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(Affiliated to Tribhuvan University)

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A MAJOR PROJECT FINAL REPORT ON

BRAIN HEMORRHAGE DETECTION FROM CT IMAGES USING CNN

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A MAJOR PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE DEGREE OF BACHELOR IN COMPUTER ENGINEERING

Submitted to:

Department of Computer and Electronics Engineering

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ABSTRACT

Intracranial hemorrhage, a condition with multifaceted causes including hyper-tension, blood thinners, vascular abnormalities, trauma, bleeding disorders, tumors, and drug usage, presents significant challenges in clinical settings. This study explores the application of deep learning techniques, specifically Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, to enhance the detection of intracranial hemorrhage in CT scans. Utilizing a meticulously prepared dataset sourced from Kaggle, the research is structured to address the detection of normal and hemorrhagic instances with a balanced 80-20 split.The dataset comprises of 4105 normal instances and 2667 hemorrhagic instances. The methodology incorporates a series of preprocessing steps, including image rescaling, data augmentation, grayscale conversion, normalization, and train-test split, followed by CNN feature extraction and classification using bidirectional LSTM and GRU layers. Training over 50 epochs, the model achieved an impressive accuracy rate of 94% and loss value of 0.1539, demonstrating its effectiveness in minimizing prediction errors. This study contributes to the development of robust and accurate models for brain hemorrhage detection, underscoring the potential of advanced machine learning techniques in healthcare diagnostics.

Keywords *– Intracranial Hemorrhage, CT, CNN*

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LIST OF ABBREVIATIONS

AI: Artificial Intelligence

CNN: Convolutional Neural Network

CPU: Central Processing Unit

CT: Computed Tomography

GPU: Graphical Processing Unit

ICH: Intracranial Hemorrhage

AVM: Arteiovenous Malformation

DIC: Disseminated Intravascular Coagulation

LSTM: Long Short-Term Memory

CHAPTER 1
INTRODUCTION

1.1 Background

Hemorrhage in the head (intracranial hemorrhage) is a relatively common condition that has many causes ranging from trauma, stroke, aneurysm, vascular malformations,high blood pressure, illicit drugs and blood clotting disorders. The neurologic consequences also vary extensively depending upon the size, type of hemorrhage and location ranging from headache to death. The role of the radiologist is to detect the hemorrhage, characterize the hemorrhage subtypes, its size and to determine if the hemorrhage might be jeopardizing critical areas of the brain that might require immediate surgery.

Causes of Intracranial Hemorrhage

- Hypertension: elevated blood pressure may cause tiny arteries to burst insidethe brain. Normal pressure is 120/80 mm Hg.
- Blood thinners: drugs such as coumadin, heparin, and warfarin used to preventclots in heart and stroke conditions may cause ICH.
- AVM: a tangle of abnormal arteries and veins with no capillaries in between.
- Aneurysm a bulge or weakening of an artery wall.
- Head trauma: fractures to the skull and penetrating wounds (gunshot) can damage an artery and cause bleeding.
- Bleeding disorders: hemophilia, sickle cell anemia, DIC, thrombocytopenia.
- Tumors: highly vascular tumors such as angiomas and metastatic tumors canbleed into the brain tissue.
- Amyloid angiopathy: a buildup of protein within the walls of arteries.
- Drug usage: alcohol, cocaine and other illicit drugs can cause ICH.
- Spontaneous: ICH by unknown causes.

Symptoms of Intracranial Hemorrhage

The symptoms usually come on suddenly and can vary depending on the location of the bleed. Common symptoms include:

- Headache, nausea, and vomiting
- Lethargy or confusion
- Sudden weakness or numbness of the face, arm or leg, usually on one side
- Loss of consciousness
- Temporary loss of vision
- Seizures

1.2 Problem Statement

Intracranial Hemorrhage (ICH) is a serious condition where bleeding occurs inside the cranium, posing life-threatening risks. When a patient shows such symptoms, highly trained radiologists typically analyze CT scans of the patient's brain to find and determine the type of hemorrhage. However, the manual analysis performed by radiologists is complicated and usually time consuming, inherently and undesirably postponing the intervention. In these circumstances, the fast and automatic detection and classification of intracranial hemorrhage is of utter importance.

1.3 Objective

I. To detect brain hemorrhage from CT images using CNN and LSTM.
II. To help to reduce diagnostic errors in identifying hemorrhage from CT images.
III. To help in quick detection of intracranial hemorrhage in brain CT scans, facilitating timely medical intervention for improved patient outcomes.

