EXPLORING DEEP LEARNING &MACHINE LEARNING APPROACH 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.

Keyword : -*Brain hemorrhage detection involves several important concepts such as medical imaging, CT scans, MRI, and radiology, which help in identifying different types of bleeding inside the brain, including epidural, subdural, subarachnoid, intraparenchymal, and intraventricular hemorrhages. .*

1. INTRODUCTION

Brain hemorrhage is a significant medical situation characterized by the occurrence of bleeding in the brain. It is also referred to as Intracranial Hemorrhage (ICH), which occurs inside the brain parenchyma, incorporating the intracranial vault and adjacent meningeal areas.This condition frequently results in profound impairment or fatality Brain hemorrhage is a prevalent occurrence that arises from various pathological factors, such as cerebral amyloid angiopathy, vasculitis, trauma, dural arteriovenous fistula, hemorrhagic transformation of ischemic infarction, venous sinus thrombo sis, hypertension, cerebral arteriovenous malformations, and cerebral aneurysms as well as other etiologies visually represents various pathological factors behind brain hemorrhage. The basic symptoms of brain hemorrhage are strong headache, problems in vision, lethargy, difficulty in speaking, lack of coordination and seizure attack, etc represents the symptoms of brain hemorrhage. Based on the site of bleeding, brain hemorrhage can be categorized into several subtypes, namely Epidural Hemorrhage (EH), Intraventricular Hemorrhage (IVH), Subdural Hemorrhage (SH), Intraparenchymal Hemorrhage (IPH), Intracerebral Hemorrhage (IH), and Subarachnoid Hemorrhage (SAH) [3]. Depending on the kind of bleeding, there is a variety of intensity and response [4]. IH accounts for roughly 10% to 15% of initial stroke occurrences, exhibiting a 30-day fatality rate varying between 35% and 52%. Additionally, nearly half of these fatalitiesoccur

within the initial two day period A study involving 1041 cases of brain hemorrhages revealed that 50% of these incidents were observed in deep brain regions, while 35% happened in lobar regions. Additionally, 10% of the brain hemorrhages were found in the cerebellum, and the other 6% were located in the brain stem [8]. The mortality rates for different types of hemorrhage are as follows: deep hemorrhage has a mortality rate of 51% within a single year, lobar hemorrhage has a mortality rate of 57%, cerebellar hemorrhage has a mortality rate of 42%, and brain stem hemorrhage has a mortality rate of 65% In 2002, the United States witnessed an estimated count of approximately 67,000 individuals who received a diagnosis of IH. It is projected that only a few, specifically 20% of these individuals, are expected to achieve a complete restoration of their functional abilities within a six-month timeframe The fundamental need for prompt and appropriate treat ment is further highlighted by the fact that about fifty percent of these fatalities take place during the initial 24 hours. Through detection at an early stage, the death rate can be reduced to a manageable level. Unenhanced Computed Tomography Image (CTI) has become the diagnostic method that is most frequently used for brain hemorrhage recognition and classification due to its widespread accessibility, afford ability, and high accuracy in distinguishing blood from brain tissue, cerebrospinal fluid, and bone. Diagnosis time includes taking a head CTI and a radiologist executing an assessment based on CTI interpretation. A CTI is a sequence of X-ray images collected from different viewpoints that are combined to develop cross-sectional three-dimensional images of the physique's soft tissues, bones, bones, and blood arteries. The capacity of radiologists to detect abnormalities is essential to the effectiveness of screening, and this duty becomes extremely challenging when only a small section of an organ is destroyed. Radiologists must be able to detect abnormalities. This indicates that the process of assessing each slice will take more time and require the radiologist or doctor to put in moreeffort. If the screening is done manually, there is also a risk of making an incorrect diagnosis, which is another potential drawback associated with this procedure. Because of advancements made in Machine Learning's (ML) image identification capabilities, ML models and Deep Neural Networks (DNN) have become more useful in the f ield of medical image processing. Deep Learning (DL) algo rithms are able to learn on their own and discover essential patterns and traits hidden inside massive datasets without being given any explicit instructions. They are consequently receptive to receiving instruction that is exhaustive. Utilizing ML to infer and perform complex cognitive operations that would normally require the skill of a radiologist, such as assessing CTI, is an example of one use of this technology. Image classification depends heavily on ML and DL, both of which may be more easily comprehended with the use of paper. This report also discusses the development of recent classification techniques for brain hemorrhage identification using diagnostic imaging tools. 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.

