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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 serious neurological condition that can lead to severe disability or death if not diagnosed promptly. Early identification of intracranial bleeding significantly improves patient survival rates and treatment outcomes. In clinical practice, computed tomography (CT) imaging is widely used for diagnosing neurological abnormalities due to its speed and accuracy. However, manual examination of CT scans by radiologists can be time-consuming and prone to human error, particularly when large numbers of images must be analyzed.Recent advances in artificial intelligence have enabled the development of automated systems capable of detecting and classifying brain hemorrhages with improved efficiency and reliability. This study presents a comprehensive review of existing approaches for brain hemorrhage detection based on both traditional machine learning and modern deep learning techniques. The review focuses on the major stages involved in automated detection systems, including image preprocessing, feature extraction, and classification. Furthermore, the performance of different algorithms is analyzed and compared based on evaluation metrics reported in previous studies.In addition, this paper discusses commonly used benchmark datasets employed for training and evaluating hemorrhage detection models. The advantages, limitations, and challenges associated with current methodologies are also highlighted. Finally, potential research directions are suggested to enhance detection accuracy, reduce computational complexity, and improve clinical applicability of automated diagnostic systems.

Keywords
Brain Hemorrhage Detection, Computed Tomography (CT), Machine Learning, Deep Learning, Medical Image Processing, Feature Extraction, Classification, Artificial Intelligence in Healthcare.

Introduction
Brain hemorrhage is a critical neurological disorder characterized by bleeding within the brain tissues. This condition can occur inside the brain parenchyma or within the intracranial cavity and surrounding meningeal layers, and is commonly referred to as intracranial hemorrhage (ICH). It represents a life-threatening medical emergency that may lead to severe neurological impairment or death if not diagnosed and treated promptly The causes of brain hemorrhage are varied and include trauma, hypertension, vascular abnormalities, and other pathological conditions.Patients experiencing brain hemorrhage may exhibit several symptoms such as intense headaches, visual disturbances, fatigue, speech difficulties, loss of coordination, seizures, and reduced levels of consciousness. The severity and presentation of these symptoms can vary depending on the type, size, and location of the bleeding within the brain Intracranial hemorrhage accounts for a significant proportion of stroke cases and is associated with a high mortality rate within the first month of diagnosis. Clinical studies indicate that a large percentage of deaths occur within the initial days after onset, highlighting the urgent need for rapid detection and treatment Research studies analyzing over one thousand brain hemorrhage cases have shown that hemorrhages frequently occur in lobar regions of the brain, although they may also develop in other areas such as the cerebellum and brainstem Epidemiological data from the United States reported a considerable number of intracranial hemorrhage cases, with only a limited proportion of patients regaining full functional recovery within six months of diagnosis Furthermore, approximately half of the fatalities associated with this condition occur within the first 24 hours, emphasizing the importance of early detection and immediate clinical intervention Medical imaging plays a crucial role in diagnosing intracranial bleeding. Among various imaging modalities, non-contrast computed tomography (CT) is the most commonly used

technique due to its wide availability, relatively low cost, and high capability to distinguish blood from surrounding tissues such as brain matter, cerebrospinal fluid, and bone structures. During the diagnostic process, CT scans produce a series of cross-sectional images of the brain by combining multiple X-ray projections captured from different angles. These images enable clinicians to visualize soft tissues, bones, and blood vessels in three dimensions.Traditionally, radiologists manually analyze CT images to identify abnormalities associated with brain hemorrhage. However, this manual interpretation process can be time-consuming and challenging, particularly when only a small region of the brain is affected. Radiologists must carefully examine each image slice to detect subtle abnormalities, which increases the workload and may lead to diagnostic errors. These challenges have encouraged the development of automated computer-aided diagnostic systems to assist medical professionals in analyzing medical images more efficiently.Recent advancements in machine learning (ML) and deep learning (DL) have significantly improved the capability of automated systems for medical image analysis. Deep learning models are particularly effective in identifying complex patterns within large datasets without requiring explicit feature engineering. These models can automatically learn important image characteristics and hierarchical patterns directly from raw data. As a result, ML and DL techniques have become valuable tools for performing tasks that that traditionally require expert radiological interpretation, such as CT image analysis.This study aims to review and discuss modern approaches used for detecting brain hemorrhages using artificial intelligence techniques. In particular, the paper focuses on classification methods that combine deep learning and machine learning algorithms to improve detection accuracy. Among the various deep learning architectures available, VGG16 has emerged as an effective convolutional neural network model for medical image classification. VGG16 can automatically learn hierarchical image features through a series of convolutional, pooling, and fully connected layers, making it well suited for identifying abnormalities in CT scans.In brain hemorrhage detection, VGG16 can extract meaningful spatial features from CT images and distinguish between normal brain tissues and regions affected by hemorrhage. These features can represent different types of intracranial bleeding, including intraparenchymal hemorrhage, subdural hemorrhage, subarachnoid hemorrhage, and other related conditions. By automating the feature extraction process, VGG16 reduces the dependence on manual interpretation and supports radiologists in making more accurate diagnoses.

