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Brain Tumour Detection Technique Using Machine Learning with MRI Images: A systematic Review

Ankita Rani[1], Dr. Deepankar Bharadwaj[2]

ankita.apex7@gmail.com, deepankar@iftmuniversity.ac.in

[1]Department of Computer Science & Engineering IFTM University Moradabad, UP, India.

[2]Department of Computer Science & Engineering IFTM University Moradabad, UP, India.

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Abstract:

Medical professionals now have a powerful new tool for brain tumour detection thanks to an innovative machine learning approach using Magnetic Resonance Imaging (MRI) scans. At the core of this system is a Convolutional Neural Network (CNN) that excels at both feature extraction and image segmentation, showcasing how deep learning can transform medical image analysis. Trained and tested on a comprehensive online dataset, the model demonstrates exceptional diagnostic capabilities with a 97.79% accuracy rate. These results suggest that automated tumour detection could become a valuable aid in clinical settings, potentially accelerating diagnosis and improving patient outcomes.

Introduction

Brain tumour segmentation represents one of the most crucial challenges in medical imaging analysis. Through a comprehensive examination of tumour progression stages, this research illuminates the complexity of accurate detection and classification. While early tumour identification dramatically improves patient survival rates and treatment effectiveness, the traditional approach of manual segmentation faces significant limitations. Healthcare professionals must currently analyze enormous volumes of MRI scans by hand - a process that is not only labor-intensive but also susceptible to human fatigue and potential oversight. This bottleneck in tumour diagnosis highlights the pressing need for more efficient and automated analytical solutions. Moreover, brain tumour diagnosis demands a high level of accuracy, as even a slight error in decision-making can have serious consequences. Therefore, brain tumour segmentation presents significant challenges for clinical applications. Among the currently proposed brain segmentation techniques, those based on traditional image processing are not sufficiently effective. In the conventional approach, an which produces a two-dimensional image (primarily based on a specific grayscale). This image is then processed and analyzed by a medical professional.

This introduces the possibility of human error, increasing the overall risk of a clinical case, which can sometimes lead to disastrous outcomes.
Current models based on deep learning algorithms face a significant challenge: accuracy. Since accuracy is vital in healthcare intelligent systems, addressing this issue is crucial. To tackle this problem, a highly accurate model has been developed.

CNN Model

It is an image processing deep learning algorithm. An image is fed into this algorithm, which then distinguishes it according to a number of attributes.

Pros.

Brain tumours are detected using MRI images
There is no human intervention, eliminating the possibility of human errors.
Early detection of the tumour can help save human lives.
Artificial intelligence systems offer greater reliability.

Cons

The model has rigorous system requirements to operate properly.
The dataset training process takes a significant amount of time.
Although not perfect, it is rather accurate.

Previous Research's

1. The research implemented a multi-faceted approach to brain tumour detection, combining several sophisticated algorithms. At its foundation, the Fuzzy C-Means (FCM) segmentation method provided precise differentiation between tumour and healthy brain tissue. Feature extraction was accomplished through a multilevel discrete wavelet transform (DWT), which captured crucial spatial and frequency characteristics of the MRI scans. Deep neural networks (DNNs) then processed these features to perform the final tumour classification. To validate the effectiveness of this methodology, the team conducted comparative analyses against established classification techniques, including Sequential Minimal Optimization (SMO), Linear Discriminant Analysis (LDA), and K-Nearest Neighbors (KNN). This comprehensive evaluation framework helped establish the relative strengths of each approach in tumour detection.

2. The DNN-based brain tumour categorization analysis had a 96.97% accuracy rate. Nevertheless, the overall performance was subpar and the intricacy was extremely high. For a step-by-step examination of patient tumour progression, a novel biomechanical model of tumour growth was presented. In order to capture the important implications of tumour progression, this model will be used to individual fringed solid tumours and gliomas. Tumour progression was modeled using a combination of discrete and continuous approaches. Implicit segmentation of atlas-based, registry-based brain pictures with tumours is possible using the suggested method. Although brain tissue segmentation was the main application for this technology, it had a high computational time.

