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Automatic Detection and Classification of Brain Hemorrhage with Deep Learning Approaches

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Abstract

Brain hemorrhage is a critical condition that needs quick and precise response and diagnosis for timely treatment. Traditional methods like CT and MRI scans depend on expert interpretation, which can be time-consuming and prone to errors. This study introduces an automated framework with deep learning to detect and classify brain hemorrhages. By utilizing convolutional neural networks (CNNs), the system recognizes important features in medical images and classifies hemorrhages into types such as intracerebral, subarachnoid, subdural, and epidural. Trained and tested on brain scan datasets, the framework depicts the potential of deep learning to deliver quick and accurate diagnoses, avoiding delays and enhancing patient outcomes significantly.

Keywords: Brain hemorrhage, deep learning, CNNs, automated detection.

I. INTRODUCTION

A brain hemorrhage occurs when there is bleeding within the brain, posing a critical, life-threatening situation that necessitates rapid diagnosis and treatment. The brain's intricate blood vessel system can be compromised if these vessels rupture or leak, increasing pressure on adjacent brain areas and potentially causing severe damage or death if not treated promptly. Hemorrhages can stem from various factors, including trauma, high blood pressure, aneurysms, and vascular abnormalities, with lifestyle choices like smoking, drug use, and aging further elevating the risk. Timely and accurate identification is essential for effective intervention, with CT scans often preferred in emergency situations due to their ability to quickly detect bleeding. MRI scans, which provide more detailed views of soft tissues and blood vessels, are also valuable but require expert radiologists to analyze the images, which can lead to delays or mistakes. Recently, artificial intelligence, particularly deep learning techniques such as Convolutional Neural Networks, has emerged as a promising tool to enhance image interpretation, offering faster and more precise diagnoses. Efficient diagnosis and prompt treatment are vital to reducing complications and improving patient survival rates. The availability of advanced imaging technologies ensures that healthcare professionals can accurately assess the severity of the haemorrhage. In addition, proper management, will play a key role.

II. LITERATURE REVIEW

Deep convolutional neural networks are used to automate the detection of intracranial hemorrhage from CT scans. This approach eliminates the need for manual feature extraction and image processing steps found in traditional methods. By incorporating image rotation and post-processing techniques, the model achieves high specificity (98%) while maintaining comparable sensitivity (81%) to previous studies. This work demonstrates the potential of deep learning for improving the accuracy and efficiency of hemorrhage detection in clinical settings [1]. Deep learning models, specifically CNNs, were used to classify brain CT scans for hemorrhage. The study compared three models: a CNN built from scratch, a fine-tuned pre-trained AlexNet, and a novel AlexNet-SVM model. Transfer learning from natural images to medical images proved effective. The AlexNet-SVM model demonstrated superior performance, suggesting potential advantages of SVM as a classifier in this context [2]. The research focuses on identifying acute intracranial hemorrhage and its subtypes through the application of artificial neural networks. Brain hemorrhage, a severe form of stroke, occurs when blood vessels within the brain rupture, leading to bleeding in the cranial cavity. This condition requires immediate diagnosis and treatment to prevent life-threatening complications. Over the years, significant advancements have been made in the automated detection and classification of brain hemorrhages, aiming to reduce diagnostic delays and enhance patient outcomes. Current methodologies include traditional approaches like the watershed algorithm and advanced deep learning techniques, which leverage neural networks to analyze medical images with high precision and efficiency [3]. Medical imaging techniques are essential for visualizing the internal structures and functions of the body. This research focuses on creating a system to identify and classify hemorrhages in CT images. The method includes several steps, such as pre-processing, morphological operations, and watershed segmentation. Active contours are then applied to extract relevant features for classification. The system demonstrates an impressive average accuracy of 98% in predicting and classifying three types of hemorrhage, assisting medical professionals in interpreting complex medical images. This high accuracy can help reduce diagnostic errors and speed up treatment decisions. The system is also capable of handling different haemorrhage types. [4].

