Cureus Journal of Computer Science
https://doi.org/10.7759/s44389-026-00211-x

Original Article

Deep Learning Approaches for Brain Hemorrhage Classification: A Comparative Evaluation

Nagaraja Perumal [1,✉], Nithya A [2], Lakshmanan S [3]

1. Computer Science, GITAM Deemed to be University, Bangalore, IND
2. Computer Science, Government Arts and Science College, Dindigul, IND
3. Computer Applications, Hindustan Institute of Technology and Science, Chennai, IND

Received: April 29, 2026 | Review began: June 05, 2026 | Review ended: August 05, 2026 | Published: August 07, 2026

Abstract

The serious medical illness linked to blood vessel rupture, intracranial hemorrhage, requires immediate attention for the best results. The classification performance of computed tomography scan bleeding detection is the main objective of this investigation. Brain hemorrhage is the term for this condition. In this life-threatening medical emergency requiring skilled medical personnel, it is crucial to promptly identify the site of bleeding before administering treatment. This study proposes the use of deep learning models, including Convolutional Neural Networks (CNNs), namely ResNetV2, DenseNet, MobileNet, VGG16, and EfficientNet architectures, for brain hemorrhage classification. The accuracy and computational capacity of the popular CNN models are increased using a dataset of 200 head computed tomography scans with an augmentation technique. The efficacy of the CNN models is investigated in this study by analyzing popular optimizers, including Adam, NAdam, AdamW, LAMB, and Lion. The precision, recall, F1-score, specificity, accuracy, and loss of the training and testing sets for the specified model are used to evaluate the performance of the given CNN models. This comparative analysis indicates that the MobileNet model with the AdamW optimizer provides the best performance among the CNN models, achieving training and testing accuracies of 99% and 98%, respectively. It also demonstrates strong performance across a wide range of evaluation metrics. The comparative investigation contributes to the early detection and treatment of serious medical disorders associated with intracranial hemorrhage by adding to the expanding corpus of knowledge in medical image analysis.

Categories: Health Informatics, Image Processing and Analysis, Deep Learning

Keywords: brain hemorrhage, classification, deep learning, cnn, image augmentation

Introduction

The brain is a vital organ in the human body, which is mainly responsible for cognitive functions, physical and mental coordination, as well as the intelligence quotient of a human being. Modern lifestyles, occupational stress, and health conditions such as hypertension and diabetes have a significant impact on an individual's overall health, as reported in medical research. Intracranial hemorrhage (ICH) is a condition that is one of the significant causes of death. While most brain ICHs result from head injuries, certain activities and lifestyle choices can significantly increase the risk. These include excessive alcohol consumption, high blood pressure, long-term cigarette smoking, the use of illicit drugs (such as cocaine), and intense physical exertion. Additionally, patients undergoing treatment with blood thinners are particularly vulnerable to developing ICH [1,2].

The American Heart Association and the American Stroke Association state that since ICH can worsen in affected individuals during the first few hours of onset, early and prompt identification is essential [3]. Non-contrast computed tomography (CT) scans are the preferred imaging technique for hemorrhage investigations because of their speed and convenience of use. This imaging modality demonstrates good sensitivity and specificity in the detection of acute bleeding [4,5].

The application of Artificial Intelligence (AI) using Machine Learning (ML), Deep Learning (DL), Convolutional Neural Networks (CNNs), Deep CNNs, transfer learning models, etc., has yielded highly promising results [6]. Moreover, incorporating such models in automatic diagnosis using a BICH system is expected to open newer dimensions. Deep neural networks (DNNs) have proved their potential in medical diagnosis using pattern recognition. The availability of enormous public medical data and image datasets facilitates researchers in developing novel AI-based diagnostic models with the highest accuracy rates [7-9].

In recent years, a number of CNN models have explored the classification of ICH from CT scans [10-12]. Chilamkurthy et al. [13] developed and validated DL algorithms to detect precarious findings in non-contrast brain CT scans, such as ICH, calvarial fractures, midline shift, and mass effect. Using a large dataset of 313,318 scans, the model showed high accuracy and potential to enhance radiologic interpretation. The system achieved strong performance levels, with area under the curve (AUC) values ranging from 0.8583 to 0.9731 across various findings in the Qure25k and CQ500 datasets.

Khan et al. [14] developed a comparative analysis of popular DL techniques for 3D visualization of ICH detection using CT scans. The study evaluated 11 popular segmentation CNN models, namely U-Net, U-Net++, and feature pyramid network architectures, using Dice similarity coefficient and intersection over union as evaluation metrics. The developed DenseNet201_U-Net models achieved the highest scores, with an 85.757% Dice similarity coefficient and 84.3% intersection over union. Leveraging this top-performing model, accurate 3D models of ICH and the brain can be generated from CT images, facilitating improved visualization of brain bleeding.

