Detection of Brain Tumor from Brain MRI Images with the Help of Machine Learning & Deep Learning

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Summary
A cerebrum or brain tumor is an unusual development of tissues inside the brain. Recognition of cerebrum tumors is a testing issue because of the complex design of the brain. MRI can give detailed data about human delicate tissue life systems, which is useful in finding brain tumors. The Discovery of cerebrum tumors includes various stages; for example, picture preprocessing, segmentation, highlight extraction, and classification. This paper sums up the investigation of different procedures for cerebrum tumors from MRI pictures. This examination presents an exhaustive survey of customary machine learning techniques and advancing deep learning techniques for brain tumor analysis. This survey paper distinguishes the key accomplishments reflected in the presentation estimation measurements of the applied calculations in the three analysis measures. Furthermore, this examination talks about the key discoveries and causes to notice the exercises learned as a guide for future exploration.

Keywords:
Magnetic Resonance Imaging, Support Vector Machine, Naïve Bayesian, Multi-Layered Perceptron, Convolutional Neural Networks, Control Experiment.

1. Introduction

Years After the invention of artificial intelligence, their techniques, and algorithms healthcare sector is modernized. Due to the advancement in the artificial intelligence Healthcare sector is also advanced in the area of diagnostics and clinical technologies etc. Today is the period of e-healthcare of patients by the doctors with the help of information technology and artificial intelligence. A brain tumor is abnormal tissues or cells in the brain which may be benign or malignant[1]. In the case of benign cancerous cells or tissues, it could be cured after some sessions of treatment. Because these types of tumors have less growth to increase and spread into the body. These are also called Grade 1 and Grade 2 brain tumors which are cured able if detected at this stage. Otherwise, benign tumor converted into Grade 3 or 4 which is malignant and has very high growth to spread into the body. Our goal through this topic is to detect tumors in the brain at an as early stage as possible may be at grade 1 or grade 2 accurately with the help of MRI images of the brain. Because 90% of patients died when a tumor was detected at stage 3 or 4[2].

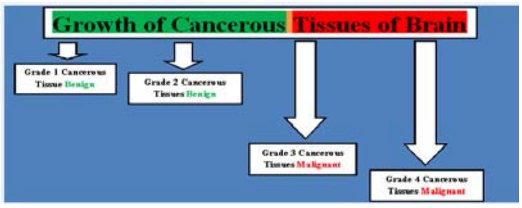

Fig. 1.

Types of Brain Tumors

2. Literature Review

In this paper study distinguishing proof and classification of tumors in the human psyche from MRI images at the beginning phase assume a critical part in the analysis of such sicknesses. This work gives the novel Deep Neural organization less number of layers and less mind-boggling in planned named U-Net(LU-Net) for the recognition of tumors. The work involved arranging the cerebrum MR images into ordinary and unusual classes from the dataset of 253 images of high pixels. The MR images were first resized, edited, preprocessed, and increased for the exact and quick preparation of deep neural models.

The presentation of the Lu-Net model is assessed utilizing five kinds of factual appraisal measurements Precision, Recall, Specificity, F-score, and Accuracy, and contrasted and the other two sorts of models Le-Net and VGG-16. The CNN models were prepared and tried on expanded images and approval is performed on 50 undeveloped information. The general precision of Le-

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Net, VGG-16 and the Proposed model got were 88%, 90%, and98% separately[3].

In the view of the study the segmentation, location, and extraction of tainted tumor regions from attractive reverberation (MR) images are an essential concern yet a monotonous and time taking undertaking performed by radiologists or clinical specialists, and their exactness relies upon their experience as it were. In this examination, to work on the presentation and decrease the intricacy includes in the clinical images segmentation measure, we have explored Berkeley wavelet change (BWT) based on brain tumor segmentation. Moreover, to work on the exactness and quality pace of the help vector machine (SVM) based classifier; applicable highlights are extricated from each portioned tissue. The trial results accomplished 96.51% exactness, 94.2% particularity, and 97.72% affectability, showing the adequacy of the proposed method for distinguishing typical and unusual tissues from mind MR images. The trial results likewise got a normal of 0.82 dice likeness list coefficient, which demonstrates better cover between the mechanized (machines) removed tumor area with physically extricated tumor locale by radiologists. [4].

This exploration paper clarifies that brain tumor classification assumes a significant part in clinical analysis and successful treatment. The study proposes a strategy for cerebrum tumor classification utilizing a troupe of deep highlights and AI classifiers. In this proposed system, it receive the idea of move learning and use a few pre-prepared deep convolutional neural networks to extricate deep highlights from cerebrum attractive reverberation (MR) images. To assess the various types of pre-prepared models as a deep element extractor, AI classifiers, and the viability of a group of deep components for brain tumor classification. Experimental results demonstrate that an ensemble of deep features can help improve performance significantly, and as a rule, support vector machine (SVM) with outspread premise work (RBF) part outflanks other AI classifiers, particularly for huge datasets[5].

This paper examines the programmed brain tumor discovery and classification of MR Images utilizing a deep learning algorithm. The Faster R-CNN algorithm was picked for identifying the tumor areas and ordering them into three classifications in particular glioma, meningioma, and pituitary tumor. For the Faster R-CNN algorithm execution, a deep convolutional network architecture called VGG-16 was utilized as the base network. The proposed algorithm effectively recognizes the brain tumor areas by picking the optimal bounding box generated by RPN. A superior mAP has been accomplished for identifying the brain tumor utilizing the test dataset. The proposed algorithm utilizes VGG-16 architecture as a base layer for both the locale proposition network and the classifier network. Identification and classification aftereffects of the algorithm show that it can accomplish a normal accuracy of 75.18% for glioma, 89.45% for meningioma, and 68.18% for a pituitary tumor. As a presentation measure, the algorithm accomplished a mean normal accuracy of 77.60% for every one of the classes[6].

