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Brain Tumor Detection Using A Novel Machine Learning Method

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Abstract

Brain tumors are growths of nerves that don't work right in the brain. They make it hard for the brain to do regular things. It's caused the deaths of many people. To keep from getting this sickness, people need to be able to get the right care and find it quickly. Finding brain cells that have been damaged by tumors is hard and takes a lot of time. On the other hand, picture processing has a lot of problems when it comes to how well and how quickly it can find brain cancers. This study paper describes a new, better, and more accurate way to find brain cancers. The improved convolution neural network (CNN) method helps us pick the best features by using grey wolf and whale optimization. Brain cancer can be found with the CNN algorithm. This system checks its performance against another optimization method that is already out there and says that its work is better based on factors like precision, accuracy, and memory. Python is the computer language that was used to make this system. This improved method has been shown to find brain cancers 98.9% of the time.

Keywords: CNN, Brain tumor, Segmentation, Cancer, MRI.

1.Introduction

The brain, is a very important structure that does many things. A network of billions of neurons send and receive chemical and electrical messages that change our lives and the things we do. [1] This amazing system is very important for learning how to see, feel, and be yourself. The brain is an example of complexity because it has many different parts that each do a specific job. The cerebellum, on the other hand, is in charge of balance and movement [2].It is very important for our daily tasks and reactions to the world around us that different parts of our brain work together in harmony. But even though the brain is strong, it is not completely safe from danger. Tumors can be found in many places, including the brain [3] To understand how tumors affect health, it is important to know the difference between healthy and unhealthy ones. When tumors are slow and limited, they are less dangerous, but they can be dangerous if they grow into important organs or tissues [4].

Learning how these tumors grow and behave is important for moving quickly and protecting the brain's many functions, which are a wonder that makes up everything we do [5]. As the name suggests, a brain tumor is an abnormal buildup of cells in the brain. These cells can come from brain tissue itself or from other parts of the body spreading to the brain during metastasis [6]. A full evaluation is needed to confirm a brain tumor diagnosis. Imagining tests and a biopsy are often used to find out the tumor's features and grade.

Brain tumors are made up of neoplasms from different types of cells. Each type has its own problems and effects that affect how they are diagnosed, treated, and how well the patient does [7]. Malignant gliomas are brain tumors that start in glial cells and can grow in any part of the brain. They need specific treatments to get through the cell matrix, which shows how important it is to have effective treatment for this tough type of tumor [8]. The meninges are the layers that protect the brain and spinal cord. Meningiomas are a type of growth that starts in these layers. It's interesting that most meningiomas aren't very dangerous and don't put your health at risk right away [9]. Schwannomas, which are made by Schwann cells that cover nerve fibers with myelin [10].Brain tumors called glioblastomas are the most deadly and dangerous kind. They are also very hard to find and treat. It is important to understand the differences between these brain cancers in order to come up with effective treatment plans. This makes the study of brain disease more complicated [11].

This never-ending search for information in neuro-oncology could lead to better ways of diagnosing and treating cancer, which would be a ray of hope for people who are struggling with the difficulties of these scary invasions into the brain [12]. Deep learning and artificial intelligence (AI) working together have led to faster diagnoses, better treatment choices, and better results for patients [13]. AI is a very important part of surgery planning because it helps doctors accurately separate brain structures and tumor boundaries, combining the need for treatment with the need to protect people's quality of life. It guesses problems, repeat rates, and treatment reactions, which helps doctors come up with the best follow-up plans and gives each patient specific help through custom screening processes [14].

You can make models that work well with less time and money spent on training and computing with transfer learning. This is an important tool in medical picture analysis. While VGG, ResNet, Inception, MobileNet, and DenseNet are just a few examples, they have all done very well in this area [15,16]. Transfer learning models look for trends in medical images that are hard to spot by using the depth and complexity of neural networks. Better and faster diagnosis of cancerous growths, especially when it comes to finding and grouping cancerous growths [17,18]. The most useful thing about our work is that it shows fresh ways to split brain tumors into four groups using machine learning and fine-tuning on MR images.