Wang et al. [15] introduced a semi-supervised technique with a multi-task attention-based U-Net for segmenting ICH from CT images and attained a Dice coefficient of 0.67 with 80% labeled data, outperforming a supervised model (0.61) and an out-of-the-box U-Net. These proposed methods have some limitations. Limited labeled medical images affect model accuracy and indicate the need for improved techniques in ICH detection.

Wang et al. [16] implemented a two-sequence model that simulates the radiologists' interpretation process by combining a 2D CNN model to accurately detect ICH and classify its subtypes. This proposed method demonstrated that the average AUC score for all types of ICH was 98.8% for the RSANA dataset, 96.8% for the PhysioNet-ICH dataset, and 95.8% for the CQ500 dataset.

Nizarudeen and Shunmugavel [17] developed advanced transfer learning approaches to analyze CT scans for acute hemorrhage, which is characterized by hyper-dense signal intensity. Their DL-based methodology demonstrated the ability to accurately detect and grade hemorrhages. The proposed approach incorporated pretrained models, including Inception, EfficientNetB0, and a novel architecture named ConceptionNet. The models were trained on 2,848 CT images. The classification accuracies achieved by EfficientNetB0, InceptionV3, and ConceptionNet were 0.96, 0.95, and 0.96, respectively.

Agrawal et al. [18] implemented a 3D CNN model for the automated detection of ICH in head CT scans of traumatic brain injury patients, using data from the All India Institute of Medical Sciences, New Delhi, and the hospital's PACS server. This method, containing three different CNN models, was developed and analyzed using ICH CT scans. The 3D CNN model achieved a sensitivity of 90%, specificity of 70%, and accuracy of 80% in its evaluation.

Anand and Shourie [19] proposed a CNN-based model for the automatic detection and classification of hemorrhages in CT scans. The architecture includes three convolutional blocks, each comprising three convolutional layers, four Rectified Linear Unit (ReLU) activation functions, one Sigmoid activation function, three max-pooling layers, a flatten layer, and a dropout layer. This model achieved an accuracy of 96.8%, which enhances diagnostic speed and reduces radiologists' workload while addressing healthcare access issues.

Kar et al. [20] implemented an innovative approach to automatically detect ICH based on advanced DL algorithms. The method being examined efficiently extracts and localizes information from CT brain data by utilizing attention processes connected to CNNs. Training and evaluating the model showed an impressive accuracy value of 99.76%. Through the incorporation of attention strategies into the CNN framework, the interpretability of the model can be enhanced, allowing for the identification of the most relevant regions for ICH detection.

This study comparatively analyzed five popular pretrained models, namely ResNetV2, DenseNet, MobileNet, VGG16, and EfficientNet. To demonstrate superiority over other CNN models, the suggested model performs a number of optimizers, which are also used in the comparative performance analysis with these CNN learning models. The following are some of the study's main conclusions:

1. Popular CNN models (ResNetV2, DenseNet, MobileNet, VGG16, and EfficientNet) were comparatively analyzed for classifying hemorrhage and non-hemorrhage images.

2. Various types of optimizers (Adam, NAdam, AdamW, LAMB, and Lion) were used in these CNN models for detecting and obtaining efficient results.

3. An extensive evaluation was performed to validate all CNN models and identify the best CNN model with an optimizer that provides admirable performance in classification tasks and better accuracy.

Materials And Methods

Dataset

The simplest and most effective method for diagnosing internal bleeding, traumatic injuries, and vein disruptions that result in strokes or death is a CT scan. The collection contains 200 CT scan images, evenly divided between brain hemorrhage (100 images) and non-hemorrhage (100 images) cases [21]. This small dataset has certain advantages, such as speeding up the CNN model's training process and lowering the likelihood of overfitting; however, it also lowers the accuracy rate, which is a challenging aspect. Data augmentation techniques are applied to enhance the accuracy rate and prevent overfitting. The sample images of the dataset utilized for this study are displayed in Figure *1*.

