

BRAIN HEMORRHAGE DETECTION USING DEEP LEARNING

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Abstract - Brain hemorrhage is a life-threatening medical condition that necessitates rapid and accurate diagnosis to prevent severe complications or fatalities. Current detection methods, such as manual analysis of CT scans by radiologists, are often time-intensive and susceptible to human error, especially in high-pressure emergency situations. This project aims to develop an advanced, automated system for detecting brain hemorrhages using deep learning techniques. The system will utilize robust neural network models such as ResNet and MobileNet to analyze medical images and accurately distinguish between normal and hemorrhagic cases. A dataset comprising both normal and hemorrhage images will be used to train the model, enabling it to learn intricate patterns and subtle variations effectively. The proposed system leverages the superior feature extraction capabilities of deep learning to achieve high precision and reliability in diagnosis. By automating the detection process, the system can significantly reduce diagnostic time and provide consistent, unbiased results, thereby supporting healthcare professionals in making timely and informed decisions. This project has the potential to improve early diagnosis, facilitate prompt treatment, and ultimately enhance patient outcomes in critical care scenarios.

Key Words: Brain hemorrhage, deep learning, automated diagnosis, medical imaging, feature extraction, hemorrhage detection, healthcare innovation, neural networks

1. INTRODUCTION

Brain hemorrhage is a critical and life threatening medical conditions causing by internal bleeding within the brain tissues or surrounding areas. These type of conditions can arise due to various reasons such as trauma, and high blood pressure, aneurysm rupture, or the excessive uses of blood thinking medications. If not diagnosis and treat promptly and brain hemorrhages can lead to irreversible brain damage, long term disability or death early detection and intervention are vital to improving several rates and preventing complications. Currently the primary method of diagnosis brain hemorrhage involves analyzing brain image scans such as computed tomography or magnetic resonance imaging. These scans are interpreted manually by radiologist who look for sign internal bleeding, abnormalities, or swelling. While the process is generally accurate it is a time consuming requires specialized expertise, and the

susceptible to human error practically high pressure environment such as emergency rooms. In rural the resource-constrained settings the ability of expired radiologists is often limited which can delay critical diagnosis. To address these challenges artificial intelligence and deep learning techniques has emerged on promising tools in medical images analysis. Deep learning and subfield of machine learning uses neural networks in mimic the human brain's ability to recognize patterns on features in data. Among the most effective deep learning models are neural networks and mobile net which have shown exceptional performance image classification task. These models can automatically learn to identify hemorrhagic features from medical images offering consistent, fast, and highly accurate predictions. This project focuses on developing an automated system that utilises CNN mobile net architectures to detect brain hemorrhage from CT and MRI images. The system includes modules for image upload, preprocessing, model selection, prediction, and visual explanation through Grad-CAM heatmaps. CNN offers high precision and is suitable for clinical diagnosis with mobile net provides lightweight and real time inference ideal for mobile and emergency scenarios. By integrating deep learning with medical imaging system aims to reduce diagnosis time minimize human errors and increasing accessibility to quality healthcare especially in underserved areas. The overall goal is to create a reliable, interpretable, and scalable diagnostic tool that supports medical professionals in making faster and more accurate decisions for patients suffering from brain hemorrhage.

1.1 LITERATURE SURVEY

Automated detection of brain hemorrhage has become a growing research area within the field of medical image analysis especially with the emergence of deep learning and computer visual techniques. Various researchers have explored mission learning and deep learning models analysis CT and MRI images to improve the accuracy and speed of diagnosis.

1. Chilamkurthy et al. (2018) proposed a deep learning model to detect critical finding in headless cities scans. Their system based on CNN achieved performance comparable school export radiologist especially in identifying intracranial hemorrhages.

2. Prevedello et al. (2017) used machine learning models for abnormality detection in CT images and emphasized the potential for real-time usage in emergency departments. The result showed how AI could reduce radiologist workload and time to diagnosis.

3. Saba et al. (2019) explored the use of deep learning for hemorrhage detection using a modified U-net architecture for segmentation tasks. They achieved high sensitivity in localizing hemorrhagic regions within the brain.

4. Titano et al. (2018) developed an ensemble of CNN models to detect hemorrhages, mass effects, and other intracranial abnormalities in head CTs. Their system performed well across multiple centers, suggesting good generalization.

