of this research is to detect various brain tumors at the preliminary stages and reduced mortality. To accomplish this task, the first step is to extract features using a Convolutional Neural Network (CNN), specifically AlexNet. The extracted features are then classified using an Ensemble classifier that includes Support Vector Machine (SVM), K-nearest neighbours (KNN), random forest, and decision tree algorithms. The rest of this research study is organized in the following way: section 2 presents a literature review followed by methodology in section 3 while experiments are conducted in section 4. Results and discussion are explained in section 5 and finally, section 6 concludes this study.

II. Literature Review

In the last few years, a variety of medical imaging tools have emerged that aid clinical experts in diagnosing the type of disease present as well as its exact location. The imaging technique also assists clinical experts in determining a patient's overall health and survival. According to the World Health Organization (WHO), approximately 13,000 people are affected by brain tumors each year. Unfortunately, the number of deaths related to brain tumors is on the rise due to delayed diagnosis. Pathologists and clinical experts face significant challenges in detecting and classifying brain tumors manually, making this a crucial area for improvement in order to improve patient outcomes. Automatic brain tumor detection was made possible with the help of a CNN framework in a study published in [4]. Fuzzy-C-means could be employed to segment and texture brain tumors, creating features that are distinct from the rest of the tumor. As a final step, these features are fed into classifiers that combine DNN and SVM to produce an accuracy of 97.5%. With an updated iteration of AlexNet CNN, Khawaldeh et al. [5] devised a non-invasive graduation scheme for brain Glioma tumors (2018). It was possible to achieve regression for whole-brain MR images by labeling images rather than pixels. The results of the experiments show that 91.16 percent of the method achieved a reasonable level of performance. Comprehensive grading methods for brain tumors were devised by Sajjad and colleagues in [6]. As a result, after data augmentation, the tumorous region was fed to a pre-trained VGG-19 CNN. The data before and after the augmentation had a rating accuracy of 87.38 and 90.67 percent, respectively. Neuromorphic, optimistic entropy of the total fuzzy expert (NS-CNN) and CNN were combined to evaluate brain tumors by Azyurtet. al;[7]. These images were then fed into a neural network (NN) to extract features. It is then fed into an SVM classifier, which has an average precision of 95.62%, to determine if a feature is benign or malignant. Reinforcement and enhancement techniques were employed in [13]. Temperature mapping of tumor regions in MRI is employed to segment the tumor. A Canny edge detector is employed to detect tumors. On BRATS 2012 and 2013, this method of detection and segmentation was compared to a Chan Vase-based method, with considerable results. For the categorization of glioma in MR images, a study in [14] employed a convolutional neural network with a genetic algorithm. The bagging method is employed to examine a network with multiple layers and parameters in this method. An accuracy percentage of 94.2 percent was obtained, demonstrating CNN's efficacy. A computer-aided diagnosis (CAD) system was introduced in a recent study [15] to aid radiologists in diagnosing brain tumors. The system employs a CNN-based multi-grade classifier to detect and classify tumors, with the pre-trained VGG 19 CNN model fine-tuned to improve classification accuracy. Deep learning techniques were also utilized to segment the tumor-affected region. Another study conducted by Cheng et al. [16] presented a content-based image retrieval framework for multi-class classification of brain tumors using a Fisher kernel framework and a closed-form metric learning technique. Their dataset consisted of 3064 images of three different types of brain tumors, with an average precision of 94.68% achieved. Sajjad et al. [17] classified multi-grade brain cancers using a deep CNN model with extensive data augmentation, obtaining an accuracy of 94.58%. Gummiet al. [18] suggested a hybrid feature extraction technique to classify brain tumours accurately. The method used normalised GIST descriptors to extract the feature vector with principle component analysis (PCA), and an extreme learning machine was used to classify brain tumours, with a success rate of 94.23%. These findings show that deep learning and machine learning techniques can help with the accurate diagnosis and categorization of brain cancers. Anaraki et al. [19] used a genetic algorithm to build a convolutional neural network architecture for classifying brain cancers. There is one fully connected layer, six convolutional and max-pooling layers, and a classification accuracy of 94.2%. Swati et al. [20] developed a system for identifying brain tumour images using transfer learning and fine-tuning. The authors employed a five-fold cross-validation strategy to acquire their 94.82% accuracy rate. Deepak et al. used deep transfer learning to construct a three-class classification system for meningioma, glioma, and pituitary cancers using a pre-trained Google Net in their work [21]. The study extracted characteristics from brain MR images with 97.1% accuracy. The algorithm was evaluated on a publicly available dataset of three types of brain tumours. Previous studies using the same dataset primarily used deep neural networks, which are vulnerable to the vanishing gradient problem. We used a Residual Network (ResNet-50) and global average pooling method to classify multi-class brain tumours to address this issue. A study in [22] suggested a modified Alex Net for the identification and classification of brain tumor pictures, with a classification accuracy of 91.6% on average. For MRI Gliomas brain tumor classification, a study in [23] suggested a deep multi-scale 3D Convolutional Neural Network. The proposed method obtained 96.49% accuracy by employing a validation dataset and data augmentation. A study in [24] suggests an ensemble classifier for multiclass class brain tumors incorporating machine learning and deep learning. The feature was extracted through Alexnet and classification is carried out through an ensemble classifier their experimentation exhibited an accuracy of 95% but their result was not statistically justified. A study published in [24] suggests using a convolutional neural network technique to diagnose breast cancer by examining ductal carcinoma tissue, with an 87% classification rate. A cervical cancer detection and classification method based on convolutional neural networks was recommended in a study [24]. Deep-learned features and an extreme learning machine (ELM)-based classifier are employed to classify the data. The proposed method had a 99.5% accuracy rate and a 91.2% categorization rate. MRI scans of Pituitary, Glioma, Meningioma, and Malignant and healthy are employed to analyze and identify subtle abnormalities in the developed model. It makes use of methods based on both image processing and machine learning. Based on CNN (Alex Net) features and an ensemble classifier, the model has been trained to correctly categorize the brain MR images.

