# Brain Tumour Disease Detection Using Machine Learning And Deep Learning

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***Abstract—***

Most people suffer from some kind of brain disease. Cell proliferation is a major contributor to neurological disorders. Consequently, it affects the normal functioning of the brain, which in turn affects the health of other vital organs. In the end, unchecked cell proliferation causes aggressive brain cancer. One of the main ways to reduce the number of people killed by brain tumors is to diagnose them early. Brain tumor identification makes use of image processing techniques to compile and analyze data from several imaging modalities, including computed tomography (CT) scans, magnetic resonance imaging (MRI) scans, and others. During the preprocessing step of the study, the sounds in the photos are removed. Support vector machines (SVMs) and convolutional neural networks (CNNs) are two examples of the deep learning techniques used to build the model. Making a model that can detect brain cancers in CT scans is the main goal of this study. To evaluate the models' performance, we considered a number of metrics, such as accuracy, recall, loss, and area under the curve. Brain tumor, subfield of deep learning, support vector machine, image processing, convolutional neural network.

## INTRODUCTION

The brain controls the actions of almost every vital organ in the body; it is part of the central nervous system, which also includes the spinal cord. An abnormal proliferation of cells—tumor cells—inside the skull and around the brain is the fundamental cause of a brain tumor. About 2,50,000 people throughout the globe are affected by brain tumors annually.

Crucial as it may be, early detection reduces cancer complexity and helps bring the mortality rate down. In most cases, noise—which might manifest as hazy images, muddled data, or other visual issues—is present in the scanning equipment used to capture images of human organs. Always bear in mind that medical images provide important details about the diseases. If accurate patient diagnoses are to be obtained, it is essential to improve the picture quality. New advances in computer vision and image processing will allow accurate data extraction from images. Imaging technologies like positron emission tomography (PET), computed tomography (CT), and magnetic resonance imaging (MRI) are also linked to this progression, as are many radiological treatments including vascular and cardiovascular contrast imaging.

## LITERATURE SURVEY

The effects of a brain tumor may be devastating, long-lasting, and even deadly. There is a wide variety of brain tumors, with roughly a hundred distinct types. Brain tumors affect around one million Americans; women make up 59% of cases, while males account for 41%. There have been about 94390 newly reported cases of brain tumors. We're looking toward 2023. Estimates indicate that 18,990 individuals will be at risk of tumor-related mortality in 2023. Consequently, a life-saving opportunity exists for those affected by the disease when diagnosed early. If we are serious about finding a way to lower the death rate from brain tumors, we need to develop an effective early diagnostic method for tumor detection. [1] [2] the third Magnetic resonance imaging, or MRI for short, is one way to detect brain tumors and provides a detailed image of the result. Nevertheless, given the speed of the MRI, it would have been better for the physicians to analyze the data and consider early treatments and possible medications that the patient may take for recovery. A more effective and expedited diagnostic approach is required for more rapid prognoses that may facilitate faster treatment. [4] On pages 5 and 6, When dealing with MRI images, a lot of computer operations are required. A problem with magnetic resonance imaging (MRI) scans is that they aren't always clear and consistent.