5. Patel et al. (2020) achieved over 90% classification accuracy for hemorrhagic vs non-hemorrhagic cases by using a CNN-based architecture on non-contrast CT scans. They used Grad-CAM graphics to highlight the expandability of the model.

6. A scalable deep learning model for imaging diagnosis utilizing 3D CNNs was presented by Arbabshirani et al. (2018). Their method facilitated the quick and precise categorization of hemorrhages from volumetric data.

7. Rajpurkar et al. (2017) created the CheXNet model for X-ray-based pneumonia identification, which sparked related research on deep learning for CT/MRI in neurological applications, such as bleeding.

8. AlexNet is a groundbreaking CNN that greatly expanded the fields of deep learning and image identification. It was first presented by Krizhevsky et al. (2012). It was later modified for use in medical imaging diagnostics, such as the detection of hemorrhages and strokes.

9. MobileNetV2, a lightweight and effective architecture tailored for mobile and embedded AI applications, was presented by Sandler et al. (2018). Its application in healthcare, especially in environments with limited resources, has shown promise.

10. To improve detection accuracy on series scan data, Banerjee et al. (2021) created a hybrid CNN-RNN model that included spatially sequential information from CT scans for bleeding classification.

1.2 ROLE OF DEEP LEARNING

Deep learning has emerged as one of the most powerful and transformative technologies in the field of medical image analysis. It mimics the structure and function of the human brain through artificial neural networks, allowing machines to learn from large amounts of data. In the context of brain hemorrhage detection, deep learning plays a vital role by automating the analysis of CT scans and identifying patterns that may not be immediately visible to the human eye. One of

the biggest advantages of deep learning is its ability to automatically extract complex features from raw image data without the need for manual intervention. Traditional image processing techniques often rely on predefined rules or handcrafted features, which can be time-consuming and less adaptable to variations in medical images. Deep learning, particularly convolutional neural networks (CNNs), overcomes this limitation by learning hierarchical feature representations directly from the data, enabling the model to identify subtle differences between normal and hemorrhagic brain tissue. In emergency medical situations, time is critical, and deep learning systems can help speed up the diagnostic process. A well-trained deep learning model can process and interpret a CT scan in seconds, providing clinicians with immediate insights that can guide treatment decisions. This is especially important in cases of traumatic brain injury or stroke, where early intervention can significantly improve patient outcomes.

2. SYSTEM EXPLANATION

The suggested approach improves and automates the identification of brain hemorrhages from medical images by utilizing cutting-edge deep learning models, particularly MobileNet and ResNet. ResNet's deep residual learning capabilities guarantee great accuracy by efficiently training very deep networks, while MobileNet's lightweight architecture is optimized for deployment in resource-constrained environments. Preprocessing is a picture data training the models and assessing their performance using metrics like accuracy, sensitivity, and specificity are the goals of the system. The suggested system aims to assist medical practitioners in establishing accurate and fast diagnoses, which will eventually improve patient outcomes, by offering a dependable and effective diagnostic tool.

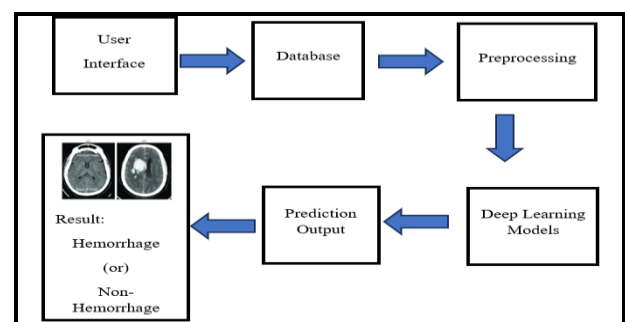


Figure 1: BLOCK DIAGRAM

1. **Image Input:** This module is in charge of taking user-provided brain scan images using a designed web interface. It checks the image format and quality before sending them for preprocessing and supports PNG and JPEG image formats.

2. **Preprocessing:** To standardize images for model input, they go through a number of preprocessing stages. This covers noise reduction, normalization, scaling to fixed

dimensions (such as 224x224 pixels), and grayscale conversion.

3. **Deep Learning Models:** Classification takes place in systems centre to distant models are used.

