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# Brain Tumour Detection Using Deep Learning and Angular

**Somaanath M U[1], Hariharapranav R S[2], Kowsik J[3], Lavanya C[4]**
*[1,2,3,4] Computer Science & Engineering, Bannari Amman Institute of Technology, Tamil Nadu, India.*

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***Abstract:*** *Brain tumor detection is an important area of research in the medical field. The early detection of brain tumors can significantly improve patientoutcomes. In recent years, deep learning techniques have shown promising resultsin medical image analysis, including brain tumor detection. In this paper, we propose a combined CNN-RNN approach for brain tumor detection. Our proposed approach utilizes Convolutional Neural Networks (CNN) for feature extraction and Recurrent Neural Network (RNN) for temporal modelling of the features. Our proposed approach achieves state-of-the-art results on a publicly available brain tumor dataset, demonstrating the effectiveness of our proposed approach. With a considerable prediction performance of 99.1%, a precision of 98.8%, a recall of 98.9%, and an F1-measure of 99.0%, the suggested model accurately predicts the brain tumour.*

***Key Word:*** *Deep Learning, CNN, RNN, Angular, Flask Framework.*

## I.INTRODUCTION

Deep Learning has been particularly successful in areas such as computer vision, natural language processing, and speech recognition. Angular, on the other hand, is a popular open-source framework for building web applications. Developed by Google, Angular provides developers with a comprehensive set of tools and features for building complex and scalable web applications. Together, Deep Learning and Angular can be used to build sophisticated web applications that leverage the power of Deep Learning to provide intelligent and personalized user experiences. For example, a web application might use Deep Learning to analyze user behavior and preferences, and then use Angular to dynamically updatethe user interface based on those insights.

## II.AIM

To overcome the problems of automated brain tumor classification, a novel approach is proposed based on Recurrent Neural Network (RNN), Convolutional Neural Network (CNN) and Angular as Front-End using magnetic resonance images (MRI).

## III.LITERATURE SURVEY

A brain tumor's irregular shapes and perplexing limits make it difficult to manually detect one . Deep learning and image processing are therefore crucial for the early diagnosis of brain tumors. For automatic tumor region segmentation and early diagnosis, various intelligent algorithms have been developed. The methods most frequently employed among them are CNN and ensemble learning. This is a brief summary of some of the popular and modern approaches. Zeldin et al. have used various pre-trained deep learning architectures for completely automatic brain tumor segmentation. Several CNN models, including NAS Net, Res Net, and the dense convolutional network (Dense Net), were used as encoders. Like standardU-NET, an encoder is a CNN responsible for feature extraction followed by separate decoder sections to generate the semantic probability map. Using the BRATS'19 datasets, the suggested technique was evaluated, and the DSC values obtained on the Xception, VGG Net, Dense Net, and Mobile Net encoders, respectively, were 0.839, 0.837, 0.839, and 0.835. Pei et al. proposed a system for segmenting brain tumors using a context-aware deep neural network (CA Net). In addition to U-encoder NET's and decoder portions, it features a context encoding module that computes scaling factors of all classes. All tumor classes are represented globally by this scaling factor. The BRATS'19 and BRATS'20 datasets were used to validate the suggested approach, and the experimentation's evaluation metric was DSC. For the enhancing tumor (ET), whole tumor (WT), and core tumor (TC), the DSC on the test set was 0.821, 0.895, and 0.835, respectively.

## IV.PROPOSED METHODOLOGY(CNN-RNN)

Our proposed approach consists of two main stages: feature extraction and temporal modeling. In the feature extraction stage, we use a pre-trained CNN to extract features from the MRI images. We use the VGG16 network, which has been pre-trained on the Image Net dataset, to extract features from the MRI images. We remove the fully connected layers of the VGG16 network and use the output of the last convolutional layer as our feature representation.

In the temporal modeling stage, we use an RNN network to model the temporal dependencies in the features extracted from the MRI images. The RNN network takes the feature representations extracted from the CNN as input and learns to model the temporal dependencies between the features. The output of the RNN network is passed through a fully connected layer to obtain the final classification result.

