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SqueezeNet Deep Learning Model for Magnetic Resonance Imaging Brain Tumor Detection

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Abstract
The growth of cells in an abnormal and uncontrolled manner leads to tumors. Tumors can be either benign or cancerous. The tenth highest trigger of mortality for both women and men is cancer of the brain and other nerve-related systems. Despite the multiple efforts and accomplishments in brain tumor detection and treatment, exact segmentation and classification continue to be difficult. This is because brain tumors can fluctuate in size, form, and position, and diagnosing one can be quite difficult. Multiclass classification of brain tumors is a consequential research area in Medical Imaging. Brain tumor imaging research has expanded significantly in recent years. More studies have been done on the use of Magnetic Resonance Imaging (MRI). This study focuses on MRI brain tumor detection using Squeezenet in its default values for extracting informative features and classifying the features by employing machine learning (ML) classifiers of the relevant features from Squeezenet using the orange data mining tool after preprocessing. The efficacy of the model was evaluated utilizing 3264 MRI brain tumor datasets comprising glioma, pituitary, meningiomas, and no tumor. Several metrics were utilized to assess the model's performance with Artificial Neural Networks (ANN) outperforming all the other classifiers with an accuracy of 91%. This study will enable the physician to detect, diagnose, and treat brain tumors at the early stages thereby reducing death and increasing the survival rate of an individual affected by this disease.

Keywords: Brain tumor, Squeezenet, Magnetic Resonance Imaging, Multiclass Classification, Artificial Neural Networks

Introduction

The unusual growth of cells in the tissues of the brain is a brain tumor. Malignant brain tumors include cancer cells, while benign brain tumors do not (fast-growing cancer cells). Some tumors originate in the brain because they are principal tumors. Others are malignancies that have spread to the brain after starting elsewhere in the body. There are over 130 different varieties of brain tumors, each with different origins in the type of cell, location within the brain, and rate of growth and expansion (Lather & Singh,2020). The brain tumor is classified as a primary and secondary tumor. The brain or spinal cord is where the primary brain tumor originates. In the United States in 2023, there will be 24,810 individuals inclusive of males and females will have a primary malignant brain or spinal cord tumor. On the other side, a secondary brain tumor develops in some other body parts like kidneys, lungs, and breasts and travels to the brain, typically via the blood (Brain Tumor-Statistics, 2023). Common brain tumor symptoms include dizziness, pain in the head, alterations to speaking, seeing, and hearing, trouble walking, vomiting, convulsions, attitude, and difficulty recalling information (Zhang et al., 2023). Different non-invasive techniques are used by medical practitioners to identify brain tumors in their early stages. Brain tumor detection in MRI and computerized tomography (CT) scan pictures has been a hot study area since recent medical imaging discoveries have focused on real-time tumor diagnosis utilizing more dependable algorithms. The most challenging part of tumor identification is image segmentation (Basu et al.,2023). To create a reliable and efficient diagnosis system, the segmentation method, also known as the separation method, is given top priority. As a result, tumor detection is improved by simpler picture analysis. For the timely and effective planning of medical treatments, digital image processing is of utmost importance in the interpretation of medical images. Every image processing application's fundamental goal is to use visual data to extract the necessary characteristics, which a machine can subsequently use to make the correct diagnosis (Puttagunta & Ravi, 2021).

One of the subject areas of artificial intelligence (AI) and computer science is ML. It focuses on leveraging data and algorithms to mimic human learning processes and increase accuracy over time (Haleem et al., 2022).

Supervised Learning trains an algorithm using a predetermined set of data inputs and actual outputs using a known dataset (referred to as the training dataset) (Sarker, 2021). Several computation techniques and algorithms are involved in learning a supervised model. Deep Learning (DL) is an aspect of ML and is a crucial component of the field of data science, which also includes modeling for prediction and statistics (Janiesch et al., 2021). DL is very helpful for data scientists tasked with gathering, examining, and extrapolating enormous amounts of data since it streamlines and accelerates the process. Instead of being linear like most ML algorithms, DL methods are designed in a hierarchy of increasing complexity and abstraction (Mathew et al., 2021). Convolutional Neural Networks (CNN) is a DL technique that can recognize various objects and characteristics in an input image, give them values, and distinguish between them. It can be built from the beginning or pretrained. The amount of data pre-trained for training has a significant impact on a CNN's classification abilities. Overfitting sets in CNN when there are minimal datasets (Krishnapriya & Karuna, 2023). Transfer Learning is reusing a previously trained model for a new task, this will prevent overfitting and make the model generalize well. Examples of popular pretrained models include the Inception-v3 model, VGG 16, VGG 19, SqueezeNet, AlexNet, etc.

