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AI-Powered Early Detection of Brain Tumours Using Medical Imaging

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Abstract: Brain tumours are often considered one of the most aggressive types of cancer. Historically, they were identified using conventional deep learning methods via MRI. Currently, studies are transitioning to advanced models that can analyse MRI scans to identify and classify tumours. Tumours are formed by abnormal cell growth in brain tissue and can be benign or malignant. Since treatment effectiveness and survival rates can be improved with early identification, this paper focuses on supervised learning approaches, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), to provide better and faster early detection.

Keywords: Brain tumour, Convolutional Neural Network, Recurrent Neural Network, Deep learning, Magnetic Resource Imaging (MRI), Artificial Intelligence, Medical Imaging, Early Detection, Tumour Classification.

I. INTRODUCTION

Brain conditions are serious, and spotting them early can save lives. Doctors have long used MRI and CT scans to find brain tumours, but these take time and can lead to errors. Today, AI is changing that.[1] Smart systems now help doctors detect tumours faster and more accurately, reducing mistakes and improving diagnosis. One of the most promising areas of AI for medical imaging is **deep learning**.[2] Specifically, methods like Convolutional Neural Networks **(CNNs)** and **Recurrent Neural Networks (RNNs)** are becoming increasingly common. **CNNs** are particularly good at analysing images.[3] They can identify meaningful spatial features, like the exact location and structure of a tumour within an MRI or CT scan. **RNNs** excel at finding patterns across a sequence of data. In a medical context, this means they can analyse a series of images over time to improve the accuracy of predictions.[4]

By combining CNNs and RNNs, we can use both image details and patterns over time to better detect brain tumours.[5] This hybrid approach makes diagnosis faster and more accurate, helping radiologists save time and plan treatments more effectively. Our goal is to show how these AI methods work in medical imaging, test their performance, and highlight their practical value in healthcare. [6].

A. Convolutional Neural Network

Convolutional Neural Networks (CNNs) are a specialized class of deep learning models designed primarily for processing visual information such as images and videos.[7] Unlike traditional approaches that require manual selection of features, CNNs autonomously learn to identify important visual elements—like edges, textures, and shapes—through layers known as convolutional and pooling layers. These layers work together to capture hierarchical patterns in the data, enabling the model to recognize increasingly complex features as it goes deeper. This automatic feature extraction makes CNNs exceptionally powerful for tasks involving pattern recognition and image analysis.[8]

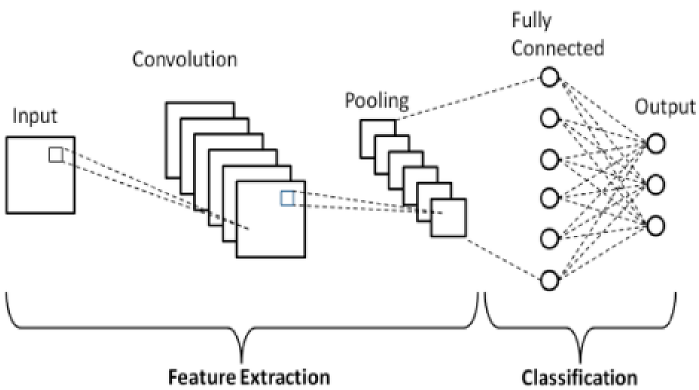

Figure 1: Architecture of Convolutional Neural Network

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Figure (1) above illustrates the overall architecture of DNN, where several layers of artificial neurons, known as perceptron, are stacked in processing complex data-dependent problems.

