International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Early Detection of Brain Tumors: A Comprehensive Study on MRI-Based Diagnosis Using a Combination of Convolutional Deep Learning and Machine Learning Techniques

Patel Rahulkumar Manilal*[1], D. J. Shah[2]

Submitted: 02/05/2024 **Revised**: 15/06/2024 **Accepted**: 22/06/2024

Abstract: Brain tumors are one of the global public health problems that affect people of every age category, and early detection of the tumor is extremely important for the life of an individual. The complicated and diverse nature of brain tumor symptoms makes their detection a challenge, necessitating improved imaging techniques for reliable diagnosis. This study applies deep convolutional learning combined with machine learning techniques to delve into early brain tumor identification using MRI-image-based classification. The model presented in this study uses an ensemble model that combines random forest and support vector machine which provides improved and more accurate early brain tumor detection. This has been proven as the ensemble model achieves an improved 97% recall rate, a 96% F-score, a 98.25% accuracy rate, and 98.89% precision in early brain tumor identification. Furthermore, the model's ability to correctly detect the type of brain tumor in the input image also highlights its ability for brain tumor classification and identification.

Keywords: *Brain Tumors, Glioma, Meningioma, Pituitary, Magnetic Resonance Imaging*

1. Introduction

In the health field, tumors are classified as either malignant or benign neoplasms, and there are over two hundred different types that can afflict humans [1]. The tissues immediately beneath the brain and skull might be severely affected by a brain tumor since the tumor develops inside the brain. There are two types of cancerous tissue and one type of benign tissue in the mass [2]. In the brain, these tumors develop erratically and cause pressure. These factors can trigger many different types of brain problems. In 2019, it is predicted that there will be close to 0.7 million persons living with brain tumors in the United States [3]. The number of cases was estimated at 0.86 million. of these people, 60,800 were classified as having no cancer, and 26,170 as having cancer. Only 35% of cancer patients in the United States will survive their disease [4]. Figure 1 represents the Brain with a tumor [5].

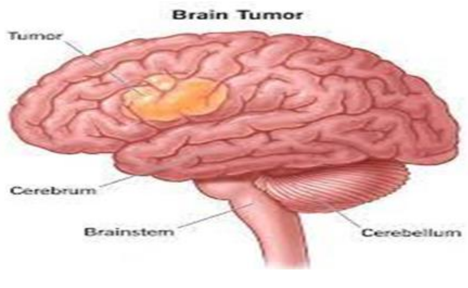

Fig 1: Brain with a Tumor

Early detection of the tumor is extremely important for survival [6]. Accurate segmentation of brain tumors is critical for treatment and intervention planning by medical staff. It takes more time for the qualified specialist to segment the tumors physically [7]. This necessitates the use of tumor quantitative analysis and computerized segmentation. Clinical diagnosis and treatment planning rely heavily on reliable magnetic resonance imaging (MRI) of brain tumors [8]. Brain tumors can have similar structures or characteristics on MRI, making manual classification a challenging undertaking because accurate diagnosis relies on the availability and expertise of a radiologist [9]. Automatic classification, which can be used to classify MRI of brain tumors with little input from human experts, is one approach to this issue [10].

The detection and categorization of patterns in medical imaging have been made possible by recent advancements in machine learning, particularly Deep Learning (DL). Because of the advancements that have been made in this field, it is feasible that shortly, rather than gaining knowledge from specialists or books written by scientists, it will be possible to learn by collecting and analyzing data. Medical applications that use machine learning to improve their performance include disease prognosis and diagnosis, molecular and cellular structure identification, tissue segmentation, and image categorization [11] [12] [13]. Since Convolutional Neural Networks (CNNs) have excellent diagnostic accuracy and several layers, they become especially effective when the number of input images grows [14] [15]. Autoencoders are a type of unsupervised learning that uses neural networks to learn representations. Amazingly, cancers (including lung tumors) and cardiovascular stenosis have been detected using different DL and ML techniques. High diagnostic accuracy has also been demonstrated through performance evaluations [16] [17] [18].