III. HARDWARE REQUIREMENTS

A. System: core i3 /i5 2.4 GHz

Figure 1: System

The term "Core i3/i5 2.4GHz" refers to a category of central processing units (CPUs) manufactured by Intel, commonly used in laptops and desktop computers. These processors are designed to deliver reliable performance across a variety of computing tasks. The "Core i3" and "Core i5" represent different tiers within Intel's lineup, with the Core i5 generally providing higher performance capabilities compared to the Core i3. This distinction makes the i5 better suited for demanding applications, such as multitasking, gaming, or running software requiring more computational power.

B. Hard Disk: 500GB

Figure 2: Hard Disk

A 500GB hard disk drive (HDD) provides 500 gigabytes of storage space. This is where the computer stores its operating system, applications, files, and other data. While sufficient for basic tasks, 500GB may become limited for users with large media libraries, numerous games, or demanding software. The listed system can be configured with either 4GB/8GB of RAM. 4GB is adequate for basic tasks, but may cause slowdowns.8 GB provides ample RAM for most users, enabling smoother multitasking and handling more demanding tasks. The amount of RAM significantly influences overall system performance and responsiveness.

C. Storage: 500GB

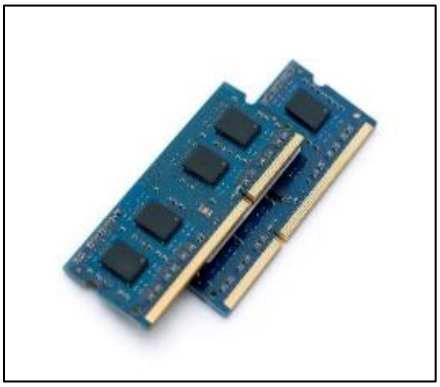

Figure 3: RAM

Random Access Memory (RAM) is a vital component in computing devices, responsible for temporarily storing data that the CPU accesses during operation. It enables quick read and write processes, significantly boosting system performance. RAM is volatile, meaning its contents are lost when the device powers off. Higher RAM capacity allows for smoother multitasking and better handling of resource intensive applications like gaming or video editing. It is also essential for efficient and proper computing with-in the system and helps build a responsive system. It also allows for efficient multitasking and faster data processing.

IV. SOFTWARE REQUIREMENTS

A. Operating System: Windows XP /Windows 7

Windows XP and Windows 7 are operating systems developed by Microsoft. Windows XP, while historically popular, is no longer supported and lacks security updates, making it vulnerable to threats. Windows 7, while also no longer officially supported. Both operating systems provide a platform for running various applications. Windows 7 introduced features like enhanced taskbar functionality and improved hardware support, making it a preferred choice for many users during its peak. Despite their contributions, both systems are now considered outdated, with newer versions like Windows 10 and 11.

Figure 4: Windows 7

B. Software Tool: Open CV

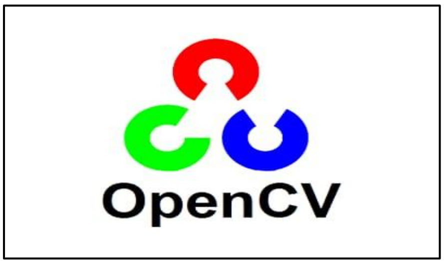

Figure 5: OpenCV

OpenCV is a dedicated library designed for various computer vision applications, providing an extensive collection of functions for processing images and videos. Python, known for its flexibility and user-friendliness, is a popular programming language in computer vision, especially due to its seamless integration with libraries like OpenCV. By combining OpenCV with Python, developers can efficiently implement and run computer vision algorithms, making Python an ideal choice for building powerful computer vision solutions. This combination enhances the ability to analyze and manipulate visual data in a variety of ways. Additionally, Python's rich libraries supports the development of good computer vision projects, from object detection to facial recognition and beyond.

