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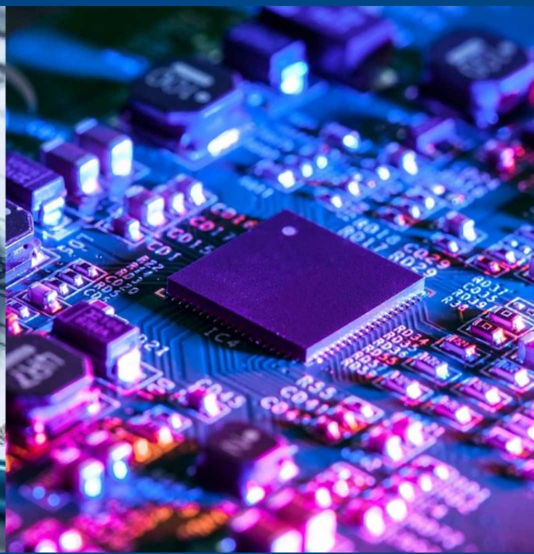

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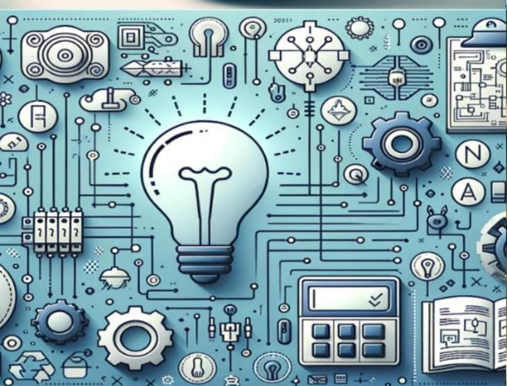

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# Brain Stroke Detection Using Deep Learning Methods

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**ABSTRACT**: Brain hemorrhage is a potentially life-threatening health condition that demands urgent and accurate diagnosis in order to enable timely treatment. Conventional diagnostic methods, including CT scans and MRI scan analysis, are highly dependent on human interpretation, which may be slow and susceptible to human errors. This work proposes a deep learning model namely MobileNet. The effectiveness of this model is tested rigorously on the basis of important performance measures such as accuracy, sensitivity, specificity, and computational cost as to certain their efficiency in medical image classification. This thesis proposed a deep learning-based method for accurate intracranial hemorrhage classification, which demonstrates superior diagnostic performance and reliability compared to existing state-of-the-art models. The proposed approach is built upon the MobileNet architecture, optimized for lightweight and efficient deployment in resource-constrained environments such as portable medical devices and edge computing platforms. Experimental evaluations reveal that the proposed method outperforms traditional deep learning models, including DenseNet and ResNet, in key performance metrics. Specifically, proposed model achieves a diagnostic accuracy of 99.7%, sensitivity of 95.8%, and specificity of 97.1%, surpassing DenseNet and ResNet by significant margins. These results highlight the strength of proposed method’s feature extraction and classification capabilities, making it a reliable and efficient solution for hemorrhage detection in real-world clinical scenarios.

**KEYWORDS*:*** Brain hemorrhage detection, deep learning, machine learning, MobileNet, DenseNet, EfficientNet and ResNet convolutional neural networks, medical image analysis, diagnostic tools, healthcare.

## I. INTRODUCTION

Brain hemorrhage, a life-threatening condition, necessitates immediate and precise identification to enable early treatment and enhance patient recovery.[1] Conventional diagnostic approaches depend heavily on the expertise of radiologists interpreting medical images, a process that is both Labor-intensive and susceptible to human error, traditional methods have limitations. Recent progress in deep and machine learning techniques has shown great promise in streamlining and improving diagnostic processes accuracy in medical image analysis.[2] This research emphasizes the utilization of advanced CNN techniques architectures, including MobileNet, DenseNet, EfficientNet, and ResNet, are utilized for brain hemorrhage detection.[3] MobileNet is designed for efficient computation, making it suitable for Implementation in environments with limited computational resources, like mobile devices, while ResNet is renowned for its deep residual learning capabilities, allowing the training of very deep networks without suffering from vanishing gradients.[4] By applying these advanced models to a dataset of brain hemorrhage images, the research aims to evaluate their Performance is evaluated based on accuracy, sensitivity, specificity, and computational efficiency.[5] The objective is to create a dependable, automated diagnostic system that supports healthcare providers in delivering timely decisions and precise diagnoses, thereby improving patient care and reducing the mortality and morbidity associated with brain hemorrhages.[6] This project not only contributes to the field of Analyzes medical images while also examining the real-world use of deep learning models within clinical environments, paving the way for more accessible and efficient diagnostic solutions.