In the world of AI, a neural network is a bit like a team of specialized workers, each with a different job to do. There are three main types of "layers" or groups of these workers: the Input Layer, the Hidden Layers, and the Output Layer.[9]

- Input Layer: Think of this as the front door. It's where all the raw data, like an image of a brain scan, first enters the system. It doesn't do any analysis; its only job is to receive the information and pass it along.
- features like lines or textures in MRI scans, while deeper layers combine them to recognize complex patterns such as the shape or location of a tumour. This is where deep learning "learns" and improves its understanding.10]
- Out Layer: This is the final stage, where all the hard work pays off. The output layer takes all the features and patterns that the hidden layers have identified and turns them into a clear, understandable result. For a brain tumour detection system, this might be a final diagnosis, a label indicating the type of tumour, or a numerical value that tells the doctor the likelihood of a tumour being present. It's the moment the network delivers its final verdict.

B. Recurrent Neural Network

A Recurrent Neural Network (RNN) is a type of deep learning architecture designed to process sequential data. Unlike traditional neural networks that treat each input independently, RNNs have a built-in memory mechanism that allows them to retain information from previous inputs. This memory helps the network understand context and relationships across time, making it ideal for tasks where the order of data matters.[11]

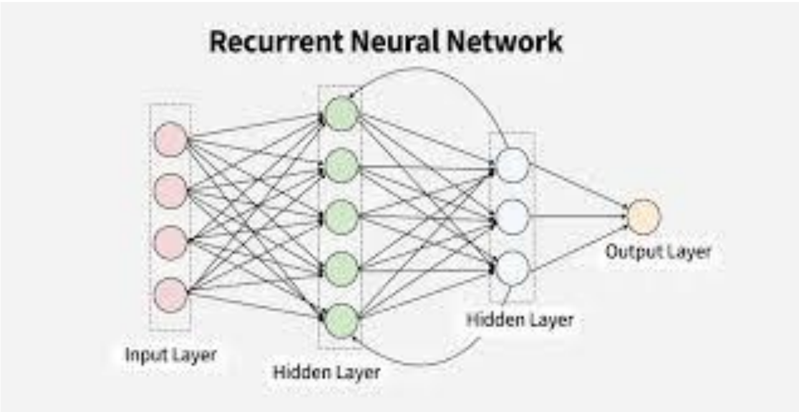

Figure 2: Architecture of Recurrent Neural Network

Figure (2) above illustrates the overall architecture of RNN, an RNN is composed of several key layers that work together to process sequential data.

- Input Layer: This initial layer receives sequential data—such as text, audio signals, or image sequences—and formats it for further processing. It acts as the entry point, passing the raw input into the network.
- Hidden Layers: These layers contain recurrent units capable of retaining information from earlier time steps. This memory enables the network to recognize patterns that evolve over time, making it suitable for tasks involving context and sequence.
- Output Layer: After the data has been processed through the hidden layers, the output layer produces the final result. This could be a prediction, classification, or any other form of output depending on the task.
- Optional Layers: Additional layers may be included to enhance the model's performance:[12]

II. LITERATURE REVIEW

The journey to using AI to detect brain tumours starts long before the algorithm gets to work. It begins with the **MRI scans themselves**. To make these images useful for AI, they first have to be "cleaned up." Researchers have developed a variety of techniques to do this, including:

- **Intensity normalization:** Making sure the brightness and contrast are consistent across different scans.
- **Filtering:** Removing noise or speckles from the image that could confuse the AI.
- **Segmentation:** Isolating the brain itself from other parts of the head, so AI focus on the most important area.[13]

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This preparation is crucial, and it's where specialized tools like the **2D Brain Extraction Algorithm (BEA)** and the **FMRIB Software Library (FSL)** come in handy. These tools are like a digital scalpel, carefully removing everything but the brain tissue.

