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An Enhance CNN Model for Brain Tumor Detection from MRI Images

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Abstract: - A Convolutional Neural Network (CNN) model for the precise classification and detection of brain tumors from Magnetic Resonance (MR) images is presented in this research. Leveraging the power of deep learning, the proposed CNN model demonstrates remarkable accuracy in distinguishing between different tumor types, aiding in effective diagnosis. The network is trained on a diverse dataset, enabling robust generalization to unseen cases. The proposed method not only enhances the classification performance but also facilitates early tumor detection. Operating on 256 x 256 image inputs, the proposed model boasts a complex architecture featuring six Conv2D layers, batch normalization, five MaxPooling2D layers, six dense layers, and an input layer. Throughout these layers, the ReLU activation function dominates with the final dense layer utilizing the sigmoid function. The potential of sophisticated CNN architectures in medical imaging is highlighted by this study. The outcomes validate the effectiveness of the CNN-based method, advancing computer-aided neuroimaging diagnostic tools and offering a useful tool for medical practitioners. The increased accuracy values demonstrate how well the sophisticated CNN model recognizes brain tumors and point to its potential as a more complex and dependable technique. It also presents a viable avenue for accurate and timely brain tumor identification.

Keywords: Convolutional Neural Network (CNN), Normalization, Medical Imaging, Brain Tumor, Deep-Learning, Magnetic Resonance Imaging (MRI), Segmentation.

I. INTRODUCTION

A person with cancer has aberrant brain cell development. Given how strongly the skull protects the brain, any growth should be treated with extreme caution. The American Cancer Society (ACS) estimates that 6.4 cases of this disease occur annually for every 100,000 individuals. The comparable yearly death rate is 4.4 per 100,000 people [1]. The identification of brain tumors is a tedious task in medical field due to the need for prompt treatment and better chances of survival. The vital signs include the patient's condition, the physical examination, and the results of the laboratory tests. CT and MRI are two examples of imaging modalities that have been included in the essential diagnostic criteria. These imaging modalities are essential for spotting early changes in the tissue, allowing for timely intervention [2].

The primary structure of the human brain, which is made up of billions of neurons, makes it highly intricate organ in the body. A characteristic of a brain tumor is the abnormal development of tissue in areas where it shouldn't be significantly growing. The classification that is discussed in the paper is based on the examination of the MRI scan. Deep learning techniques are used in this work, which are well-known to generate positive outcomes in large-scale datasets [3]. The use of computer-aided technology reduces the possibility of errors occurring during

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conventional operations. A classification technique for brain tumor pictures was presented by Arbane et al. [3]. It uses a single convolutional layer with 64 feature maps and 16 main capsules. This method was claimed to have an accuracy of 86.56%.

Brain tumor research is one of the most prominent fields in academics today. Malignant tumor classification, in general, entails segmenting and classifying tumor areas. Located in the centres of the neurological system, the brain is an essential organ. As a result, brain tumors can cause ailments that are potentially fatal, making early diagnosis of these tumors crucial.

Machine learning (ML) models may be used to classify images, but in order to make these models useful and effective; certain properties need to be included. Even if, there are many hand-crafted characteristics accessible, it might take some time to choose the right ones for a particular categorization assignment. Convolutional Neural Networks (CNNs), on the other hand, simplify the procedure and do away with the necessity for human feature selection by independently extracting features from the photos. In this paper, we have proposed an enhanced CNN model for brain tumor detection from MR images.

The remaining sections of this paper are arranged as follows: the depth analysis of relevant work is presented in Section 2, together with background information and ideas from the body of current research. After that, Section 3 describes the study's methodology in depth as well as the suggested model. The outcomes of the investigation are discussed in detail in Section 4. Section 5 concludes the research findings.