III. METHODOLOGY

Artificial Intelligence (AI) has grown increasingly important in the world of health care as current medical standards are advanced. A patient's life could be saved by employing taxonomy technology to quickly identify brain tumor images and make the correct treatment options. Classifier performance is to be improved in the proposed research. Small dataset training and low computing complexity make these classifiers suitable for computer-aided brain tumor classification. The Majority Voting Approach was employed to develop a hybrid ensemble method combining KNN, Random Forest, Support Vector Machine, and Decision Tree. Gliomas, meningioma, benign, malignant, and healthy brain tumors could all be classified using this method. Otsu's Threshold approach was employed in the beginning to segment MRI images. A CNN (AlexNet) is employed to extract characteristics for classification purposes. KNN-RF-DT hybrid ensemble classifiers (based on the majority voting approach) are employed to classify the data.

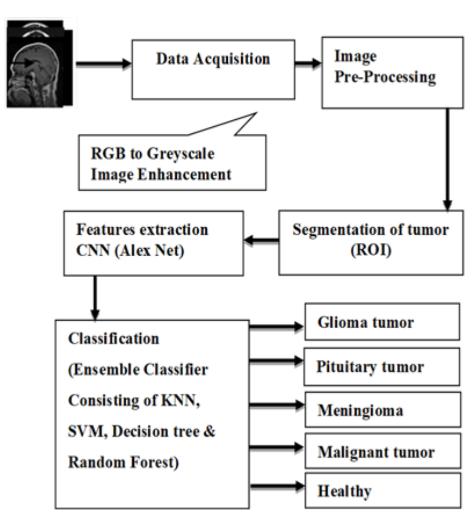


Fig. 1. Methodology Block Diagram

We have compared a variety of classifiers, including SVM, KNN, DT, RF, NB, ANN, and a proposed hybrid ensemble classifier, in our present research. Using standard classifiers, the goal was to make the system perform better. Figure 1 illustrates how the proposed model works. The data utilised in this study came from publicly available sources, specifically the "Brats-2015, Brats-2017, and Brats-2018 Brain tumour MRI Dataset." Images of the brain tumours were collected. Meningioma, glioma, malignant, benign, and pituitary tumours make up a combined total of 3061 MRI images. Data augmentation is the next phase, which could increase the precision of deep learning training by adding more data. Previous research has shown that using a weak algorithm with a massive dataset yields superior results. The enhancement technique was used to obtain more pictures. Several types of augmentation were used on the data in each category (i.e., glioma, pituitary, malignant, meningioma, and healthy). This research flipped, rotated, translated, used a mean filter, a median filter, shifted colors, and used a Gaussian filter on a total of 3061 MR images of tumours. The photos were then put through a preliminary processing phase consisting of many steps. First, we shrank each picture to a tiny 227 by 227 pixels. Many approaches were used to improve the quality of the images, such as filtering to sharpen the edges, changing the intensity, and histogram equalization to bring more contrast to the images. The tumour segmentation region of interest (ROI) was determined after MR image enhancement. Features in an image are what make it what it is, thus extracting them is crucial. Important features must be retrieved from the input tumour MR images before they can be properly identified. Feature extraction was utilised to cut down on data duplication. Upon closer study, it becomes clear that the MR images of tumours have poor shape, edge, and texture contrast.