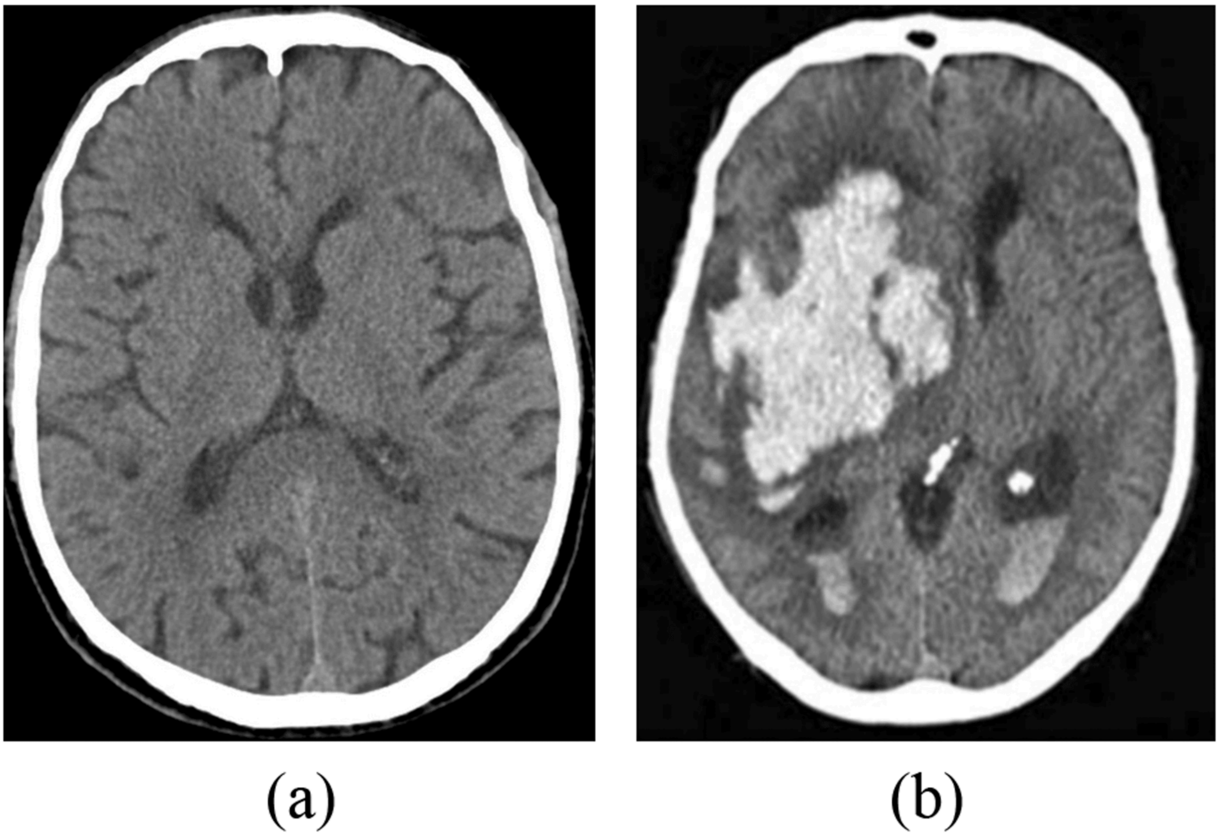

FIGURE 1: Sample brain images: (a) non-hemorrhage and (b) hemorrhage.

CNN models

ResNet50V2

Derived from ResNet50, a larger architecture known as ResNet50V2 was later enhanced to outperform prior iterations of architectures such as ResNet101. ResNet is a contemporary CNN that solves the vanishing gradient problem by utilizing residual design blocks. In a residual network, several residual blocks are stacked on top of each other. Connections that take shortcuts by omitting one or more layers make up each residual block. ResNet50V2 uses the pre-activation of weight layers. ResNet50V2 generates accurate predictions on the datasets [9].

DenseNet201

In addition to its own feature maps, every layer in DenseNet receives additional inputs from every layer that came before it. The network has fewer channels because all previous layers' feature maps are obtained; each layer consists of a 3 × 3 convolution, batch normalization, ReLU, and the growth rate k as an additional number of channels. Comprising 201 layers, DenseNet201 enables the extraction of complex and discriminative representations. The dense feature-sharing mechanism enhances gradient flow, alleviates vanishing gradient problems, and improves parameter efficiency over traditional deep architectures, resulting in superior performance in image classification and medical imaging tasks that demand precise feature learning [9].

MobileNet

A lightweight CNN architecture called MobileNet was created for embedded and mobile devices. Using depth-wise separable convolutions, which divide conventional convolutions into depth-wise and point-wise operations, it minimizes processing requirements and model size. Because of this, MobileNet can perform tasks such as object detection, image classification, and face recognition quickly and accurately [9].

VGG16

Even though it was created in 2014, the CNN architecture VGG16 is still regarded as one of the top designs for image categorization. The VGG16 network has 16 layers, including 13 convolutional layers with 3×3 filters and 2×2 max-pooling layers stacked on top of each other. Applying the activation function between these layers, there are three fully connected layers that make up the majority of the network's properties to determine the probability for each classification of pulmonary symptoms; a softmax function is then applied. The VGG16 model is a successful application of CNNs as the fundamental network in image recognition systems. It has an easy-to-modify network structure that is specific.