- **CNN:** A departure that has been thought to recognise intricate patterns in images. Ideal for obtaining high bleeding detection accuracy for intricate picture characteristics.
- **MobileNet:** An effective and lightweighting architecture present for embedded and real time applications. With its depth-wise separable convolutions it drastically cuts on computation without compromising accuracy. Evaluation criteria including as accuracy, precision, recall, F1-score, and inference time are used to compare the performance of each model, which operates separately.

4. **Output and visualization Layer:** The system indicates if the scan is normal or hemorrhagic after making a forecast. It can be expanded to identify areas of concern using Grad-CAM or other heatmap visualizations for explainability and it's also offers a probability and confidence score.

5. **Interface for Users:** Healthcare providers can upload photos and examined diagnostic results instantaneously through an intuitive Django-based online interface.

3. PROPOSED WORK

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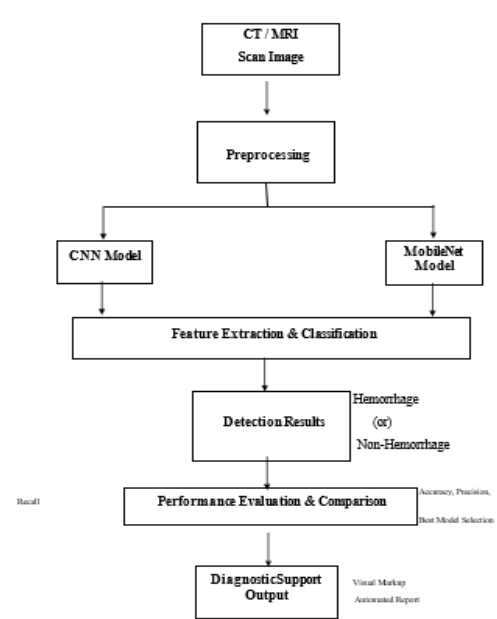


Fig. 3.2.1 PROPOSED SYSTEM

2.1 RESULT AND DISCUSSION

The proposed automated brain hemorrhage detection system was evaluated using a labeled dataset comprising CT images of both hemorrhagic and non-hemorrhagic cases. Two deep learning architectures, ResNet and MobileNet, were implemented and trained on the dataset to compare their performance in terms of accuracy, precision, recall, F1-score, and inference time. The MobileNet model demonstrated strong performance, achieving an overall classification accuracy of 95.42%, with a precision of 95% and recall of 96%. Its deep architecture allowed it to effectively extract complex features and recognize subtle patterns associated with hemorrhagic regions. The ResNet based model, a deep architecture model optimized for an embedded devices, achieved an accuracy of 72.33%, with a slightly lower precision of 77% and recall of 72% compared to MobileNet. MobileNet model has given the accuracy of 95% which is more than the ResNet accuracy of 72%.

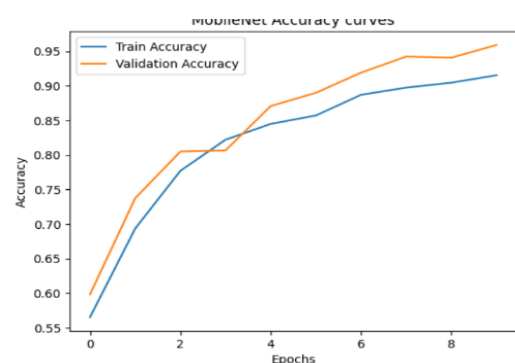


Figure 2: comparisons between Train Accuracy and Validation Accuracy for Epochs and Accuracy value curves

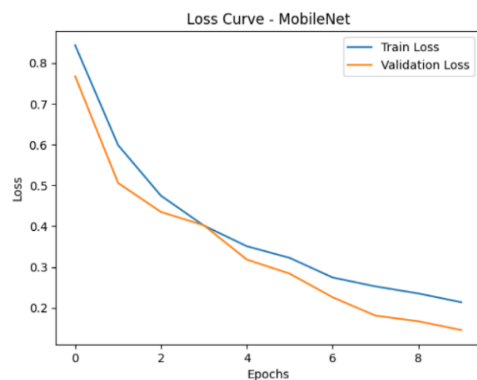


Figure 3: comparisons between Train loss and Validation loss for Epochs and loss value curve of MobileNet