In our study, we utilized the "Brats-2015, Brats-2017, and Brats-2018 Brain Tumor MRI Dataset" to curate MRI images of brain tumors. This dataset included 3061 MRI scans featuring various tumor types, such as meningioma, glioma, malignant, benign, and pituitary tumors. To enhance the deep learning training accuracy, we employed data augmentation techniques such as flipping, rotation, translation, mean filter, median filter, color shift, and Gaussian filter to increase the number of images in each class. After the photos were captured, they underwent a series of transformations, such as being scaled down to a resolution of 227 by 227 pixels, having their contrast and sharpness increased, and having their ROI for tumour segmentation defined. The MR images of tumours were analyzed, and feature extraction was used to isolate salient features and eliminate superfluous data. In contrast, there was a lack of shape, edge, and textural contrast in the MR images of tumours.

A supervised feature selection method was utilized to evaluate the efficiency and importance of the aforementioned four variables. Alex Net characteristics were employed to evaluate tumor MR images' textural qualities. Next, numerical values were extracted from an image's characteristics for classification purposes. A recurring pattern in the absorption spectra of different tissue densities is what gives tumor MR images their distinctive texture. For feature extraction, the image is divided into 3 × 3-pixel cells. After then, the cell next to it is compared to it, Pixel 1 is changed to 1, and the values of the adjacent cells are changed to 0 in this scenario.

IV. EXPERIMENTATION

This research employs unique methods to analyze and evaluate MR images. For visualization and interpretation. Once all of the features were extracted, the categorization/classification process was performed as a final step. To classify pixels in a digital image, classification was employed. Employing more than one classifier to make predictions is known as "ensemble classification" When compared to a single model, the prediction conformity of an ensemble is improved, leading to improved accuracy. By employing majority voting and making a forecast for every possible test case, this approach could achieve high levels of accuracy. Based on the number of votes cast, the final prediction was selected. Several machine learning techniques based on feature selection were employed in this work for classification. Decision Trees, Random Forests, SVM, and KNN are all instances of this type of data mining. The KNN technique is employed to find the nearest neighbour of an unknown data point. The algorithm function is affected by the value of k. It is possible to forecast the next-door neighbour if k is equal to n. Research on the topic includes Pituitary, Glioma, Meningioma, and Malignant and healthy categories. To compute different input values for required variables, a Decision Tree model was developed. The Random Forest model includes a large number of decision trees. Each decision tree has a random sample of training data. The dividing nodes were then selected employing subsets of characteristics. Random Forest could overcome the limitations of Decision Trees since it has a wider variance when fitting data. It was employed for both classification and regression with the KNN method. As a result, classification issues were the most typical use cases for this type of method. Data points were plotted in n-dimensional space, where the number of features is the number of data points in the SVM model. Each class had to be categorized on a hyper-plane, and this was the primary purpose of categorization Tumor MR Images are utilized to classify various forms of brain tumors, and these algorithms are often employed to speed up the execution time. During the experimentation phase, a tumor MR image was employed as an input. In the next step, we employed pre-processing techniques to remove any unnecessary information from the input image. Images were then decreased in size to 227x227 pixels per image before processing, and the ROI was determined. The images contained a wealth of information that might be extracted for further examination by employing CNN (Alex Net) algorithms. Also utilized in conjunction with CNN (Alex Net) features are statistical features like mean, mode, median, skewness, and kurtosis. The Ensemble Classifier model was employed on a multiclass brain tumor to classify the Pituitary, Meningioma, Glioma, Malignant and healthy images. The model was trained with 3061 tumor MR images from each category. With Ensemble Classifiers, the dataset would be optimized to detect and differentiate between several forms of brain tumors, such as meningioma, glioma, and healthy and pituitary tumors. Machine learning classifiers (KNN, SVM, Random Forest, and Decision Tree) were combined to create prediction models. The system was trained to employ brain MR scans. 70.0 percent was retained for training, whereas only 30% was employed during testing. The developed algorithm then classifies each image as Meningioma, Glioma, Pituitary, Malignant, and healthy. In this research, five-fold cross-validation is employed, and the ensemble classifier is decided based on bagging. The statistical Justification for cross-validation and result is provided.