1.4 Features

Some features of our project are:

- CT Image processing
- Detect brain hemorrhage from CT images

1.5 System Requirements

System requirements that are needed to run system include:

- Operating system: Windows 8, 8.1, 10, 11 or Linux

1.6 Development Requirements

1.6.1 Hardware Requirements

Hardware configuration and requirement for the operation are as follows:

- PC with 2GB RAM
- Intel i3 or above series processor

1.6.2 Software Requirements

Software configuration and requirement for the operation are as follows:

- Operating system: Windows 8, 8.1, 10, 11 or Linux
- Python

1.7 Deployment Requirement

Development requirements deals with mainly two types of requirements which are hardware and software. The requirement plays a vital role in the successful completion of the project which are listed below:

1.7.1 Hardware Requirements

- PC with 8GB RAM + SSD disk storage
- AMD Ryzen 5 4500u processor

1.7.2 Software Requirements

- Any operating system

1.8 Feasibility Study

1.8.1 Economic Feasibility

For the creation of this project, there's no need for any substantial amount of financial backing from the institution. We do not need any kind of new hardware. It's a one time investment and a good one considering all the advantages. The only kind of charges which the company has to incur is that of the maintenance.

1.8.2 Technical Feasibility

Our project does not require any high end computers.

1.8.3 Operational Feasibility

Users do not need to have any kind of advanced knowledge about computers. Only basic knowledge is sufficient to understand the system.

1.8.4 Schedule Feasibility

Since the development team has the capacity and basic understanding of the project the project will be completed in an 8 month time period.

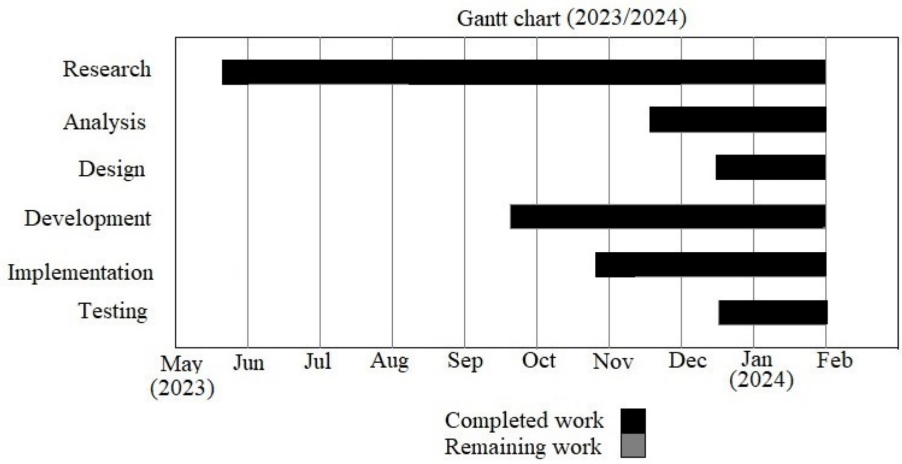

Figure 1.1: Gantt-chart

CHAPTER 2
LITERATURE REVIEW

This paper introduced a hybrid deep learning model that combines Convolutional Neural Networks (CNN) and Long-Short Term Memory (LSTM) networks for the detection of intracranial hemorrhages (ICH) in CT scans. This model is designed to analyze single-slice CT scans and detected hemorrhages, demonstrating high accuracy in sensitivity, specificity, precision, and accuracy. The CNN component extracts important features from the CT images, while the LSTM component processes these features over time to predict the presence and type of hemorrhages. The model's architecture includes convolutional layers for feature extraction, max-pooling layers for dimensionality reduction, and dense layers for classification. The paper concludes by highlighting the potential of the proposed Conv-LSTM model for ICH detection, suggesting further improvements could be made by introducing an optimization algorithm to select the optimal features and to train the model to determine the optimal weight classifier. The experimental results demonstrated the effectiveness of the proposed model in detecting hemorrhages with high accuracy. The model achieved a precision of 95.21%, and an accuracy of 95.14%. [1]

In the paper "Intracranial Hemorrhage Detection in CT Scans using Deep Learning" by Tomasz Lewicki, Meera Kumar, Raymond Hong, and Wencen Wu,they introduced a deep learning model for detecting intracranial hemorrhages (ICH) in CT scans. This model was built upon a convolutional neural network (CNN) based on ResNet for classification, utilizing a dataset of 752,803 DICOM files collected from four international universities by the Radiological Society of North America (RSNA). The model achieved an accuracy of 93.3% in making correct multiclass predictions and an average per-class recall score of 76%. The research also demonstrated the model's real-world applicability through a web application deployment, showcasing its potential for rapid and accurate diagnosis of ICH, which is crucial for timely treatment and mitigation of lasting brain damage and mortality.The research concluded by suggesting future work to further improve the model, such as evaluating it with different convolutional base architectures and introducing a doubly-weighted loss function to better address the precision/recall tradeoff during training. [2]

