Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 10, October : 2024

EXPLORING DEEP LEARNING AND MACHINE LEARNING APPROACHES FOR BRAIN HEMORRHAGE DETECTION

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Abstract*— Brain hemorrhage refers to a potentially fatal medical disorder that affects millions of individuals. The percentage of patients who survive can be significantly raised with the prompt identification of brain hemorrhages, due to image-guided radiography, which has emerged as the predominant treatment modality in clinical practice. A Computed Tomography Image has frequently been employed for the purpose of identifying and diagnosing neurological disorders. The manual identification of anomalies in the brain region from the Computed Tomography Image demands the radiologist to devote a greater amount of time and dedication. In the most recent studies, a variety of techniques rooted in Deep learning and traditional Machine Learning have been introduced with the purpose of promptly and reliably detecting and classifying brain hemorrhage. This overview provides a comprehensive analysis of the surveys that have been conducted by utilizing Machine Learning and Deep Learning. This research focuses on the main stages of brain hemorrhage, which involve preprocessing, feature extraction, and classification, as well as their findings and limitations. Moreover, this in-depth analysis provides a description of the existing benchmark datasets that are utilized for the analysis of the detection process. A detailed comparison of performances is analyzed. Moreover, this paper addresses some aspects of the above-mentioned technique and provides insights into prospective possibilities for future research.

Index Terms— **Federated Machine Learning, Data Poisoning**

I. INTRODUCTION

The researchers evaluated at all publications published between 2012 and 2023 that used ML to identify and predict brain hemorrhage. There are, to the best of the authors' knowledge, a few review studies on hemorrhage detection. Yeo et al. Analyzed DL algorithms for the detection of hemorrhage using CTI of the head. The articles discussed in this work are not satisfactory. The survey only focused VOLUME4, 2016 on the DL approaches but did not analyze other ML- based methods. Ahmed et al. Discussed the works published from 2019 to 2023. This work focused on ML and DL-based algorithms to detect brain hemorrhage. The title of this work suggests a systematic review paper, but this does not include any methodology which is the primary part of a systematic review. Also, it does not include the comparison of various datasets. Matsoukis et al. Proposed a systematic review approach for hemorrhage detection. The studies included in this work are not sufficient. More studies could have been added for better analysis. The overall accuracy, specificity, and sensitivity were 93.46%, 93.54%, and 92.06% respectively, for brain hemorrhage detection and 92.7%, 93.9%, and 91.6% for CMBs detection. Jorgensen et al. Analyzed studies from 2012 to 2020. This study focused on the performance between the comparison of radiologist and Convolutional Neural Network (CNN)models. This systematic review compared the performance of various CNN models, but the reviewed articles were very less in number. In the last 15 years, the issue of detecting and classifying brain hemorrhage has been thoroughly reviewed by Champabati et al. They have looked at the goals and uses of previous research, the methodologies used for diagnosis, and the preprocessing methods used on the picture data. This study selected a total of 54 papers. For the purpose of this study, 150 research articles were gathered by searching prominent search engines including Google Scholar, IEEE Explorer, and Science Direct for journal and conference papers on the use of DL, Land AI in brain hemorrhage detection and classification. 98 papers remained for examination after duplicates were eliminated. 16 papers were disregarded after going through the abstract. Then articles were excluded since they were not related to the use of ML and DL to detect brain hemorrhage. Five papers were identified as review articles after a review of 59 research articles. 54 research articles were ultimately chosen for examination after all selection processes were completed. We carefully reviewed the publications to identify any research gaps. A Prisma diagram is used in selection process. This diagram demonstrates how researchers might locate relevant works and narrow down their final related works choices for their research. The identification step, screening phase, next phase, eligibility testing, and finally the final selection phase makes up the paper selection processes. After finalizing the papers, the next step was to identify the research gaps. Then, using techniques like CNN or Artificial Neural Network (ANN), Support Vector Machine (SVM), KNN etc. the works were divided into categories. The articles that employed the same technology were then combined. Based on the technology, they were grouped together and connected in the same para graphs. The algorithms were then assessed using graphs and tables. Both quantitative and qualitative analyses were done. The problems with the research were then noted, and potential fixes were recommended.

