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Full Length Article

Exploring Deep Learning and Machine Learning Approaches for Brain Hemorrhage Detection

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Abstract:
Brain hemorrhage is a critical medical condition that requires rapid and accurate diagnosis to minimize mortality and long-term neurological damage. Conventional diagnostic approaches rely on manual interpretation of CT scan images by radiologists, which can be time-consuming and may introduce variability due to human factors and limited availability of specialists. To address these challenges, this work presents a deep learning-based framework for automated brain hemorrhage detection from CT images. The proposed approach follows a structured pipeline that includes preprocessing, data augmentation, feature extraction, and classification. A custom Convolutional Neural Network (CNN) and a transfer learning-based InceptionV3 model are developed and evaluated on a dataset of 2,501 CT images. The dataset consists of two classes (normal and hemorrhage) and is divided using a stratified approach to ensure balanced training. Experimental results indicate that while the custom CNN achieves strong performance, the InceptionV3 model demonstrates superior accuracy, robustness, and generalization capability. The best-performing model is further deployed as a Flask-based web application, enabling real-time predictions from uploaded CT images. These findings highlight the effectiveness of deep learning techniques as reliable decision-support tools for early diagnosis in clinical environments

Keywords*—Brain hemorrhage detection, deep learning, convolutional neural network, InceptionV3, transfer learning, CT scan, medical image classification, computer-aided diagnosis.*

Introduction

Stroke represents a global health crisis, constituting the second leading cause of death worldwide with over 6.2 million deaths annually [1,4]. Among stroke types, hemorrhagic strokes, though accounting for approximately 13% of all cases, demonstrate disproportionately severe outcomes with substantially higher mortality and morbidity rates compared to ischemic strokes [2,7]. A cerebral hemorrhage occurs when a weakened blood vessel ruptures, causing blood to accumulate within brain tissue, leading to increased intracranial pressure, cerebral edema, and progressive neuronal destruction [1,2]. Prompt identification and intervention are critical determinants of clinical outcomes, with treatment effectiveness directly correlating to time elapsed between symptom onset and diagnosis [4,9].

Computed Tomography (CT) scanning serves as the primary imaging modality for diagnosing intracranial hemorrhage due to its speed, widespread accessibility, and high sensitivity to acute bleeding [3] However, interpreting CT images requires substantial radiological expertise to identify subtle density variations, differentiate hemorrhagic regions from normal anatomy, and classify hemorrhage subtypes—each with distinct clinical management implications [10]. Emergency departments, particularly in developing healthcare systems, face critical challenges due to radiologist shortages and high case volumes, introducing diagnostic delays that adversely affect patient outcomes [4,9]. Traditional manual analysis is inherently subject to inter-observer variability and human fatigue, especially during extended shifts in high-volume clinical settings [1,4].

Artificial Intelligence, particularly deep learning approaches using Convolutional Neural Networks (CNNs), has revolutionized medical image analysis by achieving and occasionally surpassing human-level diagnostic performance [5,11,12]. CNNs excel in medical imaging applications due to their intrinsic ability to automatically learn hierarchical spatial features from raw pixel data without explicit feature engineering [5,11] Transfer learning approaches, which adapt pretrained models to specialized domains, further enhance performance by leveraging feature representations learned from large-scale datasets [6]. This methodology is especially valuable in medical imaging where annotated datasets remain scarce and expensive [6,13].

In this work, a comparative analysis of a custom-designed CNN and a transfer learning-based InceptionV3 model is performed using a unified dataset of CT images [4,13]. The study evaluates both models under consistent experimental conditions and demonstrates their effectiveness in detecting brain hemorrhage [6]. Furthermore, the best-performing model is deployed as a web-based clinical decision-support system, highlighting its practical applicability in real-world healthcare settings [4]. This approach addresses key limitations in existing research, including the lack of direct architectural comparison and limited focus on deployment [4,6].

Related Work

A. Machine Learning for Stroke Risk Prediction

Several studies have explored machine learning techniques for stroke risk prediction using clinical data. Yang et al. [7] developed predictive models using electronic medical records of hypertensive patients, achieving high accuracy with Extreme Gradient Boosting. However, their work primarily focuses on structured medical data rather than imaging-based diagnosis. Similarly, Chun et al. [8] conducted a large-scale cohort study and demonstrated that ensemble learning models outperform traditional statistical approaches in predicting stroke risk. In contrast, Uchida et al. [9] proposed prehospital stroke triage models using machine learning algorithms, emphasizing rapid decision-making in emergency scenarios. While these approaches are effective for risk prediction, they do not address image-based hemorrhage detection. However, these approaches are limited to structured clinical data and cannot effectively handle image-based hemorrhage detection tasks.