This venture examined with pre-preparing stage comprising inclination field rectification, force, and fix standardization in CNN-based strategy for segmentation of brain tumors in MRI pictures. The MRI pictures have the issue of power inhomogeneity for example distinctive force ranges among similar groupings and procurement scanners. This issue is amended by the N4ITK strategy, which empowers to recognize the dark matter, white matter, and the head independently. This model accomplishes superior before a couple of imbalanced classification brain tumor datasets with 95% precision after being prepared by a 6-crease cross-approval method and Adam optimizer. This Hybrid architecture is likewise contrasted and three famous shrewd techniques that are accessible in the writing. Because of this exploration, hybrid construction is a beneficial instrument that can be utilized in clinical picture handling applications[7].

In this paper, the study introduced three novel ConvNet architectures for evaluating brain tumors non-intrusively, into HGG and LGG, from the MR pictures of tumors and investigate move learning for a similar errand, by fine-tuning two existing ConvNet models. An improvement of about 12% as far as classification exactness on the test dataset was seen from deep ConvNets contrasted with shallow learning models and additionally saw that current ConvNets prepared on regular pictures performed sufficiently by just fine-tuning their final convolution layer on the MRI dataset. The study proposed a plan for fusing volumetric tumor data utilizing multi-planar MRI slices that accomplished the best testing exactness of 97.19%. So, infer that deep ConvNets could be a plausible option in contrast to careful biopsy for brain tumors[8].

Readings explain that the cutting edge progresses in deep learning leads the examinations and investigates in AI to advance from including designing to structural designing. Multi-classification of brain tumors for the early finding purposes utilizing CNN models whose practically all hyper-boundaries are consequently tuned utilizing network search. Three strong CNN models for three diverse brain tumor classification assignments through openly clinical picture datasets are assigned. Location of brain tumor is accomplished with high exactness, for example, 99.33% Moreover, classification of brain MR into glioma, meningioma, pituitary, ordinary brain, and metastatic is acquired with a fulfilling precision of 92.66%. At last, classification of glioma brain tumors into grade II, grade III, and grade IV is performed with an exactness of 98.14%. The CNN models set up in this paper can be utilized to help doctors and radiologists in approving their underlying evaluation for brain tumor multi-classification purposes[9].

According to the study, without the pre-trained Keras model, the train exactness is 97.5% and approval precision is 90.0%. The approval result had the best figure of 91.09% as accuracy. It is seen that without utilizing the pre-trained Keras model, albeit the preparation precision is >90%, the general precision is low, not normal for where the pre-prepared model is utilized. Additionally, when prepared dataset without Transfer learning, the calculation time was 40 min while when utilized Transfer Learning, the calculation time was 20min. Subsequently, preparing and calculating time with the pre-trained Keras model was half lesser than without. Chances of over-fitting the dataset are higher when preparing the model without any preparation instead of utilizing pre-trained Keras. Among the Keras models, it is seen that ResNet 50 has the best in general exactness just like the F1 score. ResNet is an incredible spine model that is utilized oftentimes in numerous PC vision assignments. Exactness and Recall both can't be improved as one comes at the expense of the other[10]. So, use the F1 score as well. Move learning must be applied if low-level highlights from Task 1(image acknowledgment) can be useful for Task 2(radiology conclusion). For an enormous dataset, Dice misfortune is liked over Accuracy. For the little size of information, should utilize basic models, pool information, tidy up information, limit experimentation, use regularization/model averaging, certainty spans, and single number assessment metrics. To stay away from this, we can screen testing precision, use exceptions and commotion, train longer, and think about the difference[11].

The reason for the study is to foster a deep-learning-based methodology for finding brain metastasis on MRI. The investigation type is Retrospective. Two radiologists analyzed and administered an explanation of metastases on brain MRI as ground truth. The presentation of the algorithm was assessed by utilizing affectability, bogus positive rate, and recipient's working trademark (ROC) bends. The location execution was evaluated both per-metastases and per-cut. Testing on held-out brain MRI information exhibited 96% affectability and 20 bogus positive metastases for every sweep. The outcomes showed 87.1% affectability and 0.24 bogus positive metastases per cut. The region under the ROC bend was 0.79. [12].

The principal objective of this examination is to plan effective independent brain tumor classification and restriction of the tumor with high precision, execution, and low intricacy. In the first place, the regular brain tumor classification is performed by utilizing CNN dependent on ResNet50 architecture. Further to confine the tumor in the given picture and to draw an edge around the tumor another convolution neural network-based classification, for example, ResUNet based segmentation is acquainted with the restriction of tumor in the proposed conspire. The preparation exactness is 96%. Because of the significance of the finding given by the doctor, the precision of the specialists will help in diagnosing the tumor and treating the patient with expanded exactness in a clinical determination by the proposed strategy[13].

3. Methodology

In the research methodology section, we mention the method through which proceed different steps of study and performed a systematic literature review on Analysis for detection of brain tumor from MRI images of the brain. After that the study develop a control group through which validation carried out by performing experiment on given dataset [14].

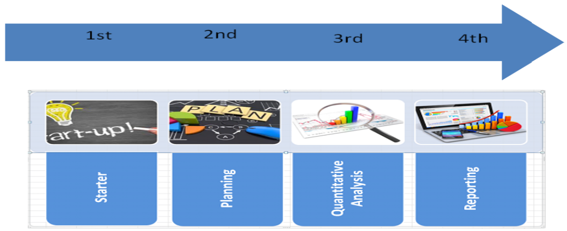


Fig. 2. Methodology

3.1 Starter

In the Starter phase, the study discusses the significance of the analysis for the detection of brain tumors and its systematic literature review.