EfficientNetB7

EfficientNetB7 is a high-performance CNN designed to achieve excellent accuracy with efficient use of parameters and computation. It belongs to the EfficientNet family, which uses a compound scaling method to uniformly scale network depth, width, and input resolution for better performance. EfficientNet-B7 is the largest and most accurate variant in the series, built on MBConv (Mobile Inverted Bottleneck) blocks with squeeze-and-excitation attention. It is well suited for high-accuracy tasks such as medical image analysis, fine-grained classification, and computer vision research [9].

Types of optimizers

Optimizers are essential components in training ML models, as they help reduce the loss function during the learning process. Each optimizer has its unique characteristics, making them more suitable for certain types of models or data, whereas others are more adaptable and can be used in a variety of situations. Some of the basic optimizers used in the suggested method's analysis are described below:

• Adam: An adaptive optimizer that combines momentum and RMSProp, adjusting learning rates per parameter for fast and stable convergence.

• NAdam: Adam with Nesterov momentum, providing a look-ahead gradient that can improve convergence speed and stability.

• AdamW: A variant of Adam with decoupled weight decay, leading to better regularization and improved generalization.

• LAMB: Layer-wise Adaptive Moments optimizer designed for large-batch training, scaling updates per layer to maintain stable training.

• Lion: A memory-efficient optimizer that uses only sign-based momentum updates, offering fast convergence with lower computational and memory costs.

Methodology

In a neural network, the connections between neurons and synapses create a mathematical representation to emulate the human brain. Essentially, DL utilizes CNN layers to train the model. A comparative analysis of five distinct CNN models for differentiating between hemorrhage and non-hemorrhage CT scan images was performed. This study compares the performance of five popular models, including ResNetV2, DenseNet, MobileNet, VGG16, and EfficientNet, and is developed through the following steps. Figure *2* provides the framework of this comparative analysis.

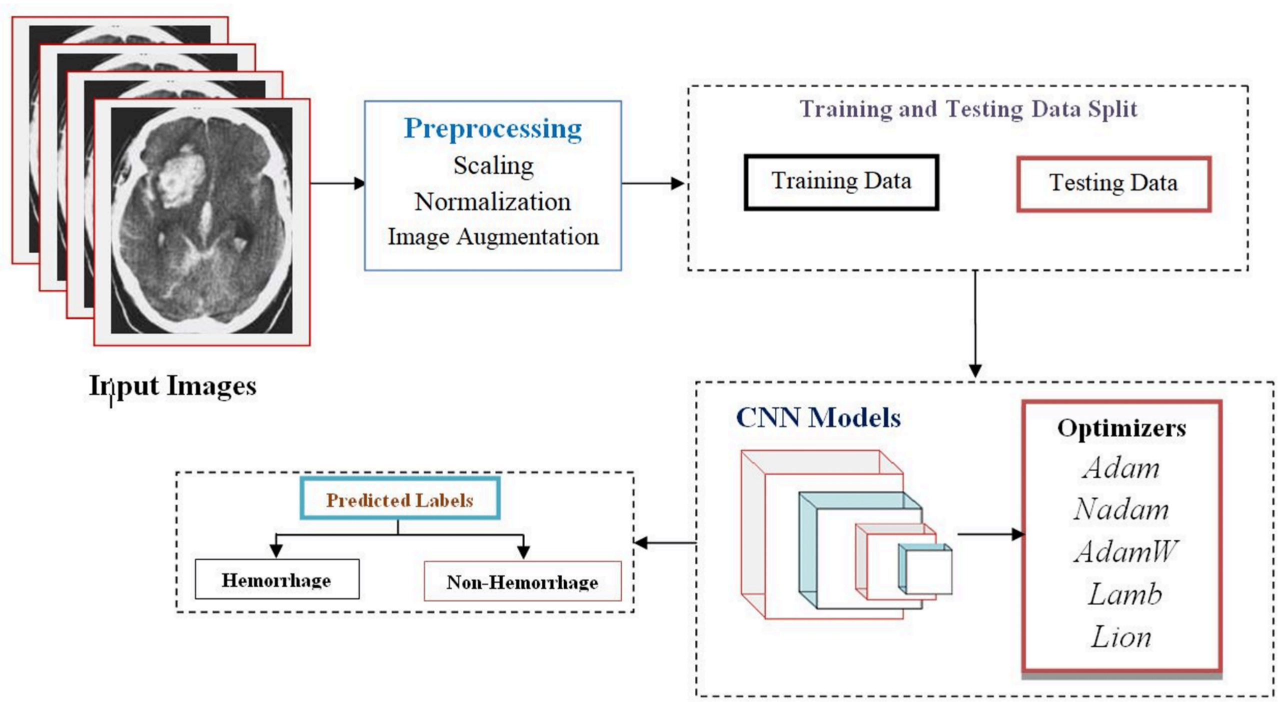

FIGURE 2: Framework of the methodology.