II. RELATED WORK

The current state of research on brain tumor early detection is examined in this section. Ginni Garg utilized an open and standard Glioblastoma Multiforme dataset, which consists of a mean of 2556 samples of T1-weighted images [4]. The dataset has been divided 85:15 for the purpose to assess the recommended methods. A hybrid ensemble classifier was utilized to extract features utilizing multiple Stationary Wavelet Transform (SWT) formats. It incorporated K-Nearest Neighbor, Random Forest, and Decision Tree. This classifier's astounding 97.3% accuracy was attained. Muhammad Khan et al. [5] proposed a “Support Vector Machine” (SVM) classifier to categorize brain tumor pictures using the BRATS dataset of 2013. With an astounding accuracy of 98.88%, they used segmentation, “Extended Features Texture Analysis” (EFTA), and “Histogram Oriented Gradient” (HOG) in their approach. Subhashis Banerjee [6] classified datasets from the Medical Image Archive using the Volume Net model, achieving a noteworthy 97% accuracy rate. Muhammad Sharif [7] worked on the key technique of lesion enhancement then segmentation and after that classification. The noble technique of Fuzzy Sets was employed in the procedure of segmentation, which was conducted on the BRATS 2012, 2013, and 2015 datasets. With 99% of the accuracy on the dataset of BRATS 2012, the Extreme Learning Machine (ELM), which is based on a single feed-forward neural network, showed impressive performance. Using frog leap optimization and an adaptive fuzzy Deep Neural Network (DNN), Daizy Deb [8] has achieved 99.6% accuracy in detecting abnormalities and normalcy in pictures. The adaptive flying squirrel algorithm has been used for the objective of segmenting aberrant photos.

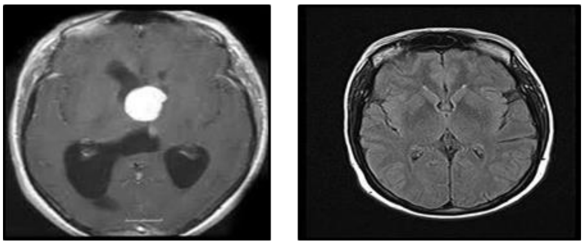
A transfer learning-based approach was used by Mohamed Arbane [3] to divide MRI pictures of brain into two binary classes. With an NVIDIA GTX 1070 GPU, this model ran with a high accuracy of 98.24%. In this study, the MobileNet-v2 architecture was used. A multiscale model for brain tumor segmentation and classification was presented by Francisco Javier Díaz-Pernas [9], who used a Deep convolutional neural network (CNN) on a dataset of 3064 MRI images that was made accessible to the public. With a remarkable 97.3% classification accuracy, the model functioned admirably. In a two-step technique, Biswajit Jena [10] used image processing for tumor extraction and supervised machine learning for tumor categorization. Using a hybrid segmentation algorithm with RF and SVM along with KNN and Ensemble methods, the practical results showed a mean dice score of 90.16% and a classification accuracy of 97% for tumor area comprehension versus ground-truth photographs. Using the BRATS dataset, G. Ramkumar [11] proposed Brain Tumor Segmentation using the Deep CNN Algorithm (DCNNA) and achieved similarity coefficient metrics of 88.86%, 83.3%, and 77.3%. The proposed non-linear approach was used with fuzzy logics to upsurge the DCNNA 's accuracy above 95%. In order to combine Convolutional Neural Networks (CNN) with conventional architectures for MRI images of brain tumor, Marcin Woz´niak et al. [12] presented a mechanism of correlation of learning (CLM) for Deep Network of Neural designs. The CLM model showed excellent precision (95%), recall (95%), and accuracy (96%).

With an astounding accuracy of 99.25%, Using MRI brain pictures, Isselmou Abd El Kader et al. [13] generated a deep Convolutional Neural Network (CNN) model for the purpose of identifying malignancies. “The Tianjin Universal Center of Medical Imaging and Diagnostic” (TUCMD) provided the 17,600 MR brain pictures utilized in this investigation. These images included T1, T2, and FLAIR shots. A CNN model was presented by Muhammad Arif et al. [14] using a dataset of binary class of MR pictures of brain. For image classification, Berkeley's Wavelet Transformation of Segmentation was used by them, and they calculated GLCM features. The model's remarkable 98.5% accuracy was attained. Using a variety of topologies, such as CNN along with “Recurrent Neural Network”, and also “Feed Forward Neural Networks”, T. Vijayakumar [15] examined the effectiveness of neural networks for tumor diagnosis and cancer forecasting. An optimization technique of hybrid manta ray foraging was presented by P. Karuppusamy [16] for feature selection from MRI images of brain tumors. An accuracy of 98.2% was attained by the use of a “Convolutional neural Network “ (CNN) to assess the optimal attributes and detect brain tumors in their early stages.