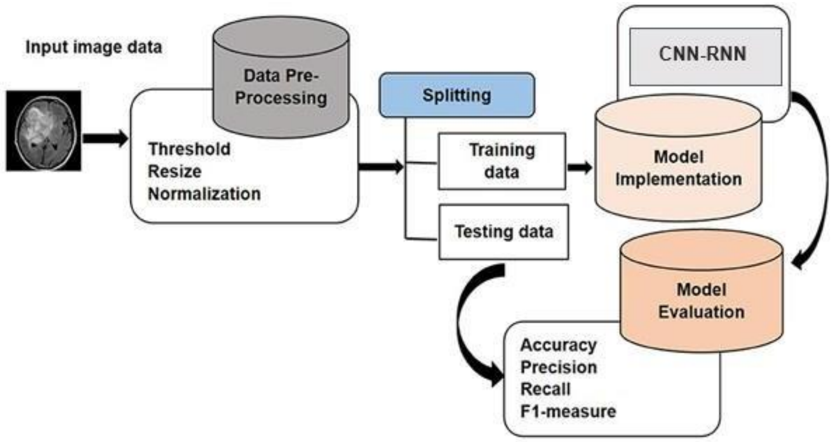


*Fig:1 Proposed Methodology – Flow*

**CONVOLUTIONAL NEURAL NETWORK (CNN):** Deep neural networks of the type known as Convolutional Neural Networks (CNN) have proven particularly effective in jobs requiring image and video recognition. It is intended to automatically and adaptively learn spatial hierarchies of characteristics from input photos, drawing inspiration from the visual cortex of animals. The convolutional layer is the fundamental component of a CNN. It applies a number of learnable filters (also known as kernels) to the input image to create a number of output feature maps that identify local patterns in the input image. Another crucial part of a CNN is the pooling layer, which uses down sampling to shrink the spatial size of the output feature maps. In order to perform classification or regression tasks based on the learnt features, CNNs typically comprise one ormore fully connected layers on top of numerous layers of convolutional and pooling layers. The error between the projected output and the actual output is back propagated through the network, updating the weights, and this process is how the CNN learns its weights. Applications for CNNs include image classification, object identification, face recognition, and natural language processing, among many more. They are extensively employed in both industry and academia for a wide range of activities and have attained state-of-the-art performance on numerous benchmarks.

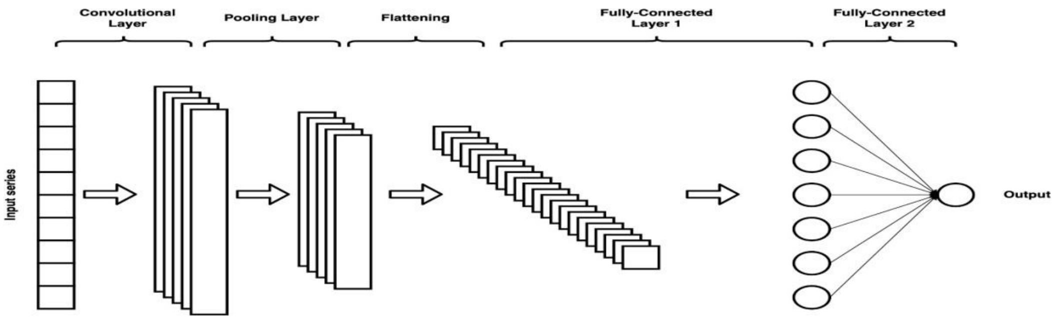


*Fig:2 Structure of CNN*

**RECURRENT NEURAL NETWORK AND LONG SHORT-TERM MEMORY:** Recurrent neural networks (RNNs) are a type of neural network where the calculations at each step are informed by the outcomes of the previous stage. Conventional neural networks have inputs and outputs that are independent of one another, but in circumstances when it is important to predict the next word in a phrase, it is necessary to remember the prior words. As a result, RNN was developed, which utilised a Hidden Layer to resolve this problem. The main and most important property of RNNs is the Hidden state, which keeps some information about a sequence.