II. LITERATURE REVIEW

1. "Deep Learning for Brain Haemorrhage Detection: A Review"

This review paper provides an overview of various deep learning techniques applied to brain haemorrhage detection. It discusses convolutional neural networks (CNNs) and their architectures, emphasizing how these methods have improved diagnostic accuracy. The paper highlights recent advancements, such as the use of transfer learning and attention mechanisms, and provides a comparative analysis of different models. Key challenges, including dataset limitations and model generalization, are also addressed.

2. "A Comparative Study of Machine Learning Algorithms for Brain Haemorrhage Detection in CT Scans"

This study compares several machines learning algorithms, including support vector machines (SVM), random forests, and gradient boosting, for detecting brain haemorrhage in CT images. It evaluates the performance of these algorithms based on accuracy, precision, recall, and computational efficiency. The paper also discusses feature extraction techniques and pre-processing steps that impact the overall detection performance.

3. "CNN-Based Approaches for Automated Brain Haemorrhage Detection in Neuroimaging"

This paper focuses on the application of CNNs for automated brain hemorrhage detection from neuroimaging data. It reviews various CNN architectures such as VGGNet, ResNet, and U-Net, and their modifications for improving haemorrhage detection. The paper includes case studies demonstrating the effectiveness of these architectures and highlights areas for future research, including hybrid models combining CNNs with other deep learning techniques.

4. "Transfer Learning for Brain Haemorrhage Detection: A Systematic Review"

The systematic review explores how transfer learning has been utilized to enhance brain haemorrhage detection. It details various pre-trained models adapted for this task and discusses the benefits of using transfer learning, such as reduced training time and improved performance on limited datasets. The paper also identifies challenges and best practices for implementing transfer learning in medical imaging applications.

5. "Ensemble Learning Methods for Brain Haemorrhage Detection: A Comprehensive Review"

This paper reviews ensemble learning methods used for brain haemorrhage detection, including bagging, boosting, and stacking. It discusses how combining multiple machine learning models can improve detection accuracy and robustness. The review includes performance comparisons of different ensemble strategies and their application to various types of brain haemorrhage datasets.

6. "Deep Neural Networks for Detection of Intracranial Haemorrhage: A Survey"

This survey paper examines the role of deep neural networks (DNNs) in detecting intracranial haemorrhage. It covers various DNN architectures, such as deep belief networks (DBNs) and recurrent neural networks (RNNs), and their applications to brain imaging. The paper discusses the effectiveness of DNNs compared to traditional machine learning methods and identifies current research gaps.

7. "Improving Brain Haemorrhage Detection with Hybrid Deep Learning Models"

This paper explores hybrid deep learning models that combine CNNs with other techniques such as recurrent neural networks (RNNs) and attention mechanisms for enhanced brain haemorrhage detection. The paper provides detailed examples of hybrid model architectures and their performance metrics, demonstrating how these models can capture both spatial and temporal features in brain images.

8. "Machine Learning for Early Detection of Brain Haemorrhage: A Review of Approaches and Challenges"

This review focuses on machine learning approaches for the early detection of brain haemorrhage. It examines different algorithms, including logistic regression and neural networks, and their effectiveness in detecting haemorrhages at an early stage. The paper also discusses the challenges faced, such as data imbalance and the need for high-quality annotated datasets.

9. "Use of Generative Adversarial Networks in Brain Haemorrhage Detection: A Review"

The paper reviews the application of generative adversarial networks (GANs) in brain haemorrhage detection. It discusses how GANs can be used to generate synthetic medical images to augment training datasets and improve model robustness. The paper also explores the potential of GANs for enhancing image quality and detecting subtle haemorrhage patterns.