Once the images are ready, the real magic of AI begins. **Deep learning models**, especially **Convolutional Neural Networks (CNNs)**, most popular choice of work. They're excellent at automatically finding subtle details in the images that might be missed by the human eye. To make them even more powerful, researchers are combining CNNs with other AI methods, such as:

- **Recurrent Neural Networks (RNNs):** These are used to analyse a series of images, helping the system learn from patterns that appear over time.
- **Generative Adversarial Networks (GANs):** These can be used to create new, synthetic images to train the model, making it more robust and accurate.[14]

The results from this research are promising. For example, one study using a CNN on a dataset of 306 MRI images achieved an impressive accuracy of **93.9%** in detecting tumour. Other studies have explored hybrid approaches, like combining **Fully Convolutional Neural Networks (FCNNs)** with **Conditional Random Fields (CRFs)**, which helps create more visually precise segmentations of the tumour.[15]

However, it's not all smooth sailing. Acknowledging the risks of medical imaging, especially radiation exposure from CT scans, highlights the need for these highly accurate, automated systems. Our review of the literature has shown that while significant progress has been made, the field is still evolving. The goal is to develop systems that are not just accurate, but also efficient and safe, ultimately providing doctors with a powerful tool to save lives.[16]

III. METHODOLOGY

Developing an AI system for early detection of brain tumours through medical imaging involves a structured, step-by-step process.

1. Data Collection and Preparation

The first step is to gather a high-quality dataset of brain MRI scans. This is the raw material the AI will learn from. The images must be labelled by medical professionals, clearly identifying which ones contain a tumour and, if possible, where the tumour is located.

2. Preprocessing

Raw data is often messy, so you need to "clean it up" before the AI can use it effectively. This involves several key techniques:

- **Noise Reduction:** Removing any visual clutter or imperfections from the scans.
- **Intensity Normalization:** Ensuring all images have a consistent brightness and contrast, so the AI isn't confused by different scanner settings.
- **Segmentation:** Isolating the brain from other parts of the head. This makes sure the AI focuses only on the most relevant area, preventing it from getting distracted by non-brain tissue.[17]

3. Model Design (The Hybrid Approach)

This is where you design the core of your AI system. Our approach uses a powerful combination of two different types of neural networks:

- **Convolutional Neural Networks (CNNs):** These are the image specialists. They analyse the still MRI scans to find **spatial features**—the specific shapes, textures, and locations that make a tumour look like a tumour.
- **Recurrent Neural Networks (RNNs):** These are the pattern detectives. If you have a series of MRI scans taken over time, an RNN can analyse the **sequential patterns**, helping to distinguish a growing tumour from a static, non-cancerous area. By combining the two, our hybrid model gets a more complete picture, using both what a tumour **looks like** and how it **behaves** over time.

4. Training, Validation, and Testing

Once the model is designed, it's time to teach it. You'll feed the pre-processed data into the model and let it learn to identify tumours. You'll split the data into three groups:

- **Training Data:** The bulk of the dataset that the model learns from.
- **Validation Data:** A smaller set used to fine-tune the model and prevent it from "overfitting"—becoming so specialized that it can't handle new images.

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- **Testing Data:** A final, completely unseen dataset used to evaluate the model's performance and ensure it's reliable and accurate.

5. Deployment

After the model is optimized and passes the final tests, it's ready for real-world use. The system can be deployed in a clinical setting, where it can be used to help radiologists and doctors make faster and more confident diagnoses.