The goal of this study is the utilization of a Squeezenet model for feature extraction from the MRI dataset and classification of the relevant features using Support Vector Machine (SVM), k Nearest Neighbor (kNN), Random Forest (RF), ANN, Naïve Bayes (NB), and Logistic Regression (LR). The performance of the classifiers was measured with metrics of evaluation. The paper is organized into sections. Section 2 presents the related works on the study. The methodology adopted for this study is discussed in detail in Section 3. Sections 4 & 5 present the results and discussions respectively. Section 6 presents the necessary conclusions and Section 7 is recommendations.

Related Works

Numerous studies on the detection of image-based brain tumors employing ML and DL have been published.
Alam et al. (2019) suggested a TKFCM approach that can more accurately identify brain tumors even the smallest ones and noisy datasets. Six features were selected from it for prediction, making it more complicated. The system was therefore required to reduce complexity. In terms of identifying and characterizing brain tumors in an MR image, the suggested method performs better than others. Compared to other cutting-edge approaches requires a substantially shorter execution time of 40–50 seconds to output the results. The authors recommended that in subsequent studies they will examine characteristics and incorporate additional attributes which will help to improve the identification and accuracy ability of the suggested model.

Tandel et al. (2020), presented a CNN transfer learning approach for the classification of MRI brain tumor data by using five clinically designed multiclass datasets. The work employed the AI approach, various cross-validation methods, and different training models in the ML and DL paradigms. The outcomes of the suggested CNN method were contrasted with those of six other machine learning techniques, including ensemble, Decision Tree, NB, KNN, SVM, and linear discrimination (LD). It was concluded that the current approach outperforms the ML techniques considered.

In the work of Dahiya et al. (2022), the research's main objective is to find tumor locations in brain MRI scans. The multiobjective ABC approach was utilized for the separation of the tumor and the brain after the grayscale MRI picture had been converted to colour. The image's RGB colour is produced by the intensity. The results were assessed using some performance measures. The efficiency of the suggested classifier was contrasted with the single-objective ABC algorithm. The outcomes demonstrate how well the suggested approach analyzes and segments the tumor from brain pictures.

In the work of Alsubai et al. (2022), CNN-LSTM was presented for MR image categorization and brain tumor prediction using a publicly available dataset. There are 253 images in the dataset, of which 155 are tumors and 98 are not. CNN was employed for the extraction of relevant features and noise while LSTM was employed for categorization of the features extracted. The experiment started with the preprocessing of the datasets by cropping the images. The features were fed into the LSTM for the categorization of the informative features into their respective groups. The model was evaluated on different parameter metrics of evaluation.

According to Ullah et al. (2022), 9 pretrained approaches were employed in their default values for the detection and recognition of brain tumors. At the preprocessing stage, the MR images were read into the training database using image DataStore, the data were augmented to increase the available dataset and to improve generalization. The input was resized depending on the pre-trained approach and afterwards the pre-trained approaches were applied to the input to categorize and detect the tumor in the datasets. Inceptionrestnetv2 outperformed all the

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other methods in categorizing and detecting pituitary, glioma, and meningioma tumors with 98.91% accuracy. The outcome was also compared to a hybrid approach and Inceptionnetv2 did better than the hybrid approach considered.

Kurdi et al. (2023) identified the gap in the current systems to improve the accuracy of precisely localizing cancer and identifying hidden edge features while minimizing computing load. They suggested HHOCNN to resolve the current issues. To reduce the false tumor recognition rate, noisy pixels were eliminated from the MRI. The tumor is identified by using the candidate region procedure. CNN was employed to categorize the numerous features extracted from the segmented region. The proposed method performed well when it was evaluated.

According to Sarkar et al. (2023), AlexNetCNN was employed for mining the informative attributes, and some ML approaches like NB were utilized for categorizing tumors. The model was assessed utilizing metrics of performance. The results showed BayesNet at 88.75%, SMO, at 98.15%, NB at 98.15%, SMO at 86.25%, and RF at 100% accuracy. Some of the drawbacks of the work are that the datasets used for examining the suggested approach are modestly sized and it hasn't been tried using actual patients' MRIs from Bangladesh. The authors concluded that by obtaining the MRIs from various hospitals and diagnostic facilities, they intend to implement this work on an on-demand medical diagnosis system in the future.