The significance of this study is that it has the potential for early brain tumor detection. It is conducted through the use of an ensemble machine learning model that is designed using a combination of machine learning classifiers: random forest and support vector machine. This model gives us hope for better patient diagnosis and classification because it does a good job of separating different types of brain tumors, such as gliomas, meningiomas, and pituitary gland tumors. This is possible because it uses a convolutional neural network to pull features from images and shares those features with the ensemble classification model, which in turn allows for more immediate treatment initiation and improved overall prospects.

2. Related Works

This section is an analysis of the research published on Early Detection of Brain Tumors: A Comprehensive Study on MRI-Based Diagnosis. Relevant work done by various authors is evaluated using both convolutional deep learning and machine learning strategies.

Allah et al., (2023) [19] present the Edge U-Net Model, a new formulation of Deep Convolutional Neural Network (DCNN) founded on the U-net architecture. The model is better at finding cancers because it uses data related to the boundaries of MRI besides core data from brain MRIs. Obtained Dice score values in the experiments indicate that the suggested framework performs better in differentiating between different brain tissues. The Dice rating for meningiomas was 88.8%, for gliomas it was 91.76, and for pituitary tumors, it was 87.28.

Saeedi et al., (2023) [20] developed several machine learning strategies, including two deep learning approaches, to analyze brain MRI data and identify gliomas, meningiomas, and pituitary gland malignancies. Both the recommended 2D CNN and auto-encoder network have training accuracies of 96.47 and 95.63 percent, respectively. Using an average of 95% accuracy, the 2D CNN and auto-encoder networks were able to identify the samples. The outcomes show that the suggested 2D CNN accomplishes state-of-the-art performance on brain cancer classification with latency-free, very rapid execution. Radiologists and doctors can include this suggested network in clinical systems for brain tumor identification because it is more user-friendly than the auto-encoder network.

Filatov and Yar, (2022) [21] suggested using CNNs that had been trained to diagnose and classify brain cancers. One set of non-tumor MRI scans was used to categorize three different kinds of cancers. Several networks have been utilized, including ResNet50, EfficientNetB1, EfficientNetB7, and EfficientNetV2B1. Because of its scalability, EfficientNet has demonstrated encouraging performance. With an accuracy of 89.55% during validation and 87.67% throughout training, EfficientNetB1 performed the best.

Almadhoun et al., (2022) [22] utilized a mixture of a conventional classifier set and a fuzzy C-Means clustering method along with a convolutional neural network. The study was an experimental one, performed on a real-time dataset with tumors of different sizes, locations, shapes, and image intensities. For the conventional classifier part, it utilized Scikit-learn's Support Vector Machine, K-nearest neighbor, Multilayer Perceptron, Logistic Regression, Naive Bayes, and Random Forest. Convolutional Neural Networks (CNNs) developed with Keras and TensorFlow replaced the older neural networks because of their superior performance. CNN's accuracy has increased to an amazing 97.87% thanks to the contributions of its users.

Senan et al., (2022) [23] identify brain cancers using a combination of DL and traditional ML techniques. To categorize and diagnose brain cancers, the support vector machine (SVM) algorithm is applied in conjunction with AlexNet and ResNet-18. To get the most useful and accurate deep features, they use DL methods like deep convolutional layers. Using deep learning algorithms like Alexines and ResNet-18 to obtain the desired attributes is the first step in integrating deep and machine learning. The AlexNet+SVM hybrid has the highest levels of accuracy (95.10%), sensitivity (95.25%), and precision (98.50%).

Soewu et al., (2022) [24] used an MRI dataset to see how well the convolutional neural network works. MRI pictures of the brain were used to teach the model how to spot tumors. It was checked to see how well the model worked and found to be 97.8 percent correct, 98.5 percent specific, 96.2 percent recall, 98.5 percent F1-score, and 97.3 percent exact.

Khan et al., (2022) [25] provided a deep learning classification hierarchy applied to brain malignancies (glioma, meningioma, pituitary) is given as an example. CNN uses parts of pictures. The authors present a method that uses convolutional neural networks and hierarchical deep learning to identify and classify brain tumors. Tumors are divided into four groups in the method: glioma, meningioma, pituitary and non-tumor. According to the suggested model, the identification of brain tumors has been made with a 92.13% accuracy and only a 7.87% failure rate which was an improvement from previous methods used for similar purposes.