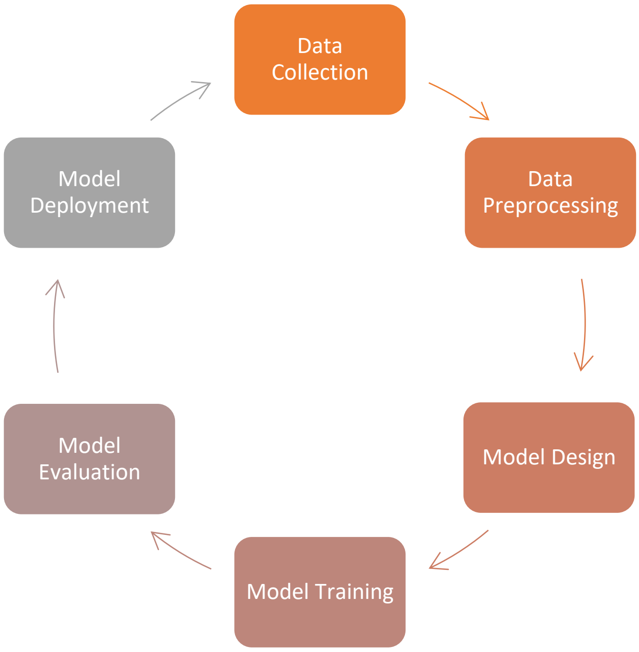

Figure 3: Proposed Methodology

IV. DATASET DESCRIPTION

Brain tumour detection with Brain MRI Images. It has a dataset comprising of 253 high-resolution brand MRI scans which are image samples. The figures are grey based and are different in size. The purpose of the dataset is to give evidence on the carrying out a picture examination to forecast whether every picture falls into Tumour or Non-tumour section.[18].

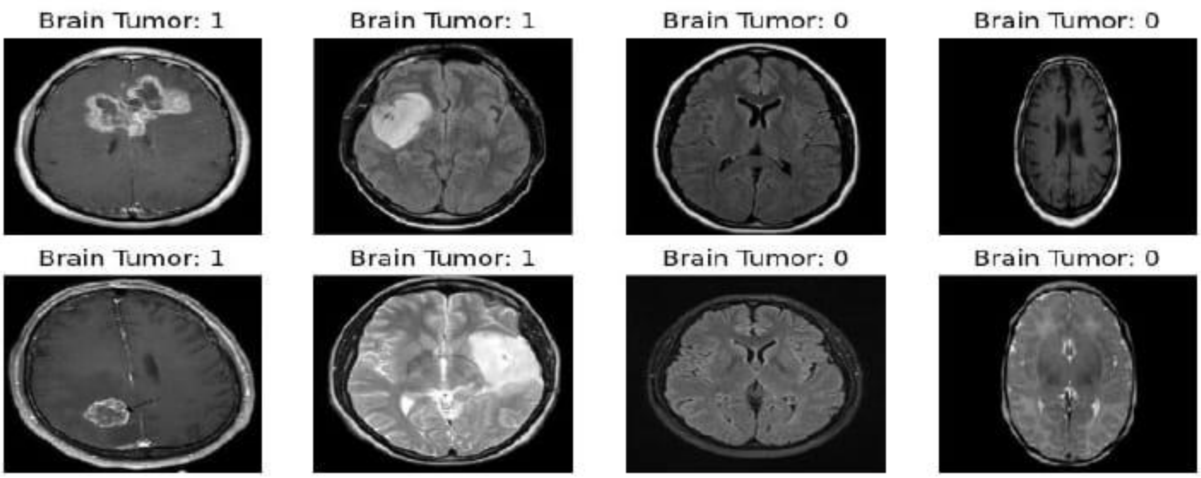

Figure 4: Brain MRI Images

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V. ARCHITECTURE SUMMARY

By combining the strengths of the CNN and the RNN, the system gets a comprehensive view. It learns to classify tumours based on both **what they look like** (the spatial features from the CNN) and **how they behave over time** (the sequential patterns from the RNN). This is especially valuable for detecting tumours at an early stage, even when the MRI data is limited, because the system can still make a more informed and accurate diagnosis by leveraging both types of information.

A. Convolutional Neural Network Model Description

1. Data Processing:

- Dataset: 253 MRI scan images (grayscale or RGB).
- Resizing: All images are resized to 224×224 pixels (to ensure uniformity).
- Normalization: Pixel intensity scaled to range [0,1].

$$X_{norm} = \frac{X - X_{min}}{X_{\max} - X_{min}}$$

- Data Augmentation: Rotation, flipping, zooming applied to reduce overfitting.