This comprehensive review illustrates cutting-edge methods for early brain tumor detection. Utilizing hybrid classifiers, SVM with segmentation, adaptive neural networks, and CNN-based optimizations, these approaches achieved exceptional high accuracy. These diverse and accurate methods hold promise for precise diagnoses, showcasing the evolving landscape in brain tumor research towards enhanced detection and diagnosis techniques.

III. RESEARCH METHODOLOGY

A) Data collection and preprocessing - The dataset in this particular research comes from two different key major sources. First, there are 1500 healthy photos and an equal number of harmful images in “BR35H: Brain Tumor” [17]. The second set of data, which has 1308 unhealthy and 1019 healthy photos, is accessible to the general public via GitHub [18]. The article uses 5327 brain pictures in total for analysis. The Color, noise, and dimension changes are common in raw MRI pictures. Image filtering is used to solve these problems and improve image quality. In order to improve edge sharpness and minimize noise, filters are used. The 'GaussianBlur' function from the OpenCV library is applied after the picture has been convolved using a kernel. An important part of this procedure is the kernel, which is a square matrix of size n × n (where n is an odd number). The MRI pictures in the dataset show a variety of intensity distributions as they were taken from several scanners using varying camera angles and settings. The suggested model has to be pre-processed in order to perform optimally. This entails gray-scale conversion and resizing the photos to 256 × 256 pixels. A visual depiction of both pictures with and without brain tumors is provided by the photos shown in Fig. 1, which are exemplary examples from the collection. These pictures highlight the significance of image pre-processing approaches in preparing the data for the proposed model by offering a glance into the wide range of cases and variations within the dataset.



(a) Affected with Tumor (b) Without Tumor

Figure. 1 Sample pictures of brain tumors

Then the used dataset is divided into major 3 parts for the training purpose, validation, and testing purpose of the suggested model of deep learning after pre-processing. Initially, 80% of the whole dataset is put aside for training and 20% is placed aside for testing. After then, the training data is separated into two parts: 20% is used for validation and the remaining 80% is used for real model training. The 5327 photos altogether in the dataset are taken; for training - 3410 images, for testing - 1060 images, and 850 images for the corroboration (validation). Fig. 2 shows approach being used for this division.

B) Proposed Model - In order to enhance accuracy, this research proposed a CNN model that offers a quick method of identifying brain tumors without segmentation. For training, the model receives 256 x 256 picture input. Six Conv2D layers make up this system: one batch normalization layer, five MaxPooling2D layers, five dense layers, and the input layer. These layers make use of the relu activation function, whereas the sigmoid function is used in the sixth and final dense layer. Fig. 3 shows the architecture of the suggested model. After 25 epochs of training, the model reaches 100% training accuracy by the 21st epoch.

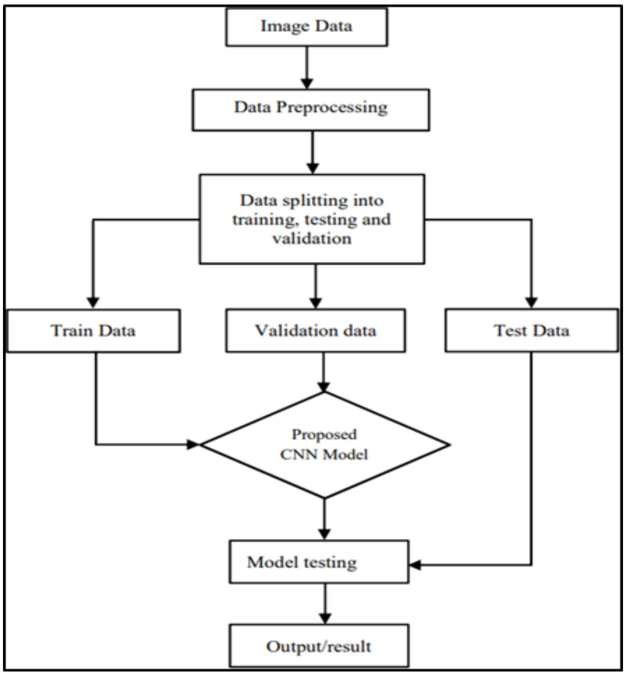


Figure. 2 Block diagram illustrating the employed approach

C) Mathematical model - A mathematical model for the proposed Convolutional Neural Network (CNN) architecture used in identifying brain tumors without segmentation is described as: Let X be the input image data of size 256×256×3 (assuming a 3-channel input, such as RGB). The architecture consists of the following layers:

1) Convolutional Layer (Conv2D) with ReLU activation:

- Filters: n1
- Filter size: f1 × f1
- Stride: s1
- Padding: p1
- Output size: (256 - f1 + 2 × p1)/s1 + 1

2) MaxPooling2D Layer:

- Pool size: psize1× p size1
- Stride: pstride1
- Output size: Output size from previous layer/ psize1

3) Repeat Convolutional and MaxPooling Layers (similar to 1 and 2) for a total of 4 times (total 5 Conv2D and MaxPooling2D layers).

4) Dense Layers (fully connected layers) with ReLU activation:

- Number of neurons: (m1, m2, m3, m4, m5)

5) Final Dense Layer with Sigmoid activation:

- Number of neurons: m6 =1 (since its performing binary classification)

The architecture summary:

- Input: $256\times 256\times 3$

-Conv2D→MaxPooling2D→Conv2D→MaxPooling2D→Conv2D→MaxPooling2D

-Dense→Dense→Dense→Dense→Dense (5 dense layers)

- Final Dense Layer with Sigmoid activation

Mathematical equations for each layer's output size, assuming a particular configuration of filter sizes, pool sizes, strides, padding, and number of neurons in dense layers, need to be provided to create an accurate model. These configurations were not explicitly mentioned in the description provided.

The training procedure includes iteratively updating the weights and biases of the networks layers to minimize a loss function (e.g., binary cross-entropy for binary classification) using a suitable optimizer (e.g., Adam, SGD) over a dataset of brain tumor images.

The statement mentions that the model reaches 100% training accuracy by the 21st epoch after training for 25 epochs, suggesting that the model may have overfit the training data. This mathematical representation requires specific numerical values for parameters such as filter sizes, pool sizes, strides, padding, and number of neurons to create mathematical model.

D) Convolutional layer - Basically, CNNs (Convolutional Neural Networks) plays a key role in the classification tasks of image. This is mostly due to their popularity, which eliminates the need for human feature extraction, since they are capable of independently learning the characteristics for every class. The convolutional layer, which is the fundamental component of CNNs, works very well with picture data. In the proposed model, six convolutional layers make up the neural network model and each one is essential to the process of extracting hierarchical features from the input data. Starting with the first convolutional layer ({conv2d}), which has 32 filters, the next layers ({conv2d_1}, {conv2d_2}, {conv2d_3}, {conv2d_4}, and {conv2d_5}) have progressively more filters—64 to 512—in order to progress. Convolutional layers are essential to the feature extraction process because they enable the model to recognize and comprehend complex patterns and representations in the input. The network can learn more intricate and abstract properties as the number of filters increases across these layers, which eventually improves the model's ability to produce precise and sophisticated predictions.

E) Dense layer - A densely connected network is produced when every single neuron in a dense layer, also known as a totally connected layer, is connected to every single neuron in the layer above it. This layer works well for deciphering intricate data linkages. The convolutional layer, on the other hand, is dedicated to picture processing. In order to extract spatial hierarchies of features and identify patterns like edges or textures, it uses filters or kernels. Convolutional layers produce outputs that capture learnt characteristics, which are subsequently sent to dense layers for additional processing and decision-making on tasks like image categorization. Neural networks are able to learn complex data representations because of its hierarchical nature. The proposed CNN model has six dense layers in total. First, there is a dense layer ({dense}) with 256 neurons. This is followed by other dense layers ({dense_1}, {dense_2}, {dense_3}, {dense_4}, and {dense_5}) that have fewer neurons—between 128 and 1. A fully linked structure is produced when each thick layer links every neuron in the next layer to every other neuron. When dealing with binary classification tasks, such as image classification or other binary decision problems, the final dense layer with a single neuron is usually utilized. The output of this layer indicates the likelihood of a certain class.