This paper presents an innovative approach to automated detection of intracranial hemorrhage (ICH) from CT scans, leveraging deep learning techniques to significantly enhance the accuracy and efficiency of ICH diagnosis. This method stands out from traditional approaches, which involve multiple manual steps such as image alignment, processing, correction, feature extraction, and classification. Instead, the researchers employ a deep convolutional neural network (CNN) that simultaneously learns features and classifications, eliminating the need for hand-tuned steps. This approach not only improves the sensitivity of detection but also significantly enhances specificity through postprocessing techniques applied to the CNN output. The study utilizes a dataset of 134 CT cases, consisting of 4,300 images, divided into training, validation, and test sets. The performance on the test set achieved an 81% sensitivity per lesion and a remarkable 98% specificity per case, showcasing the potential of this method in aiding radiologists in detecting subtle hemorrhages. This work contributes valuable insights into the application of deep learning for medical imaging analysis, offering a promising solution for the rapid and accurate detection of ICH. [3]

In the paper ”A CNN-LSTM Architecture for Detection of Intracranial Hemorrhage on CT scans” , they introduced a method that combines a convolutional neural network (CNN) with a long short-term memory (LSTM) mechanism to accurately predict intracranial hemorrhage (ICH) on computed tomography (CT) scans. This method is designed to address the challenges of dealing with the 3D representation of CT scans, which are stacks of 2D images. By stacking three different viewing windows of a single slice to form an RGB-like image, the CNN extracts features slice-wise, while the LSTM links these features across slices. The architecture is trained end-to-end, and it has shown promising results on the RSNA datasets and the CQ500 dataset. The best single model achieved a weighted log loss of 0.0522 on the RSNA leaderboard, comparable to the top 3% performances, and significantly outperformed a 2D model on the CQ500 dataset. This work demonstrates the effectiveness of the proposed CNN-LSTM architecture in detecting ICH on CT scans, offering a potential tool for enhancing the accuracy and efficiency of medical imaging analysis.[4]

In the paper ”Convolutional neural networks for detection intracranial hemorrhage in CT images” by Juan Sebastian Castro, Steren Chabert, Carolina Saavedra, and Rodrigo

Salas,they focused on using deep learning algorithms, specifically convolutional neural networks (CNN), to enhance the detection of intracranial hemorrhage (ICH) from computed tomography (CT) images. This approach is motivated by the challenge faced by physicians in accurately identifying ICH, especially in the early stages, which can lead to misdiagnosis and delayed treatment. The study utilized a dataset of 491 CT studies, totaling 193,317 slices, to train and evaluate two CNN models for classifying ICH or non-ICH. The results show that the proposed CNN models achieve a 97% recall, 98% accuracy, and 98% F1 measure, demonstrating their effectiveness in this critical diagnostic task.[5]

In the paper by Hoon Ko, Heewon Chung, Hooseok Lee, and Jinseok Lee, they introduced an approach for the automatic identification and classification of intracranial hemorrhages (ICH) using deep learning techniques, specifically a CNN-LSTM model. This method aims to improve the accuracy of ICH detection and classification. The research utilizes the Xception model as the backbone for the deep CNN and employs 64 nodes and 32 timesteps for the LSTM, processing a large dataset of head CT images. The study's results indicate a weighted multi-label logarithmic loss of 0.07528, which corresponds to a classification accuracy of approximately 92 to 93%, suggesting that the proposed method significantly enhances the accuracy of ICH identification and classification.[6]

CHAPTER 3
METHODOLOGY

3.1 Working Mechanisms

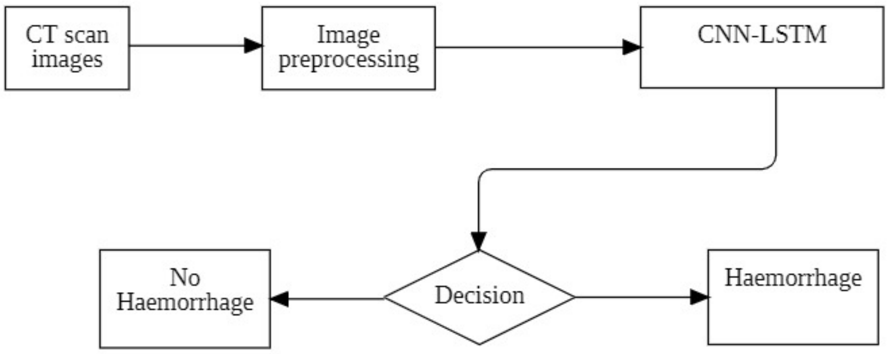

Figure 3.1: Block diagram

3.2 Preprocessing

1. **Image Rescaling:** The images are rescaled to a range of [0, 1] by dividing each pixel value by 255. This standardizes the pixel values and ensures consistency across images.
2. **Data Augmentation:** Data augmentation techniques such as zooming, shearing, rotating, and horizontal flipping are applied to the training images. This helps increase the diversity of the training dataset, which can improve the model's generalization and robustness.
3. **Grayscale Conversion:** The images are converted to grayscale before being fed into the neural network model. This reduces the dimensionality of the data while preserving important features for classification.
4. **Normalization:** The pixel values of the images are normalized to lie within the range [0, 1]. Normalization helps in stabilizing and accelerating the training process by bringing all feature values to a similar scale.
5. **Train−Test Split:** The dataset is split into training and testing sets. This allows for model evaluation on unseen data to assess its generalization performance.
6. **Shuffling:** Before splitting the data, it's shuffled using sample(frac=1) to ran-

domize the order of the samples. Shuffling prevents any inherent ordering in the data from affecting the learning process and ensures that the model learns from a variety of samples.