Majib et al., (2021) [26] developed and analyzed different ML models, which could be full ML models as well as hybrids to automatically classify photos of brain tumors. Also, 16 transfer learning models were investigated by the authors to establish the best neural network-based brain tumor classification model. Lastly, a stacked classifier exploiting various cutting-edge technologies was suggested, which proved to be better than all previous designs. The suggested method achieved an accuracy of 99.2%, recall of 99.1%, and f1 scores of 99.2%.

Noreen et al., (2020) [27] show that brain tumors can be detected early by performing multi-level feature extraction and concatenation. Its convenience is derived from the fact that it incorporates two pre-trained deep learning models (Inception-v3 and DensNet201). Pre-trained Inception-v3 was built using inception modules to form a pre-trained feature extraction model. Later, features were extracted from this model through pre-trained DensNet201 implemented in DensNet blocks. Thus, a softmax classifier provides combined features that can be employed in the classification of brain tumor types. When applied to test samples, Inception-v3 had an accuracy rate of 99.34% while DensNet201 had an accuracy rate of 99.51% for recognizing tumors in brains.

Amin et al., (2019) [28] used the Weiner filter with multiple wavelet bands is used to denoise and enhance input slices. Tumor images can be classified into multiple clusters using the potential field (PF) method. T2 MRI and Fluid Attenuated Inversion Recovery (Flair) use global threshold and other methods as well as other mathematical morphological approaches for isolating tumor regions. Precise categorization combines Gabor Wavelet Transform (GWT) and Local Binary Pattern (LBP) features. The suggested technique yields a peak signal-to-noise ratio (PSNR) of 76.38 for T2 and Flair, a mean squared error (MSE) of 0.037, and a structural similarity index (SSIM) of 0.98.

Siar et al., (2019) [29] demonstrated brain tumor identification utilizing convolutional neural networks (CNNs) and magnetic resonance imaging (MRI). CNN was the first to receive image input. The Softmax Fully Connected layer achieved a classification accuracy of 98.67% when applied to images. Using the RBF classifier, CNN gets an accuracy of 97.34%, whereas the DT classifier only gets 94.26%. The results of the classifiers demonstrate that CNN's accuracy is best tested using the Softmax classifier. Combining feature extraction techniques with CNN is a unique strategy for detecting malignant brain tumors. The method suggested a 99.12% accuracy on the test data..

3. Research Methodology

In this part, the Kaggle dataset for Brain Tumor classification is presented. Various tools, including U-Net for Image Segmentation and CNN for Feature Extraction, as well as ensemble approaches, which involve SVM and RF, are explored further in the discussion of Brain tumor classification issues.

3.1. Dataset Description

The image-based collection that was used had 3264 T1-weighted contrast-enhanced MRI images. This dataset had four types of images: glioma (926 images), meningioma (937 images), pituitary gland tumor (901 images), and healthy brain (500 pictures). Each picture was taken in a sagittal, axial, or coronal plane [30]. Table 1 represents the dataset description of the dataset used in the study.

Table 1: Dataset Description

Tumor Images	**Testing Images**	**Training Images**
Glioma	100	826
Meningioma	115	822
Pituitary Gland Tumor	74	827
Healthy Brain	105	395

3.2. Techniques Used

Several methods are vital, each offering distinct benefits, in the area of early MRI-based brain tumor identification. In addition to its superior performance in semantic segmentation tasks, the U-Net CNN architecture is well-suited for accurately outlining tumor boundaries. Accurate tumor localization relies on its capacity to capture spatial connections within pictures. CNNs can detect and pick up on minor patterns indicative of cancer because they are so good at learning hierarchical features from complex datasets like MRI scans. Classical ML models like SVM could successfully classify MRI characteristics into tumor and non-tumor categories. SVMs perform at binary classification problems and are especially helpful while working with limited datasets. The ensemble learning approach Random Forest is very effective in estimating the significance of features in high-dimensional datasets. Whenever used for the task of identifying brain tumors, Random Forest can provide reliable predictions by integrating multiple features obtained from MRI scans.