F) Layer of max pooling - Max Pooling is a dimensionality reduction approach that takes an image matrix and extracts the maximum value within a given size of the kernel of (n*n) in order to minimize processing time. This method creates a feature map that has been down sampled, or pooled. In neural networks, max pooling is frequently used to preserve important characteristics while lowering computational cost and fostering spatial invariance. It comes after the convolutional layer. Five max pooling layers make up the proposed CNN architecture, and they are all arranged to down sample the input data's spatial dimensions. The procedure is started by halving the spatial resolution in the first max pooling layer ({max_pooling2d}). Then, in a cascading fashion, the spatial dimensions are further reduced in the following layers: (`max_pooling2d_1},{max_pooling2d_2}, max_pooling2d_3}, and {max_pooling2d_4}). Max pooling layers are essential for feature extraction because they save the most important information while removing the less important aspects. This down sampling process not only aids in the model's concentration on key characteristics but also helps manage the network's computational complexity, enabling more effective and efficient learning.

G) Batch normalization layer - By normalizing inputs inside mini-batches, batch normalization improves neural network training by resolving problems such as vanishing/exploding gradients. Training is stabilized, convergence is accelerated, and sensitivity to weight initiation is decreased. Learnable parameters optimize network performance by shifting and scaling normalized inputs. Neural network designs frequently employ this method to increase stability and efficiency during training. A batch normalization layer, called `batch_normalization', is included in the proposed CNN model. Prior to the convolutional layer that follows, batch normalization is applied after the initial max pooling layer. The batch normalization layer in this particular architecture is placed in between the first max pooling layer and the convolutional layer that comes after ({conv2d_2}). By modifying and scaling the activations, batch normalization is a regularization approach that normalizes a layer's input. Reducing problems like internal covariate shift helps to stabilize and accelerate the training process and causes more stable and rapid convergence when deep neural networks are being trained. With 64 parameters, the batch_normalization layer in this model enhances the neural network's overall robustness and efficiency during the learning process. The Proposed CNN model is shown in Fig 3 and summarized in Fig. 4.

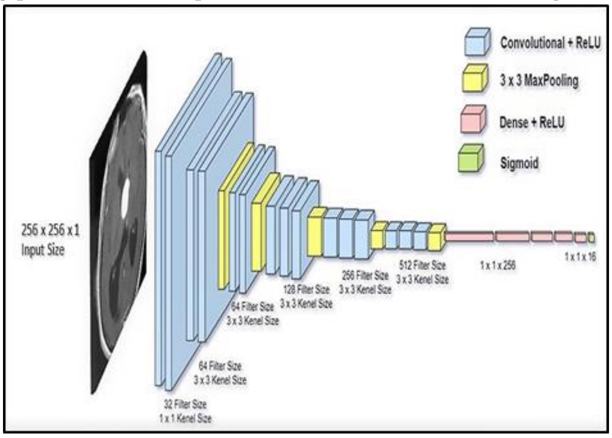


Figure. 3 Proposed CNN model

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 256, 256, 32)	64
conv2d_1 (Conv2D)	(None, 254, 254, 64)	18496
max_pooling2d (MaxPooling2D)	(None, 127, 127, 64)	0
conv2d_2 (Conv2D)	(None, 125, 125, 64)	36928
max_pooling2d_1 (MaxPooling2	(None, 62, 62, 64)	0
batch_normalization (BatchNo	(None, 62, 62, 64)	256
conv2d_3 (Conv2D)	(None, 60, 60, 128)	73856
max_pooling2d_2 (MaxPooling2	(None, 30, 30, 128)	0
conv2d_4 (Conv2D)	(None, 28, 28, 256)	295168
max_pooling2d_3 (MaxPooling2	(None, 14, 14, 256)	0
conv2d_5 (Conv2D)	(None, 12, 12, 512)	1180160
max_pooling2d_4 (MaxPooling2	(None, 6, 6, 512)	0
flatten (Flatten)	(None, 18432)	0
dense (Dense)	(None, 256)	4718848
dense_1 (Dense)	(None, 128)	32896
dense_2 (Dense)	(None, 64)	8256
dense_3 (Dense)	(None, 32)	2080
dense_4 (Dense)	(None, 16)	528
dense_5 (Dense)	(None, 1)	17

Total params: 6,367,553
Trainable params: 6,367,425
Non-trainable params: 128

Figure. 4 Summary of model

IV. RESULTS AND DISCUSSION

A machine consisting of an Intel Core i7 CPU, 64-bit Windows 11 OS, and 16 GB of the RAM was used in the research. TensorFlow, scikit-learn (sklearn), and Keras are among the Python packages that were used to train the suggested model in a Jupyter Notebook environment. 3.8.10 as well was the version of Python used in the trials. Impressive results were obtained in this study when the suggested framework was applied to a dataset of MRI pictures.