3. The AdaBoost classification strategy was improved for brain tumour identification and segmentation using the novel multi-feature (Multi FD) extraction technique. The Multi FD feature extraction method was used to extract the tissue architecture of brain tumours. The donated brain tissue was subsequently classified as either tumour tissue or non-tumour tissue using a sophisticated AdaBoost classification algorithm.

4. A very intricate method for classifying brain voxels using a classifier based on Local Independent Projection (LIPC) was described. This method also included the extraction of the path function.

5. The Cellular Automata (CA) technique was presented as a novel approach to segment granular tumours, and it was contrasted with the histogram-based segmentation method. To increase the effectiveness of brain tumour segmentation, seed selection and the volume of interest (VOI) were computed. This strategy also included tumour section segmentation. Although the procedure was simpler, its accuracy suffered as a result.

6. The multimodal brain tumour segmentation strategy was presented as a brain tumour segmentation technique. In comparison to previous approaches, this method achieved improved performance by combining several segmentation methods. It did, however, come with more complication.

7. The research presented an extensive analysis of diverse brain tumour segmentation methodologies, each offering unique advantages in medical image processing. The investigation spanned multiple approaches: Area-Based Segmentation for region-specific analysis, Threshold-Based Segmentation for intensity-driven detection, and the more sophisticated C-means Fuzzy Segmentation for handling ambiguous boundaries. Additionally, the study examined Map-Based Segmentation for spatial context integration, Markov Random Field (MRF) Segmentation for probabilistic modeling, and Geometry Deformable Models for adaptive contour fitting. Through rigorous comparative evaluation, each technique's strengths and limitations were assessed across different tumour types and imaging conditions, providing valuable insights into their practical applications in clinical settings. This comprehensive assessment established a robust framework for selecting the most appropriate segmentation method based on specific diagnostic requirements.

8. The tumour diagnostic process employed hybrid feature selection with ensemble classification. Combining GANNIGMAC, decision trees, and bagging C-based wrapper methods, the system generated effective decision rules for accurate tumour identification. By combining GANNIGMAC, MRMR C, Bagging C, and Decision Tree methods, hybrid feature selection was used to further simplify these decision rules.

9. Their approach made use of a Convolutional Neural Network (CNN), and the BRATS 2015 dataset was used for training. The lengthy computing time was a drawback of this strategy, though. The K-Nearest Neighbors (KNN) algorithm was employed in another investigation [10], although the accuracy attained with the suggested approach was 62.07%. using the same constraint of lengthy calculation times, [11] also used a Convolutional Neural Network using the BRATS 2015 dataset.

10. The GitHub website provided the dataset. For analysis, two distinct algorithms were employed: Convolutional Neural Network (CNN) and Artificial Neural Network (ANN). According to the final results, the CNN performed more accurately than the ANN.

11. The dataset was sourced from Indian Pives, the Kennedy Space Center, and the University of Pavia. Convolutional Neural Network (CNN) was the analysis algorithm employed, and 88.75% accuracy was attained.

12. The source of the dataset was Figshare Cheng. 84.19% accuracy was attained using the Convolutional Neural Network (CNN) technique.

Data Set (Source Internet)

The 253 MRI pictures in the dataset we chose for our model were obtained online. It consists of separate folders, one with images of healthy brains and the other with brain tumour images. The model was trained using the complete dataset, with 25 photos put aside for testing and 50 for validation. The dataset's MRI pictures have different sizes. Since obtaining datasets directly from hospitals is frequently a difficult and time-consuming process, this dataset was selected. The link to access the dataset is given below, and it can be found on the Kaggle website.