V. RESULTS & DISCUSSIONS

MR scans of the pituitary, glioma, meningioma, and malignant and healthy images were employed to develop the model. It utilizes image processing and machine learning techniques to accomplish its objectives. Brain MR Images were fed into the model, which was taught to recognize and analyze CNN (Alex Net) properties. Table 1 shows the pseudo-code employed to model the algorithm for the developed technique.

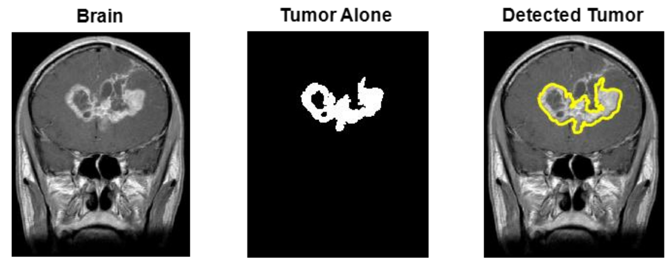
TABLE I. **PSEUDOCODE FOR THE DEVELOPED METHOD**

```
Data acquisition
Image preprocessing
// Get the labels for training dataset
lab = imdsTrain.Labels;
// Get the labels for validation dataset
lab_test = imdsValidation.Labels;
// Loop through each input image
for i = 1 to numImages
// Check if the image is in RGB format, and convert it to grayscale if necessary
if cc == 3
a = rgb2gray(a);
end if
// Extract features from each image using AlexNet
Net = alexnet;
features = extract_features(Net, a);
// Divide the data into training and testing sets
```

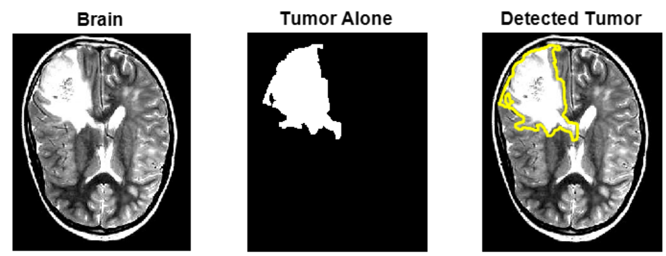
```
if i <= 0.8 * numImages
// Add features to training data
Train_Y(i,:) = features;
else
// Add features to testing data
Test_Y(i,:) = features;
end if
end for
// Loop through each image in the testing set
for i = 1 to numel(Test_Y(:,1))
z = Test_Y(i,:);
// Make predictions using the features from each image
predict1 = predict(Net, z);
predict2 = predict(Net, z);
predict3 = predict(Net, z);
predict4 = predict(Net, z);
predict5 = predict(Net, z);
// Combine the predictions to get the mode
all = [predict1 predict2 predict3 predict4 predict5];
new_lab2(i,1) = mode(all(i,1:5));
end for
Net=alexnet;
% Training, 80% data employed for training
5.          Train_Y (i, :)
% Testing, 20% data employed for testing
6. Test_Y (i, :)
for i=1: numel (Test_Y (:1))
z= Test_Y(i, :);
7. for i=1: numel (Test_Y(:1))
z= Test_Y (i,:);
all= [predict1 predict2 predict3 predict4 predict5];
for i=1: numel (Test_Y(:,1))
new_lab2(i,1) = mode(all(i,1:5))
end
```

The Pseudocodecode represents a pipeline for image classification using a deep learning model called AlexNet. First, the code acquires data by reading in the image data and storing the training and validation labels. Then, the code preprocesses the image data by checking if the input image is a 3-channel RGB image, and if so, converts it to grayscale. Next, the code extracts feature from each image using AlexNet, which is a pre-trained convolutional neural network that has been shown to perform well on image classification tasks. The code then uses 80% of the data for training and the remaining 20% for testing. During testing, the code iterates over each test image and makes a prediction using the extracted features. The code then combines the predictions from the five output layers of the AlexNet model, takes the mode of the resulting vector, and assigns it as the predicted label for the test image. Overall, this pseudocode represents a standard pipeline for image classification using a pre-trained deep learning model. By extracting features from each image and using a combination of training and testing data, this pipeline can accurately predict the class labels of new images.

