Detection of Ischemic Stroke Tissue Fate from the MRI Images

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Contents

1 Problem Statement

We have MRI images of patients and need to predict whether they are at risk of having an ischemic stroke in the future. Accurate predictions will enable effective treatment planning to prevent strokes and improve patient outcomes.

1.1 Approach

We are using deep learning, a type of artificial intelligence, to predict the thickness of the damaged brain area from primary MRI scan data. Deep learning involves using computer models called neural networks, which excel at finding patterns in data.

1.2 How Does It Work?

Imagine you have a lot of brain scan pictures from stroke patients. You feed these pictures into the neural network, and it learns to recognize patterns that predict how thick the damaged brain area will be.

2 Key Contributions

Accurate and timely detection of ischemic stroke is critical for effective treatment and patient outcomes. Traditional methods often struggle with the sensitivity and precision required for optimal performance. To address this, we applied advanced optimization techniques and fine-tuned our models to achieve superior metrics.

Our research has significantly improved the accuracy of ischemic stroke detection by enhancing the performance of Convolutional Neural Networks (CNNs) and CNN-Bidirectional Long Short-Term Memory (BiLSTM) models. By applying advanced optimization techniques, we have effectively increased the F1 score and sensitivity of these models, which are crucial for accurate and reliable stroke detection.

We applied several advanced optimization strategies to improve our models:

- **10-Fold Cross-Validation:** We used 10-fold cross-validation to ensure our model improvements were reliable and generalizable. This method tested the models across various subsets of data, verifying that our enhancements consistently led to better accuracy metrics.
- **Learning Rate Scheduler:** We implemented a learning rate scheduler that adjusted the learning rate dynamically during training. This adjustment helped the models converge more efficiently, resulting in higher F1 scores and increased sensitivity.

- **Better Initialization Technique:** We used advanced parameter initialization techniques, such as He initialization. This approach accelerated model convergence and improved stability, which was essential for better sensitivity and F1 scores.
- **Fine-Tuned RMSprop Optimizer:** We carefully fine-tuned the RMSprop optimizer, adjusting its parameters to optimize the training process. This fine-tuning was crucial for enhancing the models' accuracy, leading to significant improvements in sensitivity and F1 scores.

Our research has made significant advancements in improving the accuracy of ischemic stroke detection by enhancing the performance of both Convolutional Neural Networks (CNNs) and CNN-Bidirectional Long Short-Term Memory (BiLSTM) models. By applying advanced optimization techniques, we have effectively increased the F1 score and sensitivity of these models, which are crucial for accurate and reliable stroke detection.

3 Data Description

The dataset used in this study is available on Kaggle and can be accessed via the following link:

- **Dataset**: https://www.kaggle.com/datasets/buraktaci/mri-stroke
- **Acute Ischemic Stroke**: This folder contains a total of 1002 MRI images of patients diagnosed with acute ischemic stroke.
- **Control**: This folder contains 1008 MRI images of individuals who do not have a stroke.

The dataset is well-balanced, with a comparable number of images in both categories, providing a robust basis for training and evaluating machine learning models. This balance helps ensure that the models can be effectively trained to distinguish between stroke and non-stroke cases, enhancing their predictive accuracy.

The glimpse of our dataset is shown below:

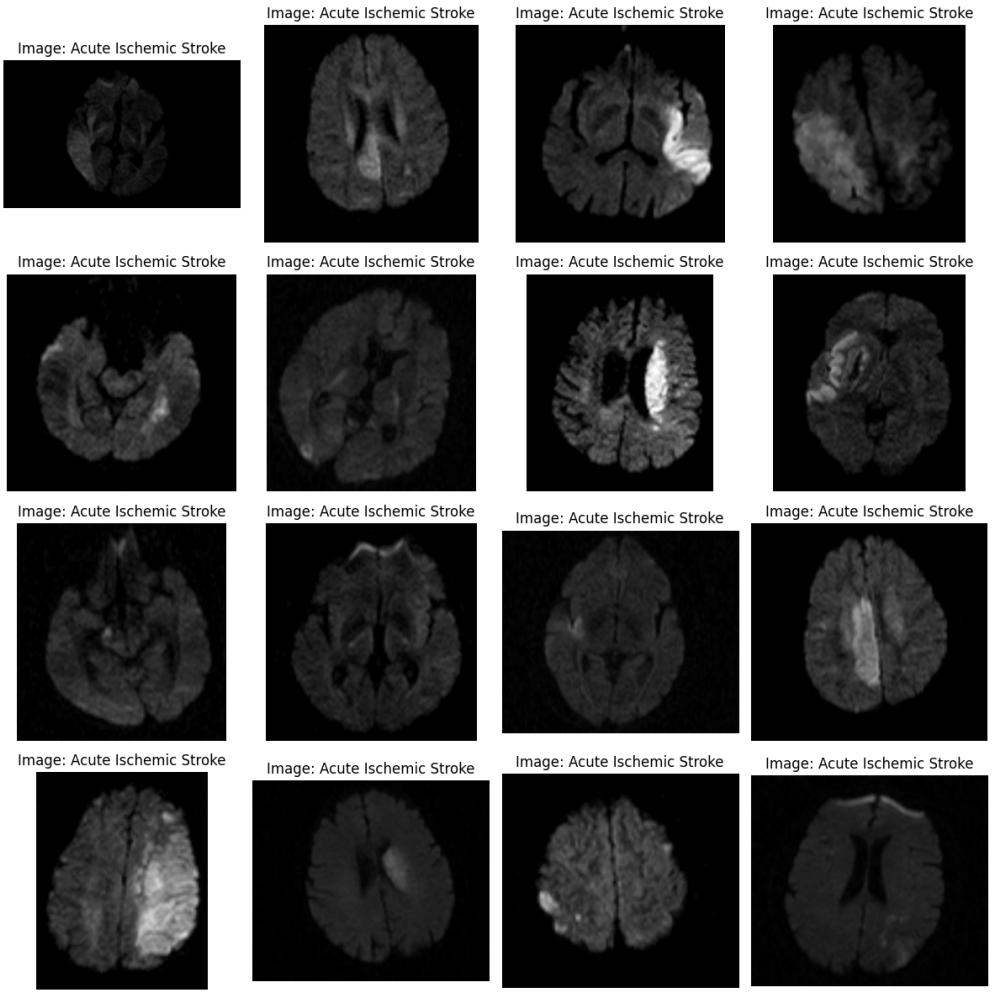

Figure 1: Acute isochemic stroke

MRI image without stroke

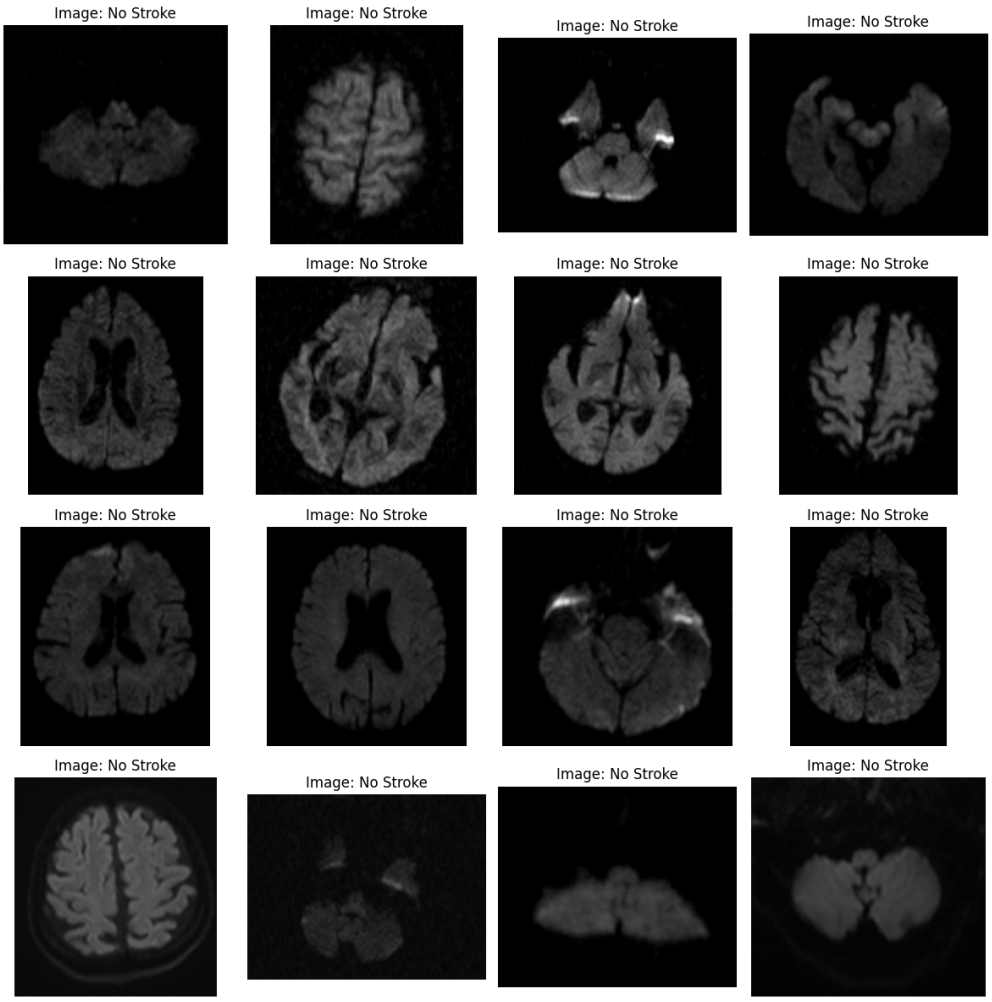

Figure 2: No stroke

Magnetic Resonance Imaging (MRI) offers several advantages for detecting and analyzing strokes:

- **High Resolution**: MRI provides high-resolution images of the brain, allowing for detailed visualization of stroke-related damage and abnormalities.
- **Early Detection**: MRI can detect early signs of ischemic stroke, even before symptoms become clinically apparent, enabling timely intervention.
- **Non-Invasive**: MRI is a non-invasive imaging technique that does not involve ionizing radiation, making it safer for repeated use.

- **Variety of Sequences**: MRI can use different imaging sequences (e.g., T1, T2, FLAIR) to highlight various types of brain tissue and abnormalities, enhancing diagnostic accuracy.
- **Identification of Infarcts**: MRI is effective in identifying infarcts and assessing the extent and location of brain damage caused by stroke.
- **Assessment of Penumbra**: MRI can evaluate the penumbra (the area surrounding the core of the stroke) to help in planning treatment strategies.
- **Monitoring and Follow-Up**: MRI is useful for monitoring stroke progression and assessing the effectiveness of treatments over time.

