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Neuroimaging of Brain Tumors: Detection and Diagnosis

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Abstract—

In society, brain-based disorders tend to be more common. Cell growth is the primary cause of brain disorders. Consequently, it affects the normal functioning of the brain, which in turn affects the health of other vital organs. Cell proliferation eventually leads to aggressive brain tumors. One of the main ways to reduce the number of people killed by brain tumors is to diagnose them early. Computerized tomography (CT) scans, magnetic resonance imaging (MRI) pictures, and other imaging modalities are combined using image processing techniques to identify brain tumors. 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. The goal of this study is to develop a model that can detect brain cancers using CT scan images. Our evaluation of the models' performance was based on a wide range of metrics, such as recall, accuracy, loss, and AUC.

Brain tumor, subfield of deep learning, support vector machine, image processing, convolutional neural network.

I. INTRODUCTION

Nearly every vital organ in the body is controlled by the brain and spinal cord, which together form the central nervous system. To put it simply, a brain tumor develops when abnormal cells, often called tumor cells, multiply inside and around the brain. Brain tumors affect over 2,50,000 people annually around the globe. Crucial since it reduces cancer complexity and mortality rate, early detection is essential. 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. Medical images portray serious diseases and conditions, thus it's important to remember that. We must prioritize the improvement of picture quality if we want accurate information for patient diagnoses. Thanks to recent advancements in IT and image processing, accurate information extraction from images will soon be within reach. 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.

II. LITERATURE SURVEY

The effects of a brain tumor may be devastating, long-lasting, and even deadly. At least a hundred distinct types of brain tumors exist, and each has its own set of symptoms and prognosis. 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. Therefore, an early diagnosis offers a potential for life-saving for those affected. In order to find a way to detect brain tumors early on and maybe lower the death rate caused by them, we need to develop a reliable diagnostic tool. [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. The physicians should have interpreted the data with early therapy and any medications that the patient may take to recover sooner since the MRI scan is so speedy. 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. But not

all MRI scans are the same and don't show the same details. Some may deviate from the norm and change from one another. If you're having trouble seeing any of the photos, try adjusting the brightness or contrast. Because of this, both practitioners and models have a hard time getting a solid grasp on the picture. 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. on pages 7–9 Utilizing deep neural networks, such as RBF NN and SVM (Support Vector Machine), might be used. 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. The tenth [11] [12] Data mining techniques may also be used to optimise MRI image processing. You may think of these data mining methods as having four distinct sections. 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. Finding the brain tumor is a part of the last step. A wide variety of characteristics may be retrieved or recognized based on shape and intensity. Neural network approaches may also be used to obtain texture-based properties. Other ML methods that are comparable include the Support Vector Machine. references [13] and [14]. Research shows that doctors and other medical professionals may play a bigger role in brain tumor detection and recovery treatments if MRI scan technology for processing continues to improve in identifying these malignancies. Magnetic resonance imaging (MRI) may be considered a successful image processing method as it uses high-resolution photographs to identify brain malignancies. [15]

METHODOLOGY

Curative potential of brain tumors may be increased with early detection using suitable medical imaging tools. Brain tumors may be detected using Magnetic Resonance Imaging (MRI), a medical imaging technique. To detect brain tumors in magnetic resonance imaging (MRI) images, a machine learning model is trained using methods like convolutional neural networks (CNN) and support vector machines (SVM). Before anything else, preconditioning has to be done. 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 images that are hazy or not clear enough. [16] [17] Two sections make up the database image: test data and train data. The model is trained using the train dataset, and then tested using the test dataset. The model development stage follows the data preprocessing and separation steps. Together, these approaches allowed us to construct the model with a positive outlook and a clear point of view. Before being evaluated for accuracy, each method undergoes training using a train dataset. The modeling procedure is completed by using the most precise way. [18] in