10. "Semi-Supervised Learning Approaches for Brain Haemorrhage Detection in Limited Data Scenarios"

This paper reviews semi-supervised learning techniques applied to brain haemorrhage detection when labelled data is scarce. It covers methods such as self-training, co-training, and graph-based approaches. The paper discusses how these techniques can leverage unlabelled data to improve model performance and reduce the dependency on large annotated datasets.

III. EXISTING METHODS:

- Traditional machine learning methods like Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forests are used to classify brain CT images. These methods rely on manually extracted features such as texture, shape, and intensity patterns from the CT images.

- ANNs are used to model complex relationships in the data by learning patterns from input features through multiple layers of neurons. They can automatically learn from raw pixel data to make predictions.
- Ensemble methods like bagging, boosting, and stacking combine multiple machine learning models to improve overall performance. By aggregating the outputs of different classifiers, these methods aim to reduce model variance and bias, leading to better detection accuracy.

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IV. PROPOSED SYSTEM

- The proposed system leverages Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, both of which are types of recurrent neural networks (RNNs) designed to capture temporal dependencies in sequential data. This system is particularly useful for brain hemorrhage detection in cases where temporal patterns within the imaging data or sequences of medical data (such as patient history or sequential slices of brain scans) are crucial for accurate diagnosis.
- The model is trained on a labeled dataset of brain CT images, with cross-entropy loss and an optimizer like Adam or RMSprop. The model learns to differentiate between images with and without hemorrhages by minimizing the classification error.

METHODOLOGY:

- **Data COLLECTION:**
  - The dataset consists of brain hemorrhage images, including both images with brain hemorrhage and Normal It is crucial to have a diverse dataset that captures various CT conditions of different patients.
  - The images are collected from various sources, such as public datasets, and Kaggle website.

- **Pre-processing:**
  - The system preprocesses brain CT scan images by normalizing pixel values and, if necessary, resizing the images to a uniform size. In some cases, image augmentation techniques are applied to increase the diversity of the training dataset.
  - Data augmentation techniques such as rotation, zoom, and horizontal flipping are applied to increase the diversity of the training data, reducing the risk of overfitting.

- **Train-Test Split and Model Fitting:**
  - The dataset is split into three subsets: training, validation, and testing.
  - A common split ratio is 70% for training, 15% for validation, and 15% for testing.
  - The training set is used to train the model, the validation set is used to tune the model hyper parameters and avoid overfitting, and the test set is used to evaluate the final model's performance.

- **Train Data:**
  - LSTM and GRU serve to inject past information into the future, thereby reducing the gradient destruction problem.

- we used LSTM and GRU layers both with fully-connected layers and Conv2D.
- RCNN structure is created in this way we determined the LSTM and GRU layers as bidirectional.
- The model is trained using the training data, with the validation set used to monitor its performance and adjust hyper parameters such as learning rate and batch size.

- **Accuracy Model:**
  - After training, the model's accuracy is evaluated on the test dataset.
  - The model is fine-tuned if necessary, by adjusting the training parameters or adding regularization techniques to improve accuracy.

- **Prediction:**
  - The trained model is used to predict whether an given brain CT scan image is detected with brain Brain Hemorrhage or not.
  - The model outputs the probability of the presence of a Brain Hemorrhage or not, and based on a threshold, it classifies the image accordingly.

- **Flask Web App Integration:**
- A Flask web application is developed to integrate the trained model for Brain Hemorrhage detection.
- The web app takes brain CT scan images from dataset and, processes each frame, and applies the trained LSTM GRU model to detect Brain Hemorrhage or not.