3.1.1 Significance

1) This paper creates awareness about Brain tumors and their types. Describe how Grade 1, Grade 2, Grade 3, and Grade 4 tumors are different from each other. Compare traditional and new techniques for the detection of a brain tumor in its early stages. This is very difficult to detect and removed because these are very fast to spread out. Discover new and significant solutions for the detection of a brain tumor in its early stages accurately through this review because no adequate solution has been found till now due to the incremental, time-consuming, and fast-spreading nature of cancerous brain cells or tissues[15].

3.2 Planning

In this phase guidelines of Barbara and charters are used for the identification of needs for a systematic review, objectives and research questions are developed [16].

3.2.1 Objectives

At first investigate the brain tumor then find out the intensity of seriousness of brain tumors in the brain.and their types. It is also explore the recent techniques used for the detection of brain tumors, compare and analyze them. At the end choose the best solution [17].

3.2.2 Research Questions

Through the literature review the study first understand the brain tumor, what are their effects on humans and secondly how brain tumors can be detected and classified. Thirdly, how many strategies and detection systems are used and also check their effectiveness of them. At last, how do we choose the best solution for brain tumor detection[18]?

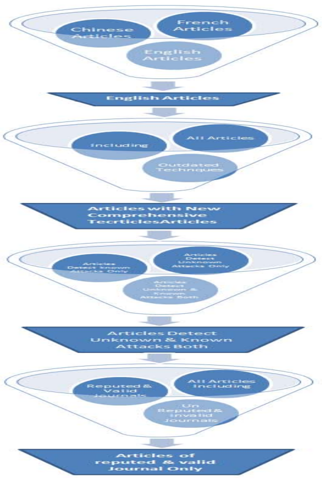


Fig. 3. Research Papers Filter

3.2.3 Digital Public Libraries.

The scheme of study uses free public digital libraries and research papers available for digital users like Google Scholar, ACM Digital Library, IEEE Xplore, Hindawi.

3.2.4 Criteria

Only research articles books are considered which are written in the English language, presented new techniques comprehensively, provide analysis for the detection of brain tumors and their types from reputed, valid journals.

3.3 Quantitative Analysis

After the planning phase with the development of protocol and criteria, the study performed an extraction of relevant research papers with their applications for the detection of brain tumors from MRI images and compare with control experiment for varification [21].

3.3.1 Data Analysis

2) The method to automatically detect brain tumors from MRI images against already feeded data The study initiate a systematic study of the characteristics of brain tumors and their impacts on the human world. Generally, brain tumor is divided into four grades. Grade 1 and grade 2 tumor are called benign tumor which is less effective and slow speed to spread in the brain and body of a human. The goal of the study is to detect brain tumors automatically at this early stage accurately with the help of MRI images. On the other hand grade, 3 and grade 4 brain tumors are called malignant which are very much effective and fast to spread out in the brain and body of the human. Malignant cancerous tissues are treated with chemotherapy and radiotherapy.

3) ***오류! 참조 원본을 찾을 수 없습니다.*** *shows a summary of all heading levels.* Take a look at multiple detection approaches, how they operate, the strengths and weaknesses of each, along with a brief discussion of deep learning techniques with a different algorithm. There are several different approaches for the detection of brain tumors which are given below in a table, including deep learning, machine learning, and artificial intelligence based techniques, and there is an ongoing debate in the healthcare industry over the efficacy - or lack thereof - of each of these approaches[22].

Table 1. Models Used for Detection of Brain Tumor

Sr. No.	Models Used for Detection of Brain Tumor
1	AlexNet
2	HCS
3	SVM
4	PatchNet
5	VolumeNet
6	VGGNet
7	ResNet
8	ANFC-LH
9	NB
10	CART
11	MLP
12	k-NN
13	Hybrid CNN-NADE
14	ResNet-50
15	VGG-16
16	GoogleNet
17	Inception V3

It is also compare different methods used for the detection of brain tumors based on collected data and proposed the best method for detecting and classifying brain tumors after analysis over historical information and behavioral patterns and made available to the research community[23].

3.4 *Reporting*

In this phase, it is explained the analyzed data in context with the answer to research questions from the selected papers. Different techniques are discussed with their effectiveness and drawbacks. We compared them for the detection of brain tumors and also mentioned the best one if possible[24].

5. Results and Discussion

3.5 *Findings*

In this phase the study selected 75 papers out of 500 for replying to the research questions asked in the methodology section.

Table. 2. Search Strings

Sr. No.	Search String	Papers
1	Detection of brain tumor from MRI images of brain	25
2	Brain Tumor Detection	21
3	Brain tumor detection by artificial intelligence	7
4	cancer in brain	4
5	Brain Tumor	4
6	brain tumor detection by deep learning	14
Total including all search Strings		75

Table 2 shows the year-wise papers with search strings. These papers are used for answering research questions which are from 2017 to 2021.