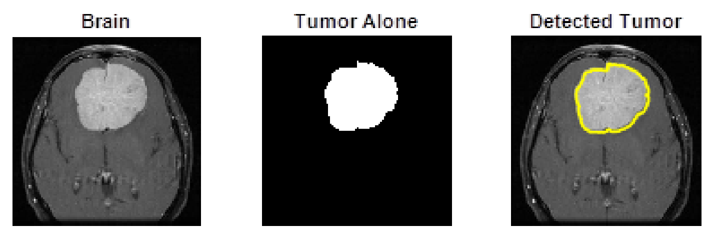
The model was then truly tested on a new set of data (not involved in training and testing). Figure 2&3 illustrates the outcomes of typical machine learning classifiers. There are five sub-sections in total: (2)(a), (2)(b), (2)(c), and (2)(d). Segmentation for the region of interest may be seen in images from Figures 2(a) to 2(e). Malignant tumors, Glioma, Pituitary, Malignant and healthy are shown in Figure 3.



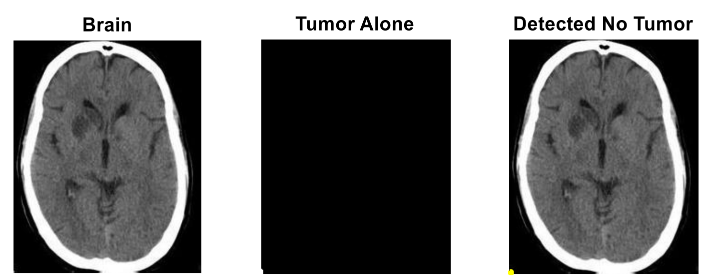
2(a)



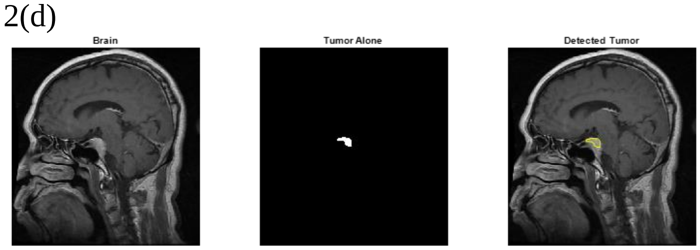
2(b)



2(c)



2(d)



2(e)

Fig. 2. (2(a) to 2(e)) Segmentation of several MR images of brain tumors

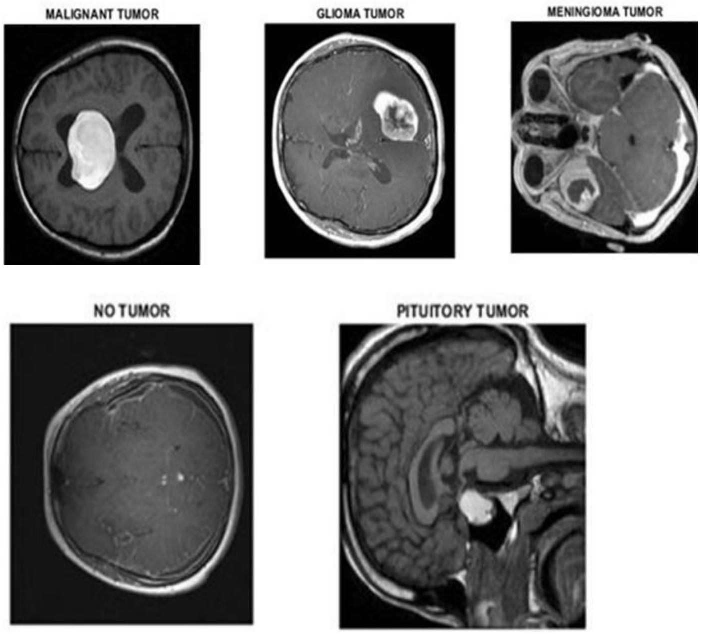


Fig. 3. MRI's based brain tumor detection

Fig. 4. Confusion Matrix

Machine Learning algorithms commissioned for this study were evaluated using a variety of performance metrics. Four performance metrics were devised for evaluation. Classification and detection modules' performance could be evaluated by comparing their results to those shown in Figure 5. As a result of this training, the model was tested in front of a Radiologist and a clinical expert, with an overall accuracy of 96 %, and the following results were obtained.