In the research of Krishnapriya and Karuna (2023), a pre-trained deep CNN (DCNN) to classify 305 brain MR images into tumor and non-tumor. The MRIs were cropped and resized to 224×224 pixels, and the bounds of the tissues of the brain were identified in the preprocessing stage. To enhance the learning results and to prevent overfitting data augmentation techniques were employed. 70%,30%, and 30% of the dataset were employed for training, testing, and validating the datasets. It was discovered that VGG-19 outperformed all the other pre-trained employed in the paper. A comparison of the transfer learning technique-pre-trained models was conducted with other cutting-edge work in the literature.

Zhao (2023) suggested a method for the classification of tumors of the brain utilizing AlexNet and VGG. The authors employed 3274 images of glioma, meningioma, pituitary, and no tumor. The data sets are normalized and augmented in the preprocessing stage. The data are in grayscale with 2875 employed for training and 398 utilized for testing. Alexnet with an accuracy of 69.54% demonstrated a better performance than the VGG. The author concluded that the suggested method has a great deal of promise for use in clinical settings as a supplemental tool to help doctors correctly diagnose brain tumors.

The objective of the work of Alrumiah et al. (2023) is to resolve the imbalance issue with the healthy class in the Kaggle MR image datasets. Two Generative Adversarial Networks (GAN) were employed to augment this imbalance class, Deep Convolutional GAN (DCGAN) and Single GAN (SinGAN). The datasets were also augmented using a rotational-based augmentation approach.VGG 16 was employed for the categorization of the images in the original and augmented datasets. VGG 16 had the greatest test loss for the original datasets as a result of the imbalance. The accuracy of the augmented datasets was low compared to the original datasets having an accuracy of 73%. The findings in the work offered an extensive perspective of how various image augmentation methods affect the size of datasets.

The objectives of the work of Gomez-Guzman et al., (2023) is the implementation of generic CNN and 6 pre-trained CNN for the categorization of tumor MR images. A total of 7023 MR images which comprises the Figshare, SARTAJ, and Br35H datasets. The preprocessing stage involves resizing, relabelling, and augmenting the datasets. The datasets were fed into the classical CNN and the pre-trained CNN for categorization. InceptionV3 outperformed all the other approaches with 97.12% average accuracy while the classical CNN had the lowest accuracy with 81.08%

Materials and Methods

The dataset and technique for the study's proposed models are described in detail in this section.

Datasets

This study utilizes MRI datasets from Kaggle (Sartaj et al., 2019). The folders for training and testing have already been created from the images. The folders have four subfolders comprising the tumor category. A total of 3264 data are in the datasets. The training data are randomly divided into 80% training and 20% test data. The details of the datasets are in Table 1.

Table 1: Description of the Dataset

Data	Glioma	Meningioma	No Tumor	Pituitary
Training	826	822	395	827
Testing	100	115	105	74
Total	**926**	**937**	**500**	**901**

The MRI images have undergone preliminary processing to facilitate additional morphological procedures for the identification of tumor size, shape, and location. Extraction and classification of significant characteristics from the visual data is the study's ultimate goal. SqueezeNet is used for the extraction of the most relevant features and SVM, k-NN, NB, ANN, RF, and LR are for the classification of the most relevant features. The suggested framework for this investigation is shown in Figure 1