3.6 *Analysis*

This paper illustrates the severeness of brain tumors and the reasons that's why conventional detection systems are useless against different types of brain tumors. It is a very hot issue in today's world to detect brain tumors accurately in the early stages as diseases increase very greatly. In this paper, we discuss and analyze different techniques. We have also discussed and analyzed problems with existing techniques regarding brain tumors and trying to provide the best but not perfect solution for the detection of brain tumors. In this combined approach, the different level has been involved as we used… The results of the study showed that a hybrid of all techniques is more appropriate in the modern world. Results indicate that from different architectures, first of all, the DenseNet-169 deep feature alone is a good choice in case the size of the MRI dataset is very small and the number of classes is 2 like normal tissues and tissues with tumors, secondly the ensemble of DenseNet-169, Inception V3, and ResNeXt-50 deep features is a good choice in case the size of MRI dataset is large and the number of classes is 2 like normal tissues and tissues with tumor and thirdly the ensemble of DenseNet-169, ShuffleNet V2, and MnasNet deep features is a good choice in case the size of MRI dataset is large and there are four classes like normal tissues, glioma tumor, meningioma tumor, and pituitary tumor[25].

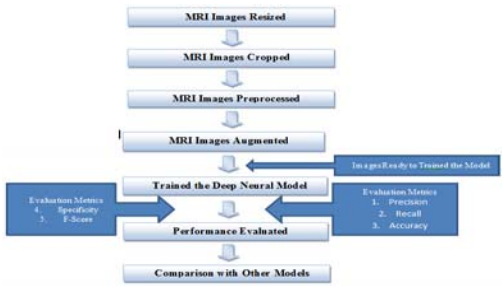


Fig. 4. Generic Data Flow of Deep Learning Model

Also, in most cases, SVM with RBF kernel outperforms other ML classifiers for the MRI-based brain tumor classification task. In summary, our proposed novel feature ensemble method helps to overcome the limitations of a single CNN model and produces superior and robust performance, especially for large datasets[26]. The Faster R-CNN algorithm was chosen for detecting the tumor regions and classifying them into three categories namely glioma, meningioma, and pituitary tumor but not good for the percentage area of tumors concerning the brain[27].

Table 3: Comparison of Models in Context with Accuracy

Sr. No	Model	Accuracy
1	AlexNet	96.60%
2	HCS	93%
3	SVM	87.92%
4	PatchNet	84.81%
5	VolumeNet	97.29%
6	VGGNet	83.66%
7	ResNet	84.91%
8	ANFC-LH	85.83%
9	NB	69.48%
10	CART	70.78%
11	MLP	78.57%
12	k-NN	73.81%
13	Hybrid CNN-NADE	96.01%
14	ResNet-50	86.11%
15	VGG-16	84.01%
16	GoogleNet	94.11%
17	Inception V3	85.10%

In some cases, the SVM model is best as seen below

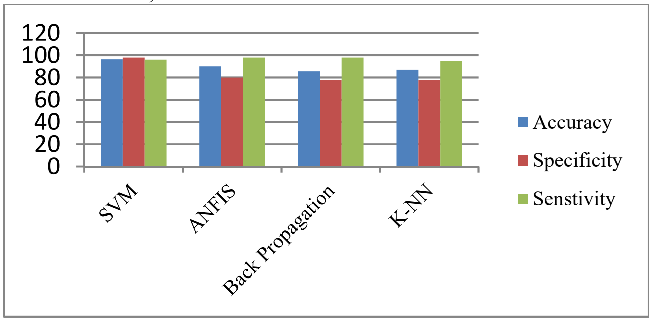


Fig. 5. Comparison of Model

4.3 *Main Results*

Classifier Reports regarding Detection of Brain Tumor by Applying Machine Learning Algorithm on Single Dataset

Machine learning Algorithms and classifiers applied to given datasets are as, Decision Tree, Random Forest, Naïve Bayesian, MLP, and SVM.

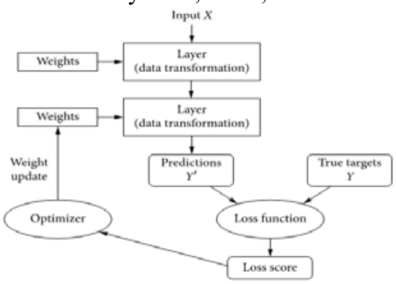
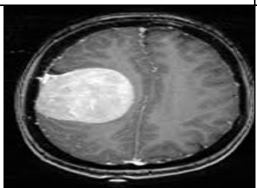
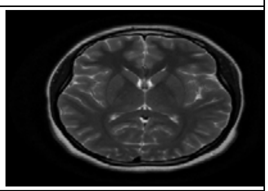
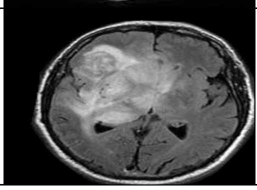
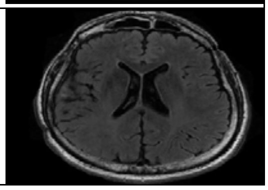
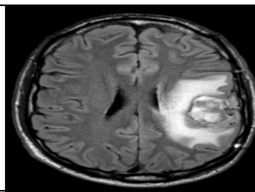
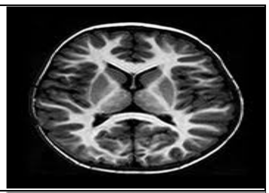
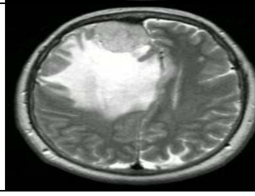
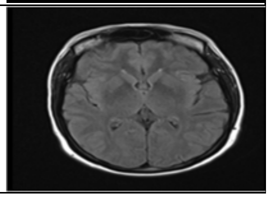


Fig. 6. Process of Neural Network

A dataset is downloaded from the site www.kaggle.com which has a total of 253 preprocessed MRI images. We show some sample dataset images which are given below. There are two classes of data sets for classification. The first class is the Tumorous MRI images class and the second is the class of the Non-tumorous image.

