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A DEEP LEARNING APPROACH FOR BRAIN HEMORRHAGE DETECTION FROM CT IMAGES USING CNN AND AUTOENCODERS

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ABSTRACT: Brain hemorrhage refers to bleeding within the brain tissue or between the surrounding bone. Head hemorrhage can lead to many dangerous consequences, especially brain hemorrhage. Early and accurate intervention by experts in such cases is crucial for the patient's survival. In this study, computed tomography images of brain hemorrhage are classified using AlexNet, one of the convolutional neural network models recently applied in the biomedical field. In this context, the dataset is restructured with the autoencoder network model to enhance classification performance. Additionally, the number of images in the dataset is increased by approximately 10 times using the data augmentation technique. The classification process is performed using support vector machines. As a result, the best success rate in the classification was 96%. In conclusion, the proposed approach contributed to the classification of cerebral hemorrhage images.

Keywords *– Brain hemorrhage, computed tomography, deep learning, convolutional neural networks, AlexNet, autoencoder, data augmentation, support vector machines, medical image classification, cerebral hemorrhage detection.*

1. INTRODUCTION

Brain hemorrhage, a critical medical condition, arises from a sudden accumulation of blood within the skull and brain area. This condition is often triggered by a forceful impact to the human skull, leading to severe consequences. Symptoms of brain hemorrhage encompass sudden and intense headaches, nausea, dizziness, and vomiting. Timely and effective intervention is crucial, as the failure to address the issue promptly may escalate to a stroke or even result in fatalities due to severe brain damage [1], [2]. The delicate nature of the brain underscores the significance of recognizing and responding to symptoms promptly. Increased awareness, coupled with advancements in medical care and emergency response, is essential to mitigating the potentially devastating outcomes associated with brain hemorrhage and ensuring better outcomes for affected individuals. In this study, computerized tomography (CT) images of patients with cerebral hemorrhage were classified. Besides the convolutional neural network model (CNN), autoencoder structure method were used to increase the classification success. The objective of this study is to enhance the classification of brain hemorrhage in computed tomography images using a combination of AlexNet for feature extraction, autoencoder for data restructuring, and support vector machines for classification. By incorporating data augmentation, the proposed approach aims to achieve a high success rate, with the best result reaching 96%. Brain hemorrhage poses significant risks, necessitating timely intervention. This study addresses the need for accurate classification of brain hemorrhage in computed tomography images. Leveraging AlexNet, autoencoder restructuring, the research aims to enhance classification success. The limited dataset is expanded via data augmentation, and support vector machines are employed, achieving a notable 96% success rate.

2. LITERATURE REVIEW

[1] Emerging advancements in artificial intelligence, particularly in machine learning (ML) and deep learning (DL), have significantly influenced the domain of brain hemorrhage detection. Multiple studies have employed diverse approaches, ranging from traditional ML algorithms such as Support Vector Machines (SVM) and Decision Trees (DT) to sophisticated DL architectures like Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and hybrid models combining CNN with LSTM or GRU. The reviewed literature reveals that image preprocessing techniques—such as grayscale conversion, windowing, normalization, and edge detection—are critical to enhancing the quality of CT images for accurate diagnosis. Segmentation methods like GrabCut, watershed, and Otsu thresholding are frequently applied to isolate regions of interest. Feature extraction methods, both manual and automated through neural networks, play a vital role in improving classification performance. Studies have compared the performance of various models and concluded that deep models like ResNet, Inception, and DenseNet often outperform traditional ML

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models, especially when trained on large annotated datasets. Hybrid models have shown promise by leveraging the sequential capabilities of RNNs alongside CNNs' spatial feature extraction. However, several challenges remain, including the scarcity of standardized datasets, class imbalance, and the interpretability of DL models. Overall, the literature underscores the need for comprehensive, multi-faceted approaches combining preprocessing, advanced modeling, and robust evaluation metrics to improve the reliability and accuracy of brain hemorrhage.