However, relying solely on deep learning models may not always produce optimal results, particularly when dealing with imbalanced medical datasets or when additional classification refinement is required. In such cases, integrating machine learning algorithms with deep learning architectures can improve performance. One such algorithm is Extreme Gradient Boosting (XGBoost), a powerful gradient boosting technique known for its high predictive accuracy and ability to handle structured data effectively.XGBoost can be applied to the features extracted by the VGG16 network to perform the final classification of hemorrhage types. By constructing an ensemble of decision trees and optimizing them through boosting techniques, XGBoost enhances model performance and reduces the risk of overfitting. This capability is especially beneficial for medical datasets, which often contain uneven class distributions.The combination of VGG16 for feature extraction and XGBoost for classification creates a hybrid framework that leverages the strengths of both deep learning and gradient boosting techniques. In this hybrid approach, VGG16 efficiently captures complex spatial features from CT images, while XGBoost utilizes these features to accurately classify different types of brain hemorrhage. Such a framework can improve diagnostic accuracy, accelerate analysis time, and provide interpretable results that assist clinicians in medical decision-making.Overall, the integration of VGG16 and XGBoost offers a promising solution for automated brain hemorrhage detection. By improving classification performance and reducing the burden on radiologists, this hybrid model can contribute to faster diagnosis and better patient outcomes in clinical practice.

Literature Review

Recent years have seen significant progress in the development of automated techniques for detecting intracranial hemorrhage using artificial intelligence and medical imaging technologies. Various studies have explored deep learning, machine learning, and hybrid models to improve the accuracy and efficiency of brain hemorrhage diagnosis.Shi et al. (2023) proposed a hybrid deep learning framework for intracerebral hemorrhage imaging using Electrical Impedance Tomography (EIT). Intracerebral hemorrhage is associated with high mortality and disability rates, making early diagnosis and continuous monitoring crucial for patient survival. Electrical impedance tomography provides an alternative imaging method by reconstructing images based on variations in conductivity within brain tissues. However, image reconstruction from EIT measurements presents a complex inverse problem that is highly nonlinear and ill-posed. To address this challenge, the authors introduced a hybrid architecture combining

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convolutional neural networks and transformer models. The proposed model was capable of learning both local and long-range dependencies within voltage measurement sequences. Experimental evaluations were conducted using simulated three-layer head models representing hemorrhage conditions under various noise levels and deformation scenarios. The results demonstrated that the hybrid model could reconstruct intracerebral hemorrhage regions accurately, confirming the effectiveness of deep learning approaches in medical imaging reconstruction.Ozaltin et al. (2023) introduced a hybrid deep learning algorithm known as OzNet for classifying brain hemorrhage CT images. In emergency situations, radiologists must analyze numerous CT scan slices to determine the presence of brain bleeding, which can be time-consuming and prone to errors. To address this issue, the authors developed a convolutional neural network architecture capable of extracting high-dimensional image features. The OzNet model extracted approximately 4096 features from the fully connected layers of the network. These features were further refined using Neighborhood Component Analysis (NCA) to retain the most informative attributes while reducing dimensionality. Multiple machine learning classifiers, including K-Nearest Neighbor, Support Vector Machine, Naïve Bayes, Decision Trees, AdaBoost, Bagging, Linear Discriminant Analysis, and Artificial Neural Networks, were evaluated using these features. Experimental results indicated that the OzNet-NCA-ANN combination achieved extremely high classification accuracy when tested on CT scan datasets, demonstrating the effectiveness of hybrid deep learning frameworks for hemorrhage detection.