4 Methodology

- **Access the Dataset**: Use the Kaggle API to download the dataset.
- **Basic Exploratory Data Analysis (EDA)**:
  - Preprocessing
  - Normalization
  - Resize all images to 168×168
  - Run images in batches
- **Model Building**:
  - Build Convolutional Neural Network (CNN)
  - Build CNN-LSTM model
  - Build CNN-BiLSTM model
- **Hyperparameter Tuning**:
  - Use Keras Tuner for hyperparameter optimization
- **Decide Threshold**:
  - Determine optimal classification threshold to reduce false negatives

5 CNN- Model

5.1 Model Architecture detail

The model architecture is built using a Sequential API and consists of several layers organized into a Convolutional Neural Network (CNN) with additional regularization techniques. Below is a detailed description of each layer and its purpose:

- **Input Layer**:
  - `Conv2D`: A convolutional layer with 128 filters, each of size 3×3, using ReLU activation. The stride is 2×2 and padding is set to 'same'. This layer processes the input image of shape $168 \times 168 \times 3$.
- **Batch Normalization**:
  - `BatchNormalization`: Normalizes the output of the previous layer, which helps in stabilizing and speeding up the training process.
- **Pooling Layers**:
  - `AveragePooling2D`: Applies average pooling with a pool size of 2×2, reducing the spatial dimensions of the feature maps.
  - `AveragePooling2D`: Applies average pooling again with a pool size of 2×2.
  - `AveragePooling2D`: Applies average pooling with a pool size of $(2, 1)$ to handle the dimensions effectively.
- **Convolutional Layers**:
  - `Conv2D`: A convolutional layer with 64 filters, each of size 3×3, using ReLU activation, a stride of 2×2, and padding set to 'same'.
  - `Conv2D`: A convolutional layer with 32 filters, each of size 3×3, using ReLU activation, a stride of 2×2, and padding set to 'same'.
- **Flattening**:
  - `Flatten`: Flattens the output of the convolutional layers into a one-dimensional vector to be fed into the dense layers.
- **Dense Layers**:
  - `Dense`: A fully connected layer with 64 units and ReLU activation. L1 regularization with a strength of 0.002 is applied to prevent overfitting.
  - `Dropout`: A dropout layer with a rate of 0.3 is added to randomly set a fraction of input units to 0 during training, which helps prevent overfitting.

- `Dense`: A fully connected layer with 8 units and ReLU activation. L1 regularization with a strength of 0.001 is applied.
- `BatchNormalization`: Normalizes the output of the previous dense layer.
- `Dropout`: A dropout layer with a rate of 0.3 is added to help with generalization.

- **Output Layer**:
  - `Dense`: The final dense layer with 1 unit and sigmoid activation function, used for binary classification tasks.

The architecture of this model is designed to capture complex patterns in the MRI images and provide a binary classification result indicating the presence or absence of stroke. Regularization techniques such as L1 regularization and dropout are used to enhance the model's ability to generalize and reduce overfitting.
Model Parameters-

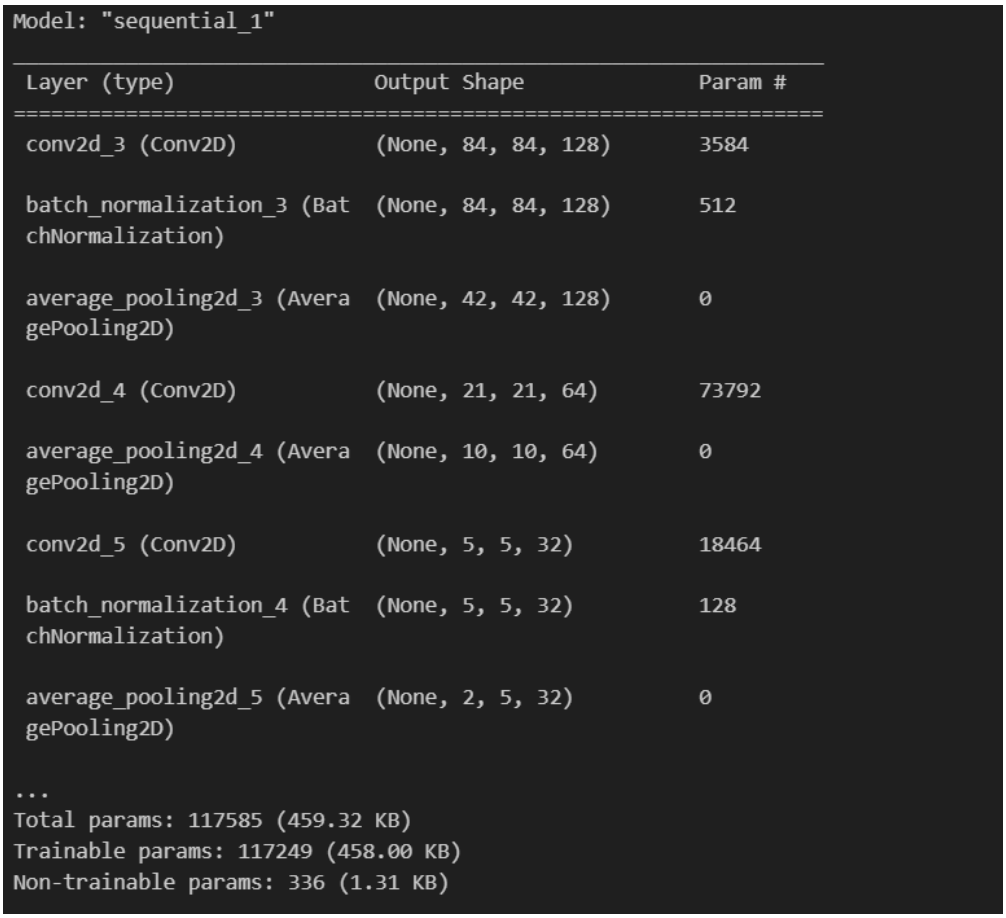

Figure 3: cnn parameter

5.2 Model Tuning

For optimizing the neural network model, we use the Keras Tuner library to systematically search for the best hyperparameters. The tuning process involves the following steps:

- **Optimizer Selection**: Determine the most effective optimizer for the model. Choices may include Adam, SGD, **RMSprop**, etc.
- **Dropout Rate**: Find the optimal dropout rate to balance model complexity and prevent overfitting.
- **Number of Hidden Layers**: Decide on the number of hidden layers to ensure the model has sufficient capacity without overcomplicating it.
- **Number of Nodes per Layer**: Optimize the number of nodes in each hidden layer to improve model performance.