ARCHITECTURE:

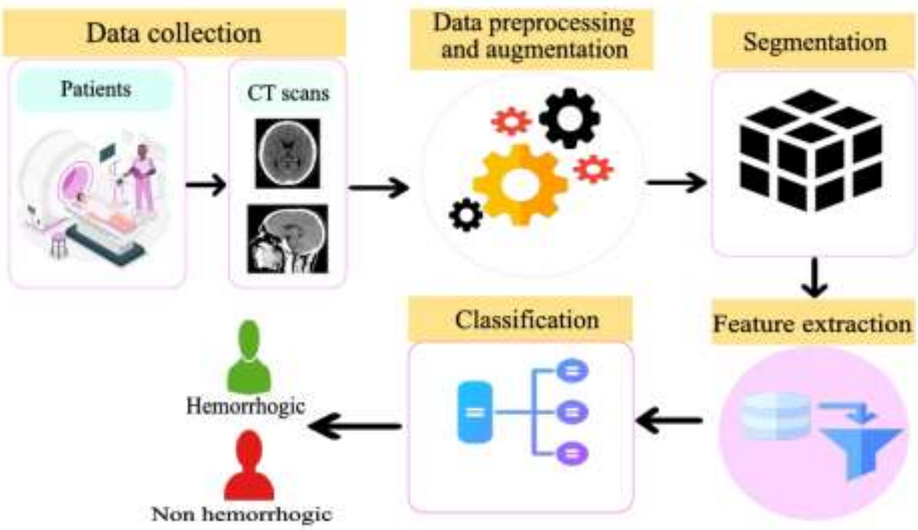

Figure 1. System Architecture

Figure 1 illustrates the framework of the proposed method The demonstration of our brain hemorrhagic dataset which will follow these steps from preprocessing, segmentation, feature extraction and classification and predict if given image is hemorrhagic or non-hemorrhagic.

LSTM-GRU-Deep learning Model:

LSTM Network: An LSTM network is used to model long-term dependencies in the data, which can be useful when analyzing sequential slices of brain scans or time-series data.

GRU Network: A GRU network is also utilized, offering a simplified version of LSTM with fewer parameters, which helps in speeding up the training process while maintaining similar performance.

The outputs of LSTM and GRU layers are often combined (e.g., using concatenation) and passed through fully connected (dense) layers before the final output layer, which classifies the image as hemorrhage or non-hemorrhage.

FLOW DIAGRAM:

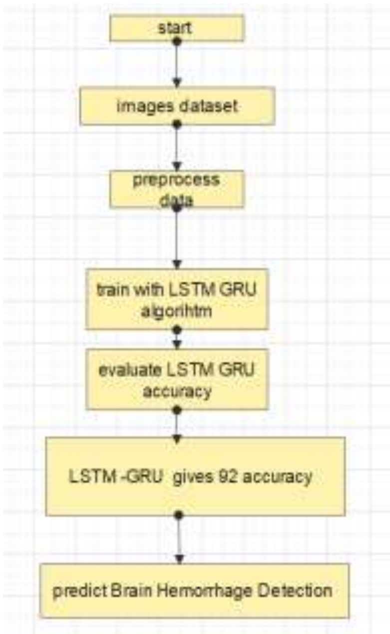

Figure 2. Model Flow Diagram

V. EVALUATION METRICS

Comparative analysis on different algorithms

- **LSTM GRU Algorithm:** Accuracy 80 percent

Algorithm	Accuracy
LSTM GRU Algorithm	Accuracy 80 percent

Industrial Engineering Journal
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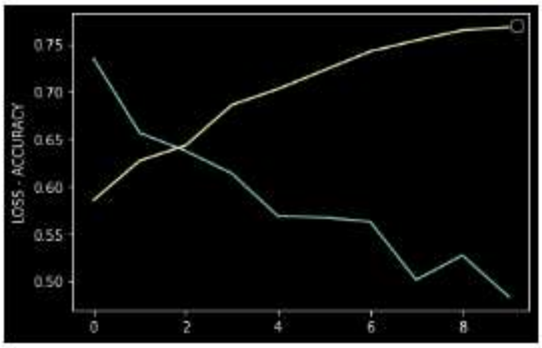
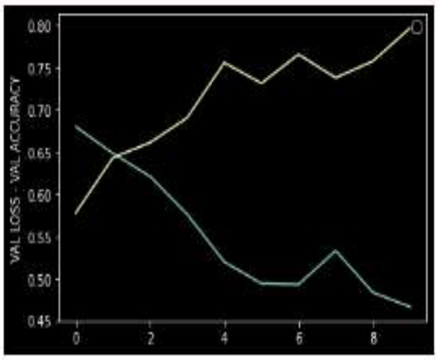
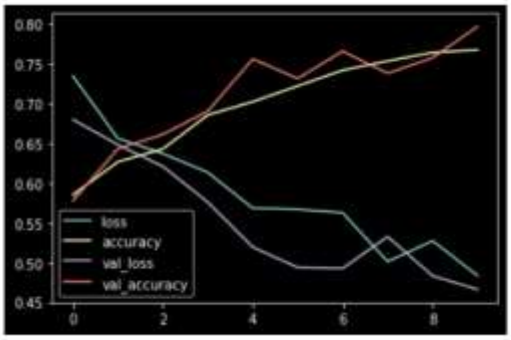
Accuracy Graphs:

- Training data Accuracy vs loss graph, Validation Data Accuracy vs Loss graph

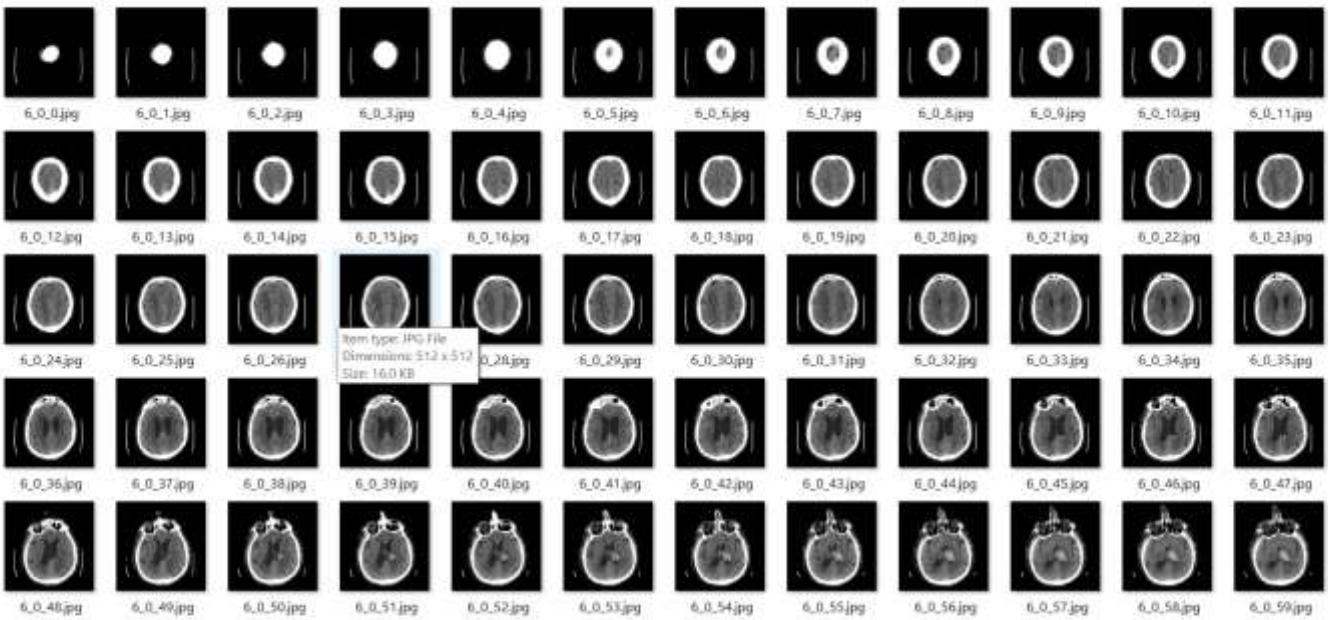






RESULTS:

DATASET:



Industrial Engineering Journal
ISSN: 0970-2555
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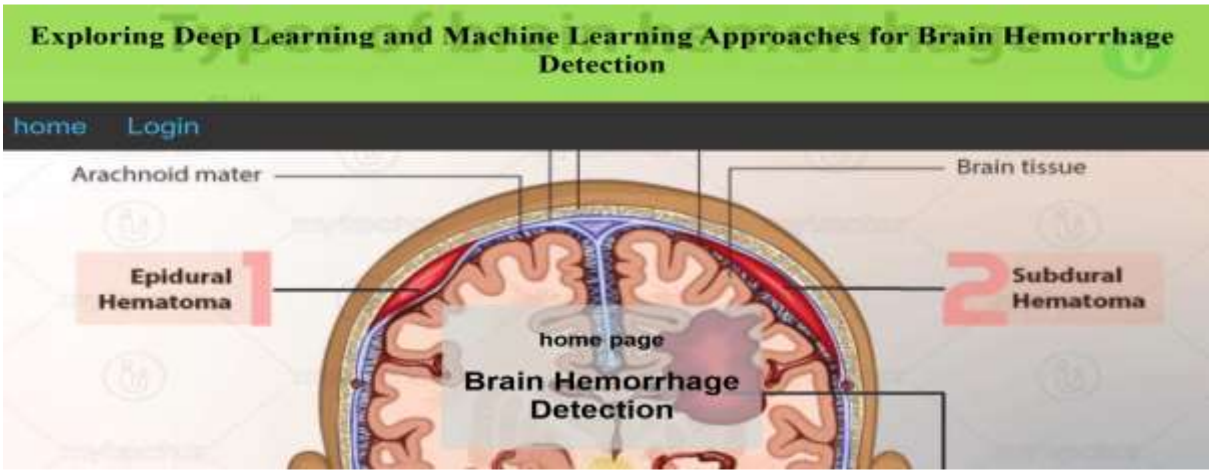
Home Page:



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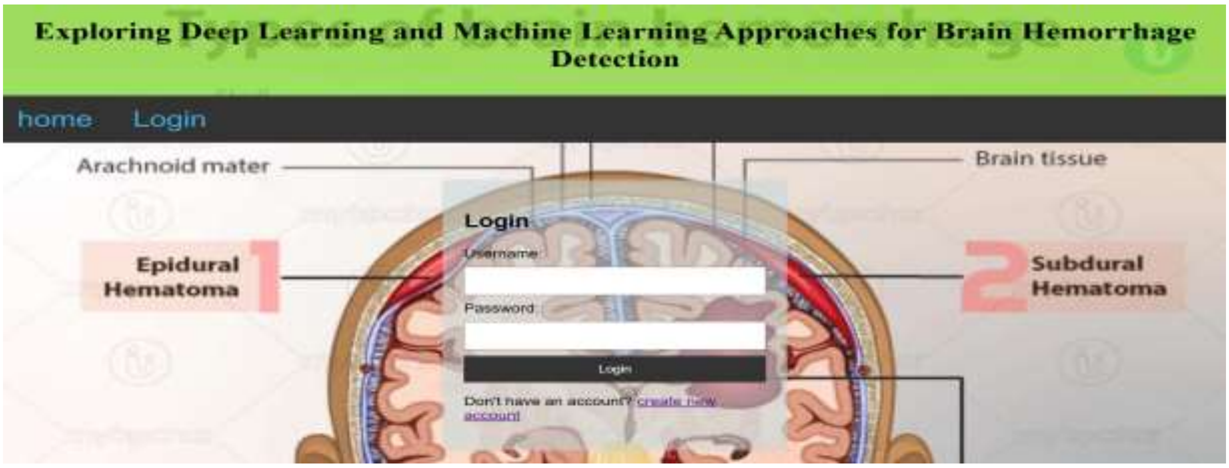