4.1 Accuracy graph

How effectively our model predicts is determined by comparing the actual values, expressed as a percentage, with the predictions made by the model. The graph in Fig 5 illustrates the model's performance over epochs, with the X-axis demonstrating the number of times the model processes the entire training dataset, and the Y-axis denoting accuracy in terms of the percentage of correct predictions. The blue line is depicting training accuracy, initiates around 75%, steadily progressing to almost 98% by epoch 20, indicating the model's effective learning from the training data. The green line, representing validation accuracy, commences around 70%, reaching approximately 94% by epoch 20, closely mirroring the training accuracy trend and implying good generalization to unseen data. This commendable performance is attributed to the well-designed model architecture, featuring six Conv2D layers for spatial feature capture, five Max pooling 2D layers for dimensionality reduction, one Batch Normalization layer for stability, and six Dense layers for complex decision- making. The activation functions, ReLU and Sigmoid, further contribute to the model's success by efficiently handling gradients and facilitating optimal binary classification for tumor identification. The generalization gap, denoting the difference between training and validation accuracy, remains relatively narrow at approximately 3-4 percentage points. This observation is indicative of the model's ability to avoid substantial overfitting, showcasing a commendable capacity to generalize effectively to previously unseen data. Furthermore, the peak performance of both training and validation accuracy is achieved around epoch 20. This convergence at the highest accuracy values suggests that the model has reached its optimal training duration, and further training may risk overfitting. Hence, this insight implies the potential benefit of stopping training to prevent unnecessary complexity and enhance the model's ability to make accurate predictions on new, unseen data.

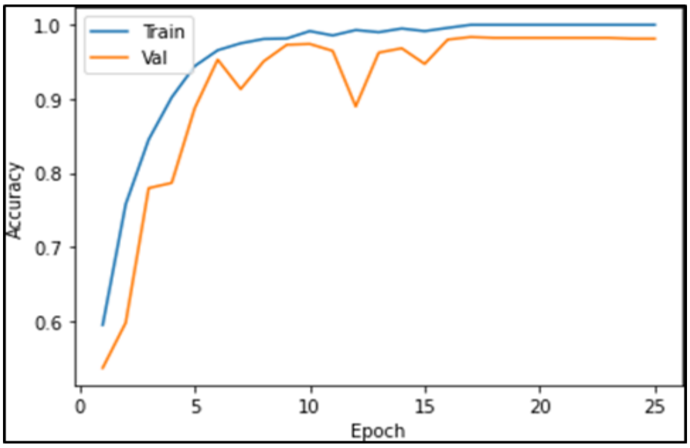


Figure. 5 Accuracy graph of Brain Tumor

4.2 Loss graph

In the evaluation of a model's effectiveness, a fundamental metric is its loss, serving as a quantitative measure that encapsulates the cumulative mistakes made during the training and learning process. This numerical representation holds significant meaning, as larger loss values correspond to suboptimal model performance, indicating a higher degree of discrepancy between predicted and actual outcomes. Conversely, smaller loss values signify superior model proficiency, suggesting a more accurate alignment between predictions and ground truth. A designated loss function, also known as a cost function, plays a crucial role in the framework's optimization process by aiding in calculating of this loss. A thorough overview of the brain tumor detection strategy training process is provided by Figure 6, which highlights important architectural components and how they affect performance. The model's advancement through the training dataset is plotted on the X-axis, which represents epochs, and the Y-axis, which represents loss, shows the difference among predicted and actual values. The model's ability to refine predictions based on training data is demonstrated by the blue line, which represents training loss and shows a steady drop. Simultaneously, the orange line, representing validation loss, undergoes a decreasing trend with occasional fluctuations, indicating the model's capability to generalize effectively to unseen data. The underlying architecture, featuring Six Conv2D layers for spatial feature extraction, five Max pooling 2D layers for dimensionality reduction, one Batch Normalization layer for stability, and six dense layers for intricate decision-making, contributes significantly to the model's success.