Enhanced CNN Model Features

In addition to basic tuning, several advanced techniques and features are utilized to improve model performance:

- **Early Stopping**: Monitor the model's performance on a validation set and stop training when performance plateaus to prevent overfitting.
- **Dropout**: Apply dropout with a tuned rate to randomly set a fraction of input units to zero during training, enhancing generalization.
- **L2 Regularization**: Use L2 regularization to penalize large weights and encourage simpler models.
- **ReLU Variant - ELU**: Experiment with the Exponential Linear Unit (ELU) activation function, which can help accelerate learning and reduce dying ReLU issues.
- **He Normal Initialization**: Employ He Normal initialization to set the initial weights, which helps maintain the scale of gradients during the early stages of training.
- **Batch Normalization**: Implement batch normalization to stabilize and speed up the training process by normalizing the inputs of each layer.
- **Padding**: Utilize appropriate padding techniques (e.g., 'same' or 'valid') to control the spatial dimensions of the output feature maps.
- **Stride**: Adjust stride values to control the step size of the convolutional filter and impact the output feature map dimensions.

By incorporating these advanced features and tuning techniques, the model is optimized to achieve better performance and robustness in stroke detection tasks.

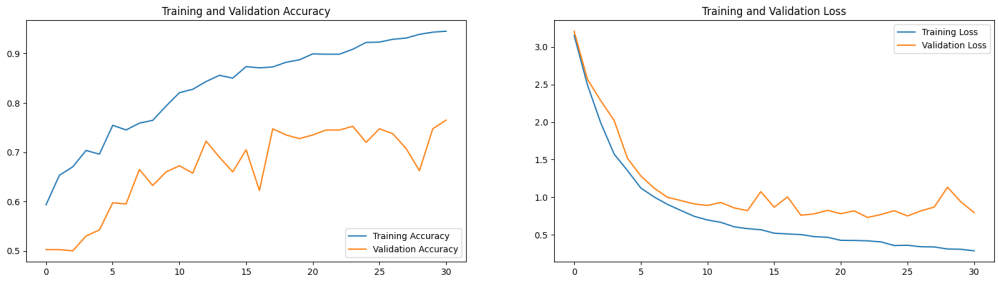

Figure 4: Accuracy graph

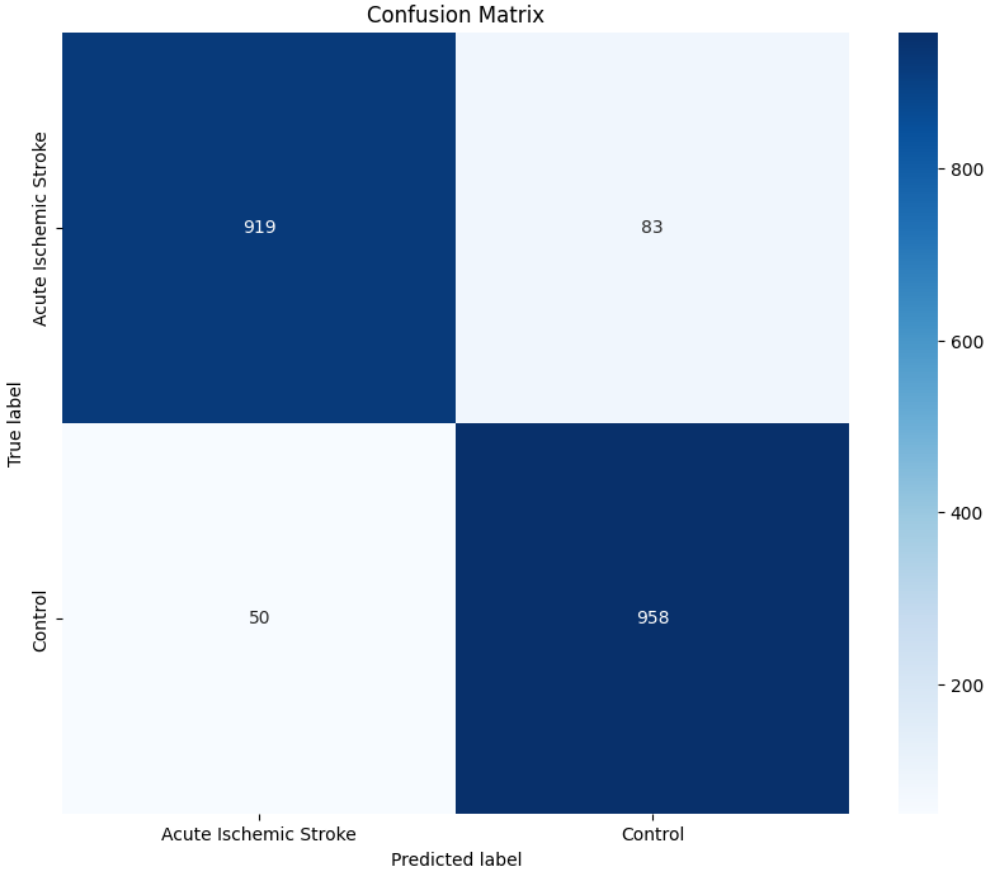

Figure 5: Confusion matrix of cnn-model

6 CNN-LSTM Model

6.1 Model Architecture Detail

The model architecture consists of a combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) layers. It is designed to handle sequential data in the form of MRI images and perform binary classification. The architecture is described as follows:

- **Input Layer**:
  - `TimeDistributed(Conv2D)`: Applies a 2D convolutional layer with 128 filters of size 3×3 to each time step of the input sequence. ReLU activation is used, and padding is set to 'same' to maintain the spatial dimensions.
  - `TimeDistributed(BatchNormalization)`: Normalizes the output of the convolutional layer for each time step to stabilize and accelerate training.
  - `TimeDistributed(AveragePooling2D)`: Applies average pooling with a pool size of 2×2 to downsample the spatial dimensions.
  - `TimeDistributed(Dropout)`: Applies dropout with a rate of 0.3 to each time step to prevent overfitting.
- **Second Convolutional Layer**:
  - `TimeDistributed(Conv2D)`: Applies a 2D convolutional layer with 64 filters of size 3×3 and a stride of 2×2. Padding is set to 'same'.
  - `TimeDistributed(BatchNormalization)`: Normalizes the output of the convolutional layer.
  - `TimeDistributed(AveragePooling2D)`: Applies average pooling with a pool size of 2×2.
  - `TimeDistributed(Dropout)`: Applies dropout with a rate of 0.3 to each time step.
- **Third Convolutional Layer**:
  - `TimeDistributed(Conv2D)`: Applies a 2D convolutional layer with 32 filters of size 3×3 and a stride of 2×2. Padding is set to 'same'.
  - `TimeDistributed(BatchNormalization)`: Normalizes the output of the convolutional layer.
  - `TimeDistributed(AveragePooling2D)`: Applies average pooling with a pool size of 2×2.
  - `TimeDistributed(Dropout)`: Applies dropout with a rate of 0.3 to each time step.

- **Flattening Layer**:
  - `TimeDistributed(Flatten)`: Flattens the output of the convolutional layers to prepare it for the LSTM layer.
- **LSTM Layer**:
  - `LSTM`: A Long Short-Term Memory layer with 112 units and ReLU activation function. It processes the sequential data from the CNN layers.
- **Dense Layers**:
  - `Dense`: A fully connected layer with 64 units, ReLU activation, and L1 regularization with a weight of 0.002. This layer helps in learning complex features.
  - `Dropout`: A dropout layer with a rate of 0.3 for regularization.
  - `Dense`: A fully connected layer with 8 units, ReLU activation, and L1 regularization with a weight of 0.001. This layer further processes the learned features.
  - `Dropout`: A dropout layer with a rate of 0.3 for regularization.
- **Output Layer**:
  - `Dense`: The final fully connected layer with 1 unit and sigmoid activation function for binary classification.
- **Compilation**:
  - `Compile`: The model is compiled using the RMSprop optimizer, binary crossentropy loss function, and accuracy as the evaluation metric.

This model architecture leverages both convolutional and recurrent layers to effectively analyze sequential MRI image data and classify it into two categories.

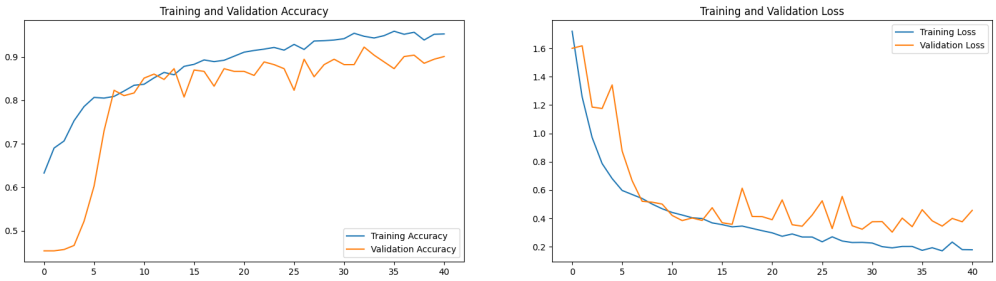

Figure 6: Accuracy graph

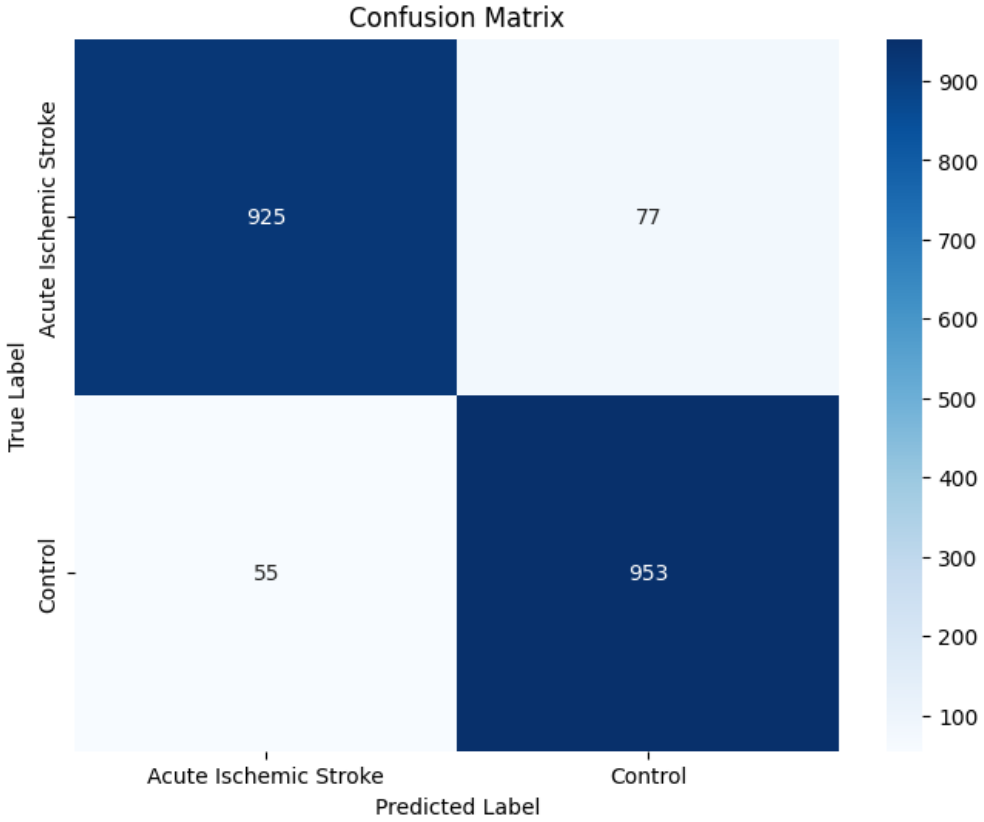

Figure 7: Confusion Matrix

7 CNN BI-LSTM

Model Architecture Detail

The following describes the architecture of the Convolutional Neural Network (CNN) combined with Bidirectional Long Short-Term Memory (BiLSTM) layers, including all parameters for each layer:

- **Conv2D Layer 1**:
  - `Filters`: 128
  - `Kernel Size`: 3×3
  - `Activation Function`: ReLU
  - `Strides`: 2×2
  - `Padding`: 'same'
  - `Input Shape`: $168 \times 168 \times 3$
  - `Kernel Regularizer`: L1 regularization with weight 0.002
  - `Kernel Initializer`: HeNormal
  - `Bias Initializer`: Zeros
- **BatchNormalization Layer 1**:
  - `Purpose`: Normalizes the output to stabilize and accelerate training.
- **AveragePooling2D Layer 1**:
  - `Pool Size`: 2×2
- **Conv2D Layer 2**:
  - `Filters`: 64
  - `Kernel Size`: 3×3
  - `Activation Function`: ReLU
  - `Strides`: 2×2
  - `Padding`: 'same'
  - `Kernel Regularizer`: L1 regularization with weight 0.001
  - `Kernel Initializer`: HeNormal
  - `Bias Initializer`: Zeros
- **AveragePooling2D Layer 2**:

  - `Pool Size`: 2×2

- **Conv2D Layer 3**:
  - `Filters`: 32
  - `Kernel Size`: 3×3
  - `Activation Function`: ReLU
  - `Strides`: 2×2
  - `Padding`: 'same'
  - `Kernel Regularizer`: L1 regularization with weight 0.001
  - `Kernel Initializer`: HeNormal
  - `Bias Initializer`: Zeros

- **BatchNormalization Layer 2**:
  - `Purpose`: Normalizes the output to stabilize and accelerate training.

- **AveragePooling2D Layer 3**:
  - `Pool Size`: 2×1

- **Flatten Layer**:
  - `Purpose`: Flattens the output of the convolutional layers to prepare it for the LSTM layers.

- **Reshape Layer**:
  - `Target Shape`: $(-1, 32)$, where 32 represents the number of features.

- **Bidirectional LSTM Layer 1**:
  - `Units`: 64
  - `Return Sequences`: True
  - `Kernel Initializer`: GlorotUniform
  - `Bias Initializer`: Zeros

- **Dropout Layer 1**:
  - `Rate`: 0.3

- **Bidirectional LSTM Layer 2**:
  - `Units`: 32

  - `Kernel Initializer`: GlorotUniform
  - `Bias Initializer`: Zeros

- **BatchNormalization Layer 3**:
  - `Purpose`: Normalizes the output to stabilize and accelerate training.

- **Dropout Layer 2**:
  - `Rate`: 0.3

- **Dense Layer 1**:
  - `Units`: 64
  - `Activation Function`: ReLU
  - `Kernel Regularizer`: L1 regularization with weight 0.002
  - `Kernel Initializer`: HeNormal
  - `Bias Initializer`: Zeros

- **Dropout Layer 3**:
  - `Rate`: 0.3

- **Dense Layer 2**:
  - `Units`: 8
  - `Activation Function`: ReLU
  - `Kernel Regularizer`: L1 regularization with weight 0.001
  - `Kernel Initializer`: HeNormal
  - `Bias Initializer`: Zeros

- **BatchNormalization Layer 4**:
  - `Purpose`: Normalizes the output to stabilize and accelerate training.

- **Dropout Layer 4**:
  - `Rate`: 0.3

- **Output Layer**:
  - `Units`: 1
  - `Activation Function`: Sigmoid
  - `Kernel Initializer`: GlorotUniform

- `Bias Initializer`: Zeros

This architecture integrates convolutional layers for feature extraction, Bidirectional LSTM layers for capturing temporal dependencies, and dense layers for final classification. Regularization techniques like dropout and L1 regularization enhance model generalization and performance.