B. Deep Learning for Image-Based Hemorrhage Detection

Recent advancements in deep learning have significantly improved medical image analysis, particularly for brain hemorrhage detection. Phong et al. [2] demonstrated the feasibility of using Convolutional Neural Networks (CNNs) to distinguish hemorrhage from normal brain CT scans, establishing a foundation for subsequent research. Building upon this, Castro et al. [3] investigated CNN-based detection techniques and highlighted the importance of preprocessing and model architecture in improving performance. Ahmed et al. [4] provided a comprehensive comparative study of machine learning and deep learning approaches, offering valuable benchmarks for evaluating different models. Furthermore, Agrawal et al. [1] presented a detailed review of automated hemorrhage detection techniques, discussing their strengths, limitations, and future research directions.

Additionally, Yeo et al. [12] focused on enhancing deep learning models through improved training strategies and data augmentation, demonstrating increased robustness in detection performance. Zhang et al. [13] extended this work by exploring segmentation-based approaches, enabling pixel-level identification of hemorrhagic regions.

C. Feature Engineering and Ensemble Approaches

Some studies have combined traditional feature engineering with machine learning techniques for hemorrhage detection. Alawad et al. [10] proposed the AIBH framework, which integrates preprocessing, Otsu's segmentation, genetic algorithm-based feature selection, and ensemble classification, achieving very high accuracy. However, such approaches require significant domain expertise and manual intervention in feature design. Similarly, Saritha et al. [11] utilized wavelet entropy-based feature extraction with probabilistic neural networks for MRI image classification, demonstrating that carefully engineered features can yield high performance. Nevertheless, these methods are less scalable compared to deep learning-based approaches. These methods require manual feature engineering, which limits scalability compared to automated deep learning approaches.

D. Research Gaps and Motivation

Despite substantial progress in both machine learning and deep learning, several limitations remain. Existing studies often focus either on traditional machine learning techniques with handcrafted features or on deep learning models independently, with limited direct comparison on a unified dataset [4] Moreover, many works do not emphasize real-world deployment, restricting their applicability in clinical environments . There is also a lack of detailed analysis of model limitations and failure cases, which is crucial for building trust among healthcare professionals.

To address these gaps, the present study performs a comparative evaluation of a custom CNN and a transfer learning-based InceptionV3 model on a common dataset and further demonstrates practical applicability by deploying the best-performing model as a web-based clinical decision-support system [4,6] Additionally, limited attention has been given to deploying these models in real-time clinical environments, which is addressed in this work.

Research Methodology

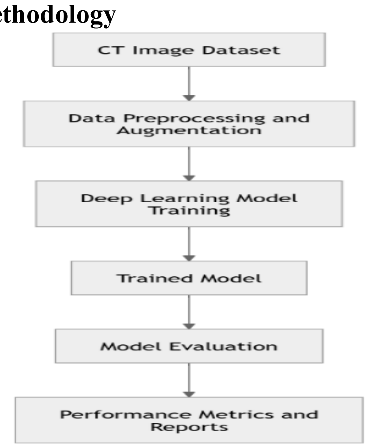

Fig 1: This figure illustrates the overall workflow of the proposed system from data input to prediction output

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A. System Architecture and Dataset

The proposed system follows a structured and modular pipeline consisting of data acquisition, preprocessing, model development, training, evaluation, and deployment stages. The dataset is collected from publicly available CT scan repositories, ensuring diversity in normal and hemorrhage cases. The dataset used in this study comprises 2,501 CT scan images categorized into two classes: Normal and Hemorrhage. A stratified data splitting approach is adopted to ensure balanced distribution across training, validation, and testing sets, thereby improving model reliability and generalization performance [2,4]

B. Data Preprocessing and Augmentation

All CT images are resized to 224 × 224 pixels to ensure compatibility with deep learning architectures and maintain uniform input dimensions. Pixel values are normalized to the range [0,1] to facilitate faster convergence during training.