4.3.1 *Sample Dataset*

Sr. No.	Image with Tumor Detected	Image with No Tumor Detected
1		
2		
3		
4		

4.3.2 *Control Experimentation for Verification*

These are the control experiments performed for the verification of results produced by the machine learning classifiers

4.3.3 *Decision Tree*

	Decision Tree	
1	Precision	80%
2	Recall	80%
3	F-Score	80%
4	Accuracy	80%

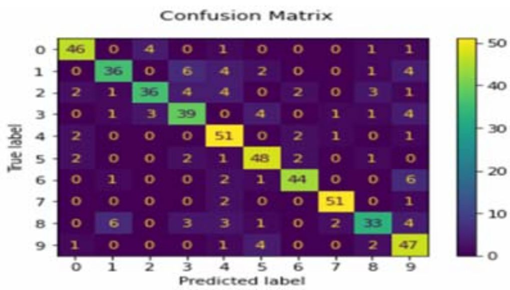
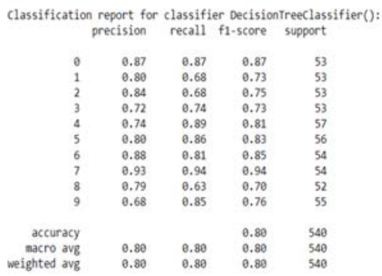


Fig. 7. Decision Tree



Classification report for classifier DecisionTreeClassifier():

	precision	recall	f1-score	support
0	0.87	0.87	0.87	53
1	0.80	0.68	0.73	53
2	0.84	0.68	0.75	53
3	0.72	0.74	0.73	53
4	0.74	0.89	0.81	57
5	0.80	0.86	0.83	56
6	0.88	0.81	0.85	54
7	0.93	0.94	0.94	54
8	0.79	0.63	0.70	52
9	0.68	0.85	0.76	55
accuracy			0.80	540
macro avg	0.80	0.80	0.80	540
weighted avg	0.80	0.80	0.80	540

Fig. 8. Results of Neural Network

4.3.4 Random Forest

	Random Forest	
1	Precision	80%
2	Recall	78%
3	F-Score	77%
4	Accuracy	79%

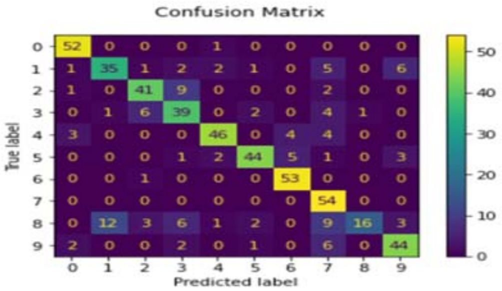


Fig. 9. Random Forest Confusion Matrix

Classification report for classifier RandomForestClassifier(max_depth=2, random_state=0):

	precision	recall	f1-score	support
0	0.88	0.98	0.93	53
1	0.73	0.66	0.69	53
2	0.79	0.77	0.78	53
3	0.66	0.74	0.70	53
4	0.88	0.81	0.84	57
5	0.88	0.79	0.83	56
6	0.85	0.98	0.91	54
7	0.64	1.00	0.78	54
8	0.94	0.31	0.46	52
9	0.79	0.80	0.79	55
accuracy			0.79	540
macro avg	0.80	0.78	0.77	540
weighted avg	0.80	0.79	0.77	540

Fig. 10. Results of Random Forest

4.3.5 *Naïve Bayesian*

	Naïve Bayesian	
1	Precision	84%
2	Recall	82%
3	F-Score	83%
4	Accuracy	83%

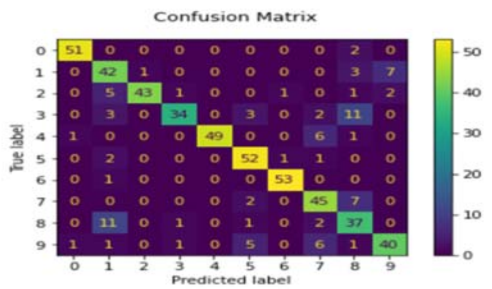


Fig. 11. Naive Besian Confusion Matrix

Classification report for classifier GaussianNB():

	precision	recall	f1-score	support
0	0.96	0.96	0.96	53
1	0.65	0.79	0.71	53
2	0.98	0.81	0.89	53
3	0.92	0.64	0.76	53
4	1.00	0.86	0.92	57
5	0.83	0.93	0.87	56
6	0.96	0.98	0.97	54
7	0.73	0.83	0.78	54
8	0.59	0.71	0.64	52
9	0.82	0.73	0.77	55
accuracy			0.83	540
macro avg	0.84	0.82	0.83	540
weighted avg	0.84	0.83	0.83	540

Fig. 12. Results of Naive Besian

4.3.6 *Multi Layered Perceptron's (MLP)*

	MLP	
1	Precision	73.20%
2	Recall	69.10%
3	F-Score	66.10%
4	Accuracy	69.20%

4.3.7 *Support Vector Machine (SVM)*

	SVM	
1	Precision	97%
2	Recall	97%
3	F-Score	97%
4	Accuracy	97%

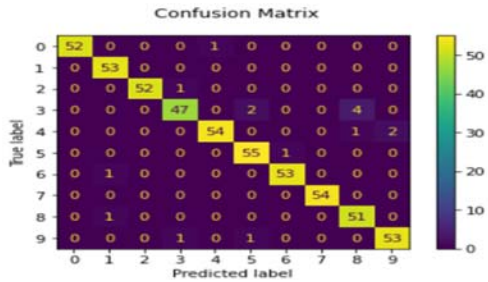


Fig. 13. SVM Confusion Matrix

Classification report for classifier SVC(gamma=0.001):

	precision	recall	f1-score	support
0	1.00	0.98	0.99	53
1	0.96	1.00	0.98	53
2	1.00	0.98	0.99	53
3	0.96	0.89	0.92	53
4	0.98	0.95	0.96	57
5	0.95	0.98	0.96	56
6	0.98	0.98	0.98	54
7	1.00	1.00	1.00	54
8	0.91	0.98	0.94	52
9	0.96	0.96	0.96	55
accuracy			0.97	540
macro avg	0.97	0.97	0.97	540
weighted avg	0.97	0.97	0.97	540