TABLE II. STATISTICAL TEST

S. No	*Classes*	Dataset for Radiology test	Predicted True	Radiologist opinion	Error Percentage
1	***Pituitary***	30	29	1	5%
2	***Glioma***	30	28	2	10%
3	***Meningioma***	30	30	0	0%
4	***No Tumor***	30	29	1	5%
5	***Malignant***	30	29	1	5%

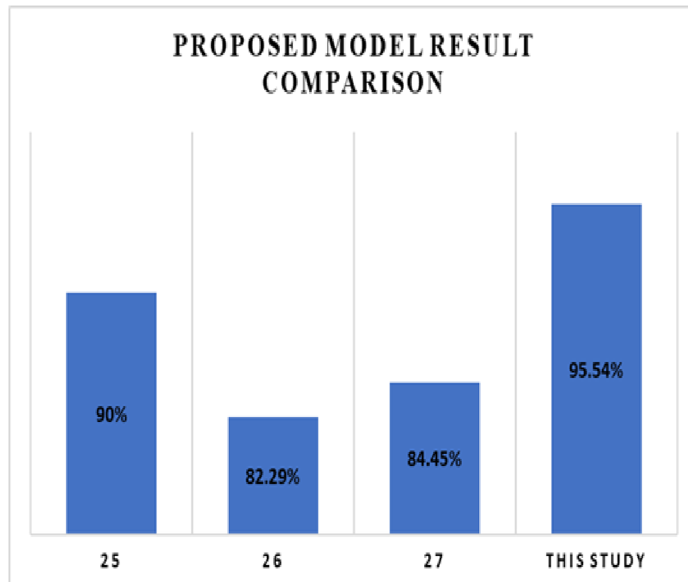


Fig. 5. Comparison of performance

Table 3 discusses the various evaluation metrics used in the study, including accuracy, precision, F1 score, and recall.

TABLE III. STATISTICAL TEST

Classes	*Precision*	*Recall*	*F1 score*	*Accuracy*
Meningioma	0.9124	0.9239	0.9180	0.954
Malignant	0.9445	0.9459	0.9451	0.954
Pituitary	0.9929	0.9901	0.9919	0.954
Glioma	*0.9706*	0.9377	0.9538	0.954
Healthy	0.9652	0.9888	0.9768	0.954

The techniques described in (V. Sabitha et al. 2021) and (Sajid Iqbal et al. 2019) could only identify tumours of all types (benign, malignant, and normal). The new technique may identify and categorise benign and malignant pituitary, meningioma, glioma, and glioblastoma brain tumours. Table 4 displays the results of a comparison between the suggested model and a selection of the existing approaches. Using k-means and the standard deep learning approach, the classifier in [24] achieved an accuracy of 84.45%. [26] Employed KPCA, and KSVM categorization to identify normal, benign, and malignant tumors in the same way. While [25] employed LSTM & ConvNet to perform segmentation for the region of interest with an accuracy of 82.29%. The proposed method is evaluated on several brain tumor detection techniques using ALexNet. To categorize the data, the suggested method makes use of an ensemble of machine learning classifiers, including KNN, SVM, Random Forest, and Decision Tree. The figure shows that the proposed method has a 95.54 percent accuracy rate.

TABLE IV. A COMPARISON FOR EVALUATION

S. No	Ref	Remarks	Methods	Accuracy
1	[24]	Segmentation of Brain tumor	LSTM & ConvNet	82.29%
2	[25]	Detection of Malignant, Normal & Benign	KSVM and KPCA	90%
3	[26]	Brain tumor location, No tumor, and tumor	K-Mean & Traditional DL algorithms	84.45%
4	**This Study**	Meningioma, glioma, Pituitary, Malignant, no tumor	KNN, CNN, SVM, Decision Tree and Random Forest	95.47%

Statistical Analysis test

Statistical analyses are carried out to justify our results that they are statistically significant for that purpose ANOVA test is carried out. So the first step is to check whether the ANOVA test is valid for that or not we first perform the test of Homogeneity of variances shown in table no.6 and check the Levene statistic as shown in table 7. Similarly, Multiple comparisons between the proposed model and other proposed methods Post Hoc test shown in Table 8 is performed and this exhibits that our proposed method is statistically significant than the other proposed method.