To enhance model robustness and reduce overfitting, data augmentation techniques such as rotation, zooming, and horizontal flipping are applied to the training dataset.

C. Model Architectures

Two deep learning models are implemented and evaluated in this study. The first is a custom-designed three-layer Convolutional Neural Network (CNN), which includes convolutional layers, pooling layers, fully connected layers, and dropout for regularization. This model serves as a baseline for performance comparison. The custom CNN model consists of three convolutional layers with 32, 64, and 128 filters respectively, each followed by ReLU activation and max-pooling layers. A flatten layer is used before fully connected layers, followed by a dropout layer to reduce overfitting. The final output layer uses a sigmoid activation function for binary classification.

The second model is based on the InceptionV3 architecture, utilizing transfer learning. Pretrained weights from large-scale image datasets are leveraged to extract high-level features, while the final classification layers are fine-tuned for the specific task of brain hemorrhage detection. This approach significantly enhances feature representation and classification performance [6] The InceptionV3 model is initialized with pretrained ImageNet weights, and the top layers are replaced with custom dense layers for task-specific classification.

D. Training Configuration

Both models are trained for 50 epochs using the Adam optimizer with a batch size of 32 and binary cross-entropy loss function. To optimize the training process, several techniques are employed, including learning rate reduction, early stopping, and model checkpointing. These strategies help prevent overfitting, improve convergence speed, and ensure optimal model performance [5,6]

E. Evaluation Metrics

Model performance is evaluated using multiple metrics, including accuracy, precision, recall, F1-score, specificity, confusion matrix, and ROC-AUC score. Among these, sensitivity (recall) is particularly important in medical diagnosis, as it reflects the model's ability to correctly identify hemorrhage cases and minimize false negatives [7,8]

Result Analysis

A. Custom CNN Model Performance

Fig 2: Training and validation performance of the custom CNN model showing accuracy and loss trends across epochs.

The custom CNN model achieved stable convergence after approximately 35 epochs, demonstrating strong classification performance. It recorded a training accuracy of 98%, validation accuracy of 97%, and test accuracy of 98%, along with an AUC score of 0.987. The model also achieved a precision of 0.98 and recall of 0.97, indicating its effectiveness in distinguishing between normal and hemorrhage cases.

The accuracy curves show minimal divergence between training and validation performance, suggesting that the model generalizes well without significant overfitting. Additionally, the loss curves exhibit a consistent downward trend, reflecting steady optimization throughout the training process.

Confusion matrix analysis further reveals a sensitivity of 91.67% and specificity of 95.42%, with 20 false negatives and 11 false positives. While the model performs reliably, the relatively lower sensitivity indicates a small risk of missing hemorrhage cases, which remains a critical concern in clinical applications.

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B. InceptionV3 Model Performance

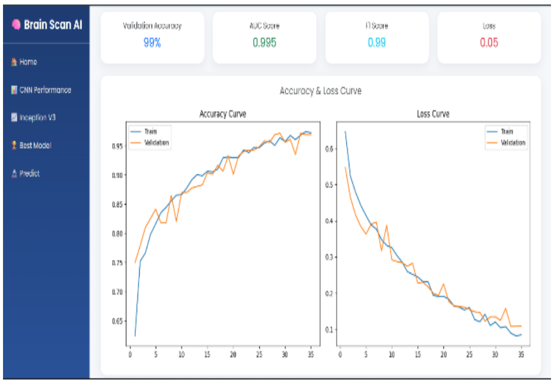

Fig 3: Performance analysis of the InceptionV3 model demonstrating improved accuracy, faster convergence, and enhanced generalization.

Notably, the InceptionV3 model demonstrated superior performance compared to the custom CNN across all evaluation metrics. It achieved a validation accuracy of 99%, an AUC score of 0.995, and an F1-score of 0.99, along with a low validation loss of 0.05. The model converged rapidly within the initial epochs and maintained stable performance throughout training.

The improved performance can be attributed to the use of transfer learning, which enables the model to leverage pretrained features for effective representation of complex patterns in CT images. As a result, the model exhibits strong generalization capability even with a moderately sized dataset.

Confusion matrix results indicate a sensitivity of 96.67% and specificity of 94.58%, with only 8 false negatives and 13 false positives. Importantly, the reduction in false negatives significantly improves the model's reliability in detecting hemorrhage cases, which is crucial for early diagnosis and treatment.