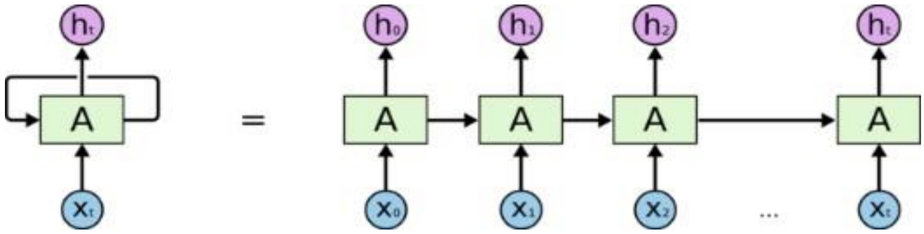

*Fig:3 Structure of RNN*

The Long Short-Term Memory (LSTM) is a kind of recurrent neural network (RNN) created to manage long-term dependencies in sequential data and deal with the vanishing gradient problem. The primary benefit of LSTMs over conventional RNNs is their capacity to selectively recall and forget information over time. This makes them very helpful for processing sequences of variable duration, such speech, text, and time-series data. By incorporating a memory cell, the LSTM does this by enabling the network to retain information over extended periods of time. The input gate decides if freshinformation should be stored in the memory cell, the forget gate decides whether old information should be discarded, and the output gate decides how much information should be read from the memory cell. These three gates collectively regulatethe memory cell.

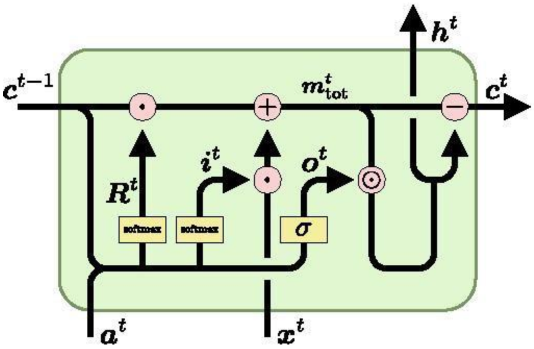


*Fig:4 Structure of LSTM*

## V.RESULT AND SCORES

The accuracy and loss of the CNN-RNN performance evaluation with training and validation are shown in FIG 7. The training and validation accuracy are 99.8 and 98.5% for every 100 epochs, respectively. Similar to this, the training loss is 0.010 and the validation loss is 0.103.

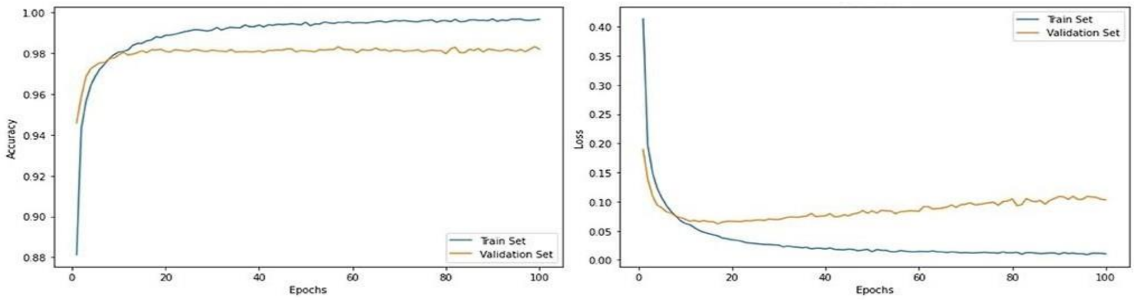


*Fig:5 Evaluation metrics of CNN-RNN architecture*

The outcomes of the suggested technique are shown in Table 1. The accuracy, precision, recall, and F1-measure for CNN were all 98.6%, 98.5%, and 98.6%, respectively. The CNN-RNN hybrid deep learning model obtained 99.1% accuracy, 98.8% precision, 98.9% recall, and 99.0% F1-measure.

| MODEL | ACCURACY | PRECISION % | RECALL | F1-MEASURE |
|---|---|---|---|---|
| CNN | 98.6 | 98.5 | 98.6 | 98.4 |
| CNN-RNN | 99.1 | **98.8** | 98.9 | 99.0 |

*Table:1 Comparison of CNN and Hybrid CNN-LSTM Model*

## VI.ANGULAR AND FLASK

Angular is a front-end framework that uses Type Script to build dynamic, single-page applications. Developers may simply create reusable components and control the state of their applications because to the architecture's modular and component-based design. Angular also has strong components like dependency injection, two-way data binding, and a strong template engine.