III. SYSTEM ARCHITECTURE

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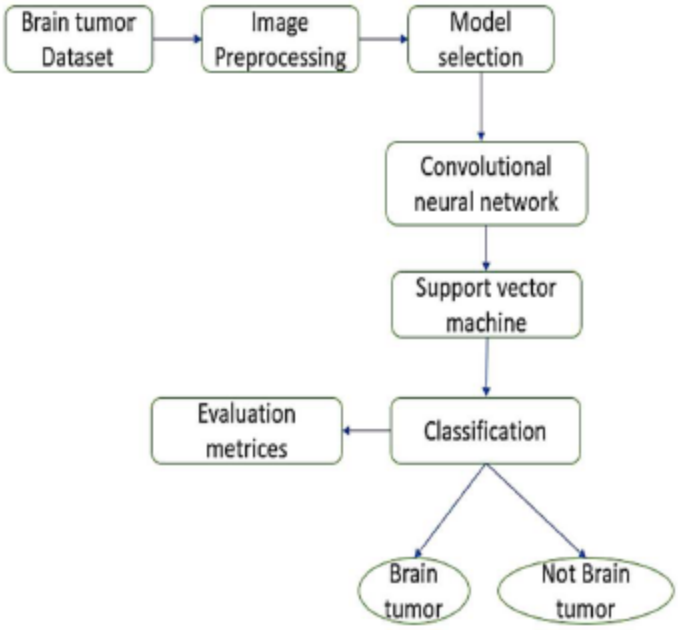

Fig.1.System Architecture for image denoising

The design, as shown in Figure 1, takes as input the MRI data of a brain tumor. Following data preparation, the processed data is fed into deep learning algorithms, such as support vector machines and convolutional neural networks. We are able to determine whether the patient has a brain tumor based on our predictions. Lastly, in order to assess the performance of the specific algorithm inside the model, we compute the evaluation metrics. The year 19

IV. PROPOSED WORK

A. DATA COLLECTION

Many various types of media, including video, audio, photos, text, and so on, are used to store medical records. Data devoid of noise is notoriously difficult to retrieve using scanning or any other method. Despite their widespread use, medical imaging techniques like CT and MRI scans may not always provide reliable results. As seen in Figure 2, the sounds are eliminated by the use of a preprocessing approach. In order to construct the effective model, these datasets include roughly 5,000 MRI pictures of brain tumors. In [20],

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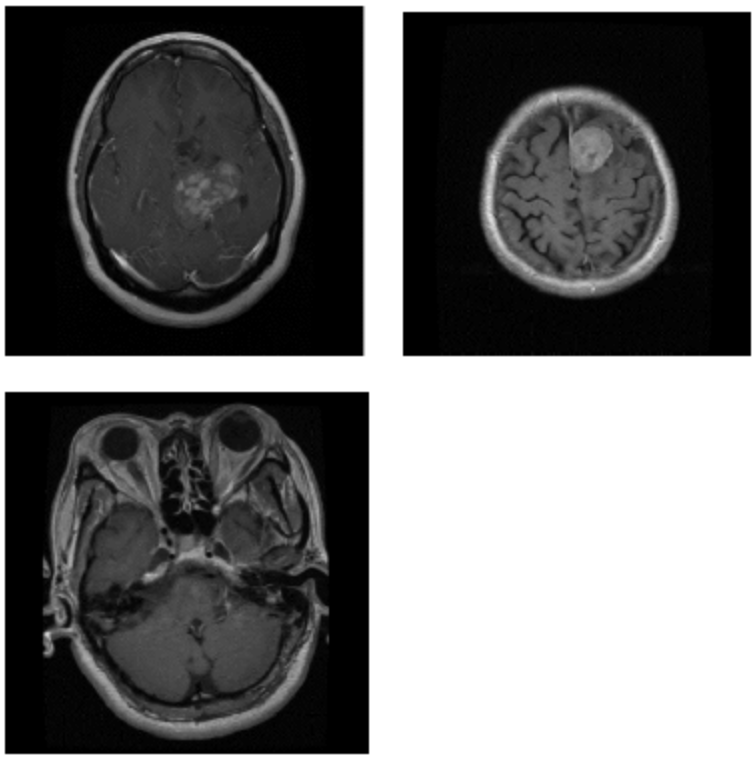