CNN, Convolutional Neural Network

Phase I: Data Preprocessing

The data must then be preprocessed. To do this, the images must be scaled down to a specific size, the pixel values must be normalized, and the dataset must be divided into training and testing sets. Twenty percent of the data was chosen for testing, while 80% of the data was chosen for training. There are 1,200 images in total, 600 of which show hemorrhage and 600 of which show non-brain hemorrhage. The 960 images utilized for training consisted of 480 randomly chosen images from hemorrhage and 480 randomly selected images from non-brain hemorrhage. The remaining 240 images, consisting of 120 images from hemorrhage and 120 images from non-brain hemorrhage, were used for testing. Detailed information of the dataset is presented in Table 1.

Class	Dataset	After Augmentation	Image Augmentation	
			Train	Test
Hemorrhage	100	600	480	120
Non-Hemorrhage	100	600	480	120

TABLE 1: Detailed information of the dataset.

Then, to improve the CNN model’s learning, image augmentation was applied to both the testing and training sets. To treat every image equally, the image dataset's pixel values were rescaled from the range of (0, 255) to (0, 1). The image augmentation technique improves the provided limited dataset for the training process by applying rescaling, zooming at a range of 0.2, rotation at a range of 30, width shift range = 0.2, height shift range = 0.2, and horizontal flipping.

Phase II: Train the Five Different Types of CNN Models

Brain hemorrhage datasets with a global average pooling layer were used to train the five different model types (ResNetV2, DenseNet, MobileNet, VGG16, and EfficientNet). An activation function is a powerhouse of a neural network used in an AI model. Two activation functions - Softmax in the fully connected layers and ReLU in the convolutional layer - were investigated in this study. To regularize the network, dropout (0.5) was employed before the fully connected layer to remove irrelevant nodes. The developed model was compiled using Adam, NAdam, AdamW, LAMB, and Lion optimizers.

Phase III: Test and Predict Hemorrhage or Non-Hemorrhage Images

Once the CNN models were successfully trained, they were evaluated using a separate test dataset to classify images as either hemorrhage or non-hemorrhage. This testing phase was conducted to assess the generalization capability and predictive performance of each model. The evaluation results indicate that, among the five implemented models, MobileNet achieved the highest prediction accuracy on the given dataset, demonstrating superior performance compared to the other models in terms of reliable and efficient classification.

Phase IV: Performance Analysis

The experimental outcomes of the five models were analyzed and contrasted using conventional performance parameters, such as accuracy and loss.

The following measuring parameters are used for the performance analysis:

$$\mathrm{Accuracy} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}} \times 100 \tag{1}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{2}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{3}$$

$$\text{F1-Score} = 2 \times \frac{(\mathrm{Precision} \times \mathrm{Recall})}{(\mathrm{Precision} + \mathrm{Recall})} \tag{4}$$

$$\mathrm{Specificity} = \frac{\mathrm{TN}}{\mathrm{FP}+\mathrm{TN}} \tag{5}$$

where TP is true positive, TN is true negative, FN is false negative, and FP is false positive.

Results And Discussion

The models were run on a Lenovo system with 8 GB of RAM using Google Colaboratory (Colab). The hyperparameters appropriate for hemorrhage and non-hemorrhage identification in brain hemorrhage images were also used to test the model's effectiveness. Table *2* provides the hyperparameter values.

Hyperparameter	Value
Epoch	50
Batch Size	16
Dropout Value	0.5
Learning Rate	0.0001
Optimizers	Adam, NAdam, AdamW, LAMB, and Lion
Pooling	Global Average Pooling
Loss Function	Categorical cross-entropy

TABLE 2: Hyperparameter values used in the proposed work.

The performance of five DL architectures, namely DenseNet, EfficientNet, VGG16, ResNetV2, and MobileNet, was evaluated using different optimizers, with accuracy and loss as the primary metrics. The output from each of the five models for the brain hemorrhage dataset is shown in Table *3*. Early stopping was applied selectively to prevent overfitting, while some configurations were trained for the full 50 epochs. For DenseNet, the best performance was achieved using the Lion optimizer with early stopping at epoch 25, yielding training and testing accuracies of 0.9797 and 0.9653, respectively. The DenseNet model, optimized using the Lion optimizer and trained with early stopping, achieved good performance.