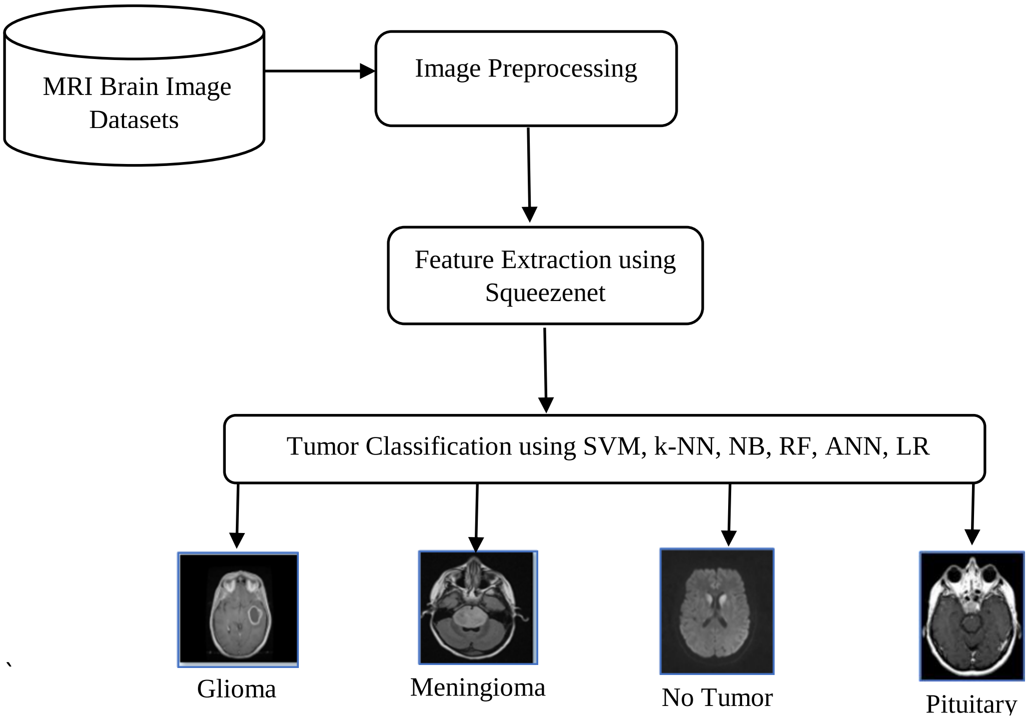

Image Processing

The magnetic resonance imaging (MRI) scans were resized following the requirement of the Squeezenet Pretrained approach. The image is processed to eliminate any denoising, which is the act of removing noise from an image, if the quality of the noisy image is not acceptable. This study employs a non-linear filter called a median filter, which preserves high-frequency MRI components without distorting the margins and eliminates salt and pepper noise and impulses. The median of the surrounding pixels in the median filter determines the values of the pixels. The basic goal of this technique is to swap out each pixel value in an image for its neighbouring pixels. If a pixel's values are significantly different from those of its neighbours, it is deleted when using the median filtering method on a picture (Methil, 2021).

Image Sharpening refers to any enhancement approach intended to draw attention to a picture's edges and small details while also reducing noise. The most popular techniques for improvement and removal are applied to achieve the greatest outcomes. More distinct edges and a sharpened image are the outcomes of enhancement; noise is minimized, which lessens the blurring effect on the image. Additionally, image segmentation is used to discover the location of the brain tumor in the enhanced image, boosting the quality of the overall image at the end when edge detection is done to find the tumor's exact location in the original image (Nithyasree et al., 2021)

SqueezeNet

Pretrained CNN learns a new task by using its prior knowledge of extracting the most pertinent features from natural images. Pretrained CNN is employed for Classification, Feature Extraction, and Transfer Learning (Saber et al., 2023). Squeezenet is employed in this work for feature extraction. It is a deep image identification model that maintains competitive accuracy with fewer parameters than the AlexNet.SqueezeNet architecture was suggested by (Iandola et al., 2016). The basic idea of a squeeze net is to utilize minimal parameters while preserving suitable accuracy. In designing this architecture, three ideas were suggested. Firstly, 1x1 filters which have minimal parameters compared to 3x3 filters were employed. By employing squeeze layers, the number of input channels was reduced to 3x3 filters, this invariably decreases the number of network weights at the second stage. To have big activation maps, the network is downsampled later at the third stage. The fully connected layers are replaced by a convolution layer in which the number of data classes and output channels are the same. This is followed by the softmax activation function and dropout layer. The fire module is the building element that helps in successfully deploying the three stages. The most informative features were extracted from the squeezenet. Figure 2 shows the macro architecture of the Squeezenet.