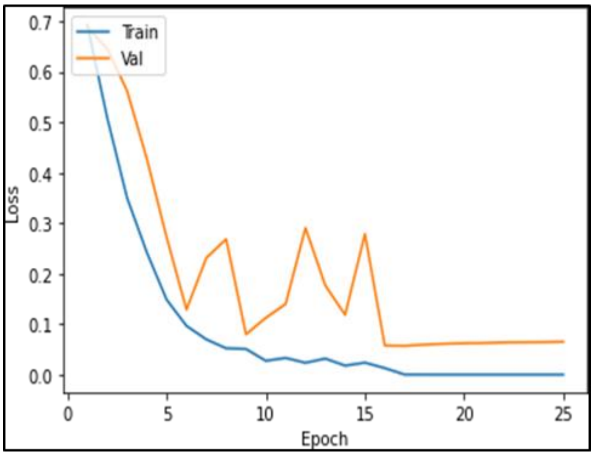


Figure. 6 Loss graph of Brain Tumor

The utilization of the rectified linear unit (ReLU) activation function in these layers facilitates efficient handling of vanishing gradients, enabling deeper networks and improved learning. The sigmoid function in the final dense layer is well-suited for binary classification, providing a probability output for tumor presence. This combination of architectural components, activation functions, and the consistent downward trend in loss collectively explains the model's commendable performance in brain tumor detection.

4.3 Analysis of Brain disease

With segmentation, Mohammad Arif [14] identified brain tumours with 98.5% accuracy. The approach avoids the issue of limited data by adding more photos to the dataset, not using segmentation, and using more CNN layers in the suggested model.

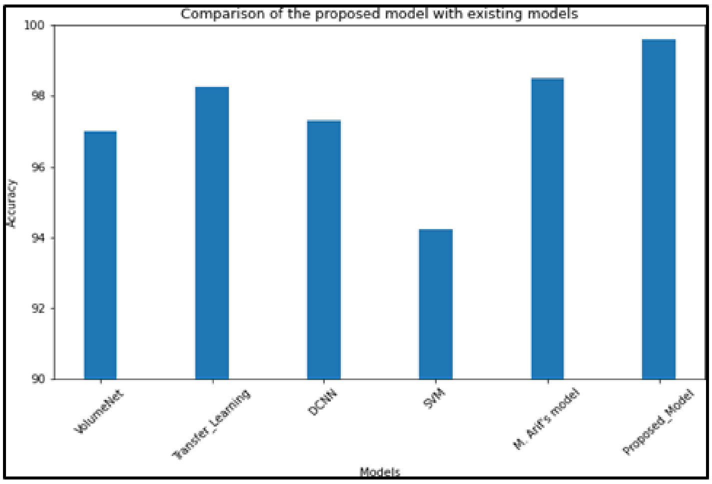


Figure. 7 Comparison of the proposed model with existing models

This reduces the temporal complexity and improves the accuracy of the model. The proposed model is contrasted with the models that are currently in use. Fig. 7 presents an accurate comparison between the proposed model and the current models. in series In our suggested model, VolumeNet is 97%, Transfer Learning is 98.24%, DCNN is 97.3%, SVM is 94.25%, and ours is 99.59%.

V.CONCLUSION AND FUTURE WORK

In conclusion, this study demonstrates the significant strides achieved in brain tumor classification and detection through the implementation of a sophisticated Convolutional Neural Network (CNN) architecture. Leveraging the capabilities of deep learning, our proposed model exhibits remarkable accuracy in distinguishing diverse brain tumor types, thus enhancing the effectiveness of diagnostic processes. The reported higher accuracy values validate the efficacy of the proposed CNN-based approach, positioning it as a promising tool for computer-aided diagnostic applications in neuroimaging. The emphasis on early tumor detection further enhances its clinical relevance, potentially leading to more timely interventions and improved patient outcomes. This research contributes to the ongoing advancements in medical imaging and establishes a valuable resource for healthcare professionals seeking reliable and sophisticated methods for brain tumor diagnosis. It has been demonstrated that using non-invasive biomarkers in machine learning architectures is a highly effective method for identifying brain tumors. The validation accuracy and recall of the proposed model for the MRI image dataset are 98.37% and 99%, respectively. The model's overall accuracy of 99.59% is rather good. This suggests that it can be implemented in real-world scenarios and robust production systems.

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