Fig.2. MRI images of Brain tumor

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. As part of the scikit-learn preprocessing package, we bring in the Min Max Scalar function. [21] [22] A smooth surface A flatten layer is included into the Convolutional neural network as part of this research. This layer, when added to the project's architecture after the convolution layer, will reduce computation time and improve performance by flattening the multidimensional array of image features into a single dimension or linear vector. This vector is then used as an input by a fully connected network to detect if a brain tumor is present in a patient's MRI image. [23] The I. Choosing the Model
The next step is to choose a model from the preprocessed dataset. Here, we choose the method for building the prediction model, which may be either deep learning or machine learning. In order to construct an effective model for predicting whether or not a given patient has a brain tumor, this study makes use of convolutional neural networks and support vector machines. CNN (Convolutional Neural Network) [24] The Convolution Neural Network (CNN) is a Deep Learning method that is used to categorize the input data in this project. Deep learning approaches make use of a plethora of algorithms. A wide variety of neural networks are at your disposal, including recurrent neural networks, multi-level perceptrons, convolutional neural networks, and long short-term memory networks. This research makes use of support vector machines (SVMs) and convolutional neural networks (CNNs). Deep learning algorithms are included in the keras packages. As a result, we bring in Keras's Conv2D, which stands for the two-dimensional convolution layer. This will filter the input image and then provide a filtered result. The images are sent in a linear fashion from the input layer to the output layer due to our sequential technique. We use a 2-dimensional convolutional layer here, with four filters—32, 64—each having a 3x3 Kernal matrix and a 2x2 Pool matrix. Feature extraction from input MRI scan photos is done using the Kernel and the Maxpool techniques. 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. Using this function, the processing speed is increased. The value of ReLU for negative samples is 0, since it has a range of 0 to positive infinity. However, we use the Sigmoid function to determine whether the image is normal or altered by a tumor. The sigmoid function is defined between zero and one. This sigmoid function introduces non-linearity, which might lead the network to learn sophisticated models. Consequently, the Sigmoid function and the rectified Linear unit function are

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both used in this project. To forecast the values from the neural network's previous layer, Adaptive Moment Estimator (Adam) is used to mechanically change the neural network's parameter in this model. This optimizer helps the model learn faster during sample training and also increases the model's accuracy. In Fig.3, we can see the results of the CNN. Twelve epochs are used to train the model in this project. 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 891ms/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: 0.3628 - 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 907ms/step - loss: 0.2982 - accuracy: 0.8799 - val_loss: 0.2546 - val_accuracy: 0.9105
Epoch 7/10
12/12 [==============================] - 11s 907ms/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: 0.1850 - val_accuracy: 0.9368
```

Fig. 3.1. Epochs

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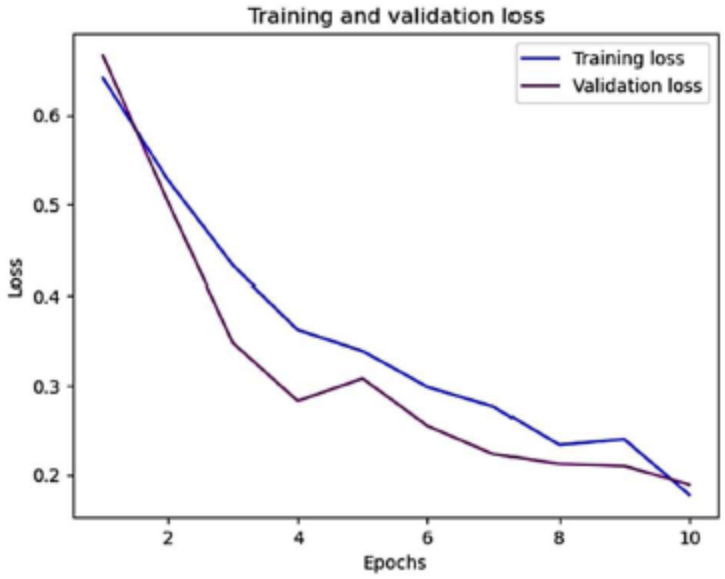

Fig.3.2. Graph for Loss

Fig.3.2. Graph for Accuracy

In terms of accuracy, convolutional neural networks (CNNs) rank at 93%. Additionally, metrics like recall, accuracy, and others are computed. Machine for Support Vectors (SVM) In this research, we use support vector machine, an additional classification technique. Using the supplied picture collection, this algorithm determines whether a patient has a brain tumor or not. An accuracy score of 83% is produced by this method. See the support vector machine (SVM) algorithm's evaluation metrics in Fig. 4. To examine the model's overall performance, several metrics are employed.

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	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

TABLE.1. EVALUATION METRICES COMPARISON TABLE

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

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

V. CONCLUSION

Since the brain is the most vital organ in the body, it is essential that we give it the attention it deserves. Predicting brain tumors using robust machine learning and deep learning methods is the focus of this research. Because these images can have a life-or-death impact on patients, medical imaging requires very high-quality data. Here, we use MRI scans that include both the tumor and normal brain from various angles to better predict where the tumor will be located in the brain. 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,f1 score,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. It is possible to test and assess several deep learning models using the preprocessed data to see whether they increase the accuracy and other performance measures. It is possible to discover a model that performs better.

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