7. **Data Generation:** The ImageDataGenerator class is utilized to generate batches of tensor image data with real−time data augmentation. This generator yields batches of images indefinitely, which can be used for training or validation.

3.3 CNN Feature Extraction

1. **Convolutional Layers:** The model starts with a convolutional layer with 12 filters of size (3,3) and ReLU activation. This layer captures low-level features like edges.
2. **Batch Normalization:** Applied after the convolutional layer to normalize activations and accelerate training.
3. **Max Pooling:** A (2,2) max pooling layer follows to reduce spatial dimensions while retaining important features.
4. **Additional Convolutional Layers:** More convolutional layers with increased complexity and dropout regularization are added to extract higher-level features.

3.4 Classification

- **Flattening:** The feature maps from the convolutional layers are flattened into a 1D vector.
- **TimeDistributed Layer:** Indicates that subsequent LSTM and GRU layers will be applied independently to each time step of the sequence.
- **Recurrent Layers (LSTM and GRU):** Bidirectional LSTM and GRU layers capture temporal dependencies and sequential patterns bidirectionally.
- **Dropout Regularization:** Applied to LSTM and GRU layers to prevent overfitting by randomly dropping units during training.
- **Fully Connected Layers:** Flattened output is passed through dense layers with ReLU activation and dropout regularization.
- **Softmax Output:** Final dense layer with softmax activation performs classifica-

tion, producing probabilities for each class.

3.5 Training and Optimization

In this study, the dataset was carefully partitioned into an 80-20 split, comprising 4105 instances labeled as normal and 2667 instances indicating hemorrhage. This balanced distribution of the dataset is essential for ensuring the development of robust and precise models. The training phase extended over 50 epochs, allowing for comprehensive model optimization and performance evaluation. The dataset was taken from Kaggle. This dataset contains images of normal and hemorrhagic CT scans collected from the Near East Hospital, Cyprus.[7]

3.6 Activation Function

ReLU (Rectified Linear Unit) is a widely used activation function in neural networks due to its simplicity and effectiveness. It operates by replacing all negative input values with zero, leaving positive values unchanged. Mathematically, ReLU is represented as $(f(x) = max(0, x))$. This non-linearity introduced by ReLU is crucial for enabling neural networks to learn complex patterns and relationships in data. Moreover, ReLU is computationally efficient and helps mitigate the vanishing gradient problem commonly encountered during training. Consequently, it finds extensive application in deep learning models, particularly in convolutional neural networks (CNNs).

On the other hand, the sigmoid activation function is characterized by a smooth, S-shaped curve that squashes input values to the range between 0 and 1. Its formula is defined as $(f(x) = frac11 + e^{-x})$. Sigmoid functions are commonly employed in binary classification tasks where the output needs to be interpreted as a probability. By mapping real-valued numbers to probabilities, sigmoid aids in making decisions based on the likelihood of an event occurring. However, sigmoid functions are prone to the vanishing gradient problem, especially for large or small input values. In practice, sigmoid activation functions are often utilized in the output layer of neural networks for binary classification tasks.

3.7 Adam Optimizer

The Adam optimizer is a popular optimization algorithm used in training deep neural networks. It combines the advantages of two other optimization techniques: AdaGrad and RMSProp. Adam maintains adaptive learning rates for each parameter by calculating an exponentially decaying average of past gradients and their squares. This allows it to dynamically adjust the learning rate for each parameter, typically resulting in faster convergence and better performance compared to traditional optimization algorithms. Adam also includes bias correction to prevent the initial steps from being too large.

Overall, Adam is well-suited for a wide range of deep learning tasks due to its efficiency, robustness, and ease of use, often requiring minimal hyper parameter tuning.

3.8 Dropout

Dropout is a regularization technique for neural networks, introduced by Geoffrey Hinton, et.al, in 2012. Dropout involves randomly setting a fraction of activation of neurons to 0. This reduces the amount of information available to each layer, forcing the network to learn multiple independent representations of the same data. This makes the network more robust to overfitting. In practice, during each forward pass, each activation in the network is set to zero with a certain probability (e.g., 50that activation and its corresponding nodes in the network. During the backward pass, the gradients are computed normally and then multiplied by a factor that corresponds to the keep probability. This allows the network to learn to 'turn on' different nodes and combinations of nodes to model the data. In a deep neural network architecture, dropout layers are inserted between the dense layers or the convolution layers. The keep probability is typically set to a value between 0.5 and 0.8, depending on the size and complexity of the network and the size of the training data.