3.2.1. U-Net

U-Net is an image recognition system based on a CNN architecture designed specifically for semantic segmentation tasks. In 2015, Olaf Ronneberger, Philipp Fischer, and Thomas Brox came up with this concept. The U-shape inspired this name. Pointwise or detailed localization can be achieved through this whereas it also broadens the search adequately. It has a descending contracting pathway that uses max pooling layers to shrink spatial dimensions and convolutional layers to enhance feature maps. In this part of the network, hierarchical features are extracted from the input image [31].

The initial design of U-net attempted to improve cell segmentation in microscope images, which is a component of biomedical image segmentation [32]. This technique is widely used in satellite imagery segmentation, road scene understanding, and other fields as a result of its successful implementation.

Complex and intricate structures found in medical images can be handled with ease by U-Net which makes it possible for the algorithm to detect brain tumors effectively through image segmentation. The design of U-Net makes it well-suited for jobs like tumor identification and delineation in medical pictures because it is built to capture both local features and global context.

U-Net has emerged as the standard for semantic segmentation, and its success has led to numerous derivative works attempting to enhance its fundamentals in different ways [33]. Figure 2 displays U-Net architecture [34].

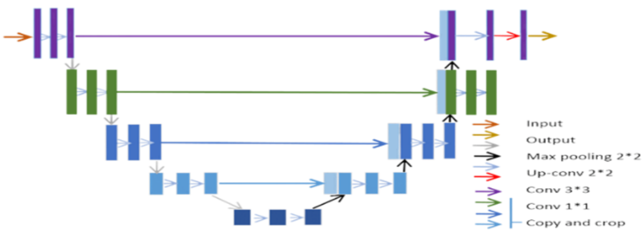

Fig 2: U-Net Architecture

3.2.2. Convolutional Neural Networks (CNN)

Convolutional neural networks are a type of deep neural network created to perform image processing and recognition tasks. They are designed using ideas of the human visual system: multisensory neural networks. Some examples of such layers are the convolutional layer, pooling layer, and fully connected layer among others [35]. Applying filters to input data, the network can automatically learn spatial hierarchies and hierarchical features through convolutional layers [36]. Pooling layers are used to reduce the spatial dimensions of the data and this way they help preserve the data's integrity by excluding the less significant parts. These networks have been very successful in numerous computer vision tasks such as image classification, object detection, and face recognition. Brain tumor identification extracts features using CNN because of their ability to automatically learn hierarchical and spatially invariant representations from imaging data [37]. Figure 3 shows the architecture of the CNN [38].

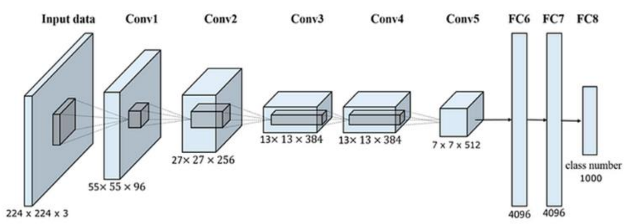

Fig 3: CNN Architecture

3.2.3. Support Vector Machine (SVM)

In the realm of supervised machine learning, Support Vector Machine (SVM) excels in solving difficult classification and regression issues [39]. Vladimir Vapnik and his colleagues developed the SVM method in the 1990s to find the hyperplane that most cleanly separates data points into their appropriate groups [40]. SVM is well-known for its capacity to handle both linear and non-linear relationships via kernel functions, and it shines in high-dimensional fields. SVM performs well in such scenarios and can handle a large number of features (dimensions) effectively. Support vectors, or data points that are closest to the decision border, constitute the foundation of the algorithm. Images, texts, and even biological data have all benefited from SVM's effective use in classification tasks. Because of its high efficiency and sound theoretical basis, it has found widespread use in a variety of fields [41]. Figure 4 shows the SVM architecture [42].