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### A.Objective of Project

This project aims to design and assess advanced deep learning models, specifically MobileNet, DenseNet, EfficientNet and ResNet to ensure precise and swift identification of brain hemorrhages using medical imaging.[7] The research intends to evaluate and contrast the effectiveness of these architectures based on metrics such as accuracy, sensitivity, specificity, and computational efficiency.[8] By leveraging these leading-edge techniques, the project seeks to create a reliable and automated diagnostic aid designed to support medical practitioners in making prompt decisions and precise diagnoses, thereby improving patient outcomes and reducing the time to treatment for brain hemorrhage patients.

### B.Problem of Statement

The problem addressed in this study is the challenge of accurately and rapidly detecting brain hemorrhages using medical imaging.[9] Current diagnostic practices, relying heavily on manual interpretation by radiologists, are time-consuming and susceptible to errors, leading to potential delays in critical treatment. This research seeks to evaluate and contrast the effectiveness of advanced deep learning algorithms, particularly MobileNet and ResNet, in automating the detection process.[10] By enhancing the accuracy and speed of brain hemorrhage diagnosis, this study aims to Enhance healthcare decisions and contribute to better patient results, ultimately reducing the associated mortality and morbidity rates.

### C.Motivation

The motivation behind this study is driven by the critical the necessity for precise and swift identification of brain hemorrhages, which can significantly impact patient outcomes.[11] Conventional diagnostic approaches are often slow and susceptible to human error, leading to delays in treatment. By harnessing the power of advanced deep learning architectures like MobileNet and ResNet, this research aims to enhance diagnostic precision and efficiency. The primary objective is to create reliable automated systems that support medical practitioners in delivering prompt and accurate diagnoses, leading to improved patient care and lowered mortality rates and morbidity associated with brain hemorrhages.

### D.Scope of Project

The scope of this project encompasses the design, optimization, and assessment of deep learning algorithms, specifically MobileNet and ResNet, for brain hemorrhage detection using medical imaging data. This includes preprocessing of image datasets, implementation of the neural network architectures, and rigorous Performance assessment is conducted using metrics like accuracy, sensitivity, and specificity.[12] The study also aims to compare the computational efficiency of the models, highlighting their potential for real-world clinical applications. Additionally, the project explores the feasibility of deploying these models In environments with limited resources, such as mobile devices, to support widespread and accessible diagnostic solutions.

## II. RELATED WORK

Early diagnosis of brain hemorrhage relied heavily on manual assessment using CT scans and MRI are examined by radiologists to identify abnormalities, but The procedure Requires significant manual effort and is prone to mistakes made by humans.[13] Various statistical and rule-based image processing techniques were introduced to enhance diagnosis. For instance, thresholding, region-based segmentation, and edge detection methods were applied to highlight hemorrhage regions.[14] However, these traditional methods lack adaptability and fail to generalize across different datasets, making automation challenging.

With the rise of ML models, including SVM, DT, and RT, have been utilized for brain hemorrhage classification.[15] ML models extract key features from images, including intensity, texture, and shape, to differentiate between hemorrhagic and non-hemorrhagic cases. Notably, studies integrating PCA and GLCM have demonstrated

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improvements in feature selection and classification accuracy. However, ML-based models are limited by the necessity of manual feature engineering, which may affect their generalizability across diverse medical imaging datasets.

Deep learning (DL) has revolutionized medical image analysis by enabling end-to-end learning without manual feature extraction.[16] Convolutional Neural Networks (CNNs), including VGG-16, ResNet, and DenseNet, have been extensively utilized for brain hemorrhage detection. Studies have shown that CNNs outperform ML models by leveraging hierarchical feature extraction, capturing both low-level and high-level image representations.[17] Research comparing VGG-16 with ResNet demonstrated that residual learning significantly mitigates vanishing gradient problems, leading to improved classification accuracy. Additionally, hybrid approaches integration of CNNs with LSTM networks has been investigated for sequence-based medical imaging analysis.

