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Classification of Brain Infarction Using Deep Learning Techniques on Magnetic Resonance Imaging (MRI)

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Abstract

This research concentrated on employing Convolutional Neural Networks (CNNs) to classify brain infarctions. A stroke occurs due to a blockage or hemorrhage in the blood vessels, which disrupts or diminishes the blood supply to the brain, leading to the death of brain cells. With the progress in machine learning techniques in medical imaging, early detection of stroke has become increasingly feasible, playing a crucial role in the diagnosis and treatment of this potentially fatal condition.Building an intelligent CNN model to classify types of brain infarction using up algorithms Median Filter preserving edges and efficient minimization of noise with durability against flowing noise, Fuzzy C – Mean to Image Segmentation and Recognition of Region of Interest for infarction location and size of the infarction for brain infarction Identification, GLCM, and FOSF. The research was carried out in a private hospital; in Baghdad, Iraq, on 60 patients with brain infarction. Included were 9 hyperacute (>6 hours post brain infarction), 19 acute (7-72 hours), 12 subacute (4-7 days), and 20 chronic (< 15 days). We have introduced a Convolutional Neural Network (CNN) model as a solution to predict the likelihood of a patient experiencing a stroke at an early stage, aiming for maximize effectiveness and precision.The ROC curve demonstrates that the average apparent diffusion coefficient (aveg(ADC) mm²/s) and relative apparent diffusion coefficient (rADC%) are two reliable and effective measures for monitoring brain infarction developments. High sensitivity indicates a strong ability to detect true positives (cases of infarction), while the shape and position of the curve suggest that average (ADC) mm²/s also maintains a reasonable specificity, minimizing false positives. This balance results in high overall diagnostic accuracy.Both rACD (%) and aveg (ADC) mm²/s are robust indicators for the imaging monitoring of brain infarction developments. The inclusion of AI in the assessment process may result marginal improvements in specificity and accuracy.

Keywords: *Brain infarction, ADC (Apparent Diffusion Coefficient) Deep learning, CNN (Convolution Neural Networks).*

Introduction

Ischemic stroke is a condition caused by a blockage or rupture of blood vessels in the brain, leading to various symptoms. These symptoms can be identified through Magnetic Resonance Imaging (MRI) examinations[1] . MRI is a diagnostic tool used in medical science.[2][3] There exist three categories of stroke: ischemic stroke, hemorrhagic stroke, and transient ischemic attack. The World Health Organization (WHO) reports that 87 percent of stroke-related deaths are due to ischemic stroke, with the remaining deaths attributed to hemorrhagic stroke and transient ischemic attack.[4][5] Thus, early prediction is essential for the detection and treatment of stroke. [6][7] Artificial intelligence has become increasingly prevalent In the healthcare and medical sectors, the rapid advancement of deep learning-based machine learning algorithms has significantly broadened the use of AI for diagnosis, risk assessment, and treatment planning. Machine learning algorithms can now effectively predict the likelihood of stroke in the medical field. [8][9][10] Although machine learning (ML) models have not yet achieved widespread implementation in clinical practice, the effectiveness of risk scores in predicting stroke in today's population is lacking. Conversely, deep learning techniques have gained prominence for their ability to automatically extract features from raw data with minimal or no preprocessing in medical applications. [11][12][13] With the continuous increase in data volume within healthcare systems, this method has proven effective for predicting various health conditions, including heart failure, osteoporosis, and the automatic detection of diabetic retinopathy. Consequently, this technique surpasses traditional machine learning algorithms, like Logistic Regression (LR) and Support Vector Machines (SVM), in terms of prediction accuracy. [14][15] Convolutional Neural Networks (CNNs) show great potential in medical applications and have delivered commendable results in disease prediction. This model utilizes a variation of multilayer perceptrons, incorporating one or more convolutional layers that may be fully connected or pooled. It surpasses other

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machine learning algorithms by autonomously identifying important features without human intervention. Consequently, in this study, we developed an advanced CNN model tailored to healthcare challenges. [16][17]

Subjects and Methods

Data Collection

This investigation was carried out at a private hospital in Baghdad. Data collection occurred during eight months from October 2023 to May 2024. This study included a total of 60 patients (42 males, 18 females, ages 35-86 years) diagnosed with ischemic stroke by a consultant in diagnostic radiology. Included were 9 hyperacute (<6 hours post- brain infarction), 19 acute (7-72 hours), 12 subacute (4-7 days), and 20 chronic (> 15 days). Five sequences were performed on the brain for each patient. Included A complete patient history was obtained, including information on hypertension, diabetes, and the onset and progression of symptoms. We verified that all patients had provided written informed consent. A head MRI examination was performed with the following procedures: A Siemens MAGNETOM Altea 1.5 superconducting MR scanning system was used. Routine MRI was first used to define T1W1, T2W1, T2 dark fluid, DWI value b 1000, and ADC.