2. CNN Model Design: The CNN architecture is built in layered form

- Input layer: Input dimension - 224×224×3.
- Convolutional Layers:
  - Extract spatial features using convolution operation:

$$(I * K)(x, y) = \sum_{m} \sum_{n} I\,(X + m, y + n) * K(m, n)$$

  - Conv Layer 1: 32 filters, kernel size 3×3, activation = ReLU
  - Conv Layer 2: 64 filters, kernel size 3×3, activation = ReLU
- Pooling Layers: Downsampling using max pooling

$$P(i, j) = \max_{(m,n)\in W} f\,(\mathrm{i} * \mathrm{s} + \mathrm{m}, \mathrm{j} * \mathrm{s} + \mathrm{n})$$

where, s=stride

  - Pool Layer 1: Max Pooling 2×2
  - Pool Layer 2: Max Pooling 2×2

- Flatten Layer: Converts 2D feature maps into 1D vector

$$Flatten(f) = [f1, f2, \dots \dots, fn]$$

- Fully Connected Layers (Dense)
  - Dense Layer 1: 128 neurons, activation = ReLU
  - Dropout: 0.5 (to prevent overfitting)
  - Dense Layer 2: 64 neurons, activation = ReLU

- Output Layer: For binary classification (Tumour / No Tumour):
  - Dense Layer: 1 neuron, activation = Sigmoid

$$\hat{y} = \sigma(z) = \frac{1}{1 + e^{-z}}$$

3. Model Training:

- Loss Function: Binary Cross Entropy.

$$\boldsymbol{L = -\frac{1}{n} \sum_{i-1}^{n} [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)]}$$

- Optimizer: Adam (learning rate = 0.001)

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- Batch Size: 16
- Epochs: 24

4. Model Evaluation:

- Metrics: Accuracy, Precision, Recall, F1-score, AUC-ROC
- Formula for Accuracy:

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN}$$

- Validation Strategy: Train-test split (80%-20%) or k-fold cross-validation.

5. Model Deployment

For our brain tumour detection system, deployment involves a few key steps:

- **Saving the Model:** The finished, trained model is saved into a single, portable file. This file contains everything needed for the model to work, including its architecture (the design of the layers) and its weights (the values it learned during training). Common file formats for this are **.h5** for models built with Kera's and **.pt** for those using Py Torch.

- **Integration:** The saved model can then be integrated into a user-friendly application, such as a website or a desktop program used by doctors. This is where the AI becomes an accessible tool, not just a line of code.

- **The Final Product:** Once integrated, the system is ready to receive new information. A doctor can upload an MRI scan, and the AI will analyse it in seconds. The system's output isn't a diagnosis; it's a **probability score**, like "95% probability of a tumours." This gives the doctor a quick, data-driven insight to help them with their final diagnosis. The AI's ability to automatically extract features from the image using its convolution and pooling layers, and then classify them, makes the entire process faster and more accurate.

Table1: CNN Model Summary

Layer Type	Output Shape	Parameters	Description
Input Layer	(224, 224, 3)	0	Input MRI image resized
Conv2D (32 filters)	(224, 224, 32)	896	Kernel:3×3, Activation: ReLU
MaxPooling2D	(112, 112, 32)	0	Pool size: 2×2
Conv2D (64 filters)	(112, 112, 64)	18,496	Kernel:3×3, Activation: ReLU
MaxPooling2D	(56, 56, 64)	0	Pool size: 2×2
Flatten	(200,704)	0	Converts 2D to 1D
Dense (128 neurons)	(128)	25,690,240	Activation: ReLU
Dropout (0.5)	(128)	0	Regularization
Dense (64 neurons)	(64)	8,256	Activation: ReLU
Output Dense (1 unit)	(1)	65	Activation: Sigmoid
Total Parameters	25,717,953	----	Trainable: **25,717,953**

The CNN model is built to carefully examine MRI scans in order to identify brain tumours. Convolutional layers extract the most relevant features from the images, while pooling layers simplify the data by reducing its size but keeping essential details intact. These processed features are then passed to dense layers, which perform the final classification. To prevent overfitting and improve generalization, dropout layers are included. With more than 25 million trainable parameters, the network is capable of learning complex patterns, making it a dependable tool for precise tumour detection using AI.