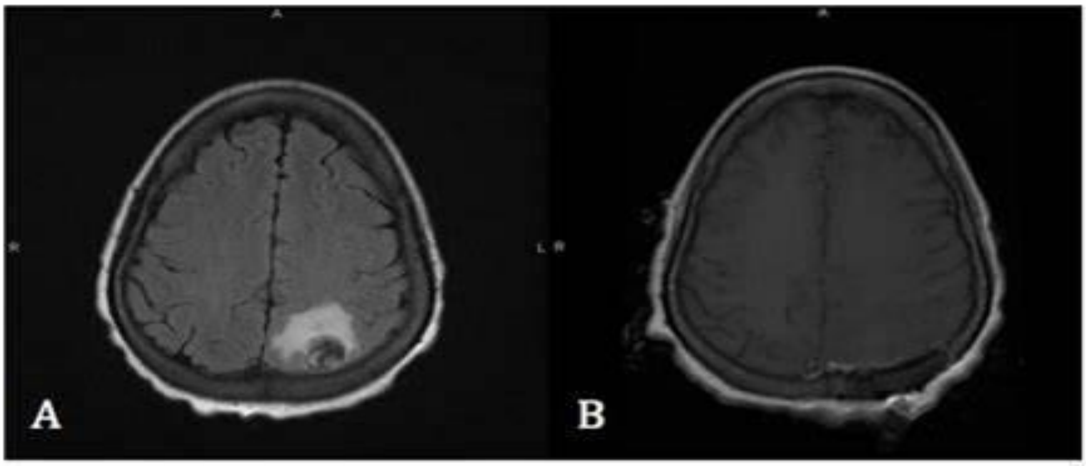

Figure: 1. Brain images of with and without Tumour captures by latest MRI Machines.