Data Set

The total number of images containing in the dataset is 1000 images divided in four groups; the first group contains 250 images (size 360*300 pixels) for 14 patients with hyper acute infarction; the second group contains 250 images (size 360*300 pixels) for 20 patients with acute infarction; the third group contains 250 images (size 360*300 pixels) for 20 patients with subacute infarction; and the fourth group contains 250 images (size 360*300 pixels) for 20 patients with chronic infarction.

Data Preprocessing

Pre-processing is a crucial step in an image classification system, preparing the data for the next phase, which is feature extraction. This step focuses on disease-specific features to enhance model accuracy, improve image quality, and eliminate unnecessary data. The pre-processing process involves three steps: converting images to Red Green Blue (RGB) format to enhance image sharpness by distinguishing light and dark areas, resizing the image to 360x300 pixels, and normalizing to adjust the pixel intensity values using Median Filter. Figure (1-1) illustrates all the steps involved.

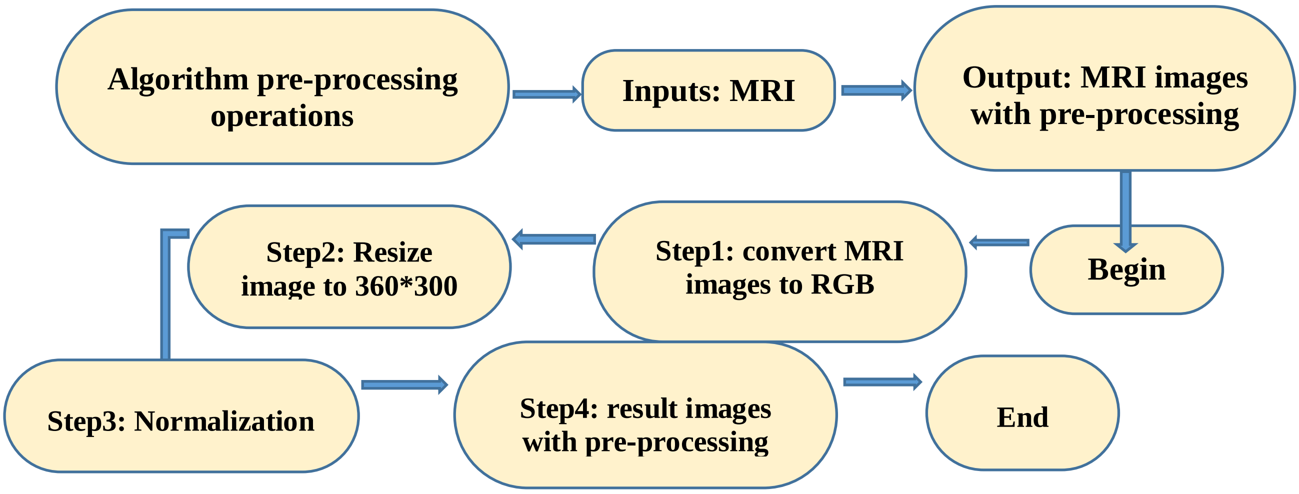

Figure 1: Algorithm Preprocessing Phase

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The Proposed CNN Classification Phase

In this stage, Once the dataset is processed through image preprocessing, it is utilized with the proposed Convolutional Neural Network (CNN) to achieve accurate MRI classification. The network processes images of size 360x300 pixels. The CNN architecture includes multiple convolutional layers and a max pooling layer to extract key features from MRI images. The feature extraction setup is as follows: the convolutional layer has 16 filters with a 2x2 filter size, valid padding, and ReLU activation. This is followed by max pooling with a 2x2 filter size and 2x2 strides. The subsequent convolutional layer contains 32 filters, followed by another max pooling layer, then a convolutional layer with 64 filters, a dropout layer with a rate of 0.5, and a flatten layer. Figure 2 illustrates the CNN architecture.