Model	**Optimizer**	**Early Stopping Epoch**	**Training**		**Testing**	
			Accuracy	Loss	Accuracy	Loss
DenseNet	AdamW	Early stopping 5	0.9820	0.0702	0.9379	0.1670
	Adam	Early stopping 26	0.9571	0.1266	0.9527	0.1537
	NAdam	Early stopping 8	0.9739	0.0908	0.9527	0.1533
	Lion	Early stopping 25	0.9797	0.0636	0.9653	0.1252
	LAMB	No early stopping	0.9251	0.2258	0.9320	0.2186
EfficientNet	AdamW	Early stopping 16	0.7775	0.5276	0.8423	0.3934
	Adam	Early stopping 5	0.7616	0.5200	0.8373	0.4325
	NAdam	Early stopping 22	0.8009	0.4393	0.9072	0.3094
	Lion	Early stopping 16	0.8254	0.3844	0.9320	0.2869
	LAMB	No early stopping	0.7425	0.5285	0.8239	0.4109
VGG16	AdamW	No early stopping	0.6765	0.3453	0.6963	0.4683
	Adam	No early stopping	0.6511	0.4234	0.7086	0.4601
	NAdam	Early stopping 21	0.7103	0.6571	0.8011	0.4532
	Lion	No early stopping	0.9321	0.1858	0.9068	0.2201
	LAMB	No early stopping	0.7622	0.5525	0.8151	0.5150
ResNetV2	AdamW	Early stopping 19	0.9658	0.1005	0.9527	0.1447

	Adam	Early stopping 7	0.9803	0.0746	0.9527	0.1306
	NAdam	Early stopping 17	0.9861	0.0550	0.9615	0.0952
	Lion	Early stopping 5	0.9507	0.1368	0.9527	0.1682
	LAMB	Early stopping 6	0.6415	0.6696	0.7692	0.5625
MobileNet	**AdamW**	**Early stopping 22**	**0.9901**	**0.0384**	**0.9813**	**0.0710**
	Adam	Early stopping 27	0.9762	0.0818	0.9749	0.0908
	NAdam	Early stopping 5	0.9889	0.0397	0.9734	0.0815
	Lion	Early stopping 5	0.9897	0.0925	0.9691	0.0928
	LAMB	No early stopping	0.9437	0.1660	0.9586	0.1492

TABLE 3: Accuracy and loss values of training and testing for CNN models.

CNN, Convolutional Neural Network

In the case of EfficientNet, the overall performance was comparatively lower than that of the other models. The highest accuracy values for both the training and testing sets were 0.8254 and 0.9320, respectively, and were obtained using Lion with early stopping at epoch 16, while LAMB showed the weakest performance with training and testing accuracies of 0.7425 and 0.8239, respectively. In VGG16, the Lion optimizer produced the best training and testing accuracy values of 0.9321 and 0.9068, respectively. LAMB and NAdam also performed well; however, Lion's accuracy noticeably decreased without early stopping. ResNetV2 routinely outperformed the majority of optimizers. With training and testing accuracies of 0.9861 and 0.9615, respectively, the NAdam optimizer with early stopping at epoch 17 produced the best result. Adam's accuracy significantly declined without early stopping, although Adam had good performance. MobileNet had the best overall performance among all the models. The model obtained training and testing accuracies of 0.9901 and 0.9813, respectively, using AdamW with early stopping at epoch 22. Strong robustness was demonstrated by the fact that all MobileNet optimizers generated efficient accuracy values for the brain hemorrhage dataset.

The findings show that optimizer choice and model architecture both significantly affect performance. In this experimental environment, lightweight and residual-based architectures like MobileNet and ResNetV2 consistently performed better than deeper or more sophisticated models like EfficientNet and VGG16. A key element in obtaining the best results was early stopping. Early stopping models typically achieved lower loss and higher accuracy in fewer epochs, indicating better generalization and less overfitting. Early stopping produced significant benefits over non-stopping configurations in DenseNet and ResNetV2, where this effect was most noticeable. When paired with early stopping, Lion, NAdam, and LAMB outperformed traditional Adam and AdamW among the optimizers. Lion outperformed DenseNet, while NAdam showed remarkable efficacy with ResNetV2. However, as demonstrated by ResNetV2, Adam without early stopping produced worse accuracy, underscoring the significance of training control methods.

Table *4* presents the performance comparison of the DenseNet, EfficientNet, VGG16, ResNetV2, and MobileNet models trained using five different optimization algorithms, namely AdamW, Adam, NAdam, Lion, and LAMB. The model performance is evaluated using AUC score, precision, recall (sensitivity), F1-score, and specificity.