The piece is put together like this: The "Related work" section gives a short outline of the important books. The "Materials and Methods" section talks about the suggested method and the experiment's setting. It also talks about how to prepare the data, train the model, and evaluate its performance. The experiment's results and a full analysis of them are given in the "Experimental results and discussion" part. "Conclusion and future work" is the last part of the piece. It tells what the results were and what other research might be able to do with them.

2.Related work

Brain cancers can be clearly put into three groups: meningioma, glioma, and pituitary adenoma. We used deep convolutional neural networks to make this possible. AlexNet, GoogLeNet, and VGGNet are three different CNN designs that we suggest be used together to get useful and strong features from MRI scans. Some transfer learning techniques we used were fine-tuning, freezing, and data enrichment. These helped us make the dataset bigger and reduce overfitting so that our models would work even better. With a detection and classification rate of up to [19].

A number of smoothing factors, such as spread, were used to test the learned classifier. As shown in the experiments, the PNN classifier is accurate 83.3% of the time, which is good considering the spread value [20]. Then, a closed-form measure learning method is used to compare the question picture to the photos in the database. This is done after features are extracted. The test was done on a large dataset with 3604 pictures showing meningiomas, gliomas, and pituitary tumors. It showed an amazing average accuracy of 94.68% in large studies [21].

AlexNet's CNN transfer learning model was used to do this. The whole testing process is faster with a 99.62% success rate thanks to our technology [22,23]. This makes healthcare more reliable, efficient, and accurate.

These results prove that the suggested method is a good way to correctly group brain tumors [24]. The study's goal is to make it easier for computers to find and spot brain cancer by using a fine-grained classification method. Another deep learning (DL) method that does not do as well as the InceptionResNetV2 TL method is the F-measure method, which has 99% F-measure rates, 98.91% accuracy rates, and 98.28% precision rates [25].

3.Methods and Material

3.1 Magnetic resonance imaging (MRI) scanning

- Brain cancer is studied with a CT scan, a PET scan, an MRI, and other tests. Right now, the MRI is the most popular way to take pictures because it makes pictures with a lot of information that are easy to see. It can also be used to see how pathological and functional changes happen in living cells. MRIs are used to look at brain tumors in order to [34].
- It doesn't use radiation that makes ions.
- It has a high quality.
- It creates 3D pictures that help figure out where a growth is located.

• The ability to get both anatomical and functional information about a growth in the same scan.

MRI is the most popular type of medical imaging these days because it lets doctors see the inside structure of the brain in great detail. The low contrast between different brain cells makes it a good way to get brain pictures that aren't as clear as those made with other imaging methods.