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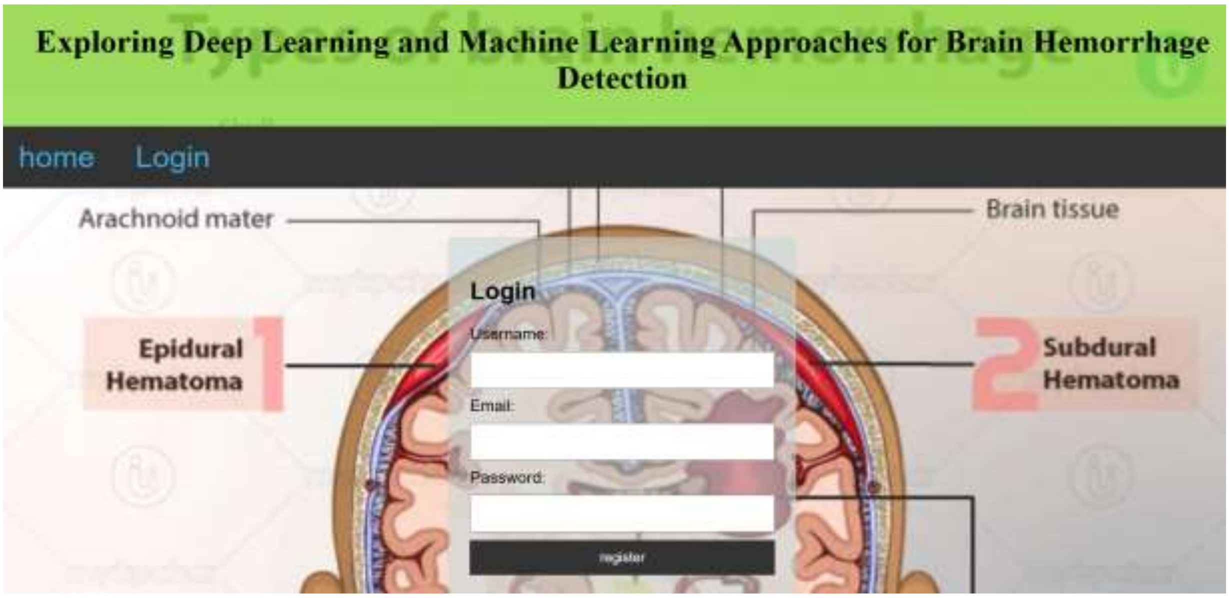
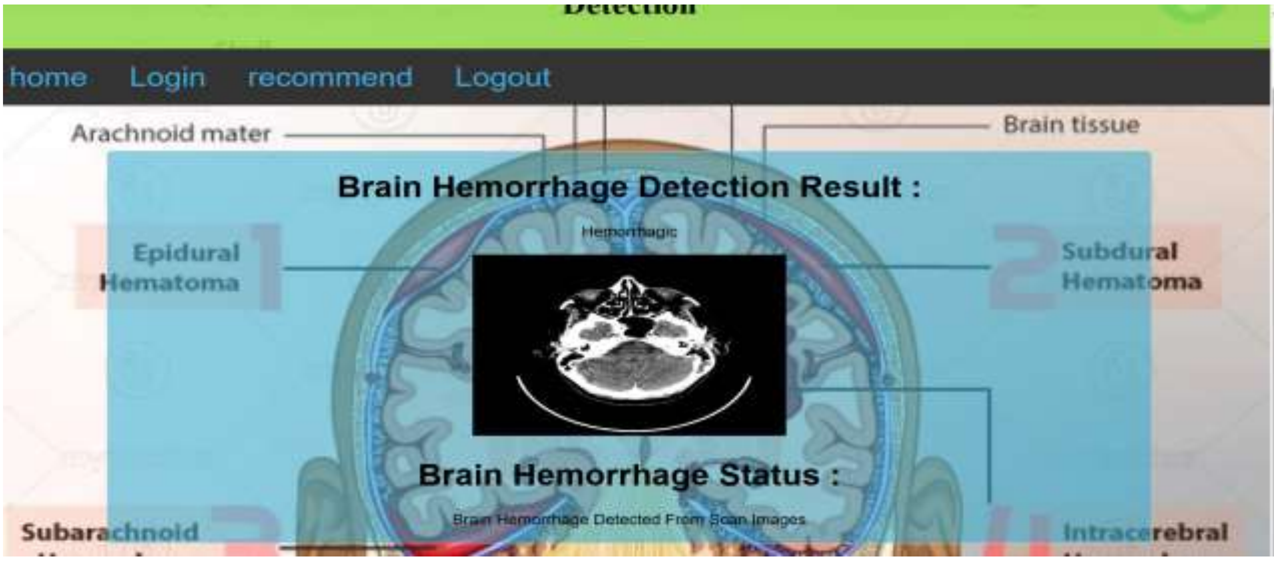
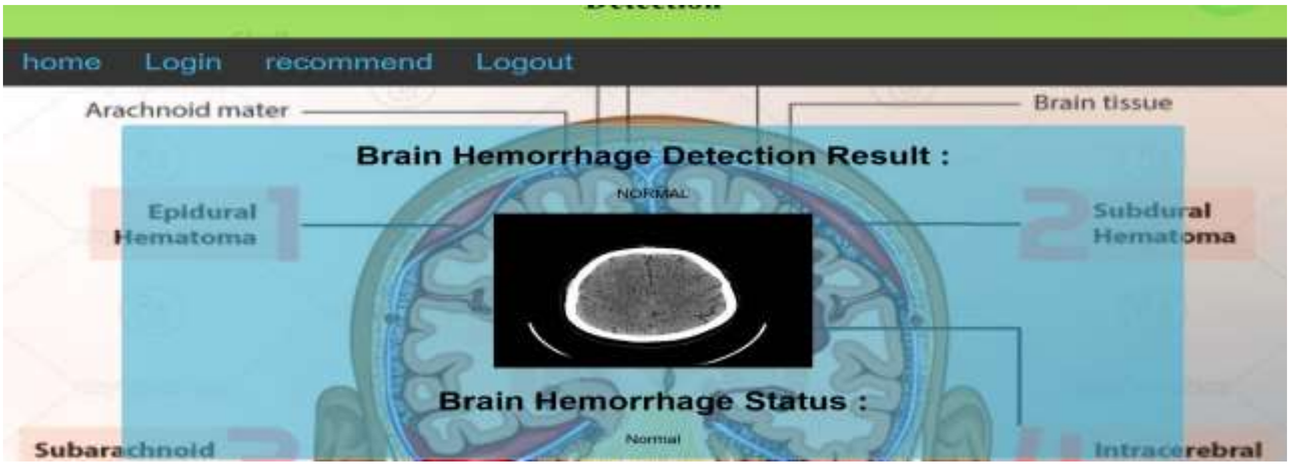