1.1 Problem Statement:

Cerebral hemorrhages are critical medical emergencies that can lead to severe neurological damage, long-term disability, or even death if not diagnosed and treated promptly. Computed Tomography (CT) scans are a primary imaging modality for detecting brain hemorrhages due to their speed and accuracy. However, interpreting CT scans, particularly in the early stages of a hemorrhage, presents significant challenges. Subtle variations in imaging can often go unnoticed by human evaluators, leading to misdiagnosis or delayed treatment.

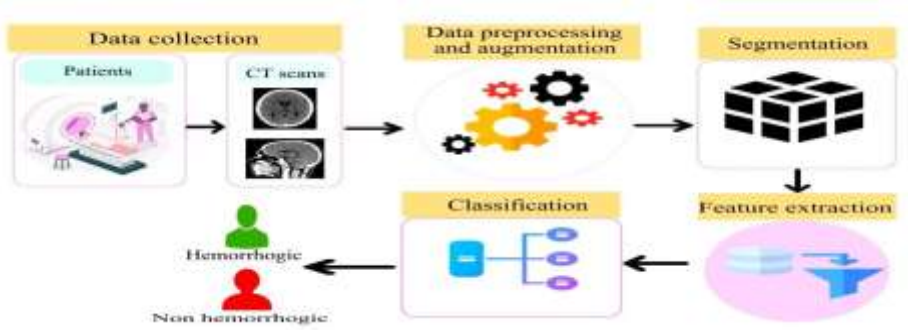
The reliance on manual interpretation introduces variability in diagnostic outcomes due to differences in expertise among radiologists, fatigue, and time constraints. In low-resource settings or emergency scenarios, the shortage of skilled radiologists exacerbates these challenges, leaving many patients without timely or accurate diagnosis. Consequently, the delay in identifying brain hemorrhages can result in missed opportunities for life-saving interventions.

1.2 Objectives:

To leverage deep learning methods, specifically convolutional neural networks (CNNs), for the identification and classification of brain hemorrhages in CT images.To address the challenges faced by physicians in accurately diagnosing brain hemorrhages, particularly in the early stages where misdiagnosis is more likely. To develop and evaluate the performance of the pre-trained ResNet50 model for distinguishing between hemorrhage and non-hemorrhage cases in CT scans. To compare the accuracy and reliability of the ResNet50 model against outcomes from previous studies in medical image analysis.

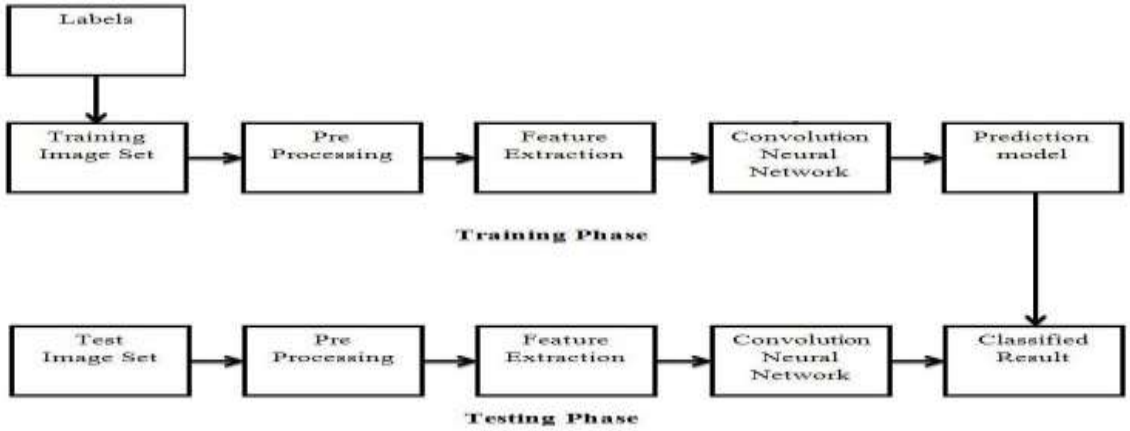
To achieve a high classification accuracy that demonstrates the potential of advanced CNN architectures in improving medical diagnostics. To contribute to the field of medical imaging by providing a robust and efficient tool for aiding in the early detection of cerebral hemorrhages.

2. METHODOLOGY



The methodology consist a Data collection from kaggle, Pre-processing, Feature extraction And Classification the give the result.
Three distinct models are utilized in this step to utilize the pre-processed data. The novelty of this study is it employs a pre-trained CNN model (Transfer Learning) to detect intracranial bleeding and its sub types. Transfer learning is applied to the processed data using pre-trained models.