Model	Optimizer	AUC Score	Precision	Recall/Sensitivity	F1-Score	Specificity
DenseNet	AdamW	0.9856	0.9347	0.9676	0.9509	0.8315
	Adam	0.9874	0.9484	0.9735	0.9608	0.9464
	NAdam	0.9863	0.9370	0.9618	0.9492	0.9345
	Lion	0.9784	0.9370	0.9618	0.9495	0.9322
	LAMB	0.9774	0.9200	0.9471	0.9333	0.9167
EfficientNet	AdamW	0.9543	0.9234	0.9245	0.9167	0.8379
	Adam	0.9438	0.9719	0.7118	0.9293	0.9792
	NAdam	0.9579	0.9104	0.8971	0.9037	0.9107
	Lion	0.9621	0.9669	0.8588	0.9095	0.9702
	LAMB	0.9542	0.9410	0.7971	0.8631	0.9494
VGG16	AdamW	0.8147	0.5757	0.9735	0.7235	0.2738
	Adam	0.8647	0.6559	0.9588	0.7790	0.4911
	NAdam	0.8936	0.7952	0.7765	0.7857	0.7976
	Lion	0.9723	0.9041	0.9147	0.9094	0.9018
	LAMB	0.9185	0.8474	0.8021	0.8230	0.8542
ResNetV2	AdamW	0.9879	0.9375	0.9706	0.9538	0.9345
	Adam	0.9884	0.9397	0.9618	0.9506	0.9375
	NAdam	0.9897	0.9432	0.9765	0.9595	0.9405
	Lion	0.9883	0.9339	0.9559	0.9448	0.9315
	LAMB	0.8238	0.7147	0.8029	0.7562	0.6756
MobileNet	**AdamW**	**0.9982**	**0.9796**	**0.9882**	**0.9839**	**0.9792**
	Adam	0.9962	0.9589	0.9618	0.9604	0.9583
	NAdam	0.9972	0.9545	0.9882	0.9711	0.9524

	Lion	0.9976	0.9415	0.9941	0.9671	0.9375
	LAMB	0.9923	0.9377	0.9735	0.9553	0.9345

TABLE 4: AUC score, precision, recall (sensitivity), F1-score, and specificity values of CNN models.

AUC, Area Under the Curve; CNN, Convolutional Neural Network

Among all the optimizers, MobileNet with the AdamW optimizer achieved the best overall performance, recording the highest AUC score of 0.9982, indicating its superior capability to distinguish between the two classes. AdamW also obtained the highest precision of 0.9796, F1-score of 0.9839, and specificity of 0.9792, demonstrating its effectiveness in minimizing both false-positive and false-negative classifications while maintaining balanced predictive performance.

The relatively poor performance of EfficientNet across all optimizers suggests that this architecture may be less suited to the dataset or training configuration used in this study. In contrast, MobileNet demonstrated excellent performance across all optimizers, indicating strong adaptability and efficiency. Overall, the findings suggest that MobileNet with AdamW is the most effective combination for achieving high accuracy and low loss. These results emphasize the importance of careful optimizer selection and the use of early stopping to maximize model performance.

The utilization of larger and more varied datasets with an ablation study is the viewpoint for further research work. The generalizability and robustness of the model will be enhanced by expanding the size and diversity of the dataset. This also helps to minimize overfitting, which can occur when a model is trained on a small dataset and then performs poorly on new data.

Conclusions

This paper comparatively analyzed popular CNN models to address the issue of hemorrhage detection and classification in CT scans. The behavior of CNN models employed for hemorrhage and non-hemorrhage detection and classification using DenseNet, EfficientNet, VGG16, ResNetV2, and MobileNet has been outlined in this comparative analysis. To find the best-fit model that produced good accuracy results for brain hemorrhage CT scans, these five pretrained models were investigated. The MobileNet model with the AdamW optimizer produced the highest accuracy value for the dataset. The goal of employing CNN was to improve medical professionals' ability to identify hemorrhages by increasing their decision-making accuracy and reducing diagnostic errors.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Nagaraja Perumal, Nithya A

Acquisition, analysis, or interpretation of data: Nagaraja Perumal, Nithya A, Lakshmanan S

Drafting of the manuscript: Nagaraja Perumal, Nithya A, Lakshmanan S

Critical review of the manuscript for important intellectual content: Nagaraja Perumal, Nithya A

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request.