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B. Network Recurrent Neural Model Description

1. Data Processing:

- Dataset: 253 MRI scan images (grayscale or RGB).
- Resizing: Images resized to 224×224 pixels.
- Flattening/Sequencing: Since RNNs process sequences, each image is reshaped into a sequence of pixel rows (or patches).
- Normalization: Pixel values scaled to [0,1]:

$$X_{norm} = \frac{X - X_{min}}{X_{\max} - X_{min}}$$

- Data Augmentation: Rotation, flipping, and zoom applied to increase training samples and reduce overfitting.

2. RNN Model Design:

- Input Layer: Input shape- (224,224) → 224 sequences with 224 features each.
- Recurrent Layers:
  - RNN Layer: Standard RNN or LSTM to capture sequential dependencies of pixel rows:

$$h_t = \emptyset(W_{ih}x_t + W_{hh}h_{t-1} + b_h)$$

where h_t= hidden state at time $t_1 x_t$= input at time $t_1 \emptyset$ = activation (usually tanh or ReLU).

- LSTM Variant:

$$f_t = \sigma(W_f * [h_{t-1}, x_t] + b_f$$
$$i_t = \sigma(W_f * [h_{t-1}, x_t] + b_i$$
$$o_t = \sigma(W_0 * [h_{t-1}, x_t] + b_o$$
$$h_t = o_t * \tanh(c_t)$$

Captures long-term dependencies better than standard RNNs.

- Dropout Layer: Applied after RNN/LSTM layer to prevent overfitting.
- Fully Connected (Dense) Layers:
  - Dense Layer 1: 128 neurons, activation = ReLU
  - Dense Layer 2: 64 neurons, activation = ReLU
- Output Layer:
  - Dense Layer: 1 neuron, activation = Sigmoid for binary classification:

$$\hat{y} = \sigma(z) = \frac{1}{1 + e^{-z}}$$

3. Model Training:

- Loss Function**:** Binary Cross-Entropy

$$L = -\frac{1}{n}\sum_{i-1}^{n}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

- Optimizer: Adam (learning rate = 0.001)
- Batch Size: 16
- Epochs: 24

4. Model Evaluation:

- Metrics**:** Accuracy, Precision, Recall, F1-score, AUC-ROC
- Validation Strategy**:** Train-test split (80%-20%) or k-fold cross-validation.

5. Model Deployment:

 Save as h5 or .pt file.
 Can be integrated into clinical diagnostic software for MRI analysis.
 Input MRI → Outputs probability of tumour presence.

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The RNN model processes MRI scans by converting each image into a sequence of pixel rows, which helps it understand spatial patterns in the data. It uses Long Short-Term Memory (LSTM) layers to capture long-range dependencies, while dense layers handle the final classification. Dropout layers are added to reduce overfitting and make the model perform better on unseen data.

Table2: RNN Model Summary

Layer Type	Output Shape	Units / Features	Activation	Parameters
Input Layer	(224, 224)	-	-	0
LSTM Layer 1	(224, 128)	128 units	tanh	197,632
Dropout	(224, 128)	-	-	0
LSTM Layer 2	(128)	128 units	tanh	131,584
Dense Layer 1	(128)	128 units	ReLU	16,512
Dense Layer 2	(64)	64 units	ReLU	8,256
Output Dense	(1)	1 unit	Sigmoid	65
Total Parameters	-	-	-	**354,049**

The RNN model applies LSTM layers to capture sequential patterns in MRI scans, enabling it to detect brain tumours with accuracy. It contains roughly 354,000 trainable parameters, which gives it enough capacity to learn effectively while still being efficient for a relatively small dataset of 253 images. Dropout layers are added to limit overfitting, helping the model stay consistent and dependable for AI-based clinical diagnosis.