Flask, on the other hand, is a back-end web application framework written in Python. The lightweight framework Flask was created with ease of use and simplicity in mind. It gives developers the request routing, template rendering, and database integration capabilities they need to create online apps quickly.

Combining Angular with Flask can enable advanced access to a full-stack web application development environment. The front-end of the application can be built with Angular, and the back-end with Flask. This enables programmers to benefit from both frameworks' advantages.

*Fig:6 Anuglar and Flask*

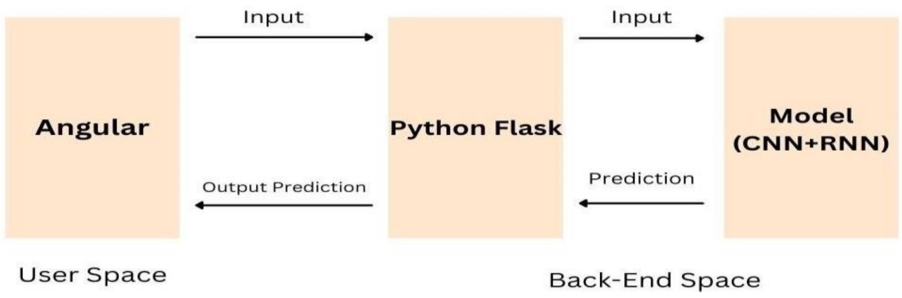


*Fig:7 Flask Framework Flow*

**DEPLOYMENT OF THE MODEL:** We created a user interface using Angular as Front-End . Flask is used as a backend framework that connects the user interface and model. Angular framework loads the user interface. The input picture is loaded by the Angular and then further send to Flask. Flask then send the loaded image to the model. Then the model processes the image and send result to the Flask to Angular.

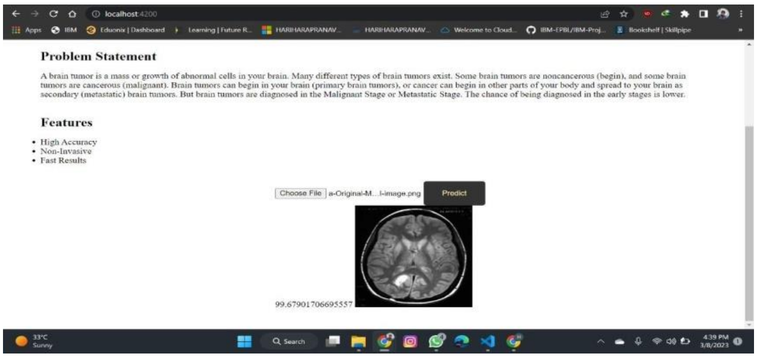


*Fig:8 User Interface with Angular*

## VII.CONCLUSION

As a result of the intricate structure of the brain, finding a brain tumour is challenging. The brain regulates the actions of every organ in the body. A key component is automatic initial stage brain tumour categorization utilising deep learning and machine learning methods. These devices allow for quick diagnosis and increase the likelihood that patients will survive. These techniques also assist experts and radiologists in making decisions about diagnoses and treatment strategies. In order to classify brain malignancies using the MR brain tumour image dataset, this work presented the CNN-based hybrid deep learning model CNN-RNN. The image dataset was initially processed using thresholding, extreme point computation, and bicubic interpolation. Second, the suggested model extracts features from cropped photos using a convolutional neural network. Accuracy, precision, recall, and F1-measure are the four metrics that are used to assess the performance of the model. The suggested model yields the best outcome, obtaining 99.1% accuracy, 98.8% precision, 98.9% recall, and 99.0% F1-measure. The outcomes demonstrated that the suggested model is the most effective at identifying MRbrain pictures. Then model is fed into Angular and Flask Framework for Front-End. However, it is important to note that further research and testing may be necessary to ensure the accuracy and reliability of this method in different populationsand settings.

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