TABLE V. DESCRIPTIVE STATISTIC OF PROPOSED METHOD

Descriptives

Accuracy

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	Upper Bound	Minimum	Maximum
25	10	89.8700	1.61662	0.51122	88.7135	91.0265	87.00	92.00
26	10	82.1000	2.13177	0.67412	80.5750	83.6250	80.00	87.00
27	10	83.0450	2.23811	0.70775	81.4440	84.6460	79.00	86.00
This Study	10	95.0066	1.28476	0.40628	94.0875	95.9257	93.48	97.00
Total	40	87.5054	5.62523	0.88943	85.7064	89.3044	79.00	97.00

TABLE VI. TEST OF HOMOGENEITY OF VARIANCES

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Accuracy	Based on Mean	0.986	3	36	0.410
	Based on Median	0.811	3	36	0.496
	Based on Median and with adjusted df	0.811	3	26.315	0.499
	Based on trimmed mean	0.931	3	36	0.436

TABLE VII. POST HOC TEST

Multiple Comparisons (Post Hoc Tests)

Dependent Accuracy

LSD

(I) Factor		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
25	26	7.77000*	0.83119	0.000	6.0843	9.4557
	27	6.82500*	0.83119	0.000	5.1393	8.5107
	this study	-5.13660*	0.83119	0.000	-6.8223	-3.4509
26	25	-7.77000*	0.83119	0.000	-9.4557	-6.0843
	27	-0.94500	0.83119	0.263	-2.6307	0.7407
	this study	-12.90660*	0.83119	0.000	-14.5923	-11.2209
27	25	-6.82500*	0.83119	0.000	-8.5107	-5.1393
	26	0.94500	0.83119	0.263	-0.7407	2.6307
	this study	-11.96160*	0.83119	0.000	-13.6473	-10.2759
this Study	25	5.13660*	0.83119	0.000	3.4509	6.8223
	26	12.90660*	0.83119	0.000	11.2209	14.5923
	27	11.96160*	0.83119	0.000	10.2759	13.6473

VI. CONCLUSION

A machine vision-based technique saves lives by early detection of multiclass brain tumours such meningioma, glioma, and pituitary tumours. With the hope of saving lives, this research set out to create a model to aid clinical professionals in the early diagnosis of the aforementioned types of brain tumours. The suggested model achieved an accuracy of 0.9557, recall of 1.00, precision of 0.9557, and F1 score of 0.977 when trained on publicly available datasets. The proposed approach has the potential to detect brain cancers that are not readily apparent to the naked eye. An effort is being made right now to incorporate a number of dominant characteristics to enhance productivity and improve efficiency. Radiologists were able to make their final conclusions more easily when the data were cross-validated with physician advice.In the future to acquire a high MCC value, it would be interesting to combine different models with an ensemble classifier.

REFERENCES

[1] M. K. Abd-Ellah, A. I. Awad, A. A. M. Khalaf, and H. F. A. Hamed, 'A review on brain tumor diagnosis from MRI images: Practical implications, key achievements, and lessons learned', Magn. Reson. Imaging, vol. 61, no. May, pp. 300– 318, Sep. 2019.

[2] B. Panda and C. S. Panda, 'A Review on Brain Tumor Classification Methodologies', Int. J. Sci. Res. Sci. Technol., vol. 6, no. 6, pp. 346–359, 2019.

[3] R. L. Siegel, K. D. Miller, and A. Jemal, 'Cancer statistics, 2020', CA. Cancer J. Clin., vol. 70, no. 1, pp. 7–30, Jan. 2020.

[4] Abbas, N., Saba, T., Mehmood, Z., Rehman, A., Islam, N., & Ahmed, K. T. An automated nuclei segmentation of leukocytes from microscopic digital images. Pakistan Journal of Pharmaceutical Sciences, (2019). 32(5), 2123–2138.

[5] Al-Ameen, Z., Sulong, G., Rehman, A., Al-Dhelaan, A., Saba, T., & AlRodhaan, M. (2015). An innovative technique for contrast enhancement of computed tomography images using normalized gamma-corrected contrast-limited adaptive histogram equalization. EURASIP Journal on Advances in Signal Processing, 2018, 32.

[6] Afza, F., Khan, M. A., Sharif, M., & Rehman, A. Microscopic skin laceration segmentation and classification: A framework of statistical normal distribution and optimal feature selection. Microscopy Research and Technique, (2019). 82(9), 1471–1488.