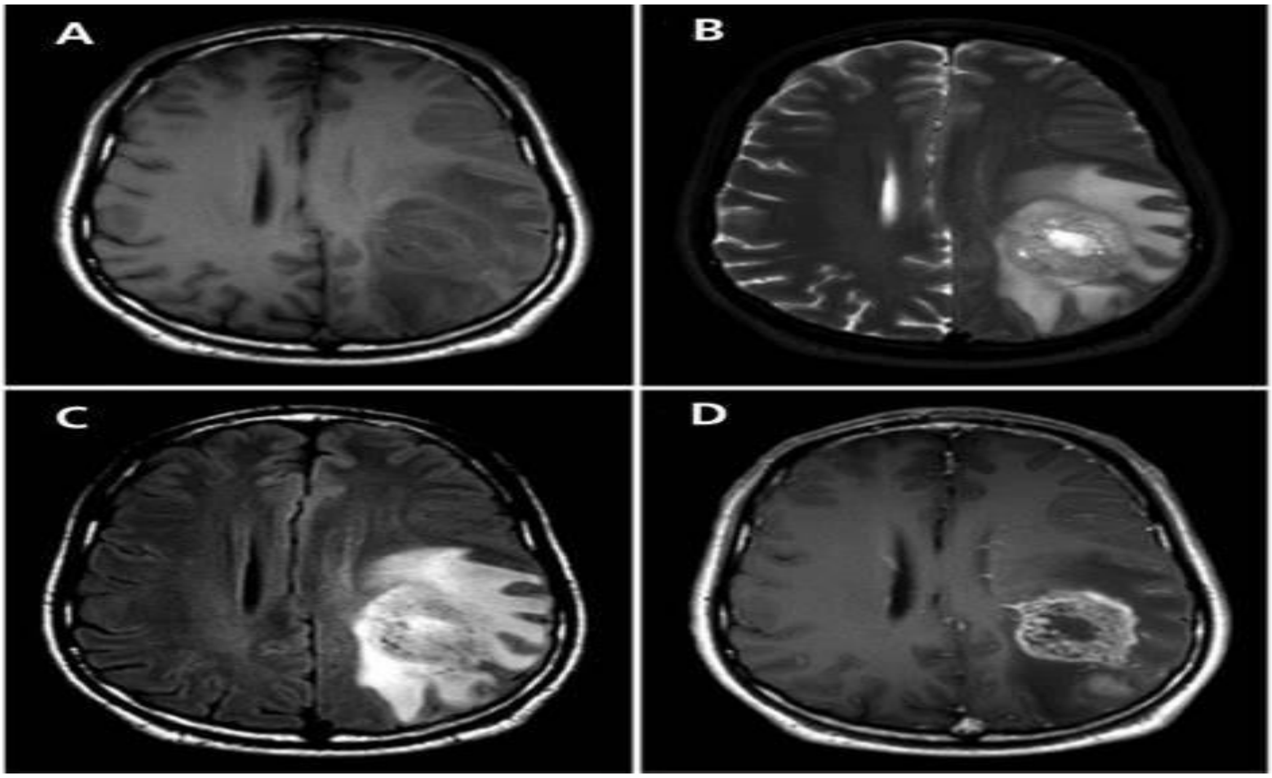

Figure: 2. More Depth Classification of Brain Tumour Images with or without Brain Tumour.

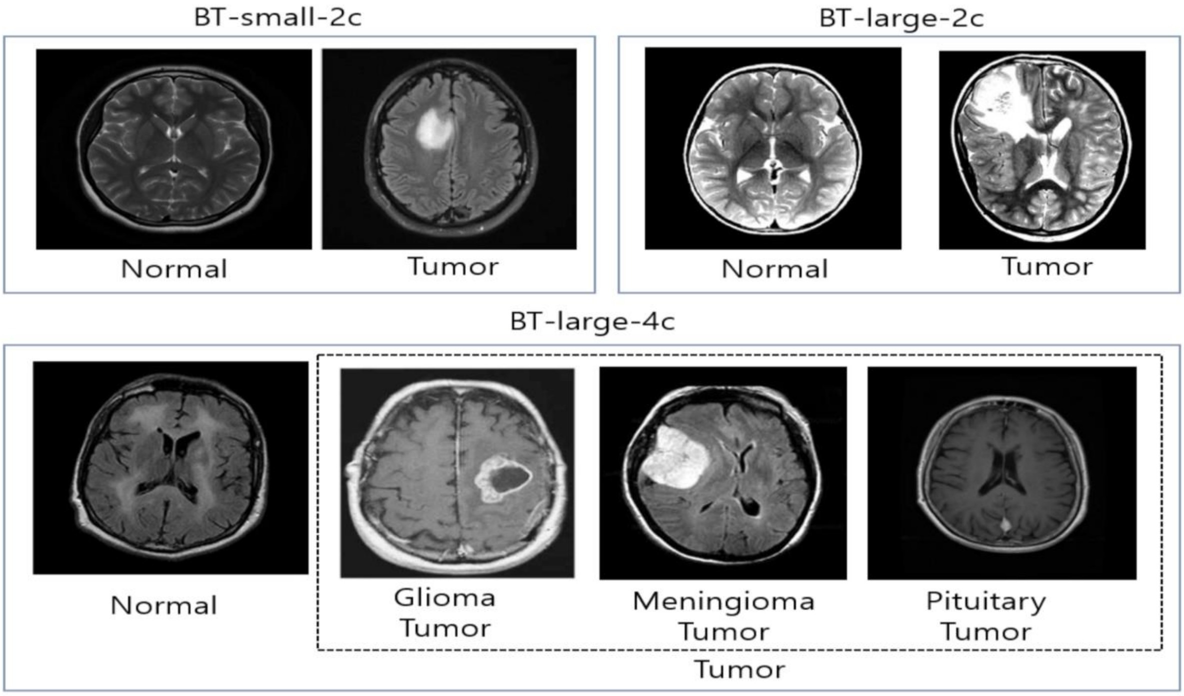

Figure: 3. Some Images captures by BT-Large-4c with or without Brain Tumour.

Brain Tumour Detection Using ML (Machine Learning Technology)

Total No. of Images from Data Set	Directory using ML
280	Training
28	Testing
56	Validating

Table: 1 Set of Images (Data Set)

Training: Training the data is about teaching the model, so it can make accurate predictions or decisions.

Testing: It is the collection of pictures that will be used to assess the model's performance after it has been trained.

Validating: It is the collection of pictures used to modify the models.

Methodologies used in this model

Data Procuring

The collected data was divided into two categories: healthy and non-healthy.