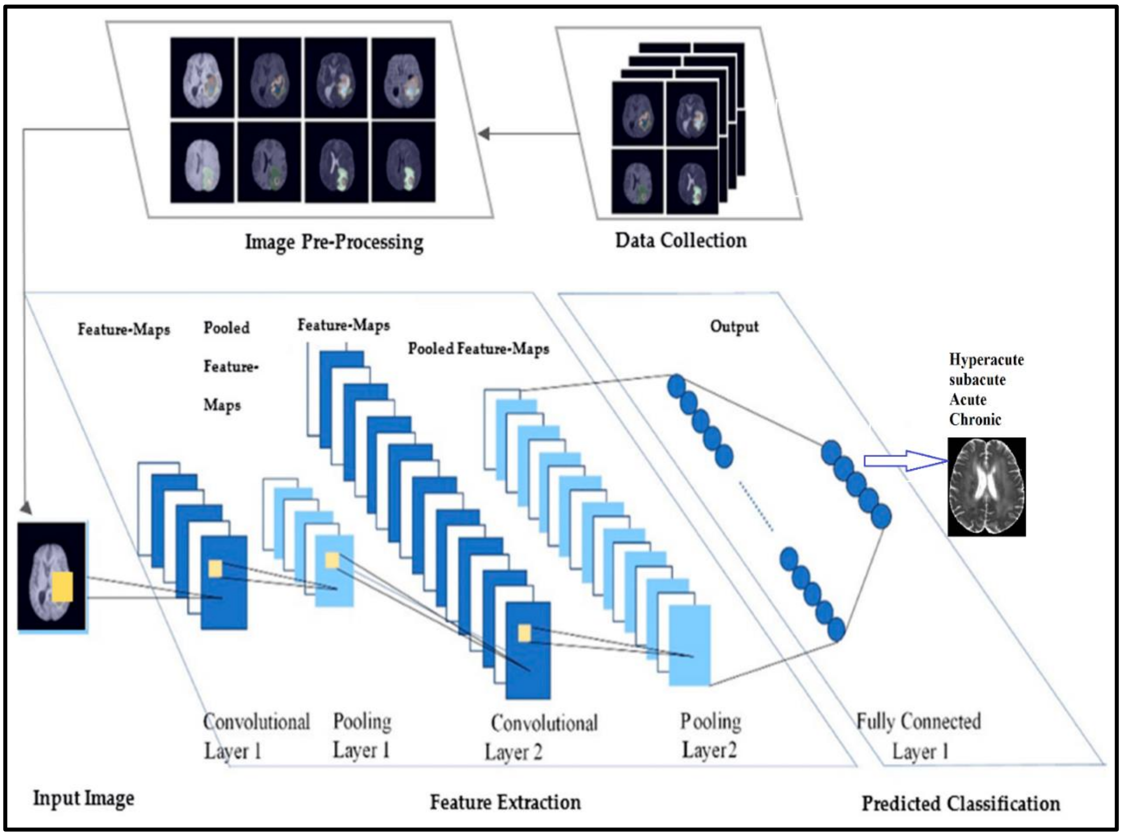

Figure 2: The Proposed CNN Diagram

Results

In the following table (1), we show the results obtained by implementing the proposed system, where the efficiency of the system and the time taken to implement the algorithm were calculated, as well as the result for each type of stroke, where feature extraction depends on the image size and resolution ratio.

The table provides statistical metrics for evaluating the performance of two different measures of ADC (relative ADC and average ADC) in the context of monitoring brain infarction developments, using both visual assessment and artificial intelligence (AI).

This analysis shows that both rACD (%) and average ADC (average(ADC) mm^2/s) are reliable indicators for monitoring brain infarction developments. While both visual and AI assessments provide high sensitivity, AI methods tend to show slightly higher specificity and accuracy, making them slightly more reliable in correctly identifying both infarcted and non-infarcted tissue.

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Table 1: Sensitivity and Specificity of Racd(%) And Aveg(ADC) Mm2 /S of Vision Visual and AI Among Cases of Brain Infarction.

		Area under the curve	P	Cut off point	Sensitivity	Specificity	Accuracy
rACD(%)	vision visual	0.872	0.001*	0.95	97.5%	62.9%	87%
	AI	0.819	0.001*	0.94	97.5%	62.75	88%
Aveg(ADC) mm²/s	vision visual	0.87	0.001*	0.66	97.5%	68.3%	87%
	AI	0.821	0.001*	0.66	97.5	70.5%	89%

Figure (3) The ROC curve is used to evaluate the effectiveness of the MRI curve for the relative apparent diffusion coefficient (rACD%). This curve is used to evaluate the diagnostic performance of rACD in monitoring brain infarction developments.