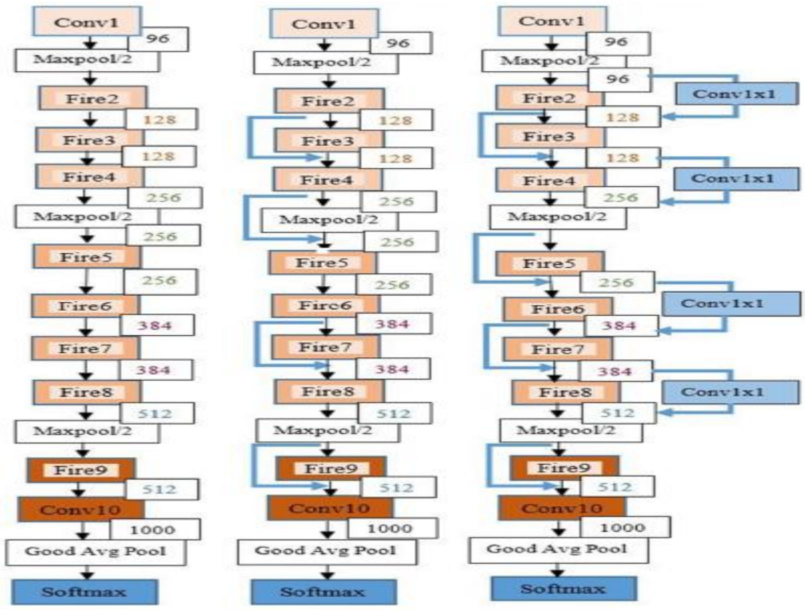

Figure 2 Squeezenet Macroarchictecture (Ullah et al., 2021)

Classifiers

After the extraction of features using SqueezeNet, the most informative features were fed into the following classifiers

Support Vector Machine

Vladimir Vapnik developed the SVM, a prominent technique that is applied to both regression and data classification. However, it is frequently utilized to build a hyperplane when the distance between two classes of data points is at its highest in classification issues (Quan & Pu, 2022). The classes of data points on either side of the decision boundary are divided by a hyperplane called the decision boundary. SVMs in ML are supervised learning (SL) models with associated learning models that examine data for classification and regression analysis (Moosaei et al.,2023).A decision border between classes is created by SVM utilizing support vectors, which are examples of training data. This is done to achieve the most impressive hyperplane isolation between instances of the various classes. The low-dimensional input data are plotted using kernel functions into a higher-dimension vector space. Linear, polynomial, radial basis function (RBF), nonlinear, and sigmoid are examples of kernel functions used by SVM (Pradeep et al.,2021).

k-Nearest Neighbor

KNN is a non-parametric, lazy, and one of the simplest supervised algorithms. It is predicated on the notion that the observations in a data collection that are most similar to a given data point are those that are closest to it. As a result, unexpected points can be categorized using the values of the existing observations that are closest to them. To classify an object, the distances between it and its labelled neighbours are calculated, and the neighbours closest to it are listed. The unlabeled object is assigned a class based on the labels of its nearest neighbours. The k-NN approach calculates how similar the training set and test sets are (Cunningham & Delany, 2021). The Euclidean and Manhattan distances are the two prominently used distance measures between any k-element and unidentified elements (Pradeep et al., 2021).

Naïve Bayes

NB classifier is a Supervised Learning that is probabilistic and based on Bayes theorem. It makes naive assumptions about the correlations between various features(Gohari et al., 2023). It can be used in a variety of domains including disease diagnosis, facial recognition, classification of news, natural language processing, classification of text, sentiment analysis, weather prediction, and recommendation systems to mention a few. Based on past knowledge of conditions that might be connected to the event, NB describes the likelihood of an event, such that the independent contribution of each feature to the probability of a classification outcome is computed (Alenazi et al., 2023). NB is simple, fast, makes real-time predictions, and works with discrete and continuous data. NB has to determine the joint probabilities of all features therefore computing cost is high. Bernoulli, Optimal ,Gaussian and Multinomial are the 4 types of NB. According to Pradeep et al. (2021) NB having a predictor x and class c can be illustrated with this formula.

$$P(a/b) = \frac{P(b/a)P(a)}{P(b)} \qquad (1)$$

Where $P(b/a)$ is the prior probability and $P(a/b)$ is the posterior probability.

Random Forest

Random Forest is a Learning approach that works with the combination of outputs of numerous decision trees. It can be employed to resolve regression and categorization issues. RF can accurately classify vast amounts of data. The trees in RF are selected at random for subsets of the training data. The model is fitted utilizing these subsets of data (Saarela & Jauhiainen, 2021). Replacement sampling allows for the repeated use of the same data, resulting in trees trained on different data sets and features for decision-making. The majority of votes determines the final categorization, and the average prediction is used to solve regression issues (Vergni &Todisco, 2023). The issue of overfitting is avoided in RF since the final output is based on average or majority rating and is generated from subsets of data.