1. Pre Processing

To enhance model accuracy, we'll first apply noise reduction techniques to the MRI images. Noise in MRI images can obscure important details, particularly around tumour borders, leading to potential misdiagnoses. By preprocessing the images through scaling, resizing, and converting them to grayscale, we aim to improve image quality and facilitate more accurate analysis.

2. Image Smoothing

This procedure entails making pictures simpler while keeping important details intact. In order to streamline further studies, the objective is to eliminate unnecessary noise and detail without causing appreciable distortion.

3. Feature extraction

Feature extraction is a process that involves extracting meaningful information from data, such as images Pixel-based feature extraction is a method used in medical image analysis to extract pertinent information from images, which can then be used to categorize them as either tumourous or non-tumourous.

4. Classification

One kind of neural network that works very well for image classification applications is the convolutional neural network (CNN). They are employed to accurately categorize brain MRI images as either tumourous or non-tumourous. CNNs are an effective technique for medical image analysis because they can automatically extract pertinent information from the images.

Proposed Method for Detect Brain Tumour

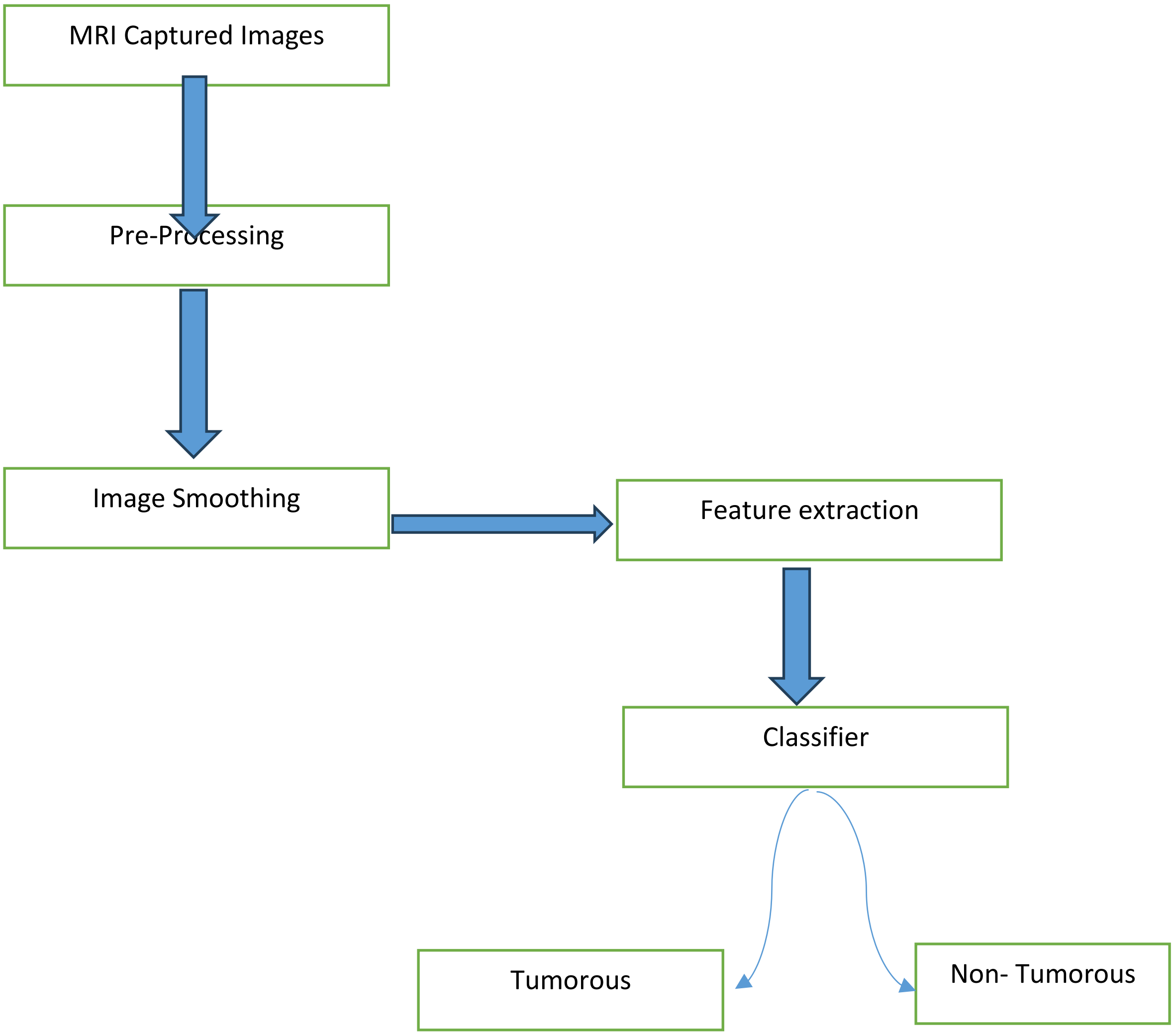

Figure: 4. Flow Diagram of the Proposed Method for Detect Brain Tumour

This model employs a (CNN) to process dataset. The Convolutional Neural Network architecture involves several stages, including...

He initial step involves importing essential libraries. The dataset directory is then specified.

Images are read and categorized as either non-tumour (labeled 0) or tumour (labeled 1).