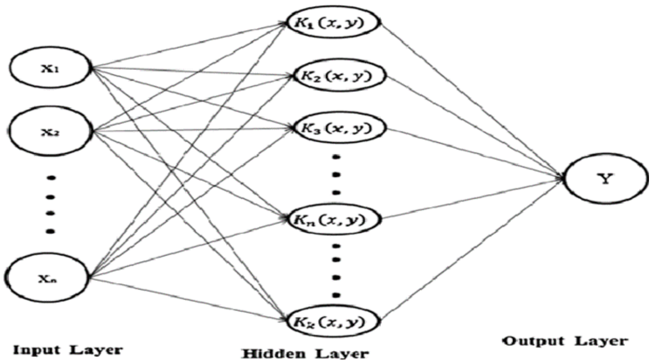

Fig 4: SVM Architecture

3.2.4. Random Forest (RF)

Random Forest is widely used in machine learning for both classification and regression ensemble learning [43]. During training, it constructs a set of decision trees and then returns to the middle class in classification problems or the average prediction when dealing with regression challenges. The training data used to construct each tree in a Random Forest is chosen at random, and at each node, characteristics are checked at random [44]. Including variables in each tree enhances the model's performance. Summing up the results of all trees in a forest gives the final forecast [45]. Random Forest has become popular not only in industry but also academia majorly because of its robustness and ability to give accurate predictions. As a method, it was first mentioned by Leo Breiman in 2001 and has been researched by many scholars since then to understand its strengths and weaknesses [46]. Random forest structure is illustrated in Figure 5 [47].

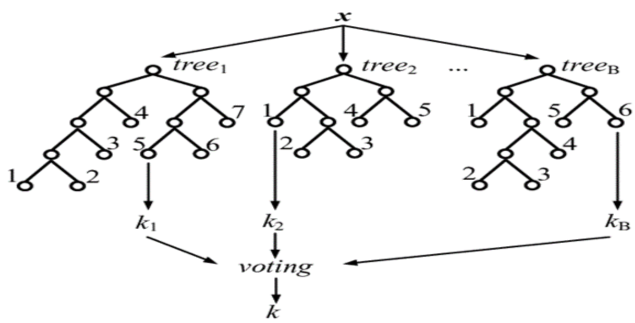

Fig 5: Random Forest Architecture

3.3. Proposed Methodology

This step involves having a large dataset with accurate annotations as well as partnering with various medical centers to obtain data from different sources when developing a brain tumor detection model from MRI scans. In this part, an MRI scan will be used to develop a brain tumor detection model. Data preparation before segmentation includes data cleaning, standardization, and normalization. U-Net architecture is then fine-tuned for better results in image segmentation. The features are extracted using pre-trained convolutional neural networks and transfer learning is used. Hybrid models use both U-Net along other traditional ML methods during their development. First, the dataset is segmented before training, validation, and testing take place. Evaluation measures like Accuracy, Precision, Recall, and F1 score are used while cross-validation ensures that the model remains consistent over different subsets of the data. The ultimate aim of this elaborate procedure is to create a dependable brain tumor detection model that offers precision. Figure 6 displays the proposed architecture of the study.

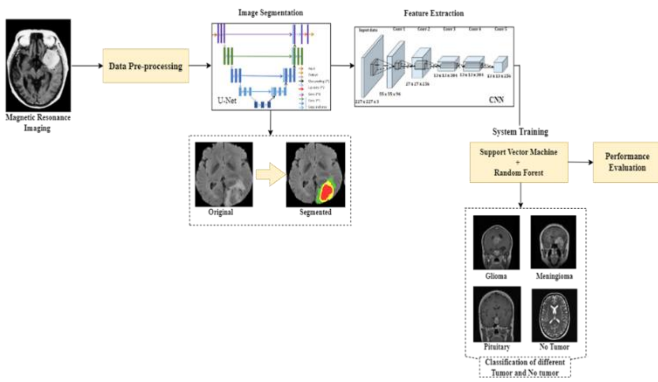

Fig 6: Proposed Architecture

3.4. Proposed Algorithm

Start

1. **Data Gathering:**

Mathematical representation: $\boldsymbol{D} = \{(\boldsymbol{X_i}, \boldsymbol{Y_i})\}$

X_i: MRI scan images,

Y_i: Corresponding annotations

2. **Data Preprocessing:**

Cleaning: Use image processing methods like noise suppression and artifact elimination.