Block Diagram



2.1 Working:

1. Dataset Collection:

Brain CT/MRI scan images are collected from medical image repositories (examples are Kaggle, hospitals , open datasets).Data includes haemorrhage and non-haemorrhage cases to ensure balanced classification.

2. Pre-processing:

Image resizing, normalization, and noise removal.Conversion to GrayScale and enhancement for better clarity.Data augmentation (rotation, flipping, zooming) to improve model robustness.

3. Feature Extraction

Deep learning model (CNN) automatically extracts spatial and structural features.Identifies key patterns like shape, intensity, and abnormal textures in CT/MRI scans.

1.convolation layer: A convolution layer is the main building block of convolution neural network(CNN).
it helps the computer see understand images by detecting important patterns like edges, colors, shapes .

2.ReLU layer(rectified liner unit): ReLU helps highlight the important activated regions(like braight area or bleeding).And ignore the unnecessary negative signals.

3.Polling layer: The pooling layer helps reduce the image size but keep bright or active region (possing hemorrhage spots)And this makes network faster and focuses on important feature only.

There are two types in polling layer.
1.Max polling : Takes the maximum value from the region.
2.Average pooling : Take the average value.
4.Fully connected layer: The convolution and polling layer extract features like shapes, braight spot, and texture.
The fully Connected layer looks at all those feature and decides: “hemorrhage” or “normal brain”.

Classification

1. Features are passed to CNN layers for classification.
2. Model classifies images as **hemorrhage detected** or **normal brain scan**.

5. Result

1. Accuracy, precision, recall, and F1-score are calculated.
2. Visual results: correctly detected hemorrhage regions in CT/MRI scans.
3. Provides early detection to assist radiologists in diagnosis.

2.2 Scope:

- The scope for brain hemorrhage detection is rapidly expanding due to its vital role in saving lives through early and accurate diagnosis.
- With increasing cases of stroke, accidents, and traumatic brain injuries, the need for fast detection has become essential in hospitals and emergency care units.
- Modern imaging techniques like CT and MRI scans allow doctors to identify the location and severity of bleeding quickly, while advanced technologies such as artificial intelligence and deep learning models—like CNNs and ResNet—are now being used to automate the process and reduce errors.
- These AI systems can analyze medical images within seconds, helping radiologists and improving treatment decisions. Additionally, the field offers wide opportunities for research, including developing new algorithms, improving detection accuracy, and creating large medical datasets.
- As healthcare systems adopt digital tools, brain hemorrhage detection also supports telemedicine and enhances medical facilities in rural areas. Overall, this field has strong medical, technological, and career growth prospects, making it an important area in modern healthcare and research.

2.3 Software requirement:

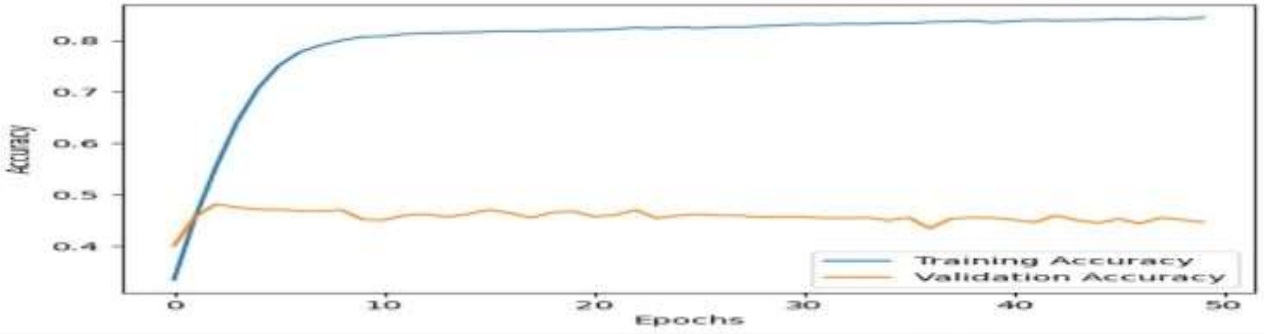
- Operating system : Windows XP/ Windows 7.
- Software Tool : Open CV or Python.
- Coding Language : Python .
- Toolbox : Image processing toolbox.
- System : intel i3/i5 2.4 GHz.
- Hard Disk : 500 GB
- Ram : 4/8 GB

3.Expectational Result:

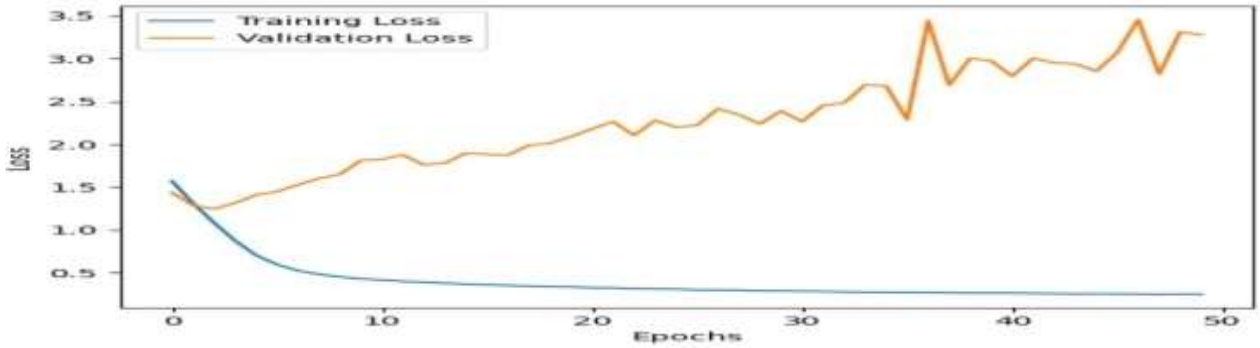
The results of brain hemorrhage detection show how accurately the system can identify bleeding within the brain from medical images such as CT scans. After training the model with many images, the system is tested on new scans to check its performance. The output usually includes accuracy, sensitivity, and specificity, which indicate how well the model can correctly detect hemorrhages and avoid false predictions. High accuracy means the system can reliably classify hemorrhagic and non-hemorrhagic cases. Sensitivity shows how well the model finds even small or early bleeds, while specificity shows how well it avoids marking normal brain tissue as hemorrhage. Overall, the results help confirm whether the detection method is effective, fast, and suitable for clinical use.

GRAFICAL REPRESENTATION :

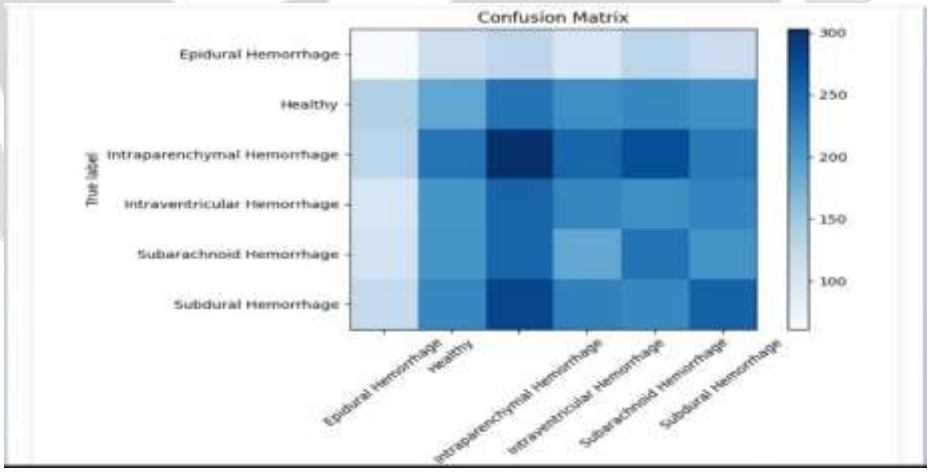
1.Training accuracy per Epochs .