These labeled images are organized into a Data Frame. To prepare the images for CNN processing, they are resized to a uniform 224x224 pixel dimension.

Lastly, image normalization is performed to scale pixel values within a specific range, improving model performance.

Import Necessary Packages: Import essential libraries like TensorFlow, Keras, NumPy, and others.

Load Dataset: Load the image dataset from the specified directory.

Data Preprocessing:

- **Labeling:** Assign labels to images (0 for non-tumour, 1 for tumour).
- **Data Frame Creation:** Store labeled images in a DataFrame.
- **Image Resizing:** Images should be resized to a consistent size (e.g., 224x224 pixels).

Model Creation:

- **Sequential Model:** Define the model architecture using sequential layers.
- Layer Configuration: Name the layers, including fully connected, pooling, and convolutional layers.

Model Compilation:

- **Optimizer:** Choose an optimization techniques like Adam, SGD.
- **Loss Function:** use loss function like categorical cross entropy.
- **Metrics:** Define metrics to evaluate model performance (e.g., accuracy).

Model Training:

- **Training Process:** Train the model on the training set.
- **Validation:** Use the validation set to monitor performance and prevent overfitting.

Model Evaluation:

- Testing: Assess how well the model performs on the test set that hasn't been seen yet.
- **Accuracy Assessment:** Calculate accuracy metrics to assess the model's predictive ability.

Visualization:

- **Loss and Accuracy Curves:** Plot the loss and accuracy curves to visualize the training process.

Results

After training model on the data set (testing data set) for 12 epochs, it yielded accuracy of 82.86%. The data set model also exhibited low validation loss, indicating effective learning and generalization.