Artificial Neural Networks

ANN are mathematical models of biological nervous systems, based on simplified neurons, with the basic processing elements being artificial neurons. The electrical activity of the nerve system and brain is simulated by ANN models (Shao & Shen, 2023). The neurons are interconnected with one another. A transfer function represents the nonlinear characteristic displayed by neurons, and the impacts of synapses are represented by connection weights that influence the effect of the related input signals in a simplified mathematical model of the neuron. The weighted sum of the input signals after they have been converted by the transfer function is then used to calculate the neuron impulse. By modifying the weights by the selected learning method, an artificial neuron can learn (Escamilla-Garcia et al.,2020). One of the most popular forms of ANN is the Multilayer Perceptron Neural Network (MLPNN). It comprises input features, hidden layers for estimating network parameters, and an output layer for generating response class labels. The MLPNN classifies input features and response categories using a chosen activation function to train network parameters (Yahya et al., 2012). ANN has been utilized in conjunction with other ML techniques such as genetic algorithms for the classification of cancer data types (Lawrence et al., 2024).

Logistic Regression

LR is a learning approach that estimates the probability that an instance would belong to a particular class. It is employed for categorization issues (Rashidi et al., 2023). It estimates the probability for the specified class using a sigmoid function. The purpose of the algorithm is to determine the decision boundaries between classes. When the focus of the research approach is on whether an event occurred rather than when it occurred, LR is applied. The most often utilized ML in the healthcare industry is LR Schober &Vetter,2021). The binary logistic model classifies into two classes while multiple classes employ multinomial logistic regression.

Evaluation Metrics

1. Accuracy: -This measures the model’s ability to correctly classify the datasets. It is given as

$$\frac{TN + TP}{TP + TN + FP + FN} \quad (2)$$

2. Precision: This metric represents the proportion of data instances that the model correctly predicts to be normal. By division of the total number of true positive results by the addition of true positive results and false positive results. It is calculated mathematically by:

$$\frac{TP}{TP + FP} \quad (3)$$

3. Recall: It's known as the proportion of all positive classifications the model correctly predicted.

$$\frac{TP}{TP + FN} \quad (4)$$

4. F1 Score: it is computed as the harmonic mean of the recall and precision.

$$\frac{2 * precision * recall}{precision + recall} \quad (5)$$

5. Matthew's Correlation Coefficient (MCC):- is a statistical model evaluation tool that evaluates the relationship between the actual and the predicted classes. A value of +1 indicates an error-free prediction, whereas a score of 0 indicates an inaccurate prediction. A value of -1 means that all negative samples were expected to be positive, and vice versa.

$$\frac{TP*TN-FP*FN}{\sqrt{((TP+FP)*(TP+FN)*(TN+FP)*(TN+FN))}} \quad (6)$$

6. Receivers Operating Curve (ROC): A graph known as the ROC displays how well a classifier performs for each possible threshold.

where TP is True Positive "accurately identifying sick persons as unwell", FP is False Positive "Falsely classifying healthy persons as ill", TN is True Negative "accurate identification of healthy people" and FN is False Negative " Falsely identifying sick persons as healthy "

Results

The experiment utilized Orange Data Mining by using 8GB RAM and a 64-bit system EliteBook 8440p, 2.80GHZ processor with Windows 10 Pro 4bit.

The performance metrics utilized in assessing the performance of the model are described in Table 1. The model has the best results for the classifiers at 20-fold cross-validation. It could be observed that ANN outperformed all the other models with an Average Accuracy of 0.919, F1 score, AUC, Precision, recall, and MCC at 0.918, 0.985, 0.919, and 0.890 respectively. SVM has the lowest metrics 0.600 average accuracy, 0.593, F1 score, 0.824 AUC, 0.605 precision, 0.600 recall, and 0.459 MCC.

Table 1: Performance Evaluation Results of Datasets

Model	**Avg Accuracy**	**F1**	**Precision**	**Recall**	**MCC**	**AUC**
SVM	0.600	0.593	0.605	0.600	0.459	0.824
kNN	0.833	0.832	0.836	0.833	0.773	0.954
NB	0.682	0.675	0.684	0.682	0.577	0.877
RF	0.820	0.820	0.821	0.820	0.756	0.949
ANN	0.919	0.918	0.919	0.919	0.890	0.985
LR	0.877	0.877	0.877	0.877	0.833	0.969