Fig. 14. Results of SVM

4.4 *Main Result*

Detection of Brain Tumor by Applying Deep Neural Algorithm on Single Dataset

4.4.1 *Simple Deep Learning*

	Deep Learning	
1	Precision	78%
2	Recall	72%
3	F-Score	73%
4	Accuracy	70%

4.4.2 *Convolution Neural Network[28] (CNN)*

	CNN	
1	Precision	92.5%
2	Recall	92%
3	F-Score	95.2%
4	Accuracy	93%

4.4.3 *Decision Tree*

Decision Tree resembles contingent control statements, which plays out the exploration tasks like decision investigation[29]. There happens the issue of over-fitting when trees become profound enough. It resembles a tree structure, where every node addresses quality or element on the bases of which one can get the result. Each leaf node holds the data identified with the class mark. The working of the decision tree is displayed in Figures. Features are utilized as inside nodes of the tree and class are leaf nodes.

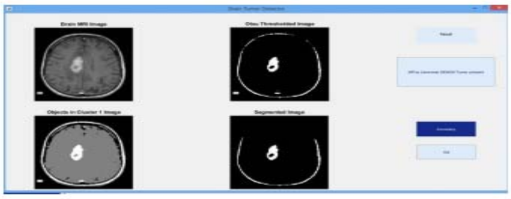


Fig. 15. Features Extraction & Classification by Decision Tree

Decision Tree		
1	Precision	98%
2	Recall	98%
3	F-Score	98%
4	Accuracy	97%

4.4.4 *Random Forest Random Forest*

Random Forest is a group classifier framed by the combination of numerous decision trees. It computes the outcome based on the larger part of casting a ballot strategy. Random forest is more prevalent than the decision tree as it overcomes the issue of over-fitting. As a tree develops profoundly, they begin to once again fit, i.e., they have a low inclination and high variance[30]. Random forest uses the various pieces of a similar preparing dataset on various trees and helps them average different decision trees and abstain from over-fitting, which expands inclination and diminishes variance, which supports execution. Inner working of random forest is displayed in Figures. We are utilizing 25 decision trees, which are prepared to utilize preparing information comprising 253 pictures by the idea of sacking[31].

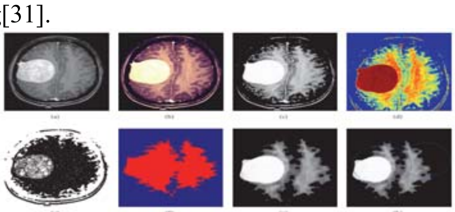


Fig. 16. Inner Working of Random Forest

Random Forest	
Precision	95%
Recall	97%
F-Score	96%
Accuracy	96.10%

4.4.5 *Naïve Bayesian*

The time consumed by Naive Bayes is not exactly other profound learning calculations or classifiers. Notwithstanding, from Table, it is portrayed that the quantity of accurately ordered occasions by Naive Bayes is not exactly other profound learning calculation or classifiers that could be hazardous for the determination, visualization, and treatment of a cerebrum tumor[32].

Naïve Bayesian	
Precision	81%
Recall	82%
F-Score	81%
Accuracy	83%
Robustness	98%

4.4.7 *Multilayer perceptron (MLP)*

Multi-layer perceptron (MLP) is a sort of neural organization which is broadly used to eliminate commotion from the input features set. In mind MR pictures, tumorous and non-tumorous information isn't directly distinct. The MLP calculation is utilized for managed learning. It is contained an info layer, transitional secret layers, and the yield layer. Barring the info nodes, the wide range of various nodes go about as neurons (handling components), having a nonlinear enactment work. A few investigations are led to picking the best number of sigmoid nodes, learning coefficient, and the number of emphases for the MLP. With a cautious investigation of results, seven sigmoid nodes, 100 emphases, and a learning rate worth of 0.2 are chosen. 253 MRI checks have been utilized for the preparation of the classifier while testing is done on 50 MRI pictures. Tumorous cases have 155 MRI images and non-tumorous cases have 98 MRI pictures with 92.59% exactness is accomplished[33].

MLP	
Precision	94.10%
Recall	94%
F-Score	94.20%
Accuracy	94%

4.4.8 *Support Vector Machine*

One of the traditional issues in picture preparation is picture classification. The significant objective of picture order is to foresee the info picture classes by utilizing the features. The best technique for classifying any picture or example is SVM. SVM is utilized to part a bunch of pictures into two different classes[34]. The characterization is finished by tracking down the hyper-plane that separates the two classes very well as given in Figures. It constructs a hyperplane dependent on a part work (K). As displayed in the Figure underneath, include vectors on the left half of the hyperplane have a place with class - 1 and the component vectors on the right half of the hyperplane have a place with class +1[35].