3.9 Evaluation Matrix

3.9.1 Confusion Matrix

A confusion matrix is a table that is often used to describe the performance of a classification model on a set of test data for which the true values are known. It provides insights into the number of correct and incorrect predictions made by the model, organized by class. It consists of four main components:

- **True Positives (TP):** The number of correct positive predictions.
- **True Negatives (TN):** The number of correct negative predictions.
- **False Positives (FP):** The number of incorrect positive predictions (Type I error).
- **False Negatives (FN):** The number of incorrect negative predictions (Type II error).

3.9.2 Accuracy

Accuracy is a common metric used to evaluate classification models. It measures the proportion of correctly predicted instances out of the total instances in the dataset. It is calculated as the ratio of the sum of true positives and true negatives to the total number of instances.

3.9.3 Loss

Loss, also known as cost or error, quantifies the difference between the predicted values and the actual values. It is a measure of how well the model is performing during training. Common loss functions include cross-entropy loss for classification tasks and mean squared error for regression tasks.

3.9.4 F1 Score

The F1 score is the harmonic mean of precision and recall. Precision measures the accuracy of positive predictions, while recall measures the ability of the model to find all positive instances. The F1 score provides a balance between precision and recall, making it suitable for imbalanced datasets. It ranges from 0 to 1, with higher values indicating better model performance.

3.9.5 ROC Curve and AUC

The ROC curve is a graphical plot that illustrates the diagnostic ability of a binary classification model across various threshold values. It plots the true positive rate (sensitivity) against the false positive rate (1 - specificity) at different threshold settings. The Area Under the ROC Curve (AUC) quantifies the overall performance of the model. A higher AUC value indicates better discrimination between positive and negative classes.

3.9.6 Classification Report

The classification report provides a summary of various metrics for each class in the dataset. It includes metrics such as precision, recall, F1-score, and support (the number of actual occurrences of the class in the dataset). It helps to evaluate the performance of the model for individual classes and identify any class-specific issues.

3.10 Software Model

Incremental Model is a process of software development where conditions are divided into multiple standalone modules of the software development cycle. In this model, each module goes through the conditions, design, perpetration and testing phases. Every posterior release of the module adds function to the former release. The process continues until the complete system is achieved.