Figure 3 shows the confusion matrix of the four datasets for the 6 classifiers (SVM, k-NN, NB, RF, ANN, and LR) considered in this study. It shows the actual, predicted data and the misclassified data of MRI tumors. The actual datasets for glioma are 926, meningioma 937, no_tumor 500, and pituitary 901 datasets. The correctly predicted data is stated in the order above (a) The predicted data by SVM for 677, 363, 290, and 627 (b) Shows the kNN predicted data as 753,741, 364, and 861. (c) NB prediction with 609 453 352, and 811. (d) RF with 732,712,399, and 834 predicted data. (e) ANN has a prediction of 810, 841, 476, and 871. (f) LR prediction with 786,775,451, and 851

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		Predicted				
		glioma_tumor	meningioma_tumor	no_tumor	pituitary_tumor	∑
Actual	glioma_tumor	677	109	41	99	926
	meningioma_tumor	391	363	31	152	937
	no_tumor	61	61	290	88	500
	pituitary_tumor	106	160	8	627	901
	∑	1,235	693	370	966	3,264

a

		Predicted				
		glioma_tumor	meningioma_tumor	no_tumor	pituitary_tumor	∑
Actual	glioma_tumor	753	145	15	13	926
	meningioma_tumor	104	741	14	78	937
	no_tumor	46	45	364	45	500
	pituitary_tumor	5	35	0	861	901
	∑	908	966	393	997	3,264

b

		Predicted				
		glioma_tumor	meningioma_tumor	no_tumor	pituitary_tumor	∑
Actual	glioma_tumor	609	161	100	56	926
	meningioma_tumor	195	453	172	117	937
	no_tumor	30	40	352	78	500
	pituitary_tumor	20	36	34	811	901
	∑	854	690	658	1,062	3,264

c

		Predicted				
		glioma_tumor	meningioma_tumor	no_tumor	pituitary_tumor	∑
Actual	glioma_tumor	732	153	15	26	926
	meningioma_tumor	132	712	16	77	937
	no_tumor	26	47	399	28	500
	pituitary_tumor	12	47	8	834	901
	∑	902	959	438	965	3,264

d

		Predicted				
		glioma_tumor	meningioma_tumor	no_tumor	pituitary_tumor	∑
Actual	glioma_tumor	810	94	16	6	926
	meningioma_tumor	60	841	7	29	937
	no_tumor	9	9	476	6	500
	pituitary_tumor	6	24	0	871	901
	∑	885	968	499	912	3,264

e

		Predicted				
		glioma_tumor	meningioma_tumor	no_tumor	pituitary_tumor	∑
Actual	glioma_tumor	786	101	28	11	926
	meningioma_tumor	114	775	15	33	937
	no_tumor	25	14	451	10	500
	pituitary_tumor	8	34	8	851	901
	∑	933	924	502	905	3,264

f

Figure 3 is the confusion matrix of the six ML classifiers
The comparison of the classifiers considered in this study with the performance metrics is shown in Figure 4.