Some may deviate from the norm and change from one another. It is possible that some of the photos are too light, while others are too dark. Models and practitioners alike have a hard time making sense of the picture because of this. Consequently, it is necessary to build and use a segmentation or filtering method, such denoising, in order to get crisp images that consistently adhere to the same process and are easy to evaluate. [7, 8, 9] Possible applications of deep neural networks include RBF NN and Support Vector Machine (SVM). It is also possible to use filtering, feature extractions, and Grey Level co-occurrence matrix extraction for visual processing and analysis. An integral aspect of image processing, feature extraction involves spotting a similar or recurrent pattern to assess the dataset's trend and provide classification assistance. The ability to recognize and create patterns is crucial when using SVM and similar algorithms. [10] the eleventh [12] Data mining techniques may also be used to the analysis of MRI images. There are four main components to these data mining techniques. Image pre-processing is the first and most important stage. The next step is to segment images for object identification. Form, color, and texture are some of the traits that may be extracted next. Steps to locate the tumor in the brain make up the last phase. It is possible to recover or identify a wide variety of characteristics, both in terms of shape and intensity. Neural network approaches may also be used to obtain texture-based properties. One comparable ML method is the Support Vector Machine. references [13] and [14]. Research indicates that doctors and other medical professionals may be able to have a bigger impact in the detection and treatment of brain tumors if MRI scan technology for processing continues to advance in the area of tumor identification. Magnetic resonance imaging (MRI) may be considered a successful image processing method as it uses high-resolution photographs to identify brain malignancies. [15]

## METHODOLOGY

Curable diseases may be advanced with the use of medical imaging tools that detect brain tumors early. Brain tumors may be detected using Magnetic Resonance Imaging (MRI), a medical imaging technique. Machine learning algorithms like Support Vector Machine (SVM) and convolutional neural network (CNN) are trained to detect brain tumors in magnetic resonance imaging (MRI) data. The first and foremost step was preconditioning. Use of medical imaging techniques, such as MRI, allows for data collecting. After the data has been extracted, it is processed. Clear and ideal skull photographs are offered by the provided picture collection, which has been cleaned up. We remove pictures that are too hazy or don't show enough detail. [16] [17] There are two distinct sets of information stored in the database: test data and train data. One uses the train dataset to train the model, while the other uses the test dataset to test the model. The construction of the model follows the preprocessing and separation of the data. In order to get a positive result and a clear perspective, we constructed the model using many ways. Before being evaluated for accuracy, each method undergoes training using a train dataset. At last, the modeling procedure employs the most precise way. [18]

## SYSTEM ARCHITECTURE

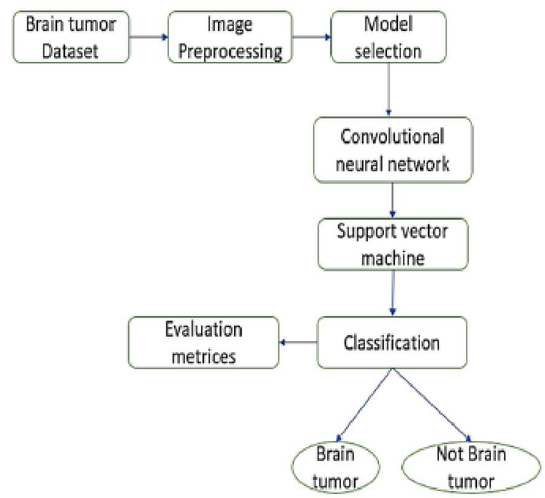


Fig.1.System Architecture for image denoising

Figure 1 displays the architecture, which takes as input the MRI data of brain tumors. After doing some preliminary processing on the input data, we feed it into the deep learning algorithms, which include CNNs and SVMs. We are able to determine whether the patient has a brain tumor based on our predictions. In the end, we check the algorithm's performance by calculating the model's evaluation metrics. The year 19

## PROPOSED WORK

### A. DATA COLLECTION

Most medical images are in the form of CT or MRI scans, and these images aren't always accurate. The noises are removed with the help of a preprocessing technique, as shown in Fig.2. These datasets contain nearly 5,000 MRI images of brain tumors, which are used to build the efficient model. The input data of medical information can be in various formats, including video, audio, images, text, and so on.