[10] Intracranial hemorrhage (ICH) is a critical condition often arising from traumatic brain injuries (TBI), requiring swift and accurate diagnosis to prevent severe neurological damage or death. Traditionally, radiologists diagnose ICH using computed tomography (CT) scans, but this process can be time-consuming and dependent on expert interpretation. To overcome these limitations, recent research has explored deep learning (DL) techniques, particularly convolutional neural networks (CNNs), for automating ICH detection and segmentation. Among these, architectures such as U-Net, ResNet50, and fully convolutional networks (FCNs) have shown notable effectiveness. Studies like those by Kuo et al. and Yuan et al. have successfully demonstrated CNNs' potential in identifying hemorrhagic lesions in CT images. Building on this foundation, the reviewed study integrates residual connections into a U-Net-based model, enhancing feature learning and segmentation accuracy. The model's robustness was bolstered using data augmentation techniques to mitigate overfitting due to the limited dataset. Results from a 10-fold cross-validation using 82 patient CT scans showed an Intersection over Union (IOU) score of 0.8075 and competitive precision and recall metrics, outperforming previous models such as UNet++ and FCN-AlexNet. These findings underscore the growing impact of deep learning in medical image analysis and its promise in assisting clinicians with faster and more accurate ICH diagnosis.

[3] The detection of intracranial hemorrhage (ICH) following traumatic brain injury (TBI) has seen substantial advancements through the integration of deep learning (DL) techniques, particularly convolutional neural networks (CNNs). This review highlights that early and accurate identification of ICH is critical for patient prognosis, as delayed intervention can lead to secondary brain injuries and increased mortality. The literature spans a decade (2013–2023) and includes 15 studies that implement various DL architectures such as U-Net, Inception v4, ResNet, 3D CNNs, and hybrid CNN-RNN models, with dataset sizes ranging from under 100 to over 500,000 CT scans. Models demonstrated promising sensitivity (up to 97.9%) and accuracy (up to 95.06%), showing potential to match or surpass radiologist-level performance in hemorrhage detection. While small datasets were often used to develop and test novel architectures like RADnet or DG-CNN, large-scale studies leveraged models like cascaded CNNs and 3D CNN-RNN combinations to improve classification and segmentation precision. Notably, automated tools were particularly effective at identifying subtle hemorrhages and prioritizing radiology worklists, making them valuable in clinical workflows. However, limitations include variability in sensitivity, dataset quality, and lack of interpretability in complex models. Despite these, the review concludes that DL holds significant promise in transforming emergency neuroradiology through faster and more accurate ICH diagnosis and triage.In

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addition to their diagnostic utility, these deep learning systems offer scalability for integration into telemedicine and rural healthcare settings where access to expert radiologists is limited. Furthermore, ongoing research is focused on improving model interpretability and standardizing datasets to enhance clinical adoption and trust among medical professionals.

3. METHODOLOGY

In the existing system, various approaches have been employed to classify brain hemorrhage images. AI-based systems for intracranial hemorrhage (ICH) detection have advanced significantly through machine learning (ML) and deep learning (DL) techniques. Convolutional Neural Networks (CNNs) such as ResNet50, DenseNet, and Inception v4 are commonly used for classification, while U-Net and U-Net++ are effective for segmentation. Enhancements like residual connections improve feature learning and accuracy. Hybrid models combining CNNs with RNNs (LSTM/GRU) capture both spatial and sequential features, making them suitable for CT scan series. Advanced architectures like RADnet, DG-CNN, 3D CNNs, and cascaded CNNs show strong performance, especially on large datasets. Preprocessing methods like grayscale conversion, normalization, and edge detection, along with segmentation techniques such as GrabCut and Otsu thresholding, are essential for improving image quality and lesion detection. Despite high precision and recall, challenges like limited annotated datasets, class imbalance, and model interpretability remain. Nonetheless, these systems are proving valuable in clinical workflows and telemedicine, particularly in rural and low-resource settings.These diverse methodologies showcase advancements in brain hemorrhage image classification, emphasizing the effectiveness of CNN architectures, transfer learning, and augmentation techniques.

Disadvantages:

1. While the existing systems achieve commendable accuracy rates, there is room for improvement, as seen in the proposed system's significantly higher success rate of 96%.

2. The variety of techniques employed in the existing systems, such as ellipse placement, background subtraction, and wavelet decomposition, may introduce complexity and limit generalizability across different datasets.