References

1. Kuo W, Häne C, Mukherjee P, Malik J, Yuh EL: Expert-level detection of acute intracranial hemorrhage on head computed tomography using deep learning. Proceedings of the National Academy of Sciences of the United States of America. 2019, 116:22737-22745. 10.1073/pnas.1908021116
2. Chelghoum R, Ikhlef A, Hameurlaine A, Jacquir S: Transfer learning using convolutional neural network architectures for brain tumor classification from MRI images. Artificial Intelligence Applications and Innovations. Maglogiannis I, Iliadis L, Pimenidis E (ed): Springer, Cham; 2020. 583:189-200. 10.1007/978-3-030-49161-1_17
3. Unnithan AKA, Das JM: Hemorrhagic Stroke Overview. StatPearls Publishing, Treasure Island, FL; 2023.
4. Badenes R, Bilotta F: Neurocritical care for intracranial haemorrhage: a systematic review of recent studies. British Journal of Anaesthesia. 2015, 115:ii68-ii74. 10.1093/bja/aev379
5. Schmidhuber J: Deep learning in neural networks: An overview. Neural Networks. 2015, 61:85-117. 10.1016/j.neunet.2014.09.003
6. Nithya A, Pichai S, Perumal N: Ablation study-based optimized residual learning model for breast cancer classification. Innovations in Communication Networks: Sustainability for Societal and Industrial Impact. Bhateja V, Hameed AV, Udgata SK, Azar AT (ed): Springer, Singapore; 2025. 1365:453-465. 10.1007/978-981-96-5223-5_36
7. Nagaraja P, Sivakumar V, Shanmugavadivu P, Rani MMS, Nithya A: Transfer learning based VGG-16 model for detection of COVID-19 from chest X-ray images. AIP Conference Proceedings. 2024, 3161:020044. 10.1063/5.0229495
8. Nagaraja P, Lakshmanan S, Shanmugavadivu P, Rani MMS: Prenatal ultrasound diagnosis using deep learning approaches. Combating Women's Health Issues with Machine Learning. Hemanth D, Gupta M (ed): CRC Press, Boca Raton, FL; 2023. 96-106. 10.1201/9781003378556-6
9. Nithya A, Shanmugavadivu P: Deep convolutional neural network models for early detection of breast cancer from digital mammograms. Deep Learning for Smart Healthcare. Murugeswari K, Sundaravadivazhagan B, Poonkuntran S, Thendral P (ed): Auerbach Publications, New York; 2024. 244-258. 10.1201/9781003469605-14
10. Burduja M, Ionescu RT, Verga N: Accurate and efficient intracranial hemorrhage detection and subtype classification in 3D CT scans with convolutional and long short-term memory neural networks. Sensors. 2020, 20:5611. 10.3390/s20195611
11. Majumdar A, Brattain L, Telfer B, Farris C, Scalera J: Detecting intracranial hemorrhage with deep learning. 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, USA. 2018, 583-587. 10.1109/embc.2018.8512336
12. Cho J, Park KS, Karki M, et al.: Improving sensitivity on identification and delineation of intracranial hemorrhage lesion using cascaded deep learning models. Journal of Digital Imaging. 2019, 32:450-461. 10.1007/s10278-018-00172-1
13. Chilamkurthy S, Ghosh R, Tanamala S, et al.: Deep learning algorithms for detection of critical findings in head CT scans: a retrospective study. The Lancet. 2018, 392:2388-2396. 10.1016/S0140-6736(18)31645-3
14. Khan MM, Chowdhury MEH, Arefin ASMS, et al.: A deep learning-based automatic segmentation and 3D visualization technique for intracranial hemorrhage detection using computed tomography images. Diagnostics. 2023, 13:2537. 10.3390/diagnostics13152537

15. Wang JL, Farooq H, Zhuang H, Ibrahim AK: Segmentation of intracranial hemorrhage using semi-supervised multi-task attention-based U-Net. Applied Sciences. 2020, 10:3297. 10.3390/app10093297

16. Wang X, Shen T, Yang S, et al.: A deep learning algorithm for automatic detection and classification of acute intracranial hemorrhages in head CT scans. NeuroImage: Clinical. 2021, 32:102785. 10.1016/j.nicl.2021.102785

17. Nizarudeen S, Shunmugavel GR: Intracranial hemorrhage grading using Novel ConceptionNet. 2022 IEEE 19th India Council International Conference (INDICON), Kochi, India. 2022, 1-6. 10.1109/INDICON56171.2022.10040029

18. Agrawal D, Poonamallee L, Joshi S, Bahel V: Automated intracranial hemorrhage detection in traumatic brain injury using 3D CNN. Journal of Neurosciences in Rural Practice. 2023, 14:615-621. 10.25259/jnrp_172_2023

19. Anand V, Shourie P: Hemorrhage classification in head computed tomography images using convolution neural network model. 2023 3rd International Conference on Innovative Sustainable Computational Technologies (CISCT), Dehradun, India. 2023, 1-5. 10.1109/CISCT57197.2023.10351262

20. Kar NK, Jana S, Rahman A, Ashokrao PR, Indhumathi G, Alarmelu Mangai R: Automated intracranial hemorrhage detection using deep learning in medical image analysis. 2024 International Conference on Data Science and Network Security (ICDSNS), Tiptur, India. 2024, 1-6. 10.1109/ICDSNS62112.2024.10691276

21. Head CT - hemorrhage. (2026). Accessed: January 15, 2026: https://www.kaggle.com/felipekitamura/head-ct-hemorrhage.