VI. RESULTS AND INTERPRETATION

A. **Brain Tumour detection with CNNs: Accuracy and Efficiency Results**

For early brain tumour detection, the CNN model uses convolutional layers to automatically identify important features from MRI scans. Pooling layers make the data more manageable without losing vital details, while dense layers perform the classification. Dropout is included to reduce overfitting and improve learning. By combining these steps, the model delivers high accuracy and efficiency, making it a reliable method for AI-based tumour diagnosis.

Tabular Result

Table 3: CNN Model Result

Metrix	**Value**
Training Accuracy	0.98
Training Loss	0.09
Validation Accuracy	0.87
Validation Loss	0.37
Test Accuracy	0.91

Table (3) The results demonstrate that the CNN model is highly effective in detecting brain tumours, achieving 91% accuracy on the test set. During training, it reached 98% accuracy, showing that it learned the features of MRI scans very well. On validation data, the accuracy was 87% with a slightly higher loss of 0.37, suggesting a small degree of overfitting. Despite this, the model still provides consistent and accurate predictions, making it a strong candidate for AI-assisted tumour diagnosis.

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Graphical Result:

Figure 5: Graphical Results of CNN Model

Figure (5) The CNN model shows strong performance in detecting brain tumours, with 91% accuracy on the test data. Its training accuracy of 98% highlights that it has effectively learned key features from MRI scans. At the same time, the validation accuracy of 87% and a slightly higher loss value of 0.37 point to a small amount of overfitting.

B**. Brain Tumour detection with RNNs: Accuracy and Efficiency Results**
The RNN model analyses MRI scans by learning sequential patterns, which helps it capture spatial relationships in the images. LSTM layers extract long-term patterns, while dense layers handle classification. This approach allows the model to achieve accurate and efficient results, making it a valuable tool for AI-assisted early detection of brain tumours.

Tabular Result

Table 4: RNN Model Result

Metrix	**Value**
Training Accuracy	98%
Training Loss	0.14
Validation Accuracy	95%
Validation Loss	0.21
Test Accuracy	95%

The RNN model achieves strong performance, reaching 98% accuracy during training and 95% on both validation and test sets, demonstrating good generalization and consistent results. Its low training loss of 0.14 and validation loss of 0.21 indicate efficient learning with minimal overfitting. Overall, the model is reliable and robust, making it well-suited for AI-assisted early detection of brain tumours.

Graphical Result:

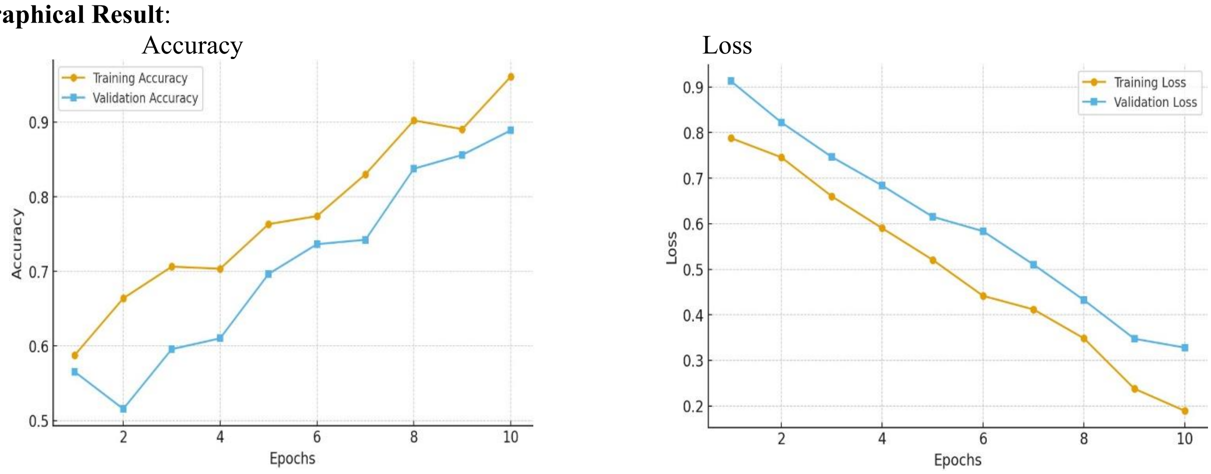

Figure 6: Graphical Result of RNN Model

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Figure (6) The results indicate that the RNN model performs very well, achieving 98% accuracy during training and 95% on both validation and test sets, showing strong generalization and consistent performance. The low training loss of 0.14 and validation loss of 0.21 further suggest that the model learns efficiently with minimal overfitting.