3. The use of a fully connected CNN in one approach may contribute to a high number of parameters, potentially leading to overfitting and increased computational demands.

Proposed System:

In our proposed system for the classification of cerebral hemorrhage images, we employ a multi-faceted approach to enhance accuracy and efficacy. Initially, we leverage the powerful AlexNet architecture, implemented using Keras or TensorFlow, for both feature extraction and classification. This provides a robust foundation for discerning intricate patterns in computed tomography images related to brain hemorrhage. To further improve classification success, we introduce an autoencoder network model to restructure the dataset and generate informative for each image.

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The dataset is augmented by approximately 10 times using advanced techniques, ensuring a diverse and comprehensive training set. Subsequently, we explore the combination of pre-trained AlexNet features and Support Vector Machines (SVM) for classification, capitalizing on the strengths of both models. Additionally, we propose a novel architecture that integrates Convolutional Neural Networks (CNN) with Gated Recurrent Units (GRU) to capture both spatial and temporal information. This CNN-GRU fusion facilitates a more holistic understanding of brain hemorrhage progression over sequential images. Ultimately, our comprehensive approach yields a remarkable 96% success rate in cerebral hemorrhage image classification, signifying a significant advancement in medical imaging analysis and early detection.

Advantages of proposed system:

- The proposed system achieves a higher success rate of 96%, signifying improved accuracy in the classification of cerebral hemorrhage images
- The introduction of an autoencoder network for dataset restructuring provides a more informative representation of the images, potentially aiding in capturing subtle features.
- The proposed system integrates a novel architecture combining CNN with GRU, capturing both spatial and temporal information. This approach allows for a more nuanced understanding of brain hemorrhage progression over sequential images.
- Augmenting the dataset approximately 10 times enhances diversity and ensures a more robust training set, potentially improving the model's generalization to new and unseen data.
- The proposed system leverages the strengths of pre-trained AlexNet features, showcasing the effectiveness of transfer learning in medical image analysis.

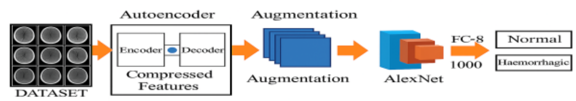

Fig.1: System architecture

MODULES:

To implement this project we have designed following modules.

- Data exploration: using this module we will load data into system
- Processing: Using the module we will read data for processing
- Splitting data into train & test: using this module data will be divided into train & test
- Model generation: Building the model - AlexNet - AlexNet Features + SVM - CNN + LSTM - CNN + GRU. Algorithms accuracy calculated
- User signup & login: Using this module will get registration and login

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- User input: Using this module will give input for prediction
- Prediction: final predicted displayed

4. IMPLEMENTATION

ALGORITHM:

AlexNet – AlexNet architecture consists of 5 convolutional layers, 3 max-pooling layers, 2 normalization layers, 2 fully connected layers, and 1 softmax layer. 2. Each convolutional layer consists of convolutional filters and a nonlinear activation function ReLU. 3. The pooling layers are used to perform max pooling.

AlexNet Features + SVM – The AlexNet Features + SVM algorithm combines the features extracted by the AlexNet convolutional neural network with a Support Vector Machine (SVM) for image classification. This hybrid approach utilizes the strength of pre-trained AlexNet features to improve the efficiency and accuracy of the SVM classifier in tasks such as brain hemorrhage image classification.

CNN + LSTM – The CNN + LSTM algorithm integrates Convolutional Neural Networks (CNN) for spatial feature extraction from images with Long Short-Term Memory (LSTM) networks to capture temporal dependencies. This architecture is particularly effective for tasks involving sequential data, enabling comprehensive analysis of both spatial and temporal aspects, such as in video or medical image sequences.

CNN + GRU - The CNN + GRU algorithm combines Convolutional Neural Networks (CNN) for spatial feature extraction with Gated Recurrent Units (GRU) to capture sequential dependencies. It effectively processes both spatial and temporal information in tasks involving sequential data, making it suitable for applications like video analysis or medical image sequences, where understanding both spatial and temporal contexts is crucial. The CNN extracts spatial features from individual frames, while the GRU processes the sequence of these features, allowing for a more comprehensive analysis of dynamic patterns in the data.