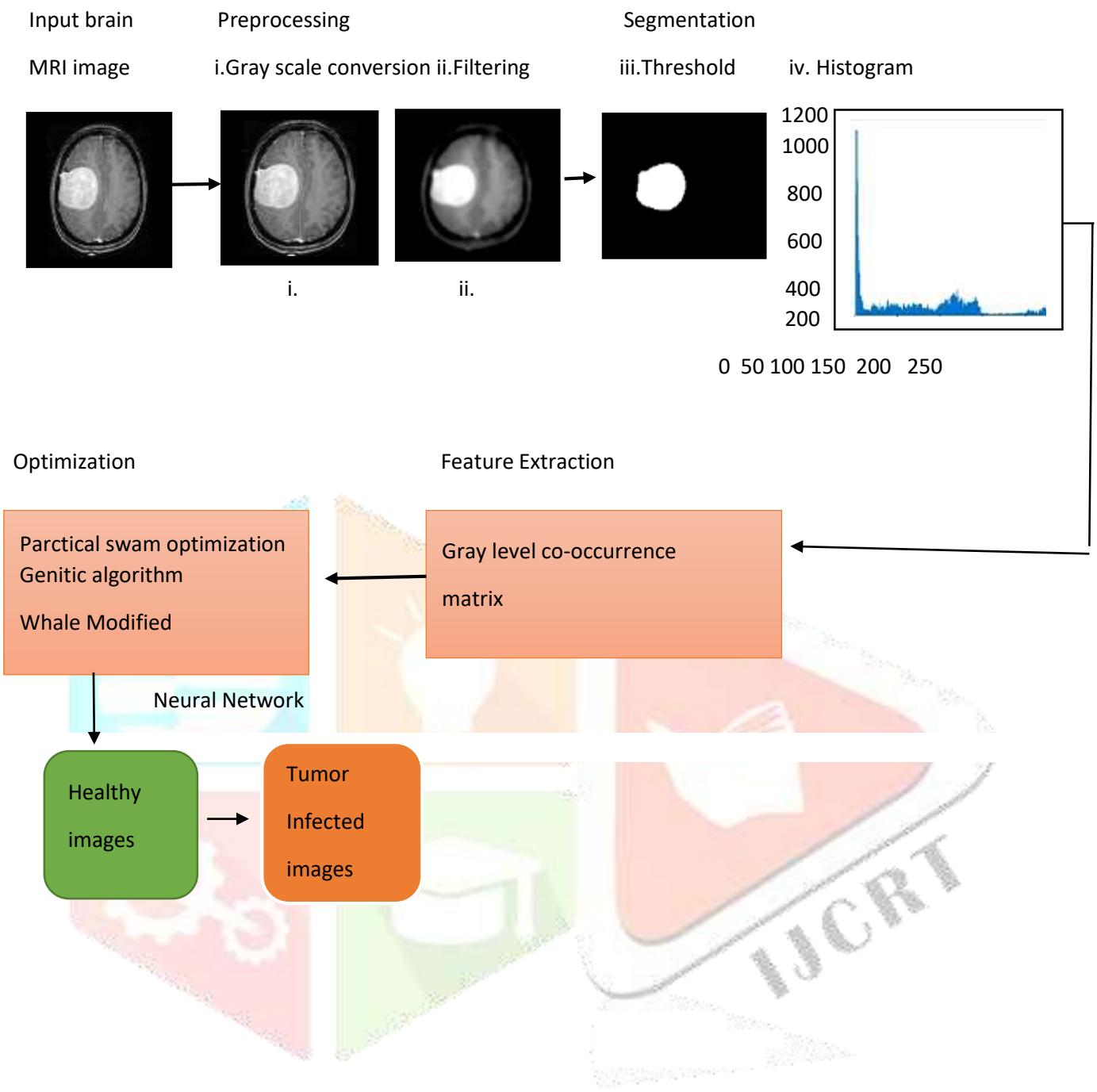
3.2 Dataset

By Class Yes and Class No, pictures of cancer and healthy cells are shown. There are 155 pictures in Class Yes and 98 pictures in Class No. You can see MRIs from different types of scans here, such as T1, T2, and Fluid-attenuated inversion recovery (FLAIR) [34]. Each picture is exactly (128, 128) pixels wide when viewed horizontally. All the photos in the dataset can be found at https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection. There are now 2318 shots in the file, which is more than before. Out of these pictures, 1622 were used to teach, 348 were used to test, and 348 were used to make sure.

3.3 Proposed architecture of brain tumor detection

Being able to find brain tumors early on is very important for keeping people from dying. A deep learning-based system design has been presented in this work. This architecture is a mix of deep learning techniques and picture classification methods. With a convolution neural network that works best for whales and wolves, brain cancer can be found.

Figure 1. Proposed architecture of brain tumor detection



3.3.1 Preprocessing

It's hard work putting together the MRI. An MRI needs to be cleaned up to get rid of any unwanted artifacts before it can be used. After the noise that isn't needed is taken out, the MRI is ready for more processing [35]. As part of preprocessing, monochrome conversion and filters are done. After the image is turned into grayscale, screening methods get rid of any extra noise. The suggested system creates a compound filter that is made up of a Gaussian filter, a mean filter, and a median filter. One good thing about the complex filter is that it keeps the MRI's lines and borders.