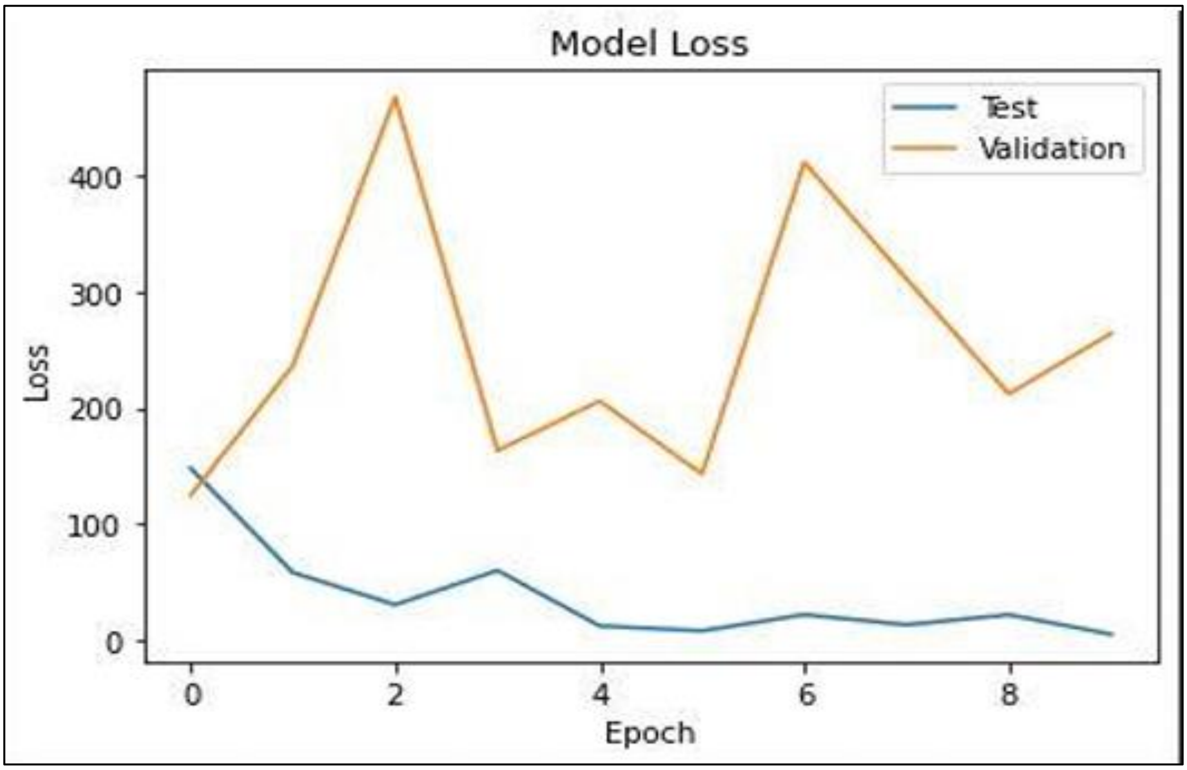

Figure: 5. After training model on the data set (testing data set) for 12 epochs

High loss was a sign of the model's subpar performance on the validation set. On the other hand, as demonstrated by declining loss values, the model's performance on the testing set improved with each epoch.