A comparative study conducted by Ammar et al. (2022) investigated the performance of several deep learning models for recognizing intracranial hemorrhage in CT scan images. Emergency departments frequently encounter patients suffering from traumatic brain injuries, requiring rapid diagnostic analysis. Because radiologists must examine multiple CT slices for each patient, automated computer-aided diagnostic systems can significantly assist in the diagnostic process. The authors evaluated five widely used deep learning architectures, including ResNet50, VGG16, Xception, InceptionV3, and InceptionResNetV2. Prior to model training, preprocessing operations such as image normalization and windowing were applied to enhance CT scan quality and highlight relevant structures. The study compared the performance of these models in identifying five different subtypes of intracranial hemorrhage. The findings revealed that deep learning networks can achieve high classification performance and assist clinicians in detecting hemorrhage patterns efficiently.Yeo et al. (2021) presented a comprehensive review of deep learning techniques for automated intracranial hemorrhage detection using CT imaging. The study highlighted the importance of combining deep learning architectures with advanced machine learning algorithms to enhance prediction performance. In particular, the integration of convolutional neural networks for feature extraction and gradient boosting methods for classification was identified as a promising strategy. Algorithms such as XGBoost have demonstrated strong performance in handling structured features extracted from image data. By combining CNN-based feature extraction models like VGG16 with powerful gradient boosting classifiers, researchers can improve model accuracy and reduce overfitting problems commonly encountered in medical datasets. The study emphasized that hybrid approaches can provide more reliable diagnostic predictions and offer interpretable insights that support medical decision-making.Luong et al. (2021) proposed a computer-aided diagnostic system for identifying intracranial hemorrhage using deep learning and traditional image processing techniques. Intracranial hemorrhage represents a severe type of stroke that requires immediate medical attention. Accurate detection is usually performed by experienced radiologists analyzing CT scan images. To support clinicians in this process, the authors developed a deep learning framework based on the MobileNetV2 architecture. The model was trained using the RSNA Intracranial Hemorrhage dataset and later validated using a local dataset collected from a hospital in Vietnam. The experimental results showed high diagnostic performance, achieving an AUC score of 0.991, sensitivity of 0.992, and specificity of 0.807. In addition to classification, the study used Hounsfield Unit analysis to highlight suspected bleeding regions in CT images. A density-based clustering algorithm was also applied to eliminate noise from detected regions. The proposed system demonstrated the potential of deep learning-based CAD systems for assisting radiologists in clinical practice.Overall, the reviewed studies indicate that artificial intelligence techniques, particularly deep learning models, have become powerful tools for detecting brain hemorrhage in CT images. Hybrid approaches that combine deep learning feature extraction with machine learning classifiers show promising improvements in accuracy and computational efficiency. These advancements provide a strong foundation for developing automated diagnostic systems that can support medical professionals in identifying life-threatening neurological conditions.

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Methodology

The proposed system focuses on developing an automated framework for detecting brain hemorrhage from CT scan images using a combination of deep learning and machine learning techniques. The approach primarily utilizes the VGG16 convolutional neural network architecture for feature extraction and the XGBoost algorithm for classification. VGG16 is widely recognized for its ability to learn hierarchical representations of images through multiple convolutional layers. By processing CT scan images through this network, the model can capture complex spatial patterns and structural abnormalities associated with different types of brain hemorrhage.After extracting high-level features using the VGG16 network, these features are provided as input to the XGBoost classifier. XGBoost is a powerful gradient boosting algorithm that builds an ensemble of decision trees to improve predictive accuracy. This hybrid architecture leverages the strengths of deep learning for image representation and machine learning for efficient classification. The overall objective of the proposed system is to automate the detection process, thereby reducing the need for manual feature engineering and minimizing the workload for medical professionals. Automated detection systems can support radiologists by providing faster and more reliable diagnostic results, especially in emergency situations where timely decision-making is critical.

Methodological Framework

The methodology of the proposed system consists of several sequential modules that process CT scan images and generate classification results.

The first stage involves data acquisition and preprocessing. A dataset containing CT scan images with and without brain hemorrhage is collected from medical sources or publicly available repositories. Each image is labeled according to the presence or absence of hemorrhage and, where possible, the specific type of bleeding. Preprocessing operations such as image resizing, normalization, and noise removal are applied to ensure consistent input data. Data augmentation techniques including rotation, flipping, and scaling are also used to increase dataset diversity and improve the generalization capability of the model.In the next stage, feature extraction is performed using the VGG16 deep learning model. VGG16 is a pre-trained convolutional neural network originally developed for large-scale image recognition tasks. In this study, the convolutional layers of the network are used to extract meaningful features from CT images while the original classification layers are removed. The extracted features represent important structural patterns such as edges, textures, and abnormal regions associated with hemorrhage.