InceptionV3 outperformed the custom CNN across all evaluation metrics, including accuracy, AUC score, F1-score, and sensitivity. Its deeper architecture and multi-scale feature extraction capability enabled better identification of complex haemorrhagic patterns.

C. Comparative Analysis

Performance Metric	Custom CNN Model	InceptionV3 Model
Model Type	Three-layer Convolutional Neural Network	Transfer Learning with Pretrained InceptionV3
Training Accuracy	98%	99%
Validation Accuracy	97%	99%
Test Accuracy	98%	99%
AUC Score	0.987	0.995
Precision	0.98	0.99
Recall (Sensitivity)	91.67%	96.67%
F1-Score	0.97	0.99
Specificity	95.42%	94.58%
False Negatives	20	8
False Positives	11	13
Convergence Speed	Moderate (≈35 epochs)	Fast (≈10 epochs)
Computational Requirement	Low	High
Memory Requirement	Low	High
Clinical Suitability	Moderate	High
Overall Performance	Strong Baseline	Superior Performance

Fig 4: Comparative analysis between the custom CNN and InceptionV3 models across key evaluation metrics such as accuracy, AUC score, and F1-score.

Although the custom CNN achieved strong performance, its shallow architecture limits representation capability. However, it remains computationally efficient and suitable for deployment in environments with limited resources. The improved performance of InceptionV3 is primarily due to its deeper architecture and ability to extract multi-scale features from CT images

Table 1: summarizes the comparative performance of both models

Model	**Accuracy**		**AUC**	**F1-score**
CNN	98%		0.987	0.98
InceptionV3	99%		0.995	0.99

D. Comparison with Existing Literature

The performance of the proposed InceptionV3 model is comparable to, and in some cases exceeds, results reported in existing studies on brain hemorrhage detection. Unlike traditional machine learning approaches that rely on handcrafted features, the proposed method leverages end-to-end deep learning, reducing the need for manual intervention while maintaining high accuracy and robustness.

Conclusion

This work demonstrated the effectiveness of deep learning techniques for automated brain hemorrhage detection using CT images. A custom-designed Convolutional Neural Network (CNN) and a transfer learning-based InceptionV3 model were developed and evaluated on a dataset of 2,501 CT images.

The experimental results demonstrate that the InceptionV3 model significantly outperforms the custom CNN in terms of validation accuracy (99%), AUC score (0.995), F1-score (0.99), and sensitivity (96.67%). Notably, the reduction in false negatives achieved by the InceptionV3 model is particularly important in clinical settings, as it minimizes the risk of missing critical hemorrhage cases.

Furthermore, the successful deployment of the best-performing model as a Flask-based web application highlights its practical applicability in real-world healthcare environments. The system enables clinicians to upload CT images and receive real-time predictions, thereby supporting faster and more informed decision-making.

Overall, the proposed approach demonstrates the effectiveness of combining deep learning and transfer learning techniques for accurate and reliable brain hemorrhage detection. The study contributes to the development of scalable, automated diagnostic tools that can assist healthcare professionals, particularly in resource-constrained settings. This system can serve as a supportive tool for radiologists, improving diagnostic efficiency and reducing workload in clinical environments

Future Enhancements

Future work can focus on extending the current system from binary classification to multi-class classification, enabling identification of different types of hemorrhage such as epidural, subdural, subarachnoid, and intraparenchymal hemorrhages.

In addition, integrating explainable AI techniques, such as Grad-CAM, can improve model transparency and help clinicians understand the reasoning behind predictions, thereby increasing trust and adoption in clinical practice.

Further improvements can include validation on larger, multi-institutional datasets and the incorporation of additional imaging modalities such as MRI. The use of advanced ensemble deep learning models and optimization techniques may also enhance performance and robustness.

Prospects

AI-based brain hemorrhage detection systems hold significant potential for improving emergency diagnosis and clinical decision-making. Such systems can function as triage tools, enabling rapid identification of critical cases and reducing delays in treatment.

With ongoing advancements in deep learning architectures, cloud computing, and medical imaging technologies, the reliability and accessibility of these systems are expected to improve further. Moreover, the integration of explainable AI and privacy-preserving techniques will play a key role in ensuring ethical adoption and widespread acceptance of intelligent healthcare solutions.

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