• Greyscale conversion

MRIs are often preprocessed by turning them into grayscale images [36]. RGB MRI has information that isn't needed for processing the picture that isn't needed. By changing RGB MRI to grayscale MRI [37], this kind of knowledge can be thrown away. MRI is split into three channels, called B, G, and R. Each channel has eight bits. The picture has different amounts of strength for each of the B, G, and R parts. Thus, for a color picture, we have different levels of brightness for each scale.

• Filtering

After the image is turned into grayscale, screening methods get rid of any extra noise. The suggested method creates a compound filter that is made up of a Gaussian filter, a mean filter, and a median filter. One good thing about a complex filter is that it keeps the MRI's lines and borders.

3.3.2 Segmentation

It is very important to have MRI Image Segmentation [38] because scanning creates a lot of pictures, and doctors can't separate them by hand in an acceptable amount of time. Image segmentation is the process of dividing MRI pictures into several parts that don't cross. Segmentation is used to find edges or objects in a picture, and the parts that are made cover the whole image. Two things about an image's intensity—similarity and discontinuity—are used by segmentation methods. There are a lot of different ways to split images, such as threshold-based, histogram-based, region-based, edge-based, and grouping methods. One method that could be used to handle the MRI pictures is threshold and histogram-based segmentation. This paper uses threshold and histogram-based segmentation methods to look at brain tumors and figure out how big the tumor is in MRI pictures. Figure 1 shows an example of what the cutoff and histogram segmentation looked like.

3.3.3 Feature Extraction

Because of feature extraction, you don't need as many tools to correctly describe a big set of data. There may be a lot of things that make it hard to look at a large set of data. When you need to look at a lot of things, it takes more memory and time to do the math. Feature extraction is the process of giving the data a correct description by putting factors into groups that make sense in this case. For this project, GLCM is used to get features based on both statistics and textures. The value of the first pixel is i and the value of the second pixel is j. This part of the matrix, Pi: d, −, shows the second-order mathematical chances that the gray levels i and j will change when the point of movement is d and the angle is ⋕.

In Table 3, you can see the traits that the recommended system gets from GLCM.

i.Contrast: This changes the level of darkness or lightness in a picture. To find it out, the following steps are taken:

$$\text{Entropy} = \sum_{I,j=0}^{n-1} P_{i,j}\log(P_{i,j}) \quad (1)$$

Energy: GLCM uses energy to figure out the sum of all the squared parts. Homogeneity is measured by energy. If the energy level is high, it means that the picture is very homogeneous, which means that the pixels are very alike.

$$\text{Energy} = \sum_{I,j=0}^{n-1} P_{i,j}2 \quad (2)$$

vi.Smoothness: Smoothness is a way to describe how smooth something is based on the difference between gray levels.

$$\text{Smoothness} = 1 - \frac{1}{1+s2} \quad (3)$$

In this case, s stands for an image's standard deviation.

vii.Kurtosis: Kurtosis is used to figure out how flat a distribution is compared to a normal distribution.

$$\text{Kurtosis} = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}\left\{\left[\frac{Pi,j-\sigma}{\sigma}\right]4\right\} -3 \quad (4)$$

$$\text{RMS} = \frac{\sqrt{|Pi,j|2}}{m} \quad (5)$$

The eight GLCM texture traits that were found for each of the 253 shots are shown in Table 1. Here they are: RMS, Energy, Smoothness, Correlation, Homogeneity, Entropy, and Contrast.