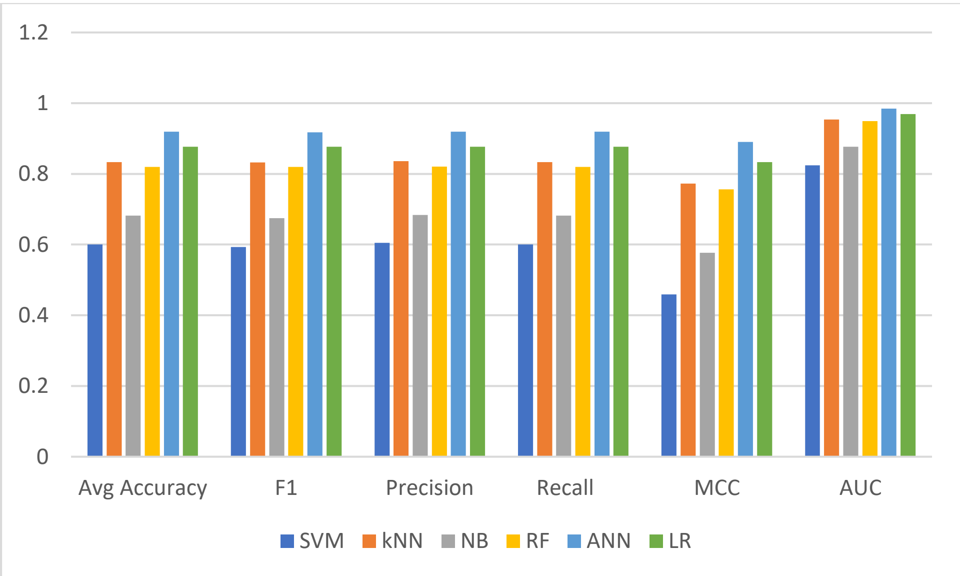

Figure 4 The performance metrics of the ML classifiers

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ANN has the highest AUC of 0.985 followed by LR at 0.969, k-NN at 0.954, and NB and SVM have the lowest values of 0.877 and 0.824 which confirm that our classifiers correctly classified the tumor to their respective classes after the feature extraction of Squeezenet.
Table 2 is the comparison of some state-of-the-art classifiers, some of which are trained approaches for predicting glioma, meningioma, no_tumor, and pituitary datasets. It can be seen that some of the classifiers considered in this study can compete favourably with the other approaches enlisted for comparison.

Table 2. A comparison of the proposed model's accuracy with some existing models.

Authors	Dataset	Methods	Average Accuracy
Ullal et al, (2022)	SARTAJ	Resnet50	67.03
		MobilenetV2	82.61
		Densenet201	68.71
		Resnet18	63.04
		Resnet101	74.09
		Shufflenet	89.31
Zhao,(2023)	SARTAJ	Alexnet	69.54
Alrumiah et al., (2023)	SARTAJ	VGG16	73
Gomez-Guzman et al. (2023)	Figshare SARTAJ Br35H	EfficientNetB0 Generic CNN	90.88 81.08
Proposed Method	SARTAJ	SVM	60
		k-NN	83.3
		NB	68.2
		RF	82.3
		ANN	91.9
		LR	87.7

Discussion

This study has made use of 3264 MRI brain tumors comprising glioma, meningioma, no tumor, and pituitary datasets. Squeezenet is a pre-trained CNN employed for the identification of informative features before the 6 classifiers were employed to classify it in this study. CNN is a suitable neural network that has enough depth to handle the variance and learn high-level features. It has proven to be more effective than other types of weaker networks at handling the complexity and uniqueness of the MRI medical datasets. The utilization of only conventional ML methods in previous studies has been tedious and time-consuming for manual feature extraction. Artificial Neural Networks achieved a better performance through the metrics employed for the evaluation of the system in the classification of the MRI brain datasets compared to SVM, k-NN, NB, RF, and LR engaged in this study. The AUC of the ML classifiers is above 0.8 which means the classifiers could distinguish between the tumor types.

MRI is the most utilized non-interfering imaging technique for detecting tumors because it doesn't involve radiation and has a great contrast resolution across a variety of tissues. As a result of overlapping intensities, noise disturbances, and low visual contrast, the classification of tumors with MRI is challenging. The study can be expanded in the future to include augmentation and using well-structured datasets to investigate if the proposed method will exhibit better results than the one obtained in this study. More so, the suggested method can be employed for other types of medical images such as X-ray, endoscopy, dermoscopy, histology, and ultrasonography. In addition, the suggested model can be employed to categorize and diagnose the Internet of Medical Things (IoMT) based datasets.

Conclusion

This work focused on using pre-trained CNN (Squeezenet) as an extractor of the most informative features and the results are fed onto 6 classifiers for the detection of tumors in MRI datasets obtained from Kaggle. The accuracy results obtained from SVM, kNN, NB, RF, ANN, and LR in percentage are 60%, 83.3%, 68.2%, 82.3%, 91.9%, and 87.7% respectively for the tumor types considered. Brain tumor diagnosis remains challenging due to tumor appearance, size, shape, and structure. MRI image segmentation method is promising but adjustments are needed for successful segmentation and tumor region identification. Deep learning approaches have made significant progress, but a general technique is needed for robustness. The robustness of the techniques is directly impacted by testing images, even when training and testing are conducted on equivalent acquisition settings (intensity range and resolution). To improve upon this work, a substantially higher accuracy can be gained by gathering a superior dataset with high-resolution images directly from the MRI scanner. The accuracy of this tool can be further improved by using classifier boosting techniques, making it an invaluable asset for any medical facility treating brain tumors.

Recommendations

1. Future research could focus on detecting brain activity using real patient data from various image capture mediums.
2. It is important to understand that the strategy for creating a brain tumor detection model is intended to enhance and make it better.
3. Also, subsequent research should focus on boosting the computational effectiveness while reducing the model complexity, to ensure smooth integration into clinical settings in real-time while increasing the accuracy of classification resulting in a robust system that is suitable for clinical applications.

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