[7] Pereira, S.; Meier, R.; Alves, V.; Reyes, M.; Silva, C. Automatic Brain Tumor Grading from MRI Data Using Convolutional Neural Networks and Quality Assessment. In Understanding and Interpreting Machine Learning in Medical Image Computing Applications; Springer: Berlin/Heidelberg, Germany, 2018; pp. 106–114

[8] H. H. Sultan, N. M. Salem and W. Al-Atabany, "Multi-Classification of Brain Tumor Images Using Deep Neural Network," in IEEE Access, vol. 7, pp. 69215-69225, 2019.

[9] Liu YH, Muftah M, Das T, Bai L, Robson K, Auer D. Classification of MR tumor images based on gabor-wavelet analysis. J Med Biol Eng 2011; 32:22–8.

[10] S.N. Deepa, B. Arunadevi, Extreme learning machine for classification of a brain tumor in 3D MR images, Informatologia 46 (2) (2013) 111–121.

[11] T.N.R.K.N. Varuna Shree, Identification and Classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network, Brain Informatics 5 (1) (2018) 23–30.

[12] Rajeswari, R., Neelima, G., Maram, B., & Angadi, A. MVPO Predictor: Deep Learning-Based Tumor Classification and Survival Prediction of Brain Tumor Patients with MRI Using Multi-Verse Political Optimizer. International Journal of Pattern Recognition and Artificial Intelligence, (2022). 2252006.

[13] A. Kabir Anaraki, M. Ayati and F. Kazemi, "Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms", J Biocybernetics and Biomedical Engineering. 2019;39: 63-74,

[14] Sajjad M, Khan S, Muhammad K, Wu W, Ullah A, Baik SW "Multi-grade brain tumor classification using deep cnn with extensive data augmentation". Journal of Computational Science 2019; 30:174–182

[15] Gumaei A, Hassan MM, Hassan MR, Alelaiwi A, Fortino G "A hybrid feature extraction method with regularized extreme learning machine for brain tumor classification". IEEE Access 2019; 7:36266–36273

[16] Anaraki AK, Ayati M, Kazemi F "Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms". Biocybern Biomed Eng 2019; 39(1):63–74

[17] Swati ZNK, Zhao Q, Kabir M, Ali F, Ali Z, Ahmed S, Lu J (2019) Brain tumor classification for mr images using transfer learning and fine-tuning. Comput Med Imaging Graph 75:34–46

[18] Deepak S, Ameer PM "Brain tumor classification using deep cnn features via transfer learning" j. Comput Biol Med 2019; 111:103345

[19] Jin, Y., Yang, G., Fang, Y., Li, R., Xu, X., Liu, Y., & Lai, X. "3D PBV-Net: An automated prostate MRI data segmentation method". J. Computers in biology and medicine, 2021; 128, 104160.

[20] R. Ezhilarasi and P. Varalakshmi, ''Tumor Detection in the Brain using Faster RCNN," 2nd International Conference on, Palladam, India, 2018, pp. 388-392.

[21] A. S. Remya Ajai and S. Gopalan, 'Analysis of Active Contours Without Edge-Based Segmentation Technique for Brain Tumor Classification Using SVM and KNN Classifiers', 2020, pp. 1–10.

[22] A. Tiwari, S. Srivastava, and M. Pant, 'Brain tumor segmentation and classification from magnetic resonance images: Review of selected methods from 2014 to 2019', Pattern Recognit. Lett., vol. 131, pp. 244–260, 2020.

[23] I. Haq, S. Anwar, and G. Hasnain, "A Combined Approach for Multiclass Brain Tumor Detection and Classification", PakJET, vol. 5, no. 1, pp. 83-88, Mar. 2022.

[24] Sabitha, V., Nayak, J., & Reddy, P.R. "MRI brain tumor detection and classification using KPCA and KSVM". Materials Today: Proceedings.2021

[25] Iqbal, Sajid & Khan, Muhammad Usman & Saba, Tanzila & Mehmood, Zahid & Javaid, Nadeem & Rehman, Amjad & Abbasi, Rashid. (2019). Deep learning model integrating features and novel classifiers fusion for brain tumor segmentation. Microscopy Research and Technique. 82. 10.1002/jemt.23281.

[26] Taş, O. (n.d.). Detection of the brain tumor existence using a traditional deep learning technique and determination of exact tumor locations US. Retrieved March 7, 2022.

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