Table 1 Extracted features of MRI images

Image	Contrast	Correlation	Homogeneity	Entropy	Energy	Smoothness	Kurtosis	RMS
I001	1.7326	0.1075	1.0987	2.4589	0.8927	0.9440	15.254	0.0845
I002	0.2414	0.1237	0.8876	3.8976	0.3686	0.9335	12.544	0.0933
I003	0.2725	0.1465	0.8745	3.1765	0.3644	0.9194	15.280	0.0919
I004	1.1327	0.1253	0.9178	2.8345	0.4168	0.9607	15.438	0.0860

3.3.4 Optimization

We use optimizers to choose the best picture traits during the optimization process. The whale and wolf optimization methods are shown here so that the suggested optimizer can be put into action. The suggested method has now been put up against a newer optimization algorithm to see which one is faster, more accurate, and needs less memory. The full steps for how the suggested optimization method would work are shown below:

•Modified Humpback whale optimization algorithm (HWOA)

Choose the best choices for image density to speed up the training process with the help of the deep learning-based HWOA. There are three ways for humpback whales to catch their prey: they find it, circle it, and make a bubble net. The name for this method is "whale optimization."

Mathematical modeling of Modified HWOA

To show how HWOA works numerically, we will talk about spiral bubble-net feeding, looking for food below, and being close to the prey.

Phase 1: Initialization

In the first step of HWOA, the first answer is picked at random. Once the MRI picture of the brain tumor has been cleaned up, the HWOA algorithm uses CNN settings to pick the best pixel size.

$(u) = (e1,e2,e3,\ldots,e_h)$ (6)

$(u)=maxi(Accuracy)$ (7)

Phase 2. Encircling prey stage

The humpback whale (agent) can find its food and circle it. Whale thinks that the best possible solution that is currently available is the best one that can be found and is close to the best solution. When the best potential answer is given, other agents use Equations 18 and 19 to try to move closer to becoming the best search agent:

$D=|C.X*(t)-X(t)|$ (8)

$D=(t+1)=X*(t)-AD$ (9)

The number of iterations is shown by t, the factors are A and C, the absolute value is ||, and X* and X are the position vectors of the best answer and the solution.

Equations (20) and (21) are used to find the values of vectors A and C:

$A=2a.r.a$ (10)

$C=2.r$ (11)

Phase 3. Exploitation or attack stage

- There are two ways to attack, which are shown below:

  • There is also a device that makes the circle smaller. A is a random number between -a and an in this system, and as time goes on, its value drops from 2 to 0. This is shown in Equation (3).

This system figures out how far away the whale is from its food based on its spiral update position device. After that, Equations (22) and (23), which show the humpback's helix-shaped movement, are used to make it.

$$(t+1)=D'.cbl.\cos(2\pi l)+X*(t) \quad (12)$$

Where,

$$D'=|X*(t)-X(t)| \quad (13)$$

(l) is a random number between -1 and 1 that tells us how far away the food or best answer is from the ith whale.

When they get close to their food, humpback whales use the two methods above. Between these two ways of updating whales' locations, there is a 50% chance that they will be chosen:

$$(t+1)=X*(t)-AD, if p<0.5 \quad (14)$$

or

$$(t+1)=D'.cbl.\cos(2\pi l)+X*(t), if p\geq 0.5 \quad (15)$$

where p is a number picked at random from 0 to 1.

Phase 5. Exploration or search stage

These whales, which are sometimes called "search agents," move around based on where another whale is to find food or the best answer. You can use math to show the exploration process in Equations 16 and 17:

$$D=|C.Xrand-X| \quad (16)$$

$$(t+1)=|Xrand-AD| \quad (17)$$

where Xrand is a random point vector picked from the current population.
The fitness method picks the best answer from the ones that have been changed.

A. Random Forest Algorithm

The random forest program can fill in the blanks on its own. We have already dealt with property values that were missing for this collection. It doesn't overfit the model if it has a lot of trees. The classification task and the regression task can both be done with this method.

Steps of Random Forest Algorithm: - We will see how random forest works with the information shown in Fig. 2 in the next few steps.

- Step 1: Pick the examples at random from the collection.
- Step 2: It is up to the program to build a decision tree for each sample. After that, each decision tree will guess what the outcome will be.
- Step 3: For the prediction result, each training sample will cast a vote.
- Step 4: At the end, pick the final guess by picking the estimate that is closest to the truth.