Standardizing and Normalizing: Reducing the range of pixel values (from 0 to 1).

3. **Image Segmentation (U-Net):**

U-Net architecture has routes for encoding (downsampling) and decoding (upsampling).

The loss function for segmentation: $\boldsymbol{L} = \sum_{i=1}^{N}[\boldsymbol{y_i}.\,\mathbf{log}(\hat{\boldsymbol{y}}_i) + (\mathbf{1} - \boldsymbol{y_i})]$

Log $(\mathbf{1} - \hat{\boldsymbol{y}}_i)$, where $\boldsymbol{y_i}$ is the ground truth and $\hat{\boldsymbol{y}}_i$ is the predicted segmentation mask.

4. **Fine-tuning:**

Getting the U-Net model right by using optimization methods based on gradient descent, like Adam or stochastic gradient descent (SGD).

5. **Feature Extraction (Transfer Learning):**

Utilize convolutional neural networks (CNNs) that have already been taught for feature extraction.

In transfer learning, some layers are frozen, and others are trained again on the brain tumor dataset.

6. **Model Development (Hybrid Strategy):**

Using several traditional machine learning methods together with U-Net, probably using ensemble techniques

7. **Dataset Splitting:**

The data should be split into test, training, and validation sets.

8. **Evaluation Measures:**

Accuracy, Precision, Recall, and F1 Score

End

4. Results and Implementation

An ensemble of ML models was used to experiment, including U-Net and CNN, and the proposed SVM and RF models. Results from these approaches were evaluated using the dataset.

4.1. Feature extraction hyperparameter of CNN

Table 2, the CNN model's hyperparameters that were used for feature extraction. The "Input Size," defines the width, height, and channel dimensions of the input images. The subsequent rows describe the CNN's architecture in detail, including values for parameters like the number of filters and kernel size for the first and second convolutional layers ("Conv1 Filters," "Conv1 Kernel Size," "Conv2 Filters," "Conv2 Kernel Size"), as well as activation functions and padding types for these layers. Further, it specifies the values for the max pooling and upsampling layers' parameters ("Pool1 Size," "Up1 Size"). Activation functions and the number of filters used for binary segmentation are displayed in the "Output Layer" row. It also defines the learning rate, batch size, loss function, optimization algorithm ("Optimizer"), and number of epochs for training the model, among other important training parameters. To set up and comprehend the CNN's architecture and training procedure for picture segmentation, this data is vital.

Table 2: Feature extraction hyperparameter table of CNN

Hyperparameter	Value	Description
Input Size	(256, 256, 1)	Dimensions of the input images (width, height, channels)
Conv1 Filters	64	Number of filters in the first convolutional layer
Conv1 Kernel Size	(3, 3)	Kernel size of the first convolutional layer
Conv1 Activation	ReLU	Activation function for the first convolutional layer
Conv1 Padding	Same	Padding type for the first convolutional layer
Pool1 Size	(2, 2)	Pooling size for the first max pooling layer
Conv2 Filters	128	Number of filters in the second convolutional layer
Conv2 Kernel Size	(3, 3)	Kernel size of the second convolutional layer
Conv2 Activation	ReLU	Activation function for the second convolutional layer
Conv2 Padding	Same	Padding type for the second convolutional layer
Up1 Size	(2, 2)	Upsampling size for the first upsampling layer
Output Layer	1	Number of filters in the output layer (binary segmentation)
Output Activation	Sigmoid	Activation function for the output layer
Loss Function	Binary Crossentropy	The loss function for model training
Optimizer	Adam	Optimization algorithm for model training
Learning Rate	Default	The learning rate for the Adam optimizer
Batch Size	32	Number of samples per gradient update during training
Number of Epochs	10	Number of times the entire dataset is passed through the model

4.2. Hyperparameter of the Ensemble Classifier

Table 3 shows the Ensemble Classifier's hyperparameters that were used for brain tumor categorization.