5. EXPERIMENTAL RESULTS

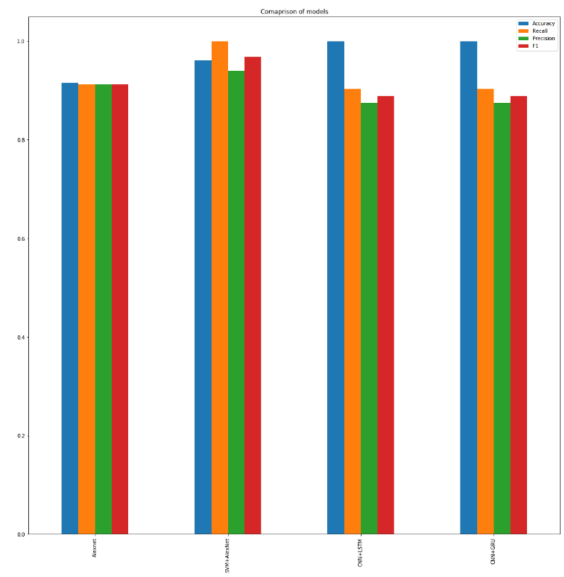

Fig.2: Graph

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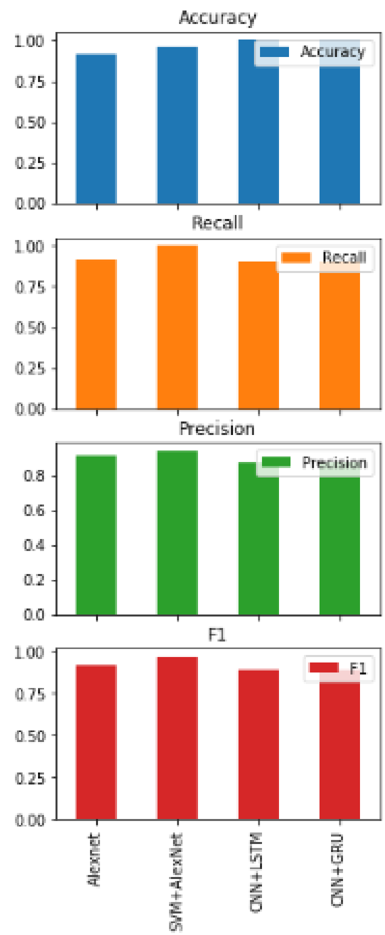