X-axis (100-specificity) represents the false positive rate (FPR). Lower values indicate higher specificity, and the Y-axis (sensitivity) represents the true positive rate (TPR). Higher values indicate higher sensitivity.

The ROC curve for rACD (%) approaches the top-left corner, indicating high diagnostic accuracy.

The Area Under the Curve (AUC) is likely high, showing that rACD is an effective measure for distinguishing between infarcted and non-infarcted tissue.

High sensitivity (true positive rate) suggests that rACD (%) is effective at correctly identifying cases of brain infarction.

Specificity (true negative rate) can be inferred from the curve; higher values on the y-axis and lower values on the x-axis indicate better specificity.

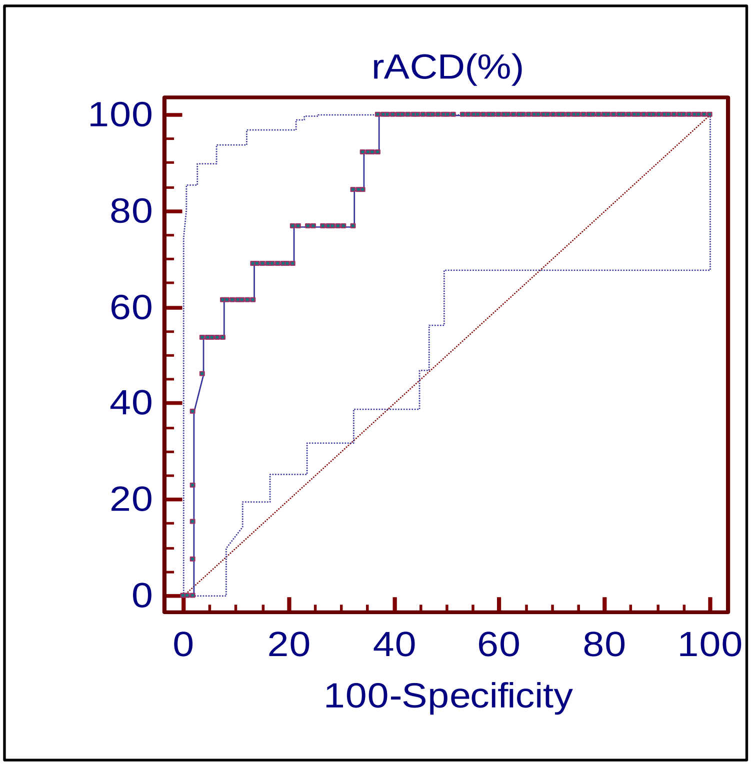

Figure3: Sensitivity and Specificity of Racd (%) Of AI Among Cases of Brain Infarction.

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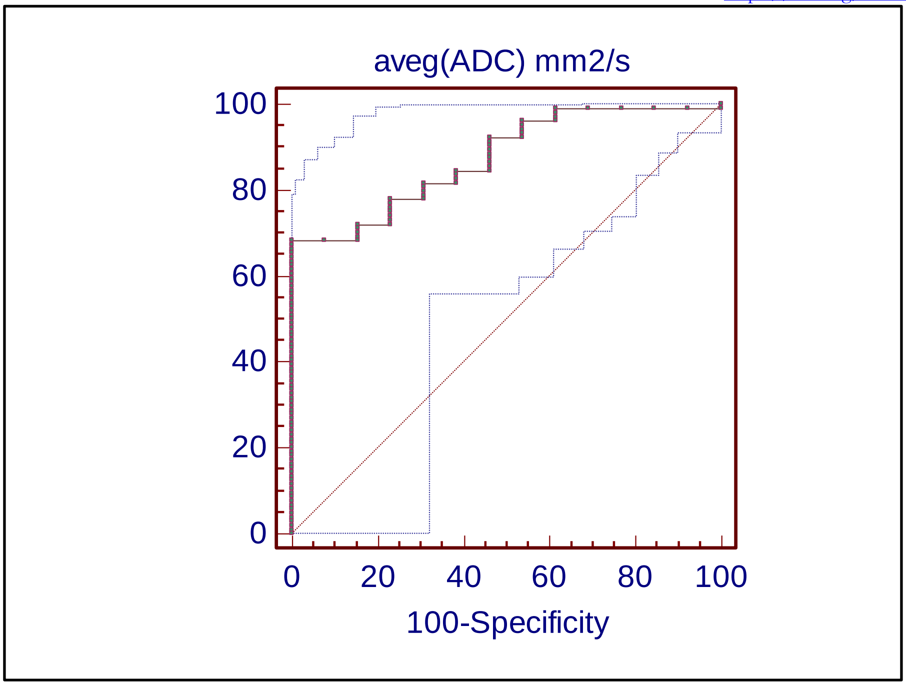