Once the features are obtained, they are used to train the XGBoost classifier. XGBoost constructs multiple decision trees sequentially, where each tree attempts to correct the errors made by previous trees. Hyperparameters such as learning rate, tree depth, and number of estimators are adjusted to optimize classification performance. The training process enables the model to learn the relationship between extracted features and hemorrhage categories.

The trained model is then evaluated using performance metrics including accuracy, precision, recall, F1-score, and the area under the ROC curve. The dataset is divided into training and testing subsets to assess how well the model performs on unseen data. Visualization techniques such as confusion matrices are used to analyze classification results and identify potential weaknesses in the model.Finally, the system can be deployed and integrated into medical imaging environments. The trained model can be implemented on local servers or cloud platforms to process CT images in real time. Integration with hospital imaging systems enables the model to assist radiologists by automatically analyzing CT scans and highlighting potential hemorrhage regions.The system is implemented using Python and several widely used machine learning libraries, including TensorFlow and Keras for deep learning operations, XGBoost for classification, NumPy and Pandas for data processing, and Scikit-learn for model evaluation and preprocessing tasks.

Algorithms and Techniques

Traditional convolutional neural networks (CNNs) have been widely used for medical image analysis. In brain hemorrhage detection, CNN models process CT scan images through multiple layers to identify patterns associated with bleeding. Convolutional layers extract features such as edges and textures, while activation functions introduce non-linearity to improve model learning capability. Pooling layers reduce the spatial dimensions of feature maps, which decreases computational complexity while preserving important information. Finally, fully connected layers interpret the extracted features to determine whether a hemorrhage is present.Although CNN models can perform classification directly, the proposed system introduces a hybrid strategy that combines the feature extraction capability of VGG16 with the classification power of XGBoost. VGG16 processes CT images resized to a standardized resolution and extracts high-level feature representations through its convolutional architecture. These feature vectors are then passed to the XGBoost algorithm, which constructs an ensemble of decision trees to perform the final classification. Each decision tree improves the prediction accuracy by correcting the errors of the previous tree. This fusion approach improves classification performance by utilizing the strengths of both deep learning and machine learning techniques.

Requirements Engineering

The implementation of the proposed brain hemorrhage detection system requires both hardware and software components. The hardware configuration includes a dual-core processor, at least 4 GB of RAM, and sufficient storage capacity to handle medical imaging datasets. The software environment consists of the Windows operating system and Python-based development tools such as Spyder or Jupyter Notebook. Python programming language is used due to its extensive libraries and strong support for machine learning frameworks.Functional requirements of the system include collecting CT scan images, preprocessing the data, extracting features using deep learning models, performing classification using machine learning algorithms, and generating diagnostic predictions. Non-functional requirements focus on usability, reliability, performance, and supportability. The system is designed to operate automatically with minimal user intervention while maintaining high reliability and fast response time. Cross-platform compatibility ensures that the system can operate on different hardware and software environments.

System Design

System design involves translating functional requirements into structured representations that guide the implementation process. Unified Modeling Language (UML) diagrams are used to illustrate the architecture and workflow of the system. The use case diagram describes the interactions between users and the automated detection system, including data input, preprocessing, feature extraction, classification, and prediction generation.

Class diagrams represent the relationships between system components such as data processing modules, feature extraction modules, and classification models. Object diagrams illustrate how instances of these classes interact during system execution. Activity diagrams describe the step-by-step workflow involved in analyzing CT scan images, while sequence diagrams demonstrate the order in which operations occur during the detection process.Component diagrams provide an overview of the system architecture by showing how different modules interact to form the complete software system. Data flow diagrams illustrate the movement of information between different stages of processing, from initial data acquisition to final classification results. Deployment diagrams describe how the software components are distributed across hardware resources, including servers and processing units.