Recent advancements in lightweight and efficient architectures have paved the way for real-time and mobile-compatible brain hemorrhage detection systems. MobileNet, known for its depthwise separable convolutions, offers Optimized for computational efficiency, it is well-suited for deployment in mobile and embedded systems.[18] DenseNet improves information flow by utilizing dense connections, reducing redundancy and enhancing feature reuse EfficientNet utilizes a compound scaling method that balances network depth, width, and input resolution to improve performance with minimal computational overhead.[19] ResNet remains a benchmark model due to its deep residual learning, addressing vanishing gradient issues in deep networks. Comparative studies suggest that a hybrid approach integrating EfficientNet and ResNet can enhance both speed and accuracy in hemorrhage detection.

Despite the promising results achieved using deep learning models, several challenges persist in real-world implementation.[20] One major issue is data scarcity, as high-quality labeled medical images are limited due to privacy concerns and annotation costs. Additionally, deep learning models require extensive computational resources, limiting deployment in low-resource settings.[21] Model interpretability and explainability also remain crucial concerns for gaining clinical acceptance. Future research directions include improving dataset augmentation techniques, implementing federated learning for privacy-preserving model training, and integrating attention mechanisms for enhanced feature localization in hemorrhage detection.

## III. METHODOLOGY

The proposed methodology for brain hemorrhage detection leverages Deep learning methods are utilized to construct An accurate and efficient classification system is developed, starting with the collection and preprocessing of a brain hemorrhage image dataset is acquired from publicly available sources or hospital databases. The images undergo preprocessing steps including techniques like denoising, enhancing contrast, resizing, and normalizing to maintain consistency throughout the dataset. Additionally, data augmentation techniques such as rotation, flipping, and brightness adjustments are applied to improve model generalization and mitigate overfitting.

Following preprocessing, feature extraction and model selection are carried out using Cutting-edge Convolutional Neural Network (CNN) architectures, including MobileNet, DenseNet, EfficientNet, and ResNet. Each of these models is fine-tuned to optimize performance in medical image classification tasks. MobileNet, known for its lightweight design, is particularly useful for deployment in real-time scenarios with limited computational resources, while DenseNet and EfficientNet enhance feature propagation and computational efficiency. ResNet, with its deep residual learning framework, is utilized to address the vanishing gradient problem, promoting stable training in deeper neural networks.

The training and validation phase involves splitting the dataset into subsets for training, validation, and testing. The models are trained using transfer learning techniques, initializing with Pre-trained weights from extensive image

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datasets like ImageNet are utilized. Hyperparameter tuning, including batch size optimization, learning rate adjustment, and dropout regularization, is performed to enhance model accuracy.

Finally, a comparative analysis is performed to identify the most effective model for optimal performance brain hemorrhage detection. The best-performing model is integrated into a user-friendly interface, enabling seamless deployment in clinical settings. This methodology ensures a robust, automated system for early brain hemorrhage detection, aiding in timely diagnosis and treatment.