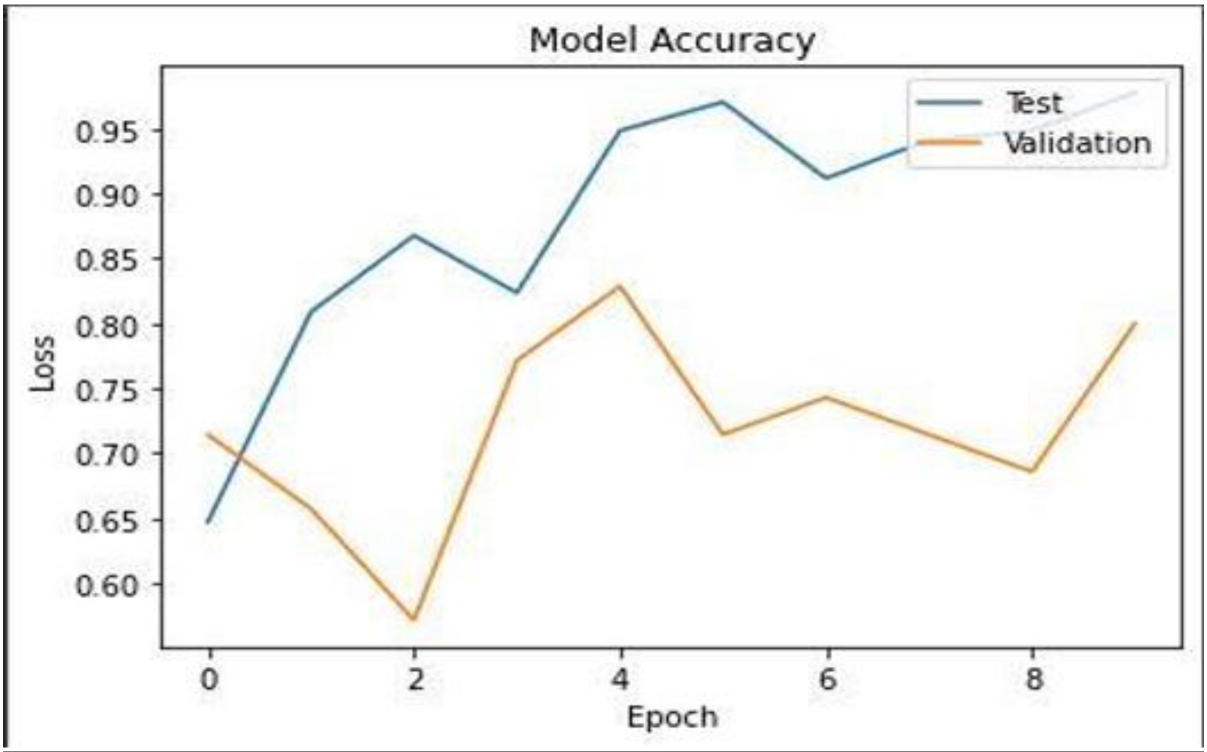

Figure: 6. sign of the model's subpar performance on the validation set

Model Accuracy

The convolutional neural network model, when used with the test set, exhibited a great degree of precision of 97.79% while incurring minimal loss as the number of training epochs increased. Notably, There was a noticeable discrepancy in accuracy between the training and validation datasets.

```
Epoch 1/10
34/34 [==============================] - 13s 102ms/step - loss: 147.7111 - accuracy: 0.6471 - val_loss: 124.3809 - val_accuracy: 0.7143
Epoch 2/10
34/34 [==============================] - 3s 87ms/step - loss: 57.7995 - accuracy: 0.8088 - val_loss: 236.2032 - val_accuracy: 0.6571
Epoch 3/10
34/34 [==============================] - 3s 87ms/step - loss: 30.1085 - accuracy: 0.8676 - val_loss: 467.5966 - val_accuracy: 0.5714
Epoch 4/10
34/34 [==============================] - 3s 87ms/step - loss: 59.6556 - accuracy: 0.8235 - val_loss: 162.9036 - val_accuracy: 0.7714
Epoch 5/10
34/34 [==============================] - 3s 87ms/step - loss: 11.8455 - accuracy: 0.9485 - val_loss: 205.6509 - val_accuracy: 0.8286
Epoch 6/10
34/34 [==============================] - 3s 88ms/step - loss: 7.5634 - accuracy: 0.9706 - val_loss: 142.7784 - val_accuracy: 0.7143
Epoch 7/10
34/34 [==============================] - 3s 88ms/step - loss: 21.5333 - accuracy: 0.9118 - val_loss: 411.3341 - val_accuracy: 0.7429
Epoch 8/10
34/34 [==============================] - 3s 87ms/step - loss: 12.8651 - accuracy: 0.9412 - val_loss: 310.6860 - val_accuracy: 0.7143
Epoch 9/10
34/34 [==============================] - 3s 86ms/step - loss: 21.4763 - accuracy: 0.9485 - val_loss: 211.8233 - val_accuracy: 0.6857
Epoch 10/10
34/34 [==============================] - 3s 87ms/step - loss: 4.6714 - accuracy: 0.9779 - val_loss: 263.9219 - val_accuracy: 0.8000
```

Result using some experiment on python

The model's accuracy increased with more epochs, while the testing loss decreased.

Conclusion

This paper aims to highly accurate CNN-based model for detecting brain tumours in MRI images. Utilizing a dataset of 280 brain MRI images, the model effectively processes and classifies images by reducing their size without compromising crucial information. The accuracy was 97.79%, while on the validation set, it was 82.86%. The concept loss dropped as the number of training epochs rose, suggesting better performance. However, performance of the model on the validation set was less impressive, suggesting potential overfitting. Future work will involve testing the model on diverse datasets to enhance its generalizability and accuracy.

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