C. Comparative Analysis of Convolutional Neural Network and Recurrent Neural Network

Early detection of brain tumours is crucial for effective treatment and better chances of survival. The use of artificial intelligence, particularly deep learning, has greatly improved the analysis of medical images. Convolutional Neural Networks (CNNs) are excellent at identifying important features and spatial patterns in images, while Recurrent Neural Networks (RNNs) are effective at processing sequential data and capturing patterns over time. Both models have shown strong potential for detecting and classifying tumours, and comparing them helps to understand their accuracy, performance, and suitability for clinical applications.[14]

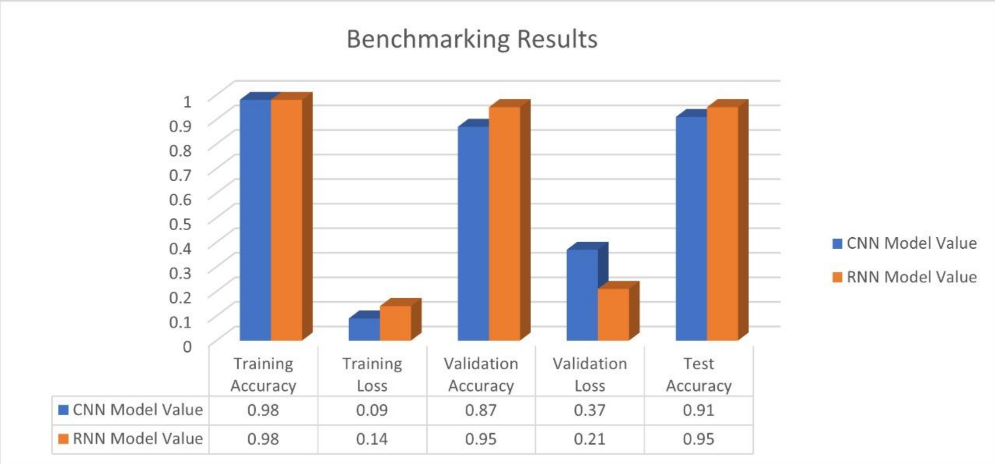

Figure 7: Comparative results of CNN and RNN model

The above figure 7, The comparison of results highlights the differences in performance between CNN and RNN models for early brain tumour detection. Both models achieved a high training accuracy of 98%, showing that they learned the data effectively. However, the CNN model had a lower validation accuracy of 87% and a higher validation loss of 0.37, suggesting a small degree of overfitting.

In contrast, the RNN model showed better performance, with a validation accuracy of 95% and a lower validation loss of 0.21, indicating stronger generalization. This advantage was also reflected in the test results, where the RNN achieved 95% accuracy, outperforming the CNN model, which reached 91%.

Overall, the results indicate that although CNN is effective at identifying features in MRI scans, the RNN model provides more consistent and robust performance on this dataset. This makes RNN a more dependable choice for the early detection of brain tumours.

VII. CONCLUSION

This study demonstrates that AI techniques using CNN and RNN algorithms can significantly enhance the early detection of brain tumours through medical imaging. Both models achieved high accuracy, but the RNN outperformed the CNN in validation and test results, showing stronger generalization. These results confirm that deep learning models are effective in analysing complex medical data and can assist clinicians in making timely and accurate diagnoses. The comparison also provides valuable insights for selecting the most suitable model for clinical applications, ultimately contributing to better patient outcomes.

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