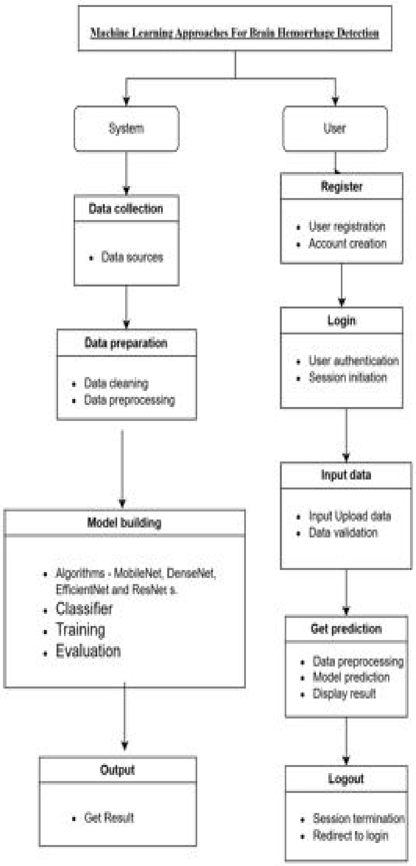


Fig 1: Block Diagram of Proposed System

## IV. IMPLEMENTATION

### A.MobileNet

The primary objective of implementing MobileNet in brain hemorrhage detection is to develop an efficient and lightweight deep learning model capable of classifying hemorrhage cases with high accuracy while maintaining low computational complexity. MobileNet is specifically designed for environments with limited resources, including mobile and edge devices, this makes it a suitable option for real-time medical applications. The model aims to enable rapid and precise diagnosis, depth wise separable convolutions are utilized, reducing both the number of parameters and computational cost compared to conventional convolutional networks. By incorporating MobileNet, the system seeks to achieve a balance between model efficiency and classification performance, ensuring that it can be deployed in remote healthcare facilities, emergency response systems, and mobile diagnostic applications. Furthermore, the objective includes optimizing MobileNet's architecture through transfer learning and fine-tuning techniques to enhance its ability to detect brain hemorrhages in CT and MRI images with minimal latency and high sensitivity.

**Model Training:**

The training process of MobileNet for brain hemorrhage detection begins with the acquisition and preprocessing of a well-curated dataset. The images are resized to fit the input dimensions required by MobileNet (e.g., 224×224 pixels), normalized to improve convergence, and augmented using techniques Including methods like image rotation, horizontal flipping, and contrast adjustment to enhance the model's ability to generalize. Transfer learning is implemented by initializing MobileNet with pre-trained ImageNet weights, enabling the model to utilize previously learned representations while adapting to medical image classification. The dataset is partitioned into training, validation, and testing sets to maintain a well-balanced framework for assessing model performance.

During training, cross-entropy loss serves the objective function is used to guide the model, which is optimized with the Adam optimizer and a learning rate that adjusts dynamically. Dropout regularization is employed to avoid overfitting, along with batch normalization to stabilize training. The model is fine-tuned by unfreezing the later layers of MobileNet, enabling it to learn domain-specific features related to brain hemorrhage detection. The optimal model is chosen by evaluating the highest accuracy on the validation set along with the lowest validation loss, ensuring it is well-generalized for real-world deployment in medical settings.

**B.DenseNet**

The primary objective of implementing DenseNet in brain hemorrhage detection is to enhance the model's feature learning capability through dense connections, ensuring efficient gradient flow and improved representation learning. DenseNet, or Densely Connected Convolutional Network, is structured to address the issues of vanishing gradients and redundant feature extraction effectively by introducing direct connections between all preceding and subsequent layers. This architecture maximizes feature reuse, decreases the parameter count and enhances training efficiency, making it highly effective for medical image classification tasks. The model aims to leverage feature propagation to extract hierarchical features of brain hemorrhage patterns from CT and MRI scans, enabling precise differentiation between hemorrhagic and non-hemorrhagic cases. Additionally, the objective includes optimizing DenseNet for high classification accuracy with minimal computational overhead, ensuring that the model is not only robust and accurate but also deployable in clinical decision-support systems for real-time hemorrhage detection and diagnosis.

**Model Training:**

The training process of DenseNet for brain hemorrhage detection starts with the preprocessing of medical images, ensuring that they are standardized for optimal model input. Images are resized (e.g., 224×224 pixels) and normalized to scale pixel values between 0 and 1. Data augmentation techniques such as flipping, rotation, and brightness adjustments are applied to improve generalization and minimize overfitting adjustment are implemented. DenseNet is initialized with pre-trained weights from ImageNet, leveraging previously learned representations while fine-tuning the model for hemorrhage detection. The data is split into training, validation, and testing sets to enable effective performance assessment across varied data distributions.

The batch size is carefully chosen to maintain computational efficiency without compromising performance. Dropout and L2 regularization are applied to prevent overfitting, while batch normalization ensures stable weight updates. DenseNet's architecture, with shorter connections between layers, facilitates better information flow, improving training speed and reducing redundancy. The training process is monitored. The final trained model, achieving high

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classification performance, is integrated into a clinical framework for automated hemorrhage detection, assisting radiologists in early and accurate diagnosis.

**C.EfficientNet**

The primary objective of implementing EfficientNet in brain hemorrhage detection is to achieve high classification accuracy while maintaining computational efficiency. EfficientNet utilizes an innovative compound scaling technique that efficiently balances network depth, width, and input resolution for optimal performance, enabling the model to perform efficiently while utilizing fewer parameters than conventional deep learning models. The model is designed to extract detailed spatial features from brain hemorrhage images while optimizing computational resources, making it suitable for both cloud-based and edge-device deployments. The goal is to leverage EfficientNet's scalable architecture to enhance feature learning, improve model generalization, and ensure robust performance across different datasets. By utilizing EfficientNet, This research seeks to develop a resilient deep learning framework that assists radiologists in their analysis and decision-making Medical experts in achieving early and precise diagnosis of brain hemorrhages, ultimately enhancing diagnostic accuracy and patient care.