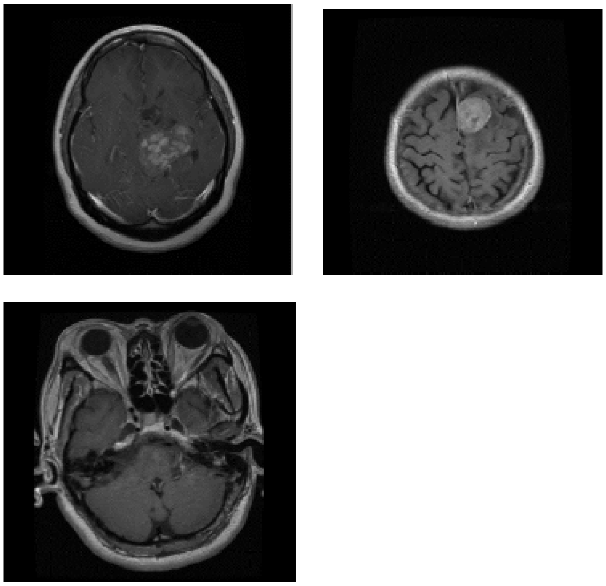

Fig.2. MRI images of Brain tumor

## B. DATA PREPROCESSING

A preprocessing approach is used to sanitize the dataset after its collection. Here, we preprocess the input picture of a brain tumor dataset using minmax-Scalar ethos. From scikit-learn's preprocessing package, we pull out the Min Max Scalar function. [21] [22] is a

## FLATTEN LAYER

A flatten layer is included into the Convolutional neural network as part of this research. Placing this layer next to the convolution layer will enhance computation speed and overall performance in this project. It does this by reducing the array of image features from multiple dimensions to a single vector. This vector is then used as an input layer by a fully connected network to determine if a brain tumor is present in a patient's MRI image. [23] The

## C. MODEL SELECTION

The next step is to choose a model from the preprocessed dataset. At this point, we decide whether to construct the prediction model using a deep learning or a machine learning technique. As part of this study, we developed an effective model to predict whether or not a given patient has a brain tumor using a combination of a convolutional neural network and a support vector machine method. [24]

## CONVOLUTIONAL NEURAL NETWORK (CNN)

To begin this project's data classification process, we work using a deep learning method called a convolution neural network (CNN). Deep learning approaches make use of a plethora of algorithms. You may choose from a variety of neural networks, including convolutional, artificial, multi-level perceptron, recurrent, and long short-term memory networks. Both support vector machines (SVMs) and convolutional neural networks (CNNs) are used in this investigation. Deep learning algorithms are included in the keras packages. Thus, we bring in Keras's Conv2D, which stands for the two-dimensional convolution layer. Filtering the input image in this way will result in a filtered output. The images are sent in a linear fashion from the input layer to the output layer due to our sequential technique. In this case, we use a 2-dimensional convolutional layer that has four filters—32, 64—each with its own 3x3 Kernal matrix and 2x2 Pool matrix. Kernel and Maxpool are the approaches used to extract features from the input MRI scan photographs. This model's activation function, the Rectified Linear Unit, is used to activate neurons as needed during training, and non-linear functions are inserted into the network to regulate it. This function is used to speed up the computation speed. For negative samples, ReLU has no value since its range is from zero to positive infinity. Conversely, we use the Sigmoid function to determine whether the image is normal or altered by a tumor. You can find the sigmoid function in the interval [0, 1]. Due to the non-linearity introduced by this sigmoid function, the network is capable of learning complex models. Consequently, the Sigmoid function and the rectified Linear unit function are both used in this project. Adaptive Moment Estimator (Adam) is used in this model to estimate the values from the neural network's previous layer and mechanically change the neural network's parameter. This optimizer helps the model learn faster during sample training and also increases the model's accuracy. Viewed in Fig.3 is the CNN output. In this project, we use 12 epochs to train the model. The convolutional neural network's training epochs are shown in Fig. 3.1. Figure 3.2 displays the model's training-stage accuracy and loss.