V. PROPOSED METHODOLOGY

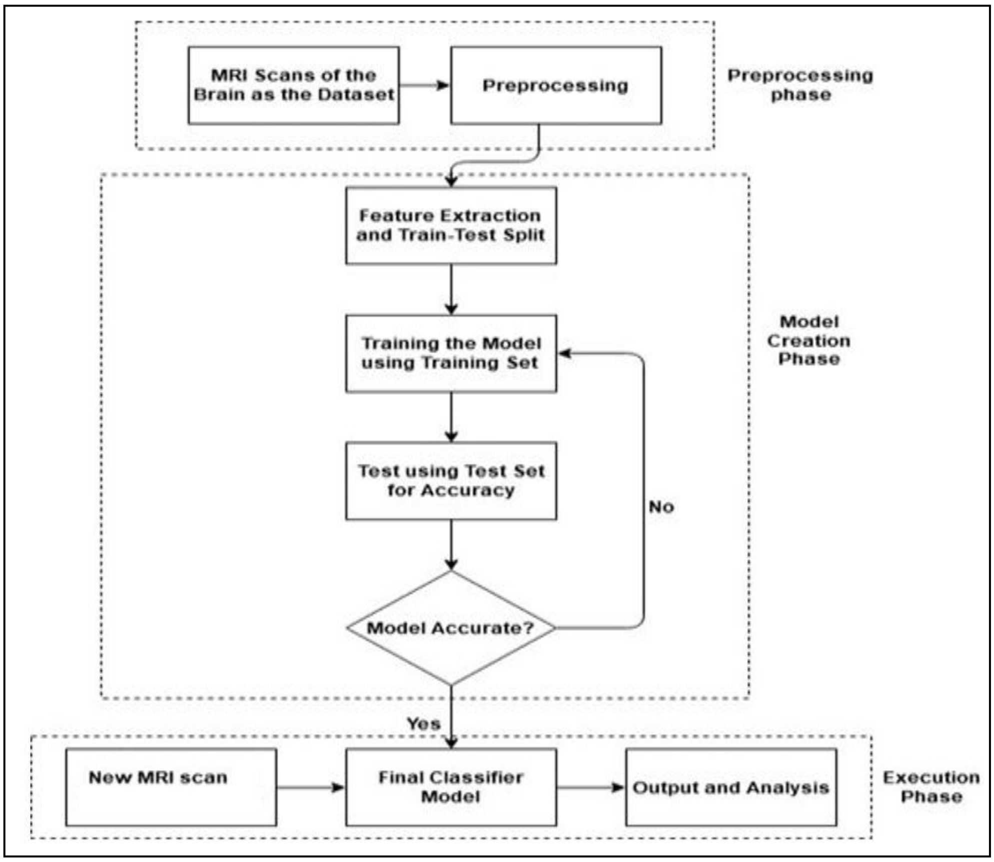

Figure 6: System Architecture

1. Data Set: The dataset that is used to train is acquired from Brain CT scan Image Visuals.

2. Image Segmentation: Segmentation is the process where an image is divided into many sections, typically to recognize boundaries and objects within it. This process simplifies the interpretation of an image by transforming it into a structured and easily understandable form.

3. Pre-Processing: The median filter is used during the pre-processing step to mitigate the effects of acquisition degradations and to improve the quality of the image visuals under analysis. It recognizes numerous preprocessing and segmentation techniques for lung nodules. The filter shows effects by replacing each pixel's intensity value with the median value of its neighboring pixels, thereby removing outlier pixels that definitely differ from their surroundings.

4. Convolutional Neural Networks: Convolutional Neural Networks (CNNs) use regularization techniques to improve the performance and avoid overfitting. These networks are designed to automatically recognize and enhance similar features through the application of filters, also known as kernels. Their ability to extract and fine-tune features without human intervention makes them both highly versatile and relevant. CNNs utilize the hierarchical feature extraction, with the lower layers concentrated on detecting edges and textures in smaller regions of the input. As the data goes deep through the deeper layers, the network recognizes more abstract and delicate features by analyzing information within huge contexts. CNNs use hierarchical feature extraction, where the lower layers focus on detecting edges and textures from small regions of input. In deep layers, network captures more intricate details.