Figure 4: Sensitivity and Specificity of Aveg(ADC) Mm2/S of AI Among Cases of Brain Infarction

When implementing the proposed system using MATLAB, the main interface of the system appears through which we can perform operations on the image, as in the following figure. Through the main interface we can read the image and then perform an improvement by using filters for the image, removing noise, and then extracting the stroke features of the image used. After that, the stroke is classified using the artificial intelligence algorithm, where in the following figure the result is hyperacute.

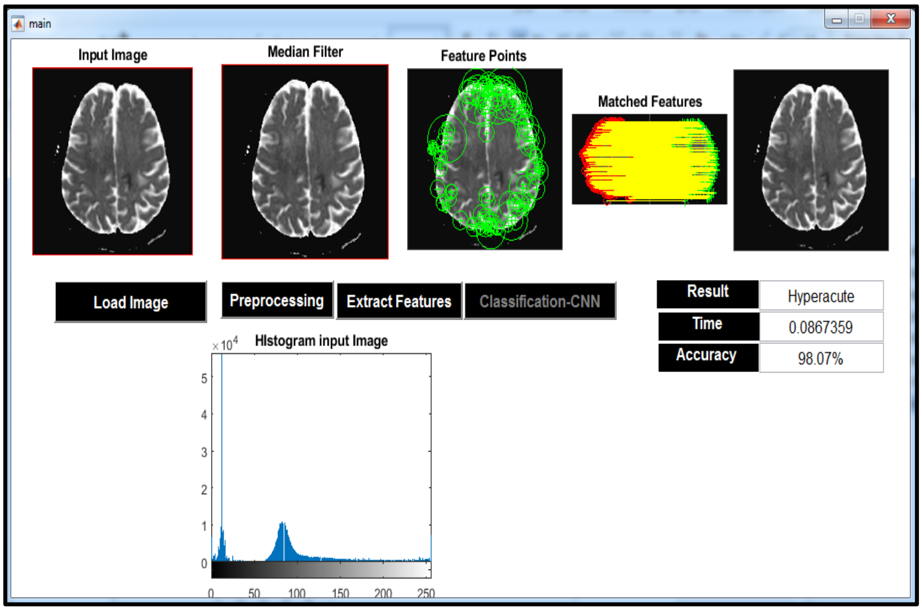

Figure 5: MATLAB Hyper Acute Infarction.

Discussion

We have analyzed the different attributes of people to determine the chance of stroke disease. The experiment was conducted using a healthcare dataset. To investigate the dataset, we have used different classification models. Besides, we have developed a CNN model to predict the possibility of whether a person will be getting a stroke or not, followed by evaluating the model's performance. The experimental result shows that the proposed model is more effective than some other existing models with a promising 99.93 percent accuracy. We can use this model to diagnose a patient to determine the risk of stroke in patients.

The results indicate that both the relative apparent diffusion coefficient (rACD%) and the average apparent diffusion coefficient average (ADC) mm²/s) are effective tools for monitoring brain infarction developments. The high sensitivity observed across all metrics and methods suggests that these tools are particularly good at identifying true positive cases of brain infarction. This is critical in clinical settings where early and accurate detection of infarction can significantly impact patient outcomes.

The slightly higher specificity and accuracy of AI assessments compared to vision visual assessments suggest that AI could play a valuable role in reducing false positive rates and improving overall diagnostic performance. This aligns with the growing body of literature that supports the integration of AI in medical imaging to enhance diagnostic accuracy and efficiency.[18] Moreover, the statistically significant P-values (<0.05) across all comparisons reinforce the reliability of these findings. The consistent cut-off points for rACD and Aveg (ADC) across both assessment methods provide a standardized reference for clinical applications.

Conclusion

Both rACD (%) and Aveg(ADC) mm²/s are robust indicators for the imaging monitoring of brain infarction developments. The incorporation of AI in the assessment process may offer marginal improvements in specificity and accuracy, highlighting its potential as a complementary tool alongside traditional vision visual assessments. Future research could further explore the integration of AI in clinical practice and its impact on long-term patient outcomes.

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