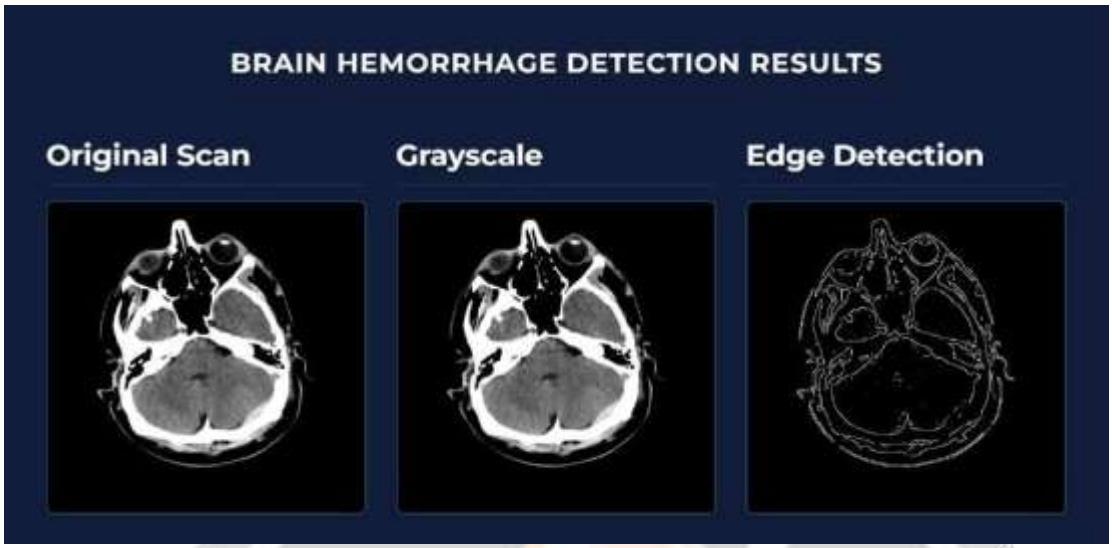
2.Training loss per Epochs.



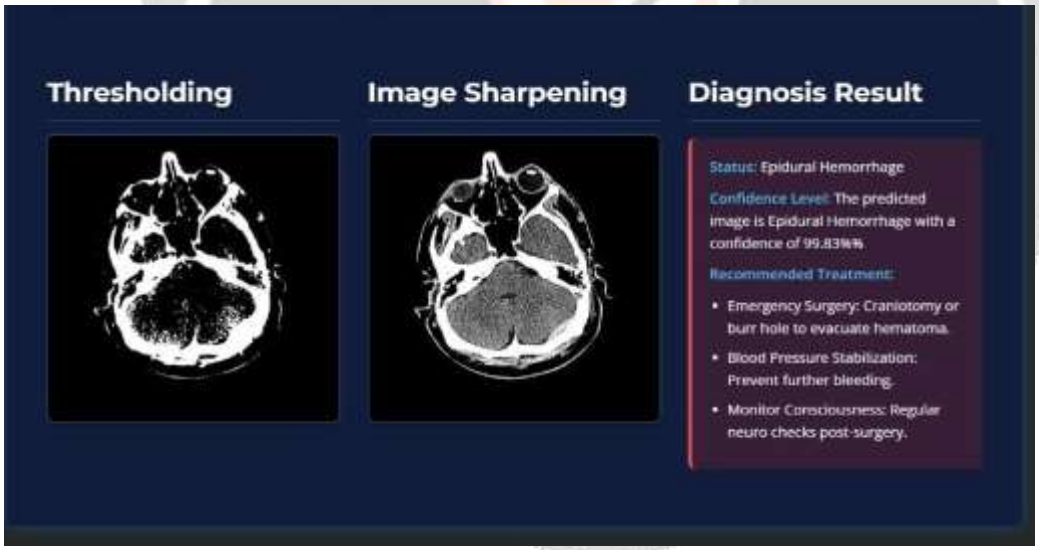
3.Confusion Matrix:



Brain Hemorrhage detection Results:



Diagnosis Result:



The system processes the uploaded brain CT scan through multiple image-enhancement steps such as grayscale conversion, edge detection, thresholding, and sharpening to highlight critical structures. After analysis, the model identifies the scan as showing an Epidural Hemorrhage with a very high confidence level of 99.83%. This suggests the presence of bleeding between the skull and the dura mater. The highlighted edges and enhanced contrast help the model detect abnormal dense regions that indicate bleeding. Based on the result, emergency medical intervention is recommend.

4.CONCLUSIONS

Brain hemorrhage detection is a critical aspect of medical diagnosis that directly influences patient survival and recovery. With the increasing availability of advanced imaging techniques such as CT scans, MRI, and AI-assisted analysis, healthcare professionals can identify bleeding regions in the brain with greater speed, accuracy, and confidence. Early and precise detection helps in determining the type, location, and severity of the hemorrhage, which is essential for selecting the right treatment approach. This not only reduces the risk of long-term neurological damage but also improves overall patient outcomes. Furthermore, modern computer-aided detection systems support radiologists by enhancing image clarity, highlighting abnormal areas, and reducing human error. As research and technology continue to advance, brain hemorrhage detection is becoming faster, more efficient, and more reliable, ultimately contributing to better healthcare quality and saving countless lives.

5.REFERENCES

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