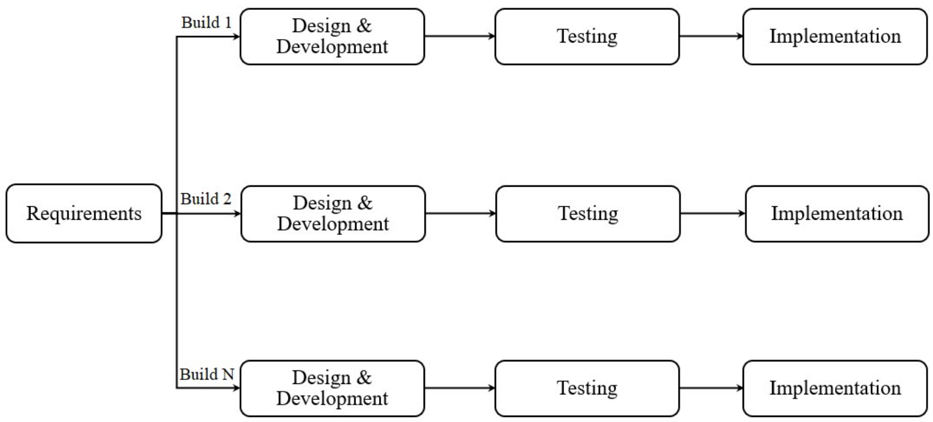

Figure 3.2: Incremental model

3.11 System Diagrams

3.11.1 Use-case Diagram

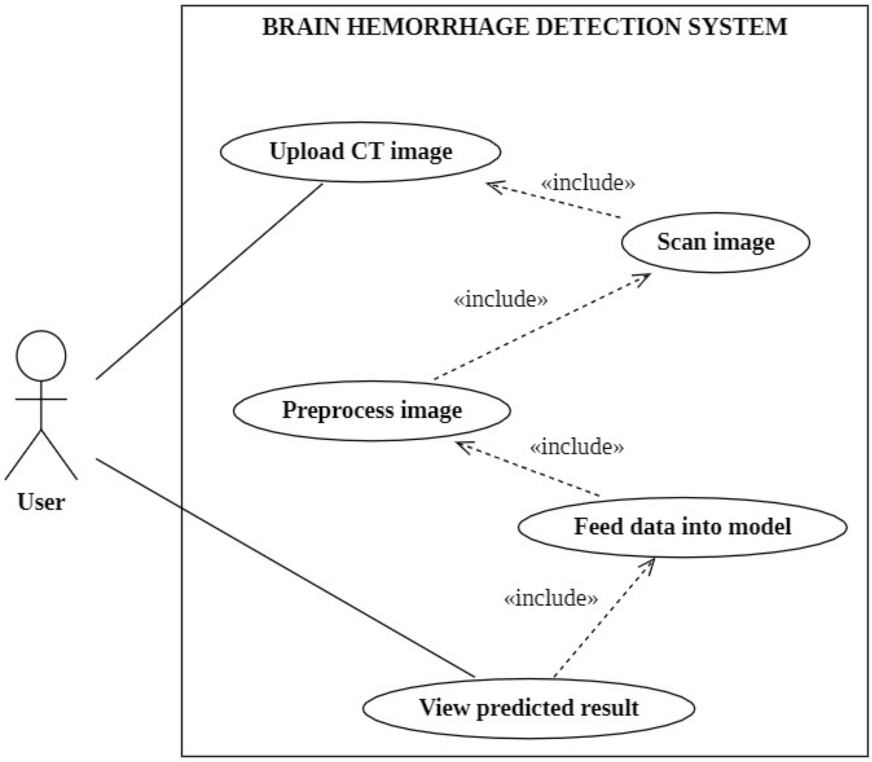

Figure 3.3: Use-case diagram

3.11.2 Flowchart

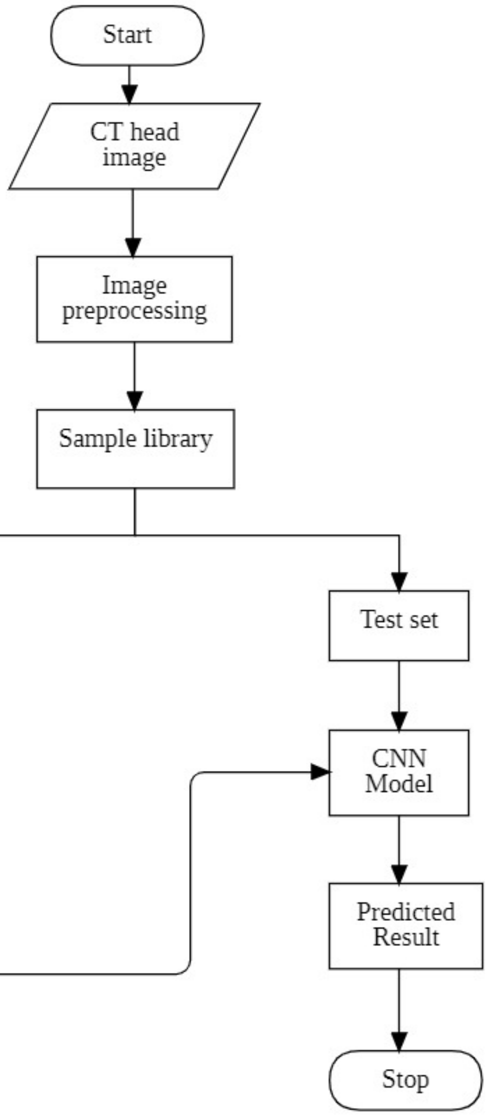

Figure 3.4: Flowchart diagram

CHAPTER 4
RESULT AND DISCUSSION

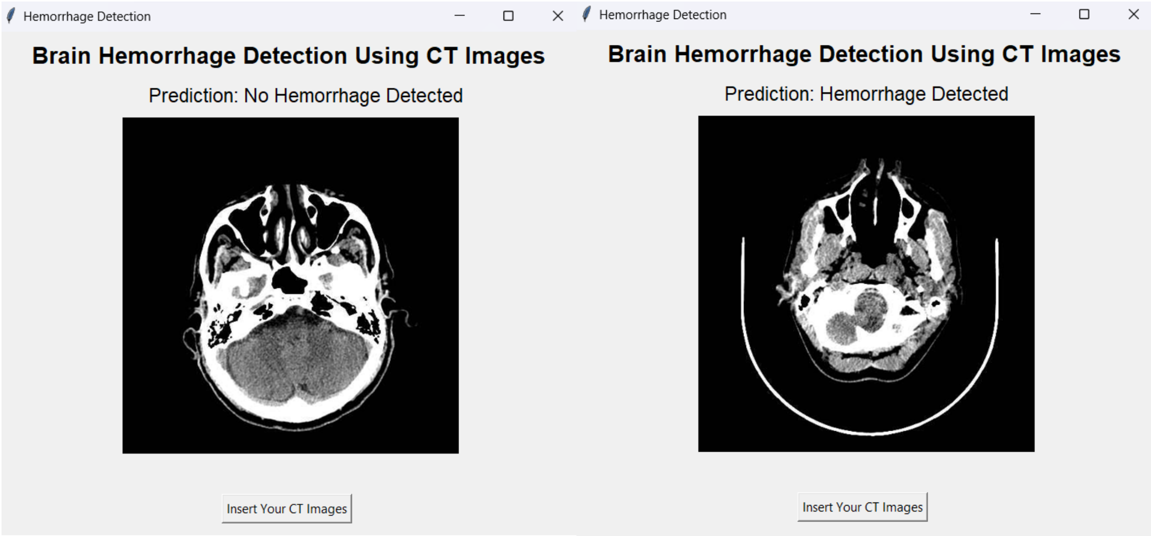

Figure 4.1: Screenshots of output

The research conducted focuses on the development and evaluation of a brain hemorrhage detection system leveraging advanced machine learning techniques, specifically Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The dataset utilized in this study was meticulously divided into an 80-20 split, consisting of 4105 instances categorized as normal and 2667 instances exhibiting signs of hemorrhage. This balanced dataset distribution is crucial for training robust and accurate models. Throughout the training process, which spanned 50 epochs, the model demonstrated significant performance, achieving an impressive accuracy rate of 94%. This accuracy rate indicates the model's capability to correctly classify brain scans as either normal or hemorrhagic with a high degree of precision. Additionally, the loss value of 0.1539 further underscores the effectiveness of the model in minimizing prediction errors during training.

```
F1 Score:
0.49564185321127346

Classification Report:
              precision    recall  f1-score    support
Hemorrhage     0.387234  0.411765  0.399123  221.00000
Normal         0.575163  0.550000  0.562300  320.00000
accuracy       0.493530  0.493530  0.493530    0.49353
macro avg      0.481199  0.480882  0.480712  541.00000
weighted avg   0.498394  0.493530  0.495642  541.00000
```