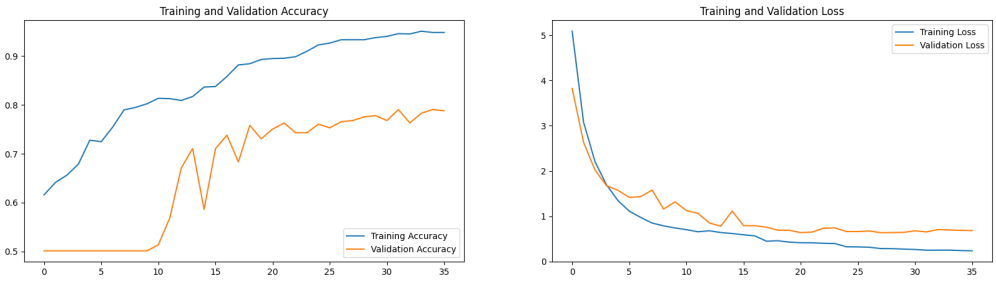

Figure 8: Accuracy graph

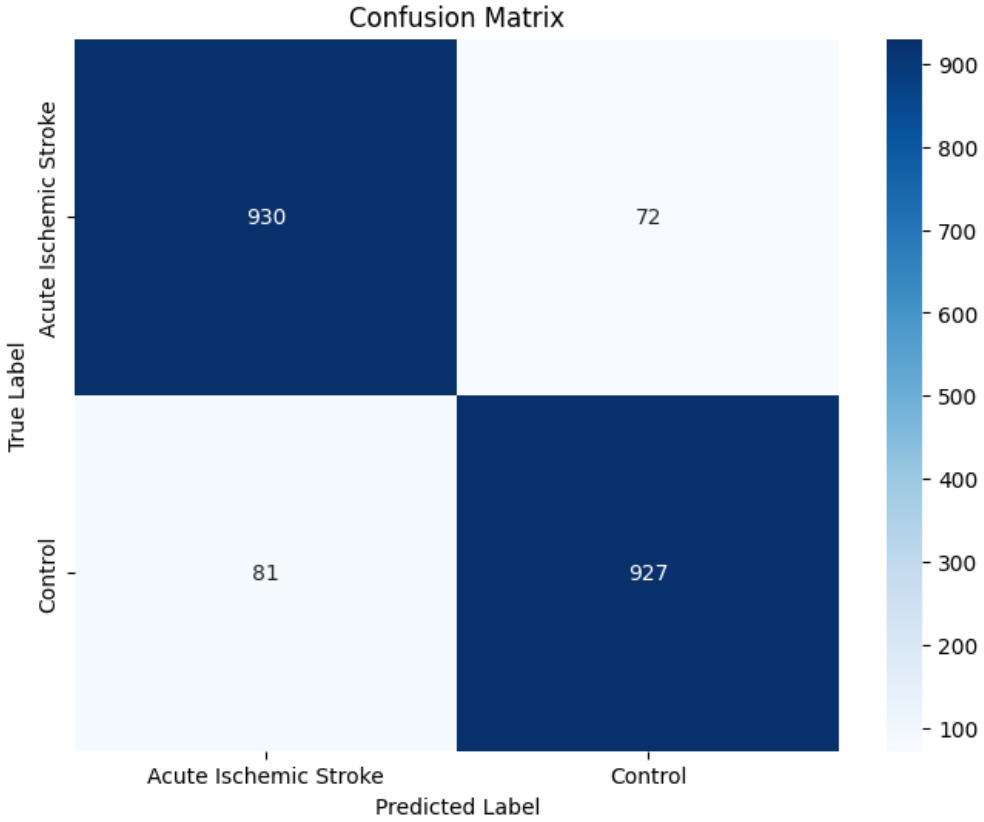

Figure 9: Confusion matrix

8 comparison

Model	Accuracy	Recall	F1 Score
CNN	0.929	0.973	0.932
CNN-LSTM	0.935	0.945	0.936
CNN-Bi-LSTM	0.938	0.954	0.939

Table 1: Performance metrics

Model	Specificity	Sensitivity	FNR	FPR
CNN	0.884	0.973	0.027	0.116
CNN-LSTM	0.924	0.945	0.055	0.076
CNN-Bi-LSTM	0.922	0.954	0.046	0.078