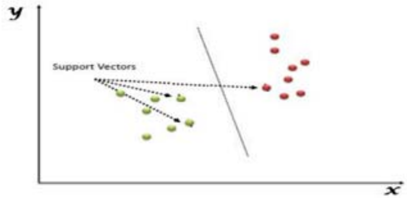


Fig. 17. Support Vector Machine Graph

SVM	
Precision	96%
Recall	96%
F-Score	97%
Accuracy	97%


Fig. 18. Image Acquisition

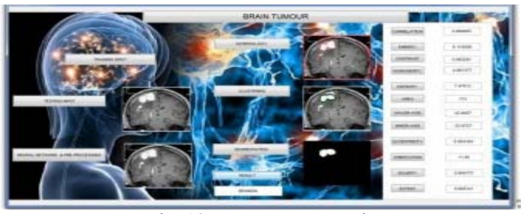


Fig. 19. Image Segmentation

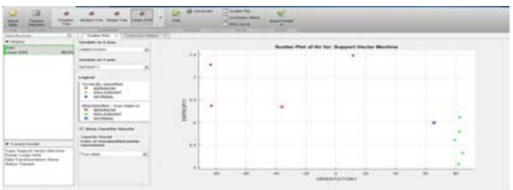


Fig. 20. Scatter Plot of Linear SVM Classifier

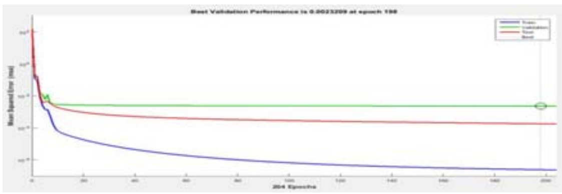


Fig. 21. Performance of Training Process

4.4.9 *Convolution Neural Network*

The fundamental objective of this exploration work is to plan effective programmed cerebrum tumor classification with high accuracy, execution, and low intricacy. In the regular brain, tumors classification is performed by utilizing Fuzzy C Means (FCM) based division, surface and shape highlight extraction, and SVM and DNN based classification are done[36]. The intricacy is low. Be that as it may, the calculation time is high in the meantime accuracy is low. Further to work on the accuracy and to decrease the calculation time, a convolution neural network-based classification is presented in the proposed conspire. Likewise, the classification results are given as tumor or ordinary mind pictures. CNN is one of the profound learning techniques, which contains a succession of feed-forward layers[37]. Additionally, python language is utilized for execution. Picture net information base is utilized for classification. It is one of the pre-prepared models. So the preparation is performed for just the last layer. Likewise, crude pixel esteem with profundity, width, and stature include esteem are extricated from CNN. At last, the Gradient nice-based misfortune work is applied to accomplish high accuracy[38].

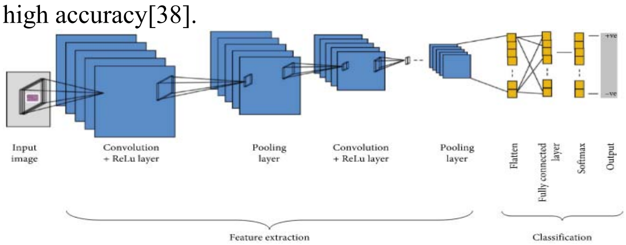


Fig. 22. CNN Architecture for Detection of Brain Tumor

	CNN	
1	Precision	92.50%
2	Recall	92%
3	F-Score	95.20%
4	Accuracy	93%

4.4.10 *AlexNet with FC6, FC7, & FC8*

AlexNet is used to classify brain tumors with some fully connected layers FC6, FC7, and FC8. Turbulent bat calculation Chaotic bat calculation (CBA) has a place with a multitude of keen optimization techniques, which are advanced from bat calculation [31]. Motivated by the echolocation conduct of bats, CBA utilizes a bunch of bats with possible answers for searching the arrangement space by specific procedures. In each cycle, the boundaries of the bats will be refreshed including the position, speed, and recurrence dependent on the ideal arrangement observed to be up until this point. The bat calculation is better compared to conventional PSO for optimization, and we acquaint turbulent guide with work on its looking through capacity[39].

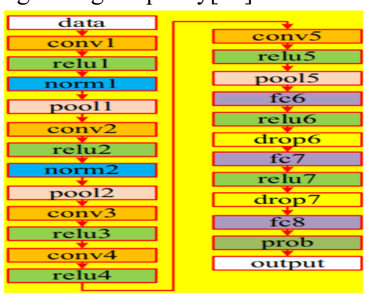


Fig. 23. AlexNet with FC6, FC7, & FC8

AlexNet with FC6, FC7, & FC8		
1	Precision	92.20%
2	Recall	90.50%
3	F-Score	84.50%
4	Accuracy	85.20%

4.5 *Comparison of different Deep Learning Classifiers applied to a single dataset*

Classifier	Precision	Recall	F-Score	Accuracy
Decision Tree	98	98	98	97
Random Forest	95	97	96	96.1
Naïve Bayesian	81	82	81	82
MLP	94.1	94	94.2	94
SVM	96	96	97	96
CNN	92.5	92	95.3	93
Simple Deep Learning	78	72	73	70
AlexNet with FC6, FC7, & FC8	92.2	90.5	93	93

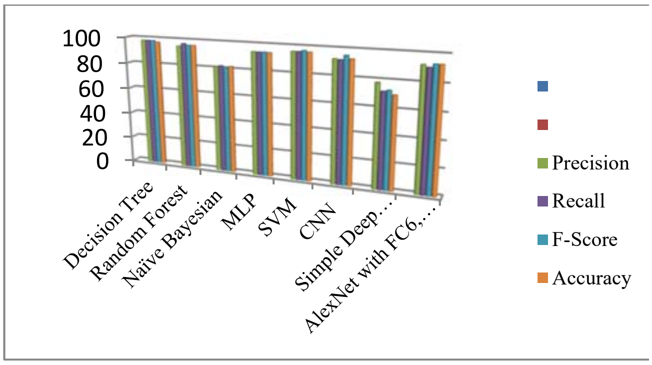


Fig. 24. Comparison of Different Deep Learning Classifier

4.6 *Comparison of different Machine Learning Classifiers with Deep Learning Classifiers when applied to a same MRI images dataset*