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv2d_4 (Conv2D) | (None, 148, 148, 32) | 896 |
| activation_5 (Activation) | (None, 148, 148, 32) | 0 |
| max_pooling2d_3 (MaxPooling2D) | (None, 74, 74, 32) | 0 |
| conv2d_5 (Conv2D) | (None, 72, 72, 32) | 9248 |
| activation_6 (Activation) | (None, 72, 72, 32) | 0 |
| max_pooling2d_4 (MaxPooling2D) | (None, 36, 36, 32) | 0 |
| conv2d_6 (Conv2D) | (None, 34, 34, 64) | 18496 |
| activation_7 (Activation) | (None, 34, 34, 64) | 0 |
| max_pooling2d_5 (MaxPooling2D) | (None, 17, 17, 64) | 0 |

Fig.3. Output of CNN

```
Epoch 1/10
12/12 [==============================] - 16s 938ms/step - loss: 0.6416 - accuracy: 0.5989 - val_loss: 0.6665 - val_accuracy: 0.5842
Epoch 2/10
12/12 [==============================] - 11s 893ms/step - loss: 0.5277 - accuracy: 0.7467 - val_loss: 0.5034 - val_accuracy: 0.7737
Epoch 3/10
12/12 [==============================] - 11s 897ms/step - loss: 0.4325 - accuracy: 0.8034 - val_loss: 0.3476 - val_accuracy: 0.8684
Epoch 4/10
12/12 [==============================] - 11s 924ms/step - loss: 0.3610 - accuracy: 0.8377 - val_loss: 0.2826 - val_accuracy: 0.9105
Epoch 5/10
12/12 [==============================] - 11s 916ms/step - loss: 0.3383 - accuracy: 0.8641 - val_loss: 0.3077 - val_accuracy: 0.8947
Epoch 6/10
12/12 [==============================] - 11s 980ms/step - loss: 0.2982 - accuracy: 0.8799 - val_loss: 0.2546 - val_accuracy: 0.9105
Epoch 7/10
12/12 [==============================] - 11s 987ms/step - loss: 0.2765 - accuracy: 0.8892 - val_loss: 0.2234 - val_accuracy: 0.9211
Epoch 8/10
12/12 [==============================] - 11s 953ms/step - loss: 0.2335 - accuracy: 0.9103 - val_loss: 0.2121 - val_accuracy: 0.9368
Epoch 9/10
12/12 [==============================] - 12s 971ms/step - loss: 0.2397 - accuracy: 0.9103 - val_loss: 0.2098 - val_accuracy: 0.9263
Epoch 10/10
12/12 [==============================] - 11s 941ms/step - loss: 0.1777 - accuracy: 0.9406 - val_loss: 0.1890 - val_accuracy: 0.9368
```