Table 3: Ensemble Classifier's hyperparameters that were used for brain tumor categorization

Hyperparameter	SVM	Random Forest	Voting Classifier
C(regularization parameters)	[0.1, 1, 10]	N/A	N/A
Kernel	['linear', 'rbf']	N/A	N/A
gamma	['scale', 'auto']	N/A	N/A
n_estimators	N/A	[50, 100, 200]	[10, 50, 100]
max_depth	N/A	[None, 10, 20]	N/A
min_samples_split	N/A	[2, 5, 10]	N/A
min_samples_leaf	N/A	[1, 2, 4]	N/A
voting	N/A	N/A	['hard', 'soft']

4.3. Performance of Machine Learning Classifier

Table 5 shows the results of a classification test using three different machine learning models: Ensemble Model, Random Forest, and Support Vector Machine. The models are assessed based on four criteria: Accuracy, Precision, Recall, and F-score.

Recall and F-score are both highest for Random Forest at 95%, but Accuracy is lowest at 82%. That it accurately identifies most positive situations but fails to catch some true positives is a reasonable interpretation. Precision is 98% for SVM, Accuracy is 63.53% and Recall is 73%. So, it's great at predicting false positives but often misses the mark when it comes to positive cases. Impressively, the Ensemble Model outperforms all other models concerning Accuracy (98.25%), Precision (98.89%), Recall (97%), and F-score (96%). Since it accurately identifies positive and negative cases, it is likely the top-performing model in the final analysis. Table 4 shows the Performance of Machine Learning Classifier

Table 4: Performance of Machine Learning Classifier

Model	Precision	Recall	F-score	Accuracy
Random Forest	94 %	95 %	94 %	82 %
SVM	98 %	73 %	84 %	63.53 %
Ensemble Model	98.89 %	97 %	96 %	98.25 %

4.4. Model Accuracy and Loss Graph

The validation accuracy begins at approximately 0.979 and grows marginally to approximately 0.9798 after 8 epochs, as seen in Figure 7. The graph shows that the model can take in information from the training set and use it to get better at the validation function. The model might be getting close to its optimal performance on this task, though, since the improvement in accuracy is quite small. It appears from this graph that the deep learning model can do well on the train simulator challenge, but there might not be a lot of scope for improvement.

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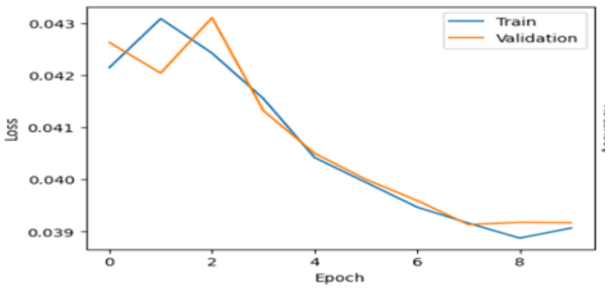

Fig 7: Ensemble Loss

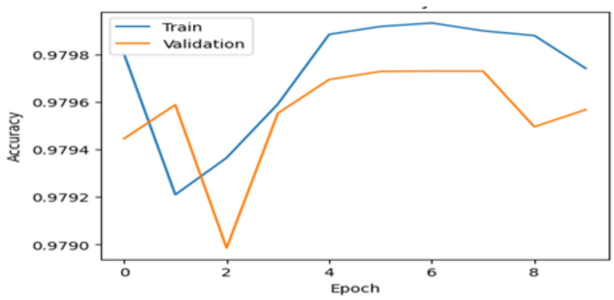

Fig 8: Ensemble Accuracy

4.5. Ensemble Confusion Matrix

An ensemble classifier's efficiency in a four-category classification problem is illustrated by the ensemble confusion matrix. The ensemble classifier considers the predictions of numerous base classifiers before arriving at a final prediction (Fig 9).