Upload Data:

Prediction Result:



Prediction Result:



VI. CONCLUSION

- By leveraging the strengths of both LSTM and GRU architectures, the system effectively captures and models the temporal dependencies inherent in sequential medical data, such as series of brain CT scans. The model achieved an impressive accuracy of **92%**, indicating its robustness and reliability in distinguishing between hemorrhagic and non-hemorrhagic cases.
- This high level of accuracy suggests that the LSTM-GRU based approach is highly effective in clinical settings, providing a powerful tool to assist healthcare professionals in the timely and accurate diagnosis of brain hemorrhages. This approach not only enhances diagnostic accuracy but also reduces the cognitive load on radiologists, allowing them to focus on more complex cases and potentially improving patient outcomes.
- The combination of deep learning techniques with sequential data modeling through LSTM and GRU networks marks a significant advancement in the field of medical imaging and artificial intelligence in healthcare.

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VII. FUTURE SCOPE

Future work could focus on enhancing the model's performance by incorporating more diverse datasets and exploring hybrid models that combine LSTM-GRU with other deep learning architectures. Additionally, real-time implementation and integration into clinical workflows could be pursued to assess the system's impact in practical settings. Further refinement of the model to handle various types of hemorrhages and imaging modalities would also be valuable. Finally, efforts to interpret and explain the model's decisions could improve its transparency and adoption in medical practice.

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