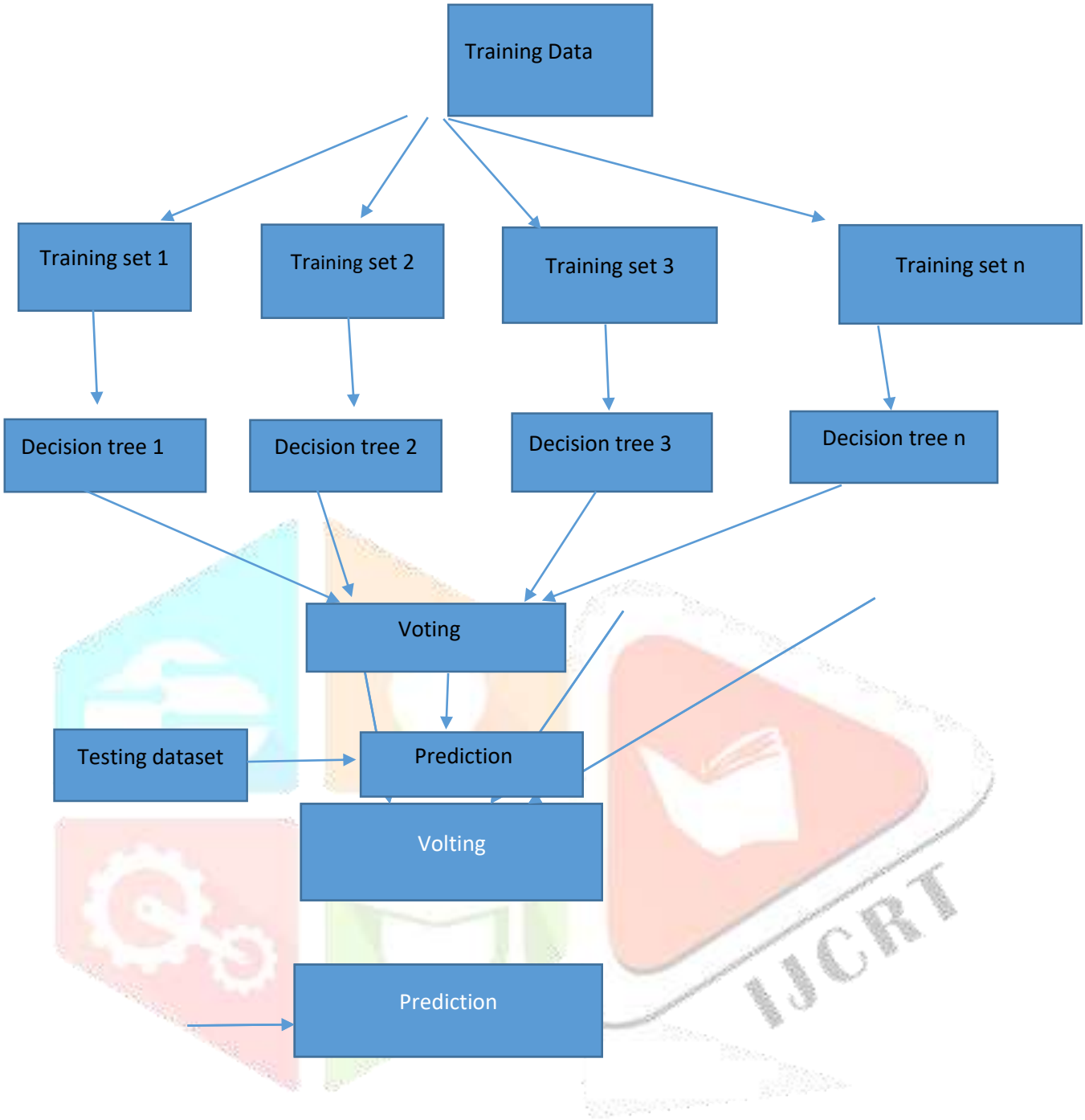


Fig.2: Random forest steps

B. Model Validation

In this step, you check to see if the model will work correctly with the testing data. If not, you'll need to train the model all over again. Figure 3 shows how to use the confusion matrix to find the accuracy.