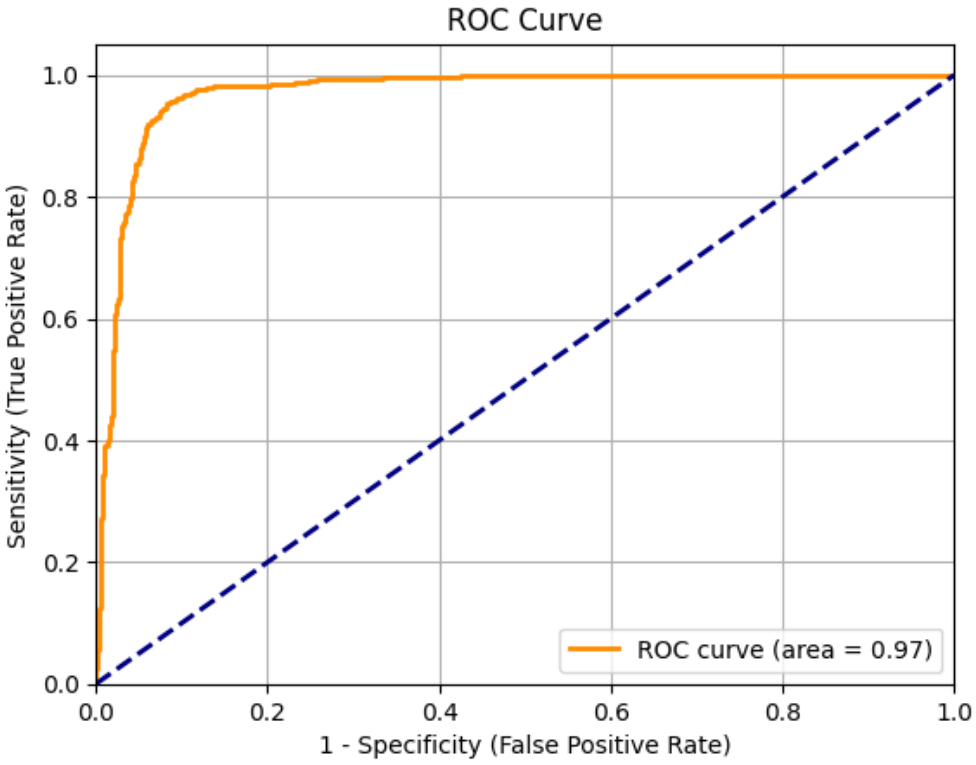

Figure 10: Roc curve

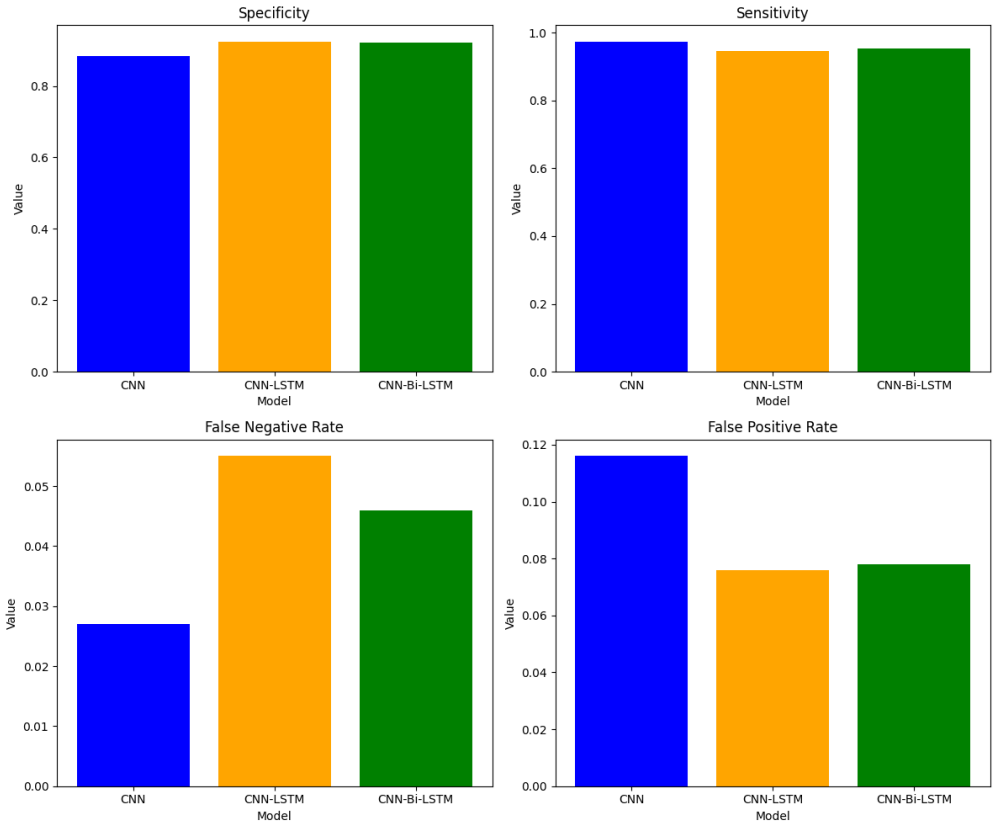

Figure 11: Accuracy graph

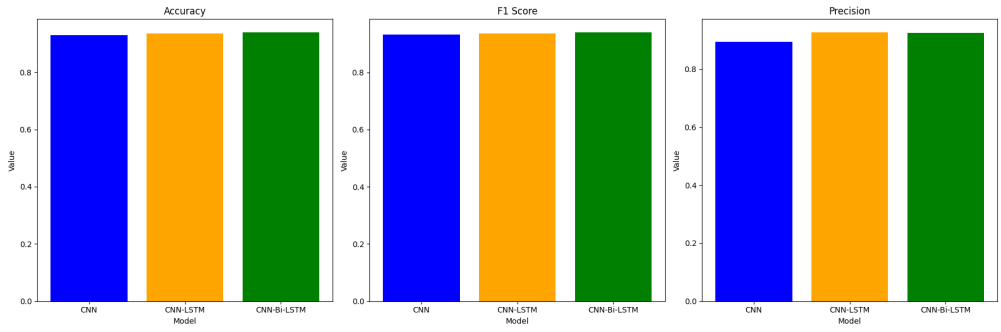

Figure 12: Accuracy graph

9 Model Selection: CNN vs. CNN-Bi-LSTM

In the evaluation of models for stroke detection, both the Convolutional Neural Network (CNN) and the Convolutional Neural Network with Bidirectional Long Short-Term Memory

(CNN-Bi-LSTM) were considered. Each model demonstrated similar accuracy levels, but the selection was based on the ability to minimize false negatives, which is crucial for early stroke detection.

9.1 Convolutional Neural Network (CNN)

The CNN model showed robust performance with the following characteristics:

- **Accuracy: 0.929** - This indicates a high level of overall correct predictions.
- **Sensitivity: 0.973** - High sensitivity is crucial for detecting strokes and preventing missed diagnoses.
- **Specificity: 0.884** - While high sensitivity is important, a balance with specificity is necessary to minimize false positives.

However, the CNN model has some limitations:

- **Higher False Negative Rate (FNR):** The CNN model's higher FNR implies that some stroke cases may go undetected, which could delay treatment.
- **Limited Temporal Analysis:** CNNs focus primarily on spatial hierarchies and lack inherent mechanisms to analyze temporal or sequential data.

9.2 Convolutional Neural Network with Bidirectional Long Short-Term Memory (CNN-Bi-LSTM)

The CNN-Bi-LSTM model offers several advantages:

- **Sensitivity: 0.954** - The highest sensitivity among the evaluated models, indicating a strong ability to identify stroke cases accurately.
- **Specificity: 0.922** - The ability to correctly identify non-stroke cases, reducing false positives.
- **F1 Score: 0.939** - This metric reflects a good balance between precision and recall.
- **Temporal Analysis:** The inclusion of Bidirectional LSTM layers allows the model to capture temporal dependencies, which can be crucial for sequential data analysis.

Despite its strengths, the CNN-Bi-LSTM model also has drawbacks:

- **Increased Complexity and Training Time:** The addition of LSTM layers increases model complexity and computational requirements, leading to longer training times.
- **Potential for Overfitting:** The model's complexity may lead to overfitting if not properly managed, particularly with limited training data.

9.3 Decision Justification

The decision to choose the CNN-Bi-LSTM model over the CNN model is based on the following considerations:

- **Minimizing False Negatives:** The CNN-Bi-LSTM model's superior sensitivity directly addresses the need to minimize false negatives. This is critical for early stroke detection and timely treatment.
- **Balanced Performance:** The CNN-Bi-LSTM model provides a better balance between sensitivity and specificity, ensuring that strokes are detected while minimizing false positives.
- **Advanced Capabilities:** The model's ability to analyze temporal patterns offers advantages in scenarios where sequence and temporal context are important for accurate predictions.

Thus, the **CNN-Bi-LSTM** model is chosen for deployment. Its enhanced sensitivity and balanced performance metrics make it the most suitable model for improving stroke detection and ensuring effective treatment.

References

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