**Model Training:**

The training process of EfficientNet for brain hemorrhage detection begins with data preprocessing, where medical images are resized (e.g., 224×224 pixels) to match EfficientNet's input requirements. The images undergo normalization and Augmentation methods like flipping, rotation, contrast modification, and the addition of Gaussian noise, to improve generalization and mitigate overfitting. The dataset is Split into training, validation, and test sets, maintaining balanced class representation to ensure effective model assessment.

To leverage pre-trained knowledge, EfficientNet is initialized with ImageNet weights, and transfer learning is employed by fine-tuning the top layers while freezing the initial layers. The training process utilizes the model utilizes categorical cross-entropy as the loss function, with optimization carried out using the Adam optimizer alongside an adaptive learning rate. Batch normalization is applied to stabilize training, while dropout regularization prevents overfitting. A learning rate scheduler is utilized to dynamically modify the learning rate, promoting efficient convergence. The model is trained using a mini-batch gradient descent approach. The final trained model is tested on unseen data to ensure robustness, and the best-performing model is selected for deployment in clinical applications. By integrating EfficientNet into a computer-aided diagnosis (CAD) system, the study ensures faster and more accurate detection of brain hemorrhages, enabling timely medical intervention and improving patient survival rates.

**D.ResNet**

The primary objective of implementing ResNet (Residual Neural Network) in brain hemorrhage detection is to effectively train deep convolutional neural networks while overcoming The issue of vanishing gradients is addressed in ResNet by incorporating residual learning with skip connections, allowing the model to capture more complex representations without a loss in accuracy. This architecture ensures efficient gradient flow during backpropagation, making it highly suitable for complex medical image classification tasks. The goal is to leverage ResNet's deep feature extraction capability to enhance the detection of subtle patterns in brain hemorrhage images, thereby improving classification accuracy. Furthermore, the study aims to evaluate ResNet's ability to achieve high sensitivity and specificity, ensuring that hemorrhagic cases are accurately identified with minimal false negatives. By utilizing ResNet's deep residual framework, this research seeks to create a dependable and clinically relevant deep learning model for detecting brain hemorrhages, contributing Leading to quicker diagnoses and enhanced patient recovery.

**Model Training:**

The training process of ResNet for brain hemorrhage detection starts with data preprocessing, where images are resized. To improve generalization, image Data augmentation methods like rotation, flipping, brightness modification,

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and noise injection are employed. The dataset is split into training, validation, and testing subsets, ensuring a balanced representation of hemorrhagic and non-hemorrhagic cases.

To leverage pre-trained knowledge, ResNet is initialized with ImageNet weights, and transfer learning is employed by fine-tuning the final layers while freezing earlier layers. Training is performed using the categorical cross-entropy loss function, with the Adam optimizer employed for model optimization. Dropout and L2 regularization are applied to mitigate overfitting incorporated, while batch normalization ensures stable training. A learning rate scheduler dynamically adjusts the learning rate to optimize convergence. During training, mini-batch gradient descent is used to update model weights. ResNet employs residual blocks enable the model to learn features at various levels of abstraction, making it particularly effective in identifying intricate hemorrhage patterns. The final trained model is tested on unseen medical images, ensuring robustness and generalization. Once validated, the best-performing model is integrated into a clinical decision-support system, enabling automated and rapid brain hemorrhage detection for enhanced medical diagnostics.