1) True Positive (TP): The observation is good, and it is expected to be positive as well.
2) False Negative (FN): The observation is good, but the prediction is negative.
3) True Negative (TN): Observation is bad, and it is expected to be negative as well.
4) False Positive (FP): The observation is negative, but the prediction is positive.

		0	1
Actual	0	TN	FP
	1	FN	TP

Fig.3: Confusion matrix

C. Model Implementation

The last step is to put the plan into action.

4. Result analysis

Two hundred and fifty pictures are picked at random for the project. The model is taught with 150 photos, and it is tested with 100 pictures. This method is used to make pictures better. With the K Means algorithm, images are broken up into parts. This division makes it easier to find the exact area of interest. PSO particle swarm optimization method picks out the features. The XGBoost, Naïve Bayes, and ID3 algorithms are used for classification. The findings of the experiments are shown in Figs. 5 and 6.

Accuracy = (TP + TN)/(TP + TN + FP + FN)
Sensitivity = TP/(TP + FN)
Specificity = TN/(TN + FP)
Precision = TP/(TP + FP)
Recall = TP/(TP + FN)
Where

TP = True Positive
TN = True Negative

FP = False Positive
FN = False Negative

5.1. Confusion matrix

In order for our model to find brain tumors to work well, the uncertainty matrix is very important. The Extra Trees model works really well for finding brain cancer. It's clear that this is the case since it has many TP and TN numbers and few FP and FN values. This makes it a very useful tool for finding brain cancers properly. Figure 4 shows the plots that show what people don't understand.

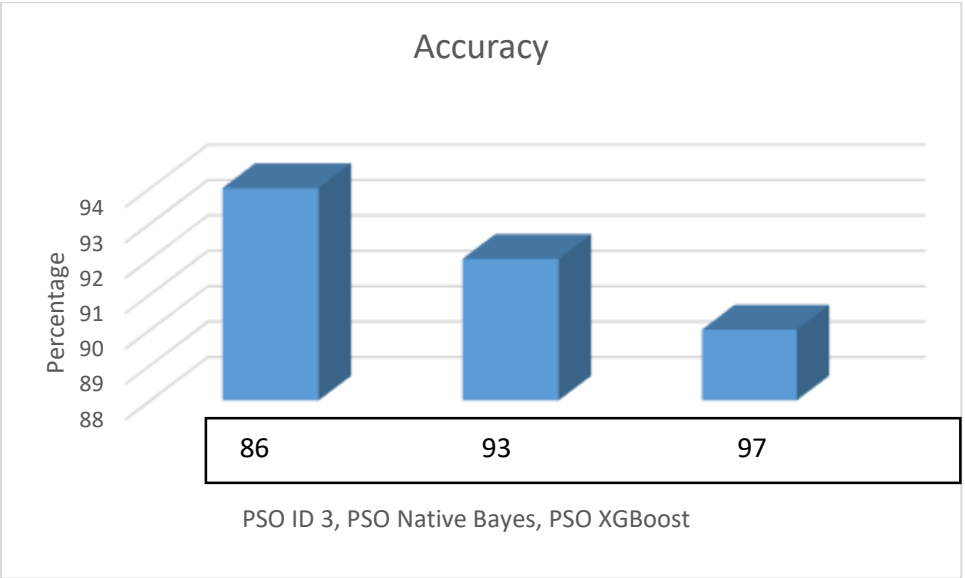


Fig. 4. Accuracy of Classifiers for Brain Tumor Detection.