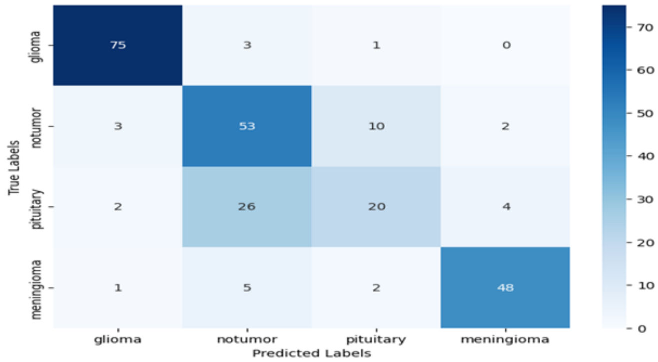

Fig. 9. Ensemble Confusion Matrix.

4.6. Predicted Result by the Model

As shown in Figure 10, the suggested model could accurately identify a meningioma brain tumor in the input image.

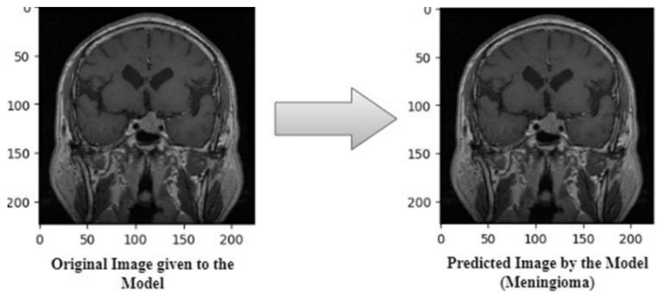

Fig 10: Result provided by the proposed model

5. Comparative Analysis

Classifier performance is determined by comparing studies and evaluating the classifiers' accuracy. Comparison among classifiers such as 2D CNN, VGG-16, and Ensemble method. The Ensemble methods have the highest 98.25% accuracy. Second, the EfficientNetB1 method has the lowest 87.67 % accuracy. Table 6 shows the comparison of the above-related work based on temperature.

Table 5: Comparative Analysis

Author	**Technique**	**Outcome**
Saeedi et al., (2023) [20]	2D CNN	96.45 %
Filatov et al., (2022) [21]	EfficientNetB1	87.67 %
Proposed method	Ensemble (RF+SVM)	98.25 %

6. Conclusion

Brain tumors are a major focus of this study, which concludes by outlining the problem and the difficulties that people of all ages face as a result. Advancements in early brain tumor identification through MRI-based diagnostics have been greatly facilitated by the integration of convolutional deep learning and machine learning techniques. Specifically, the Ensemble Model (RF + SVM) has been utilized. With impressive measures including a Recall of 97%, an F-score of 96%, an Accuracy of 98.25%, and a Precision of 98.89%, the Ensemble Model emerges as the clear winner in the thorough comparative analysis. The Ensemble Model’s performance is incredible because it has great power to accurately diagnose meningioma brain cancers and can also recognize both positive cases and negative ones. This novel approach is capable of early identification of brain tumors with accuracy that could entirely change the field of brain tumor diagnostics. These advances are important as they can lead to better patient outcomes due to more efficient and timely ways of treatment. The findings in this study contribute important information for the ongoing efforts on trying to address public health implications regarding brain tumors, which are closer to a day when early detection becomes paramount in improving the lives of those who suffer from these conditions. Investigate complex Deep Learning Architectures or ensemble models to further improve tumor detection performance.

Acknowledgements

I would like to express my heartfelt gratitude to all the individuals and organizations who have contributed to the successful completion of my research paper on " Early Detection Of Brain Tumors: A Comprehensive Study On MRI-Based Diagnosis Using A Combination Of Convolutional Deep Learning And Machine Learning Techniques." Their unwavering support, guidance, and encouragement have been invaluable throughout this academic journey. I extend my deepest appreciation to my supervisor who supported me during this research whose expertise and dedication have been instrumental in shaping the direction of this research. Their insightful feedback and constant motivation have greatly enriched the quality of this work. In conclusion, the successful completion of this research paper would not have been possible without the collective efforts and support of all. Thank you all for being an integral part of my academic journey.

Author contributions

Patel Rahulkumar Manilal: Conceptualization, Methodology, Software, Field study, Visualization, Investigation **D. J. Shah:** Data curation, Writing-Original draft preparation, Software, Validation., Field study, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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