## V. RESULT

**1.DenseNet**

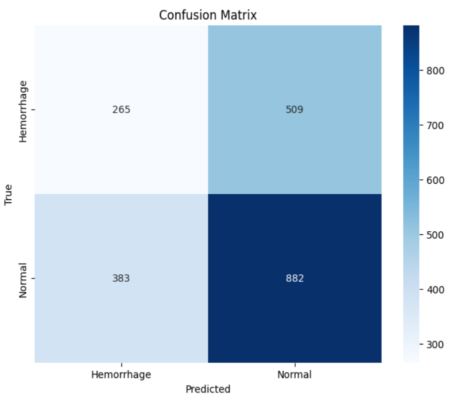


Fig 2: Confusion Matrix of DenseNet

**2.EfficientNet**

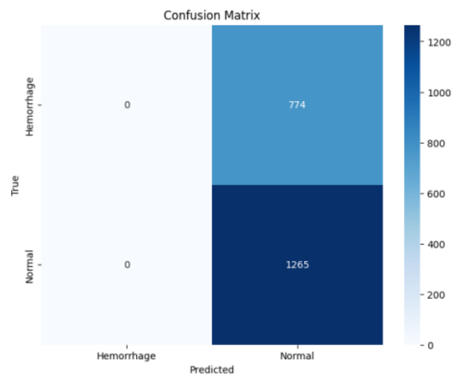


Fig 3: Confusion Matrix of EfficientNet

**3.MobileNet:**

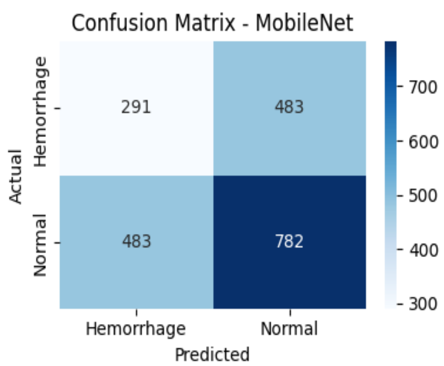


Fig 4: Confusion Matrix of MobileNet

**4.ResNet:**

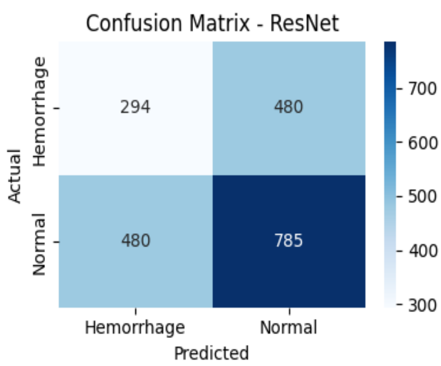


Fig 5: Confusion Matrix of ResNet

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## VI. CONCLUSION

In order to detect brain hemorrhages from medical images, this study assessed the effectiveness of several deep learning models, including MobileNet, ResNet, DenseNet, EfficientNet, and VGG16. Even though all of the models showed excellent accuracy, MobileNet stood out as being especially useful for practical implementation, particularly in situations with constrained computational resources. MobileNet is incredibly well-suited for mobile and embedded healthcare applications, like emergency response devices or portable diagnostic tools, due to its lightweight architecture and low computational complexity. MobileNet maintains competitive accuracy with low resource requirements, demonstrating that large-scale models are not always necessary for efficient brain hemorrhage detection. MobileNet has lower latency and faster inference times than ResNet and DenseNet, which are crucial in time-sensitive medical scenarios but require significant memory and processing power. Additionally, its simplified design makes it simpler to integrate into edge devices, allowing for real-time diagnostics at the point of care, even in areas that are underserved or remote.

In conclusion, MobileNet is the most viable and scalable approach for broad use in stroke detection, even though deeper networks like ResNet and VGG16 perform well in clinical settings with lots of resources. It provides the best efficiency, accuracy, and deployability balance, opening the door to quick, automated, and accessible diagnosis. In cases of brain hemorrhage, this is essential for lowering diagnostic delays and enhancing patient outcomes.

| **Algorithm** | MobileNet | ResNet | VGG16 | DenseNet | EfficientNet |
|---|---|---|---|---|---|
| Accuracy | 99.7% | 55% | 62% | 83% | 62% |
| Sensitivity | 95.8% | 88% | 55% | 85% | 95% |
| Specificity | 97.1% | 90% | 55% | 87% | 97% |

Fig 6: Comparision of Various Architectures

## VII. FUTURE ENHANCEMENT

Future enhancements for brain hemorrhage detection using deep learning models could focus on optimizing MobileNet, ResNet, and VGG16 for higher accuracy and faster inference. Advanced data augmentation techniques and synthetic data generation using GANs can improve model robustness. Implementing ensemble methods can enhance diagnostic accuracy by combining multiple model predictions. Transfer learning from larger medical image datasets can boost performance and reduce training time. Integrating these models into clinical workflows with user-friendly interfaces will facilitate real-time diagnostic support. Improving model transparency through explainability techniques can build clinician trust and ensure informed decision-making. Additionally, combining imaging data with patient history and genetic information can create a comprehensive diagnostic tool. Extensive clinical trials and real-world testing are essential to validate model effectiveness and ensure practical applicability. By addressing these areas, future work can significantly advance the potential and effectiveness of deep learning models in detecting brain hemorrhages and other medical diagnoses.