Figure 4.2: Classification of dataset

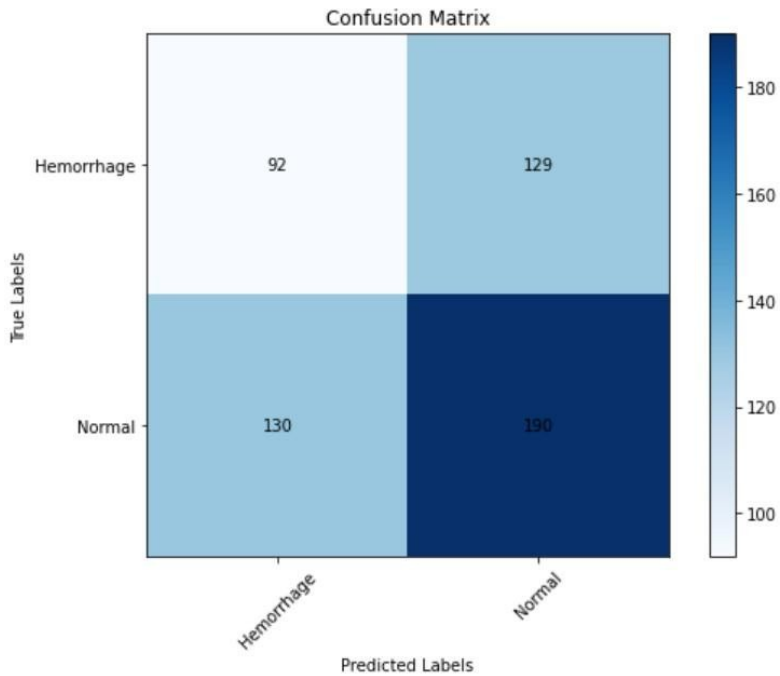

Figure 4.3: Confusion matrix

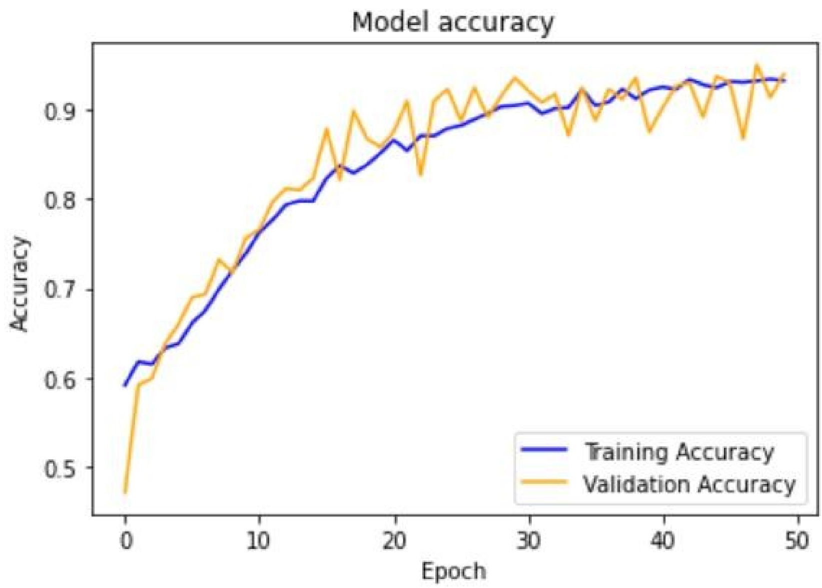

Figure 4.4: Training and Validation accuracy

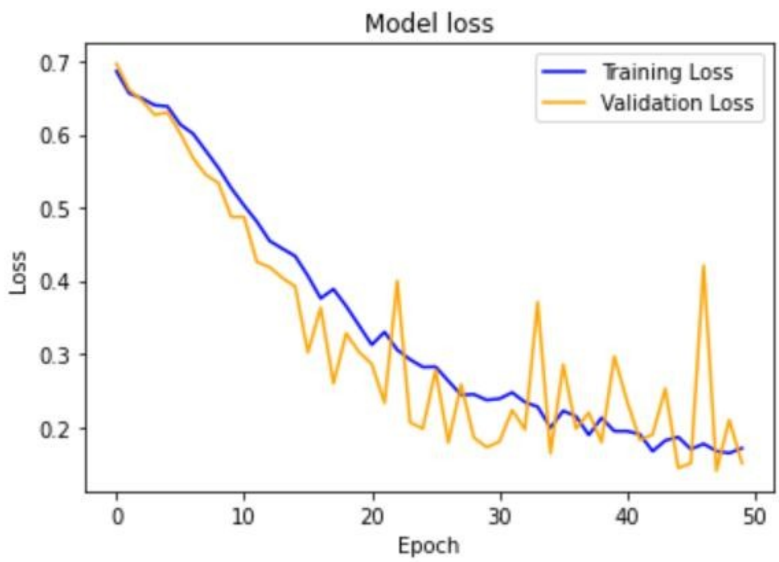

Figure 4.5: Training and Validation loss

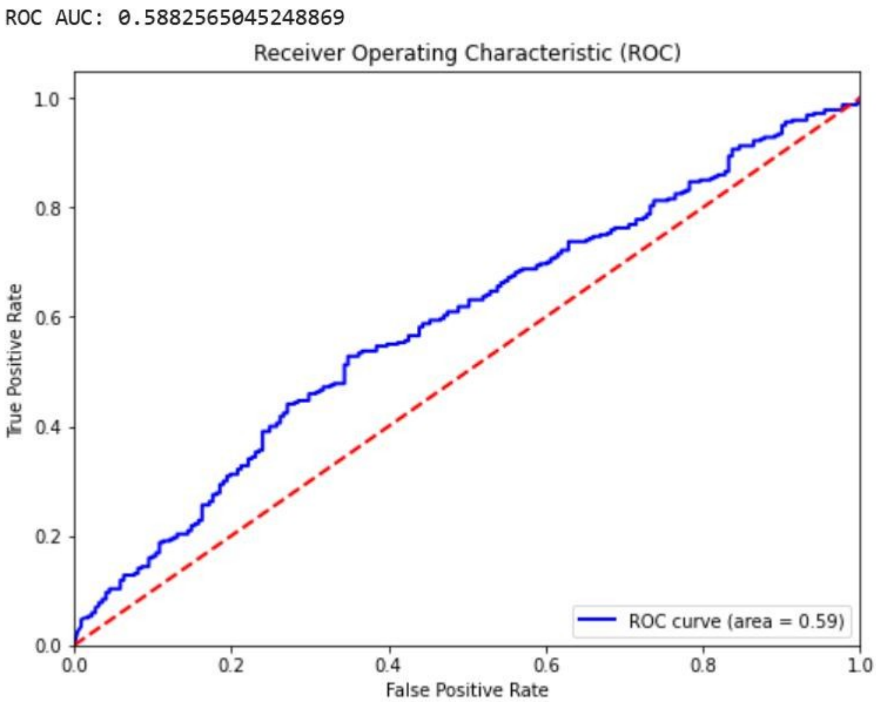

Figure 4.6: ROC curve

CHAPTER 5
CONCLUSION, LIMITATIONS AND FUTURE ENHANCEMENT

5.1 Conclusion

Therefore, in conclusion, this system proves insufficient for real-world applications. Given the critical nature of the condition, achieving higher accuracy and correctly identifying the hemorrhage are imperative for the system to gain sufficient acceptance.

Moreover, the model stands to benefit from further enhancements such as employing more efficient algorithms, optimizing the network architecture, increasing the number of hidden layers, and augmenting the dataset. These measures can lead to significant improvements in accuracy and overall performance.

5.2 Limitations

1. This system can predict only in desktop computer.
2. This system requires CT scan which leads to increase risk because of radiations during CT scanning.
3. The obtained accuracy is 93.9% which can be further improved with future enhancement. Thus, for now this system is inadequate to use in the real system.

5.3 Future Enhancement

Our future plans include the following improvements:

1. Developing a lightweight and portable web application that can be hosted on the cloud.
2. Incorporating newer algorithms to enhance accuracy.
3. Expanding the dataset to further improve performance.

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