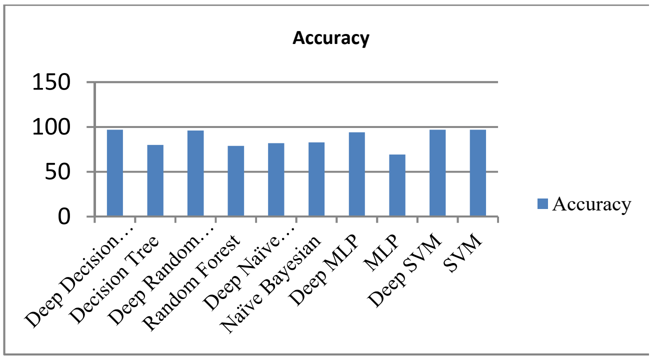
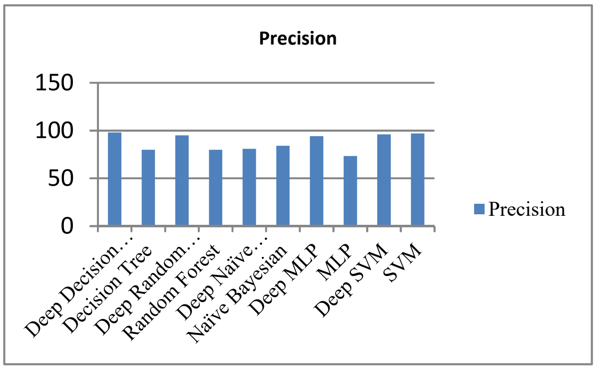


Fig. 25. Accuracy Comparison of Machine Learning Classifiers with Deep Learning Classifiers

4.7 *Precision Comparison of Machine Learning Classifier and Deep Learning Classifier*

Fig. 26. Precision Comparison of Machine Learning Classifiers with Deep Learning Classifiers



4.8 *Recall Comparison of Machine Learning Classifier and Deep Learning Classifier*

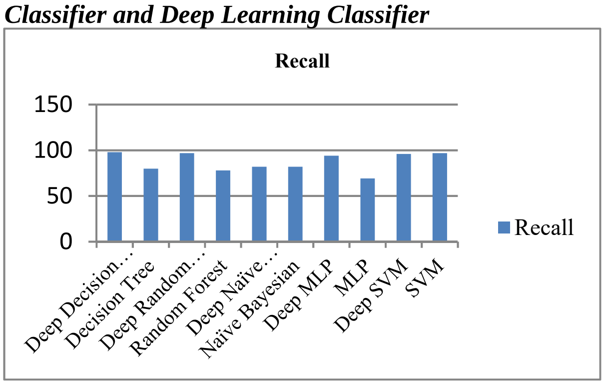


Fig. 27. Recall Comparison of Machine Learning Classifiers with Deep Learning Classifiers

1.9 F-Score Comparison of Machine Learning Classifier and Deep Learning Classifier

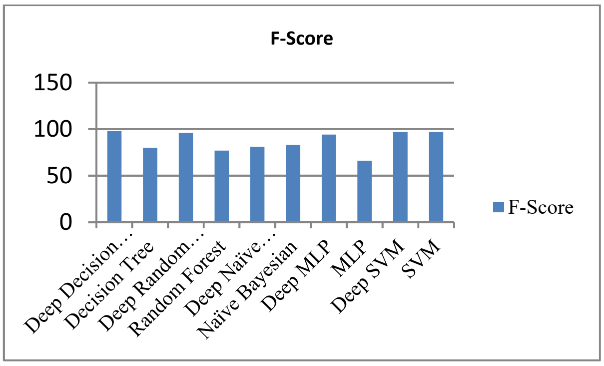


Fig. 28. F-Score Comparison of Machine Learning Classifiers with Deep Learning Classifiers

Hence, according to the results the deep learning technique with different classifiers work better as compared to machine learning techniques and simple deep learning technique.

6. Conclusion and Future Work

Perhaps the most significant job in any brain tumor identification framework is the confinement of unusual tissues from typical brain tissues. Curiously, the area of brain tumor investigation has successfully used the ideas of clinical picture preparing, especially on MRI pictures, to computerize the center advances, for example, extraction, division, and arrangement for general recognition of the tumor. Exploration is more disposed towards MRI for its non-intrusive imaging properties. Computers helped determination or recognition frameworks are getting testing are as yet an open issue because of changeability in shapes, regions, and sizes of tumors. The previous works of numerous specialists under clinical picture preparing and delicate figuring have made vital survey examination on programmed brain tumor discovery techniques centering division just as order and their blends. In the original copy, different brain tumor recognition techniques for MRI pictures are evaluated alongside the qualities and lack experienced in each to identify different brain tumor types[40]. The current division, grouping, and identification techniques are likewise given underscoring the advantages and disadvantages of the clinical imaging approaches in every methodology. The study introduced here plans to assist the analysts with determining the fundamental attributes of brain tumor types and distinguishes different division/arrangement techniques which are fruitful for the discovery of the scope of brain infections. Some type of hybrid model is good enough like the Deep learning model with CNN, GoogleNet/ VolumeNet/ AlexNet, and NADE to overcome the drawbacks of techniques used and sum up the benefits of all best techniques as required but all of this done with the help of clinical advisors, radiologists and software engineers, etc.

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