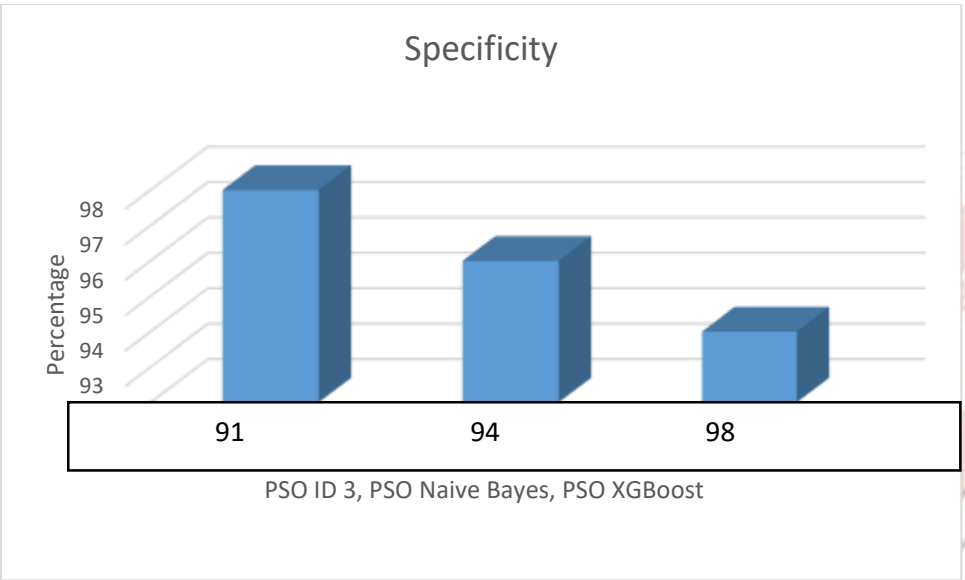


Fig 5 Specificity of Classifiers for Brain Tumor Detection.

5.2. ML models performance analysis

All of the accuracy, precision, memory, and F1 scores we see in this part are shown in Table 3. At 0.93, Extra Trees had the highest precision of all the models. Naïve Bayes and Support Vector Machine (SVM), on the other hand, only work 79% of the time and 67% of the time, making them not as good. The recall rates for all models are pretty much the same, but SVM is the most accurate. Because of these results, we can say that Extra Trees is the best model for using the features that were picked during the feature selection process to find brain cancer.

6. Discussion

The talking part of our study paper talks about how important it is to use our suggested way to group brain tumors into different groups. The model got even better when the value of features and hyperparameters were tweaked. Extra Trees came out on top with an amazing 0.98 accuracy. When we compare our results to those of other studies (Table 5), we can see that our way of finding brain cancer is better. The results of our study

show that machine learning could help doctors find brain tumors more accurately and with more confidence. This looks like it could be very useful in real life for doctors and patients.

7. Conclusion

Finding and locating cancers as soon as possible are very important for their good treatment. In medical imaging, it is normal for structures to be complicated and for structures to be accurately identified through segmentation. As the number of pictures goes up, the doctor will look at each one by hand, which means there is a chance that he or she will come to the wrong decision. Medical picture review and labeling can go wrong when done by hand, so we need an automatic method. This study uses feature selection and picture segmentation to show how the suggested method can be made better for more accurate brain tumor detection. The picture quality will be better if you use the CLAHE method. With the K Means method, pictures are split up to make parts inside them. With this division, we were able to zero in on the area that was most important to us. The particle swarm optimization (PSO) method is used to pick characteristics. XGBoost, Nave Bayes, and the ID3 algorithm are all used to sort data into groups. Brain cancers can be found more easily with XGBoost. The test results showed that the suggested model was 97% accurate, 97% sensitive, 98% precise, and 98% remember.

It is important to quickly and correctly diagnose brain cancers without any delay. That is why our future research will focus on creating new, powerful combination methods for organizing brain tumors. These methods will be easier to use and take less time to put into action. Additionally, the suggested methods can be used along with MRI and CT tests to help find different types of cancer.

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