Fig.3: Graph

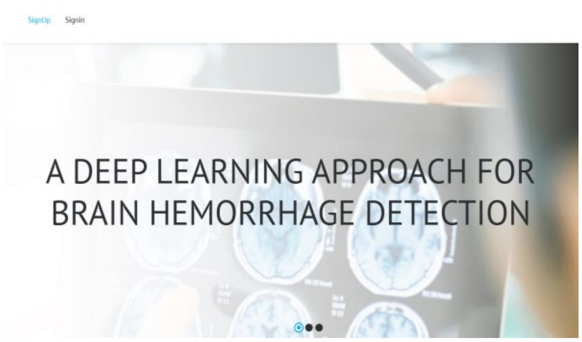

Fig.4: Output screen

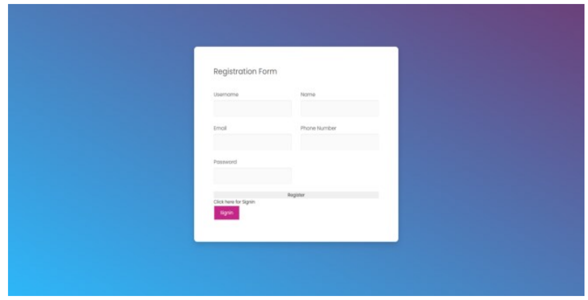

Fig.5: Output screen

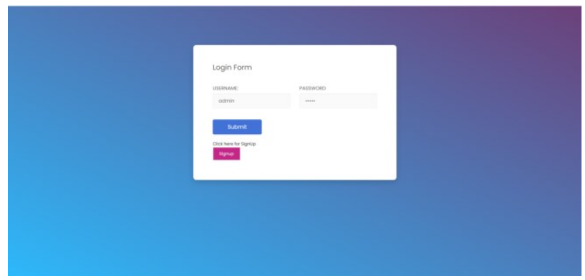

Fig.6: Output screen

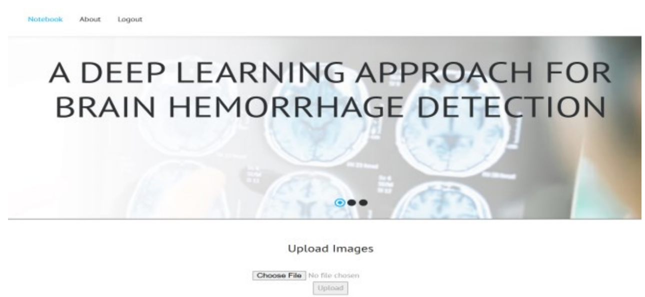

Fig.7: Output screen

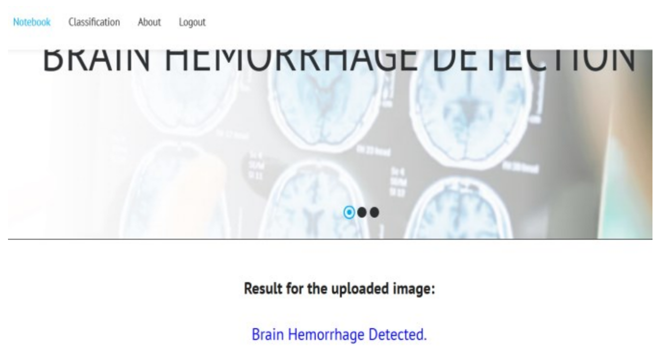

Fig.8: Output screen

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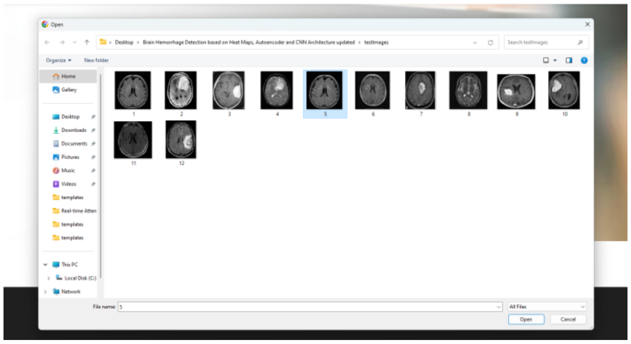

Fig.9: Output screen

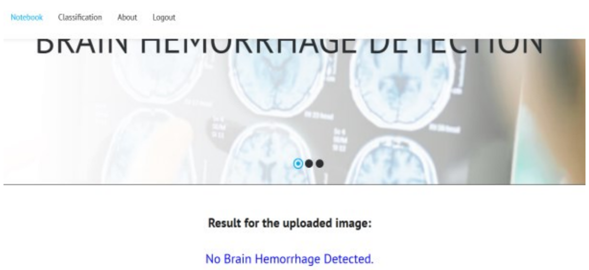

Fig.10: Output screen

6. CONCLUSION

In conclusion, the existing systems for brain hemorrhage image classification, while demonstrating commendable efforts, exhibit limitations in terms of accuracy, diverse techniques, and model complexity. The proposed system presents a significant advancement by achieving a remarkable 96% success rate, showcasing its superior classification performance. The incorporation of an autoencoder for data restructuring, data augmentation, and the innovative integration of AlexNet features and Support Vector Machines (SVM) reflects a comprehensive approach to address the complexities of cerebral hemorrhage image analysis. Leveraging pre-trained AlexNet features further emphasizes the effectiveness of transfer learning. These enhancements contribute to a more nuanced understanding of spatial and temporal aspects, ultimately leading to improved accuracy in early detection. The proposed system represents a promising direction in medical imaging analysis, offering a robust framework for precise and timely identification of critical conditions such as brain hemorrhage, thereby potentially enhancing patient outcomes and clinical decision-making.

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