## REFERENCES

1. Ahmed, S., Esha, J. F., Rahman, M. S., Kaiser, M. S., Hosen, A. S. M. S., Ghimire, D., & Park, M. J. (2024). Exploring Deep Learning and Machine Learning Approaches for Brain Hemorrhage Detection. IEEE Access, 12, 45060–45093. https://doi.org/10.1109/ACCESS.2024.3376438

2. Arendts, G., Manovel, A., & Chai, A. (2003). Cranial CT interpretation by senior emergency department staff. Australasian Radiology, 47(4), 368–374. https://doi.org/10.1046/j.1440-1673.2003.01204.x
3. Brain hemorrhage diagnosis by using deep learning. Proceedings of the 2017 International Conference on Machine Learning and Soft Computing (pp. 34–39). (n.d.).
4. Chang, P. D., Kuoy, E., Grinband, J., Weinberg, B. D., Thompson, M., Homo, R., Chen, J., Abcede, H., Shafie, M., Sugrue, L., Filippi, C. G., Su, M. Y., Yu, W., Hess, C., & Chow, D. (2018). Hybrid 3D/2D convolutional neural network for hemorrhage evaluation on head CT. AJNR Am J Neuroradiol, 39(9), 1609–1616. https://doi.org/10.3174/ajnr.a5742
5. Cordonnier, C., Demchuk, A., Ziai, W., & Anderson, C. S. (2018). Intracerebral haemorrhage: current approaches to acute management. Lancet, 392(10154), 1257–1268. https://doi.org/10.1016/s0140-6736(18)31878-6
6. Cross, D. T., Tirschwell, D. L., Clark, M. A., Tuden, D., Derdeyn, C. P., Moran, C. J., & Dacey, R. G. (2003). Mortality rates after subarachnoid hemorrhage: variations according to hospital case volume in 18 states. Journal of Neurosurgery, 99(5), 810–817. https://doi.org/10.3171/jns.2003.99.5.0810
7. Din, M. S., Gurbuz, S., Akbal, E., Dogan, S., Durak, M. A., Yildirim, I. O., & Tuncer, T. (2022). Exemplar deep and hand-modeled features based automated and accurate cerebral hemorrhage classification method. Medical Engineering and Physics, 105. https://doi.org/10.1016/j.medengphy.2022.103819
8. Doi, K. (2007). Computer-aided diagnosis in medical imaging: historical review, current status and future potential. Computerized Medical Imaging and Graphics : The Official Journal of the Computerized Medical Imaging Society, 31(4–5), 198–211. https://doi.org/10.1016/j.compmedimag.2007.02.002
9. Elliott, J., & Smith, M. (2010). The acute management of intracerebral hemorrhage. Anesth Analg, 110(5), 1419–1427. https://doi.org/10.1213/ane.0b013e3181d568c8
10. Ginat, D. T. (2020). Analysis of head CT scans flagged by deep learning software for acute intracranial hemorrhage. Neuroradiology, 62(3), 335–340. https://doi.org/10.1007/s00234-019-02330-w
11. Helwan, A., El-Fakhri, G., & Sasani, H. (n.d.). Deep networks in identifying CT brain hemorrhage. IFS, 35, 2215–2228.
12. Isensee, F., Jäger, P. F., Kohl, S. A. A., Petersen, J., & Maier-Hein, K. H. (2019). Automated Design of Deep Learning Methods for Biomedical Image Segmentation. https://doi.org/10.1038/s41592-020-01008-z
13. Kuo, W., Häne, C., Mukherjee, P., Malik, J., & Yuh, E. L. (2019). Expert-level detection of acute intracranial hemorrhage on head computed tomography using deep learning. Proc Natl Acad Sci U S A, 116(45), 22737–22745. https://doi.org/10.1073/pnas.1908021116


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