VI. DESIGN & IMPLEMENTATION

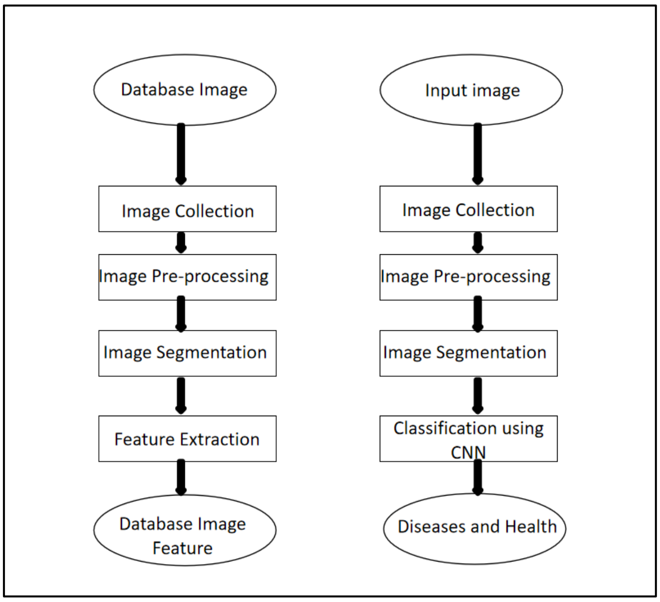

Figure 7: Module Specification

The process begins with collecting the required image dataset, followed by image preprocessing, which enhances data quality by converting images to grayscale, reducing noise using median filtering, and emphasizing key features through image enhancement. Next, image segmentation is performed using methods like mean shift clustering to identify densely packed regions. Feature extraction focuses on key attributes such as color, texture, and shape, enabling effective image analysis. Training involves building a dataset of labeled images, using classifiers and feature sets to improve precision through classification graphs. Finally, classification employs Convolutional Neural Networks (CNNs) as binary classifiers, utilizing hyperplanes to distinguish classes. CNNs excel in high-dimensional pattern recognition by mapping non-linear input data into linear representations and optimizing class separation through maximum margin techniques.

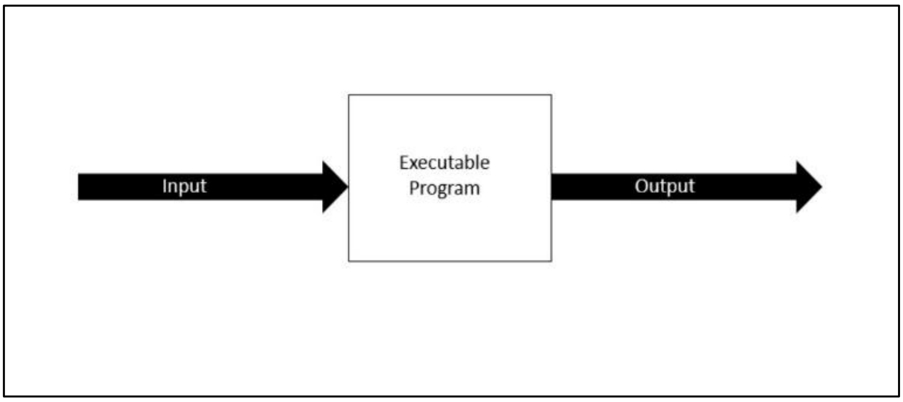

Figure 9: Test Box

Testing evaluates a system or its components to ensure they meet predefined requirements, identifying flaws or unmet criteria. System testing examines an integrated environment to verify it fulfills specifications, focusing on external behavior rather than internal logic, as seen in black-box testing. It combines tested components to identify issues in their interactions. System testing, guided by Functional Requirement Specifications (FRS), assesses functionality, behavior, and user experience within and beyond specified parameters. Functional testing, a black-box approach, verifies software behavior by comparing outputs to expected functionality through three steps: identifying functions, creating aligned test inputs, and validating outputs against intended performance.