Workflow of the Proposed System

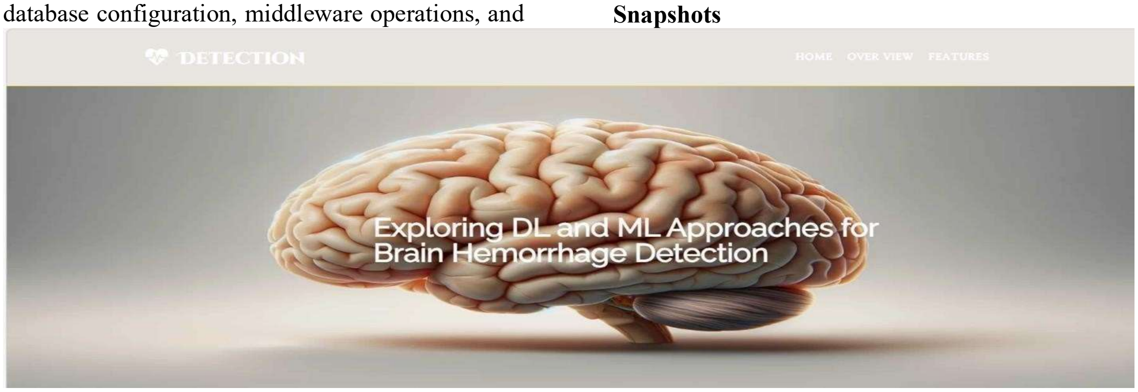
The detection process begins with collecting CT scan images from medical datasets. These images are preprocessed through resizing, normalization, and noise reduction techniques to ensure consistent input quality. Data augmentation methods are applied to increase dataset size and improve model robustness.Next, the system performs segmentation to isolate the region of interest within the brain image. Removing irrelevant background regions allows the model to focus on areas most likely to contain hemorrhage patterns. Feature extraction is then performed using deep learning architectures such as VGG16 or VGG19, which generate feature vectors representing the important visual characteristics of the images.The extracted features are subsequently fed into the XGBoost classifier, which analyzes these features and determines whether the CT image indicates a hemorrhagic or non-hemorrhagic condition. The final output of the system is a classification result that assists medical professionals in diagnosing brain hemorrhage.

Implementation

System Implementation

The proposed brain hemorrhage detection system was implemented using the Python programming language along with the Django web framework. Django was selected because it enables the development of scalable and secure web applications while providing efficient integration with machine learning models. The system allows users to upload CT scan images through a web interface, after which the trained deep learning model analyzes the image and predicts whether the scan indicates hemorrhage or a normal brain condition.In the implementation phase, a pre-trained deep learning model stored in the file keras_model.h5 is loaded when the server starts. This model performs prediction on incoming CT images. The application provides several web pages including the home page, abstract page, about section, contact page, performance visualization page, result display page, and an upload interface. When a user uploads an image, the file is temporarily stored on the server using Django’s file storage system.Once the CT image is uploaded, the preprocessing stage begins. The image is converted into RGB format and resized to 224 × 224 pixels, which matches the input size required by the VGG-based neural network architecture. The pixel values are normalized to a range between 0 and 1 to ensure stable model performance during prediction. The processed image is then converted into a NumPy array and expanded into the required input dimensions before being passed to the trained model.The model then generates prediction probabilities for each class. Based on the predicted output, the system determines whether the CT scan represents a hemorrhagic or non-hemorrhagic brain condition. The predicted medical label is displayed to the user through the web interface. After the prediction process is completed, the uploaded file is automatically deleted from the server to maintain storage efficiency and protect user data privacy.The Django framework also manages URL routing, database configuration, middleware operations, and template rendering. The system uses SQLite as a lightweight database for storing application information. Static files such as CSS, JavaScript, and images are handled using Django's static file configuration. This implementation provides a user-friendly interface that allows medical practitioners or researchers to analyze CT scans efficiently without directly interacting with the underlying machine learning model.

Snapshots



Home Screen

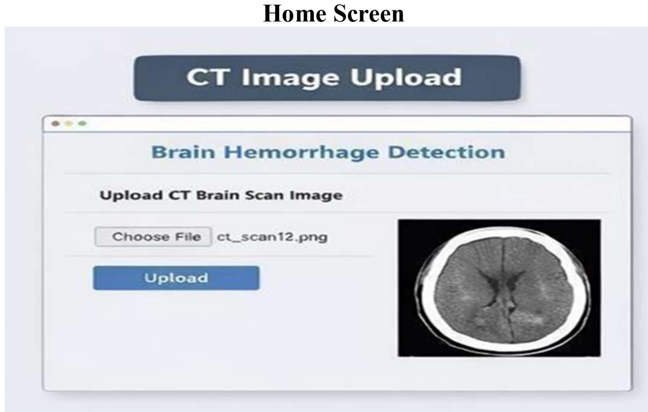