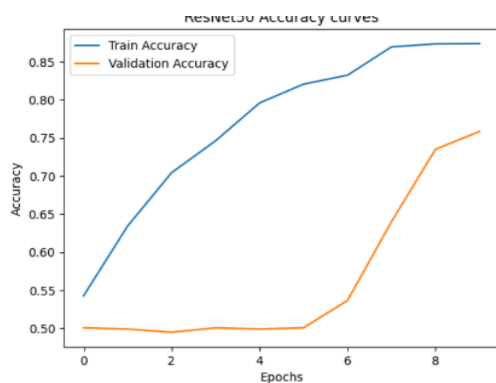


Figure 4: comparisons between Train Accuracy and Validation Accuracy for Epochs and Accuracy value changing curves

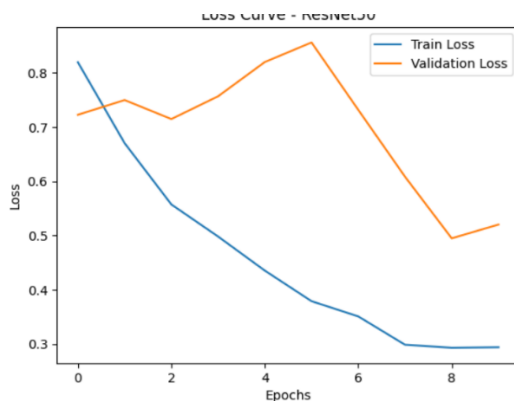


Figure 2: comparisons between Train Loss and Validation Loss for Epochs and Loss curve

3. CONCLUSIONS

This project has explored the application of deep learning techniques for the automated detection of brain hemorrhages in CT scan images. The study demonstrates that deep learning models, particularly convolutional neural networks such as ResNet and MobileNet, can significantly enhance the diagnostic process by providing high levels of accuracy, efficiency, and consistency. Through the use of

annotated datasets comprising both normal and hemorrhagic brain images, the models were trained to recognize intricate features and subtle anomalies often missed during manual inspection, especially under time constraints or in high-pressure scenarios. The automated system not only reduced the dependency on constant human interpretation but also minimized the chances of misdiagnosis due to fatigue or oversight. Furthermore, the system’s ability to provide consistent outputs regardless of external factors highlights its potential to assist healthcare professionals in making timely and informed decisions. By integrating this technology into clinical workflows, especially in emergency rooms and intensive care units, the turnaround time for diagnosis can be significantly shortened, thereby facilitating quicker medical intervention and potentially saving lives. Despite the promising results, this study also acknowledges the limitations encountered, including data availability, model generalization, and the challenge of clinical validation in real-world scenarios. Nonetheless, the foundation laid by this work opens up a wide range of opportunities for further innovation and improvement in AI-driven medical diagnostics.

REFERENCES

- [1] D. Kornack and P. Rakic, “Cell Proliferation without Neurogenesis in Adult Primate Neocortex,” *Science*, vol. 294, Dec. 2001, pp. 2127-2130, doi:10.1126/science.1065467.
- [2] M. Young, *The Technical Writer’s Handbook*. Mill Valley, CA: University Science, 1989.
- [3] R. Nicole, “Title of paper with only first word capitalized,” *J. Name Stand. Abbrev.*, in press.
- [4] K. Elissa, “Title of paper if known,” unpublished. Howard A.G., Zhu M., Chen B., et al. MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. *arXiv preprint*, 2017. arXiv:1704.04861.
- [5] Simonyan K., Zisserman A. Very Deep Convolutional Networks for Large-Scale Image Recognition. *arXiv preprint*, 2014. arXiv:1409.1556.
- [6] Yasaka K, Akai H, Abe O, Kiryu S. Deep Learning with Convolutional Neural Network for Differentiation of Liver Masses at Dynamic Contrast-Enhanced CT: A Preliminary Study. *Radiology*, 2018; 286(3): 887–896.doi: 10.1148/radiol.2017170706.
- [7] Suzuki K. Overview of Deep Learning in Medical Imaging. *Radiological Physics and Technology*, 2017; 10(3): 257–273. doi: 10.1007/s12194-017-0406-5