Fig. 3.1. Epochs

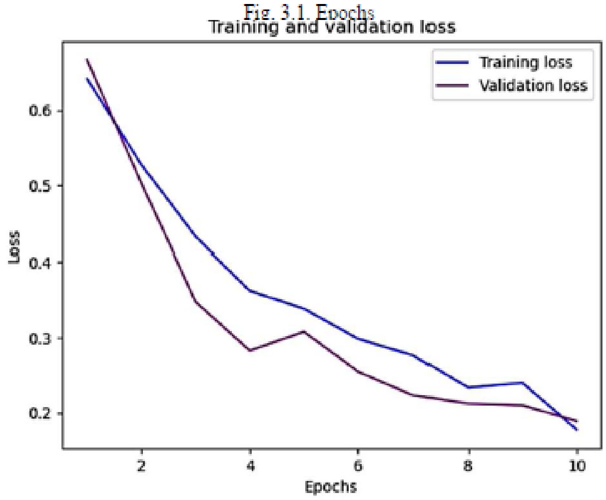


Fig.3.2. Graph for Loss

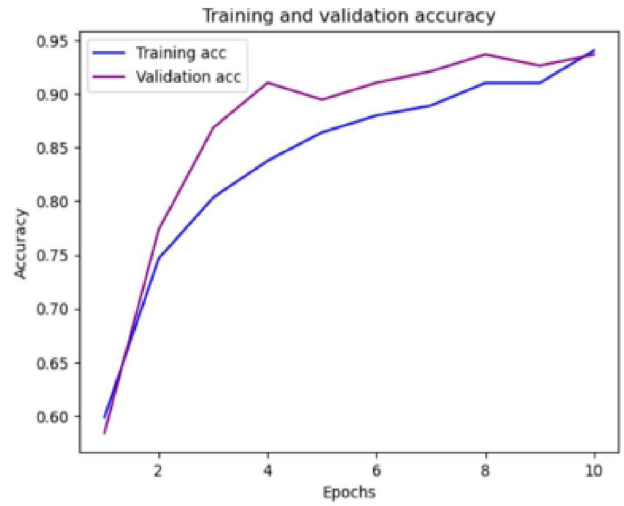


Fig.3.2. Graph for Accuracy

Convolutional neural networks (CNNs) have an accuracy score of 93%. Additionally, metrics like recall, accuracy, and others are computed.

## SUPPORT VECTOR MACHINE (SVM)

Within this research, we use a different classification approach known as support vector machine (SVM). Using the supplied picture collection, this algorithm determines whether a patient has a brain tumor or not. An 83% accuracy rate is produced by this algorithm. The support vector machine (SVM) algorithm's evaluation metrics are shown in Figure 4. To examine the model's overall performance, several metrics are employed.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.78 | 0.93 | 0.85 | 95 |
| 1 | 0.91 | 0.74 | 0.81 | 95 |
| accuracy | | | 0.83 | 190 |
| macro avg | 0.84 | 0.83 | 0.83 | 190 |
| weighted avg | 0.84 | 0.83 | 0.83 | 190 |

Fig.4. Evaluation metrices of SVM

Fig.4. Evaluation metrices of SVM

TABLE.1. EVALUATION METRICES COMPARISON TABLE

| Evaluation metrices | Convolutional neural network | Support vector machine |
|---|---|---|
| Accuracy score | 93% | 83% |
| Precision | 0- 0.84<br>1- 0.96 | 0- 0.78<br>1- 0.91 |
| Recall | 0- 0.88<br>1- 0.95 | 0- 0.93<br>1- 0.74 |
| F1-score | 0-0.952<br>1-0.924 | 0- 0.85<br>1-0.81 |

The TABLE. 1 shows that the value of different evaluation metrices of Convolutional neural network and the support vector machine algorithms.

## CONCLUSION

Since the brain is the most vital organ in the body, it is essential that we give it the attention it deserves. This research explores the use of advanced machine learning and deep learning methods for the prediction of brain tumors in humans. First and foremost, medical images must have high-quality data because they determine human lives. Here, we use MRI images that include both the tumor and normal brain from different angles to better predict where the tumor will be located in the brain. The images are then preprocessed and resized. the preprocessing technique used is minmax scalar available in scikit library and the images are resized with the help of CV2 package for maintaining uniform size for all the training, testing and validation images then the noises are removed from the image to lower the SNR ratio and get a less noise images after the preprocessing the images are converted into multidimensional NumPy array for the model to learn from it, in this there are two models used such as CNN and SVM for prediction and the CNN is built by adding multiple layers to it and making it efficient in learning by specifying activation and dropouts and other hyper parameters of the model and then the model is used to predict the results with the test dataset and these predictions and the actual results are compared with the scikit metrics such as classification report which gives the recall,f1score,accuracy and support by this the accuracy of the CNN model is 93% and the same dataset after the same preprocessing is given to the SVM model for learning and it is tested with classification report to see its performance and it has an accuracy of 83% and other metrics also shows less performance by SVM model by this we can see that the CNN model has performed better on the data available than that of SVM model. Several deep learning models may be trained on the preprocessed data and then tested to see whether they enhance accuracy or any of the other performance indicators. Perhaps a more effective model can be discovered.

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