Table 1: Test Case - 1

S1 # Test Case:	UTC-2
Name of Test	Uploading image
Items being tested	Tested for uploading different images
Sample Input	Upload Sample image
Expected output	Image should upload properly
Actual output	Upload successful
Remarks	Pass

Unit testing involves evaluating individual source code units, program modules, control data, usage instructions, and operating procedures to ensure their adequacy. A unit is the smallest testable component of an application. During development, syntax errors and other issues are identified and resolved. The testing process ensures that every instruction or path within the program or module is tested. Randomly selected data is used to validate all potential branches and loop conditions, ensuring comprehensive coverage.

This rigorous process helps identify and rectify issues early, ensuring robust module performance. Additionally, the process includes tables for image uploading and CT scan image detection, which provide a structured approach to analyzing and validating specific functionalities, as demonstrated in the referenced tables. This thorough evaluation ensures that the individual components of the application function correctly, contributing to the overall reliability and effectiveness of the system.

VII. RESULT & DISCUSSIONS

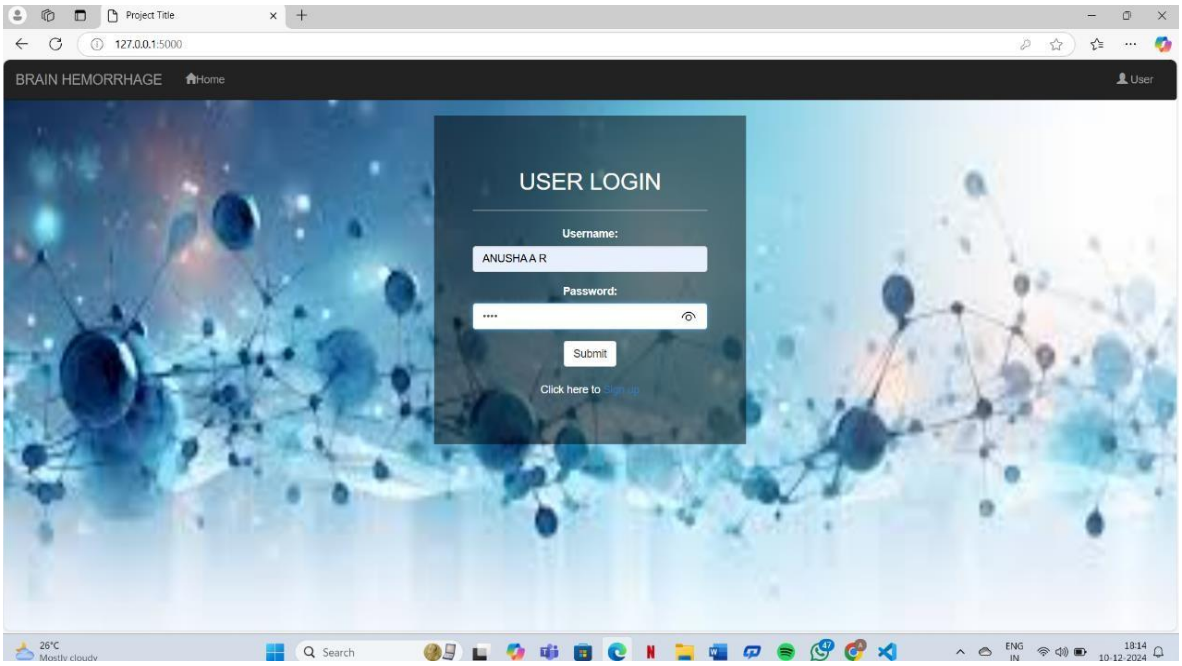

Figure 10: User Login

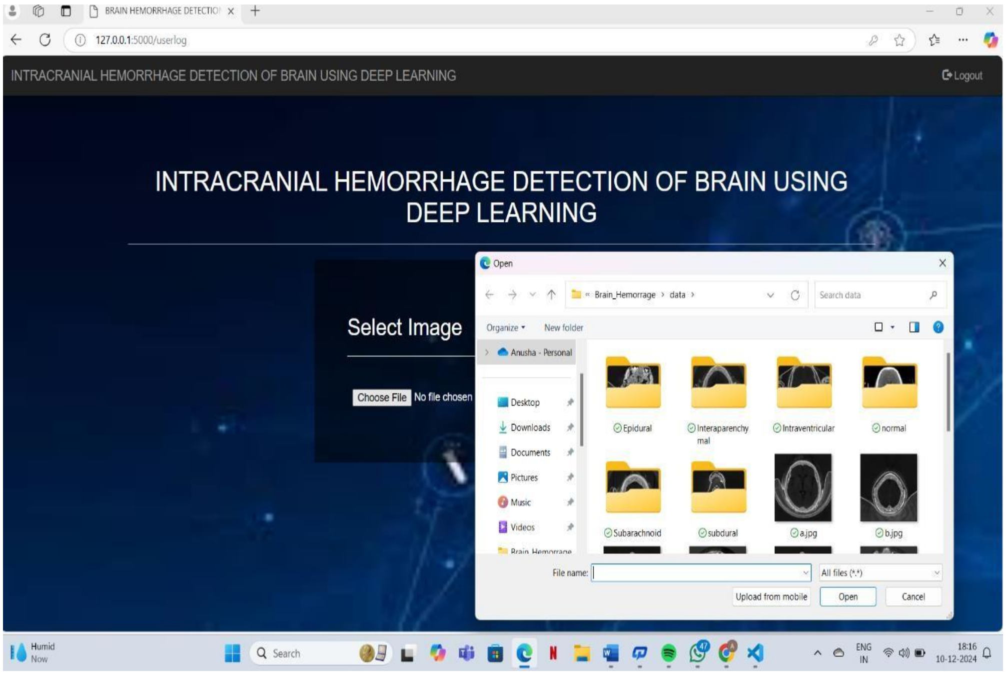

Figure 11: Choosing Files from Folders

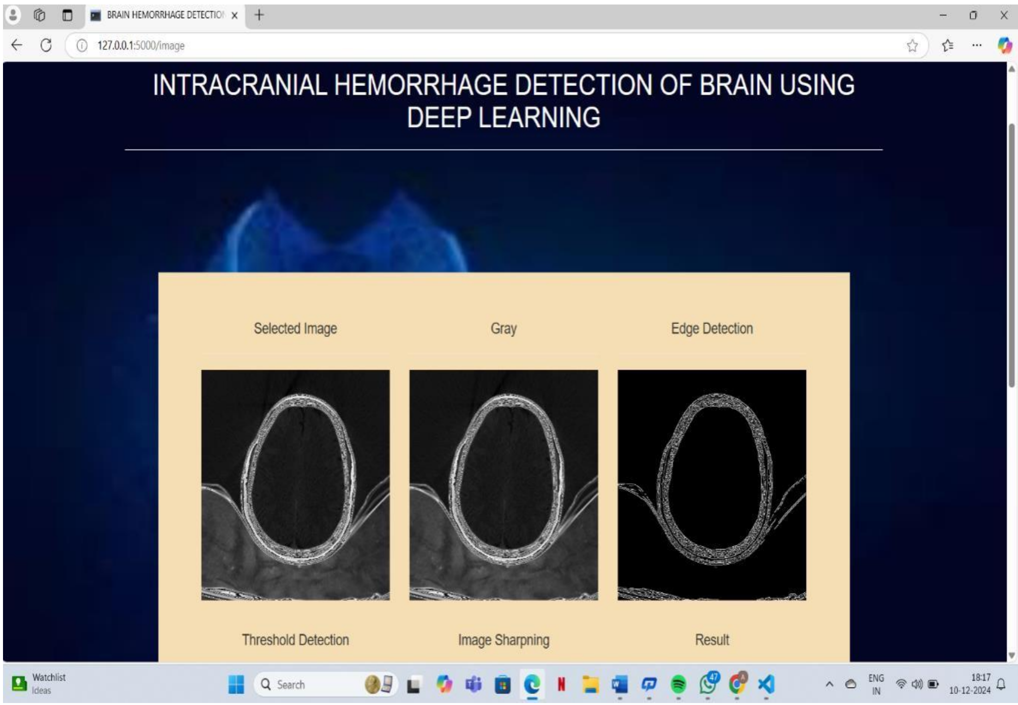

Figure 12: Output

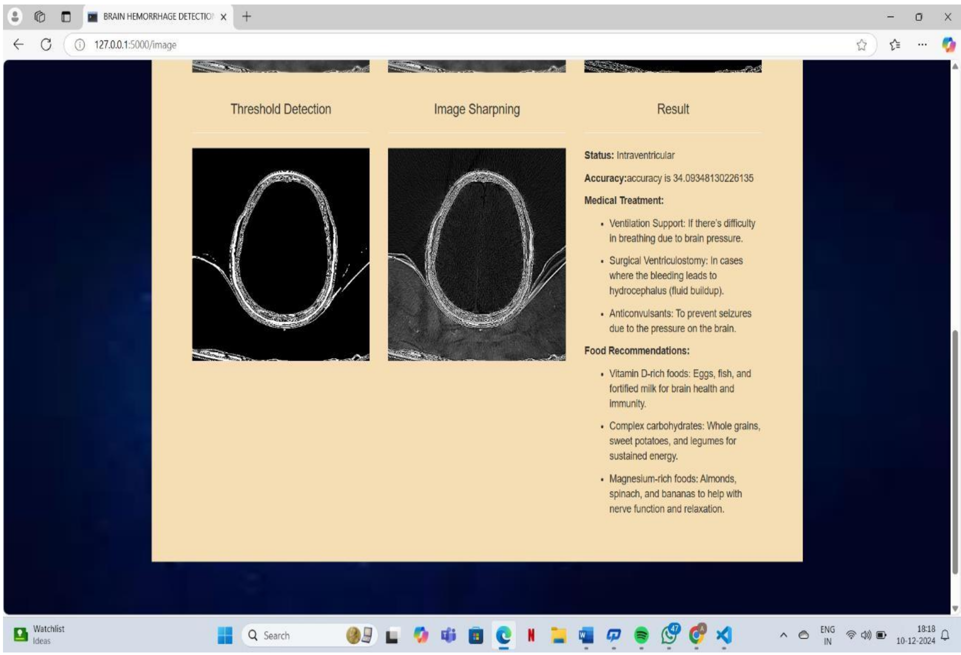

Figure 13: Output

The system starts with a user login web page titled "Brain Hemorrhage," where users will have to enter their username and password and click on the submit button to access the platform. After logging in, users are now supposed to select a file from the appropriate folder for further analysis. They can convinienly navigate through the folders and choose the image they would want to detect. Once the desired image is selected, then clicking on the "Analyze" button will trigger the detection process, which will provide detailed results. The output includes enhanced threshold detection and image sharpening, including a classification of the hemorrhage status. Also adding to the result, the system offers medical treatment suggestions and dietary recommendations to help with the user's recovery.

This easy process enables users to acquire real-time, accurate insights into brain hemorrhage detection with a seamless effort. The platform's user-friendly web interface allows the both medical professionals and patients to conveniently access and interpret the outcomes. It additionally supports numerous image formats, giving users flexibility in uploading different types of scans. The application web page is designed to handle a high-resolution medical images proficiently, giving precise and reliable analysis in a short span of time.

VIII. CONCLUSION

The classification results for the five types of brain hemorrhages are given, highlighting each of their strengths and weaknesses. Subarachnoid hemorrhage displayed the best performance with a precision of 0.23 and an F1-score of 0.23. Intraventricular hemorrhage came close, with a precision of 0.20 and an F1-score of 0.22. The classification for Epidural and Intraparenchymal hemorrhages was average, with F1-scores of 0.19 and 0.18, respectively. While the classification outcomes for subdural hemorrhage shows few difficulties, it displays promise for enhancing the classification of other hemorrhage types, giving a strong foundation for further enhancements. This indicates that with further optimization and training, the model's accuracy could be significantly improved. Continued research and refinement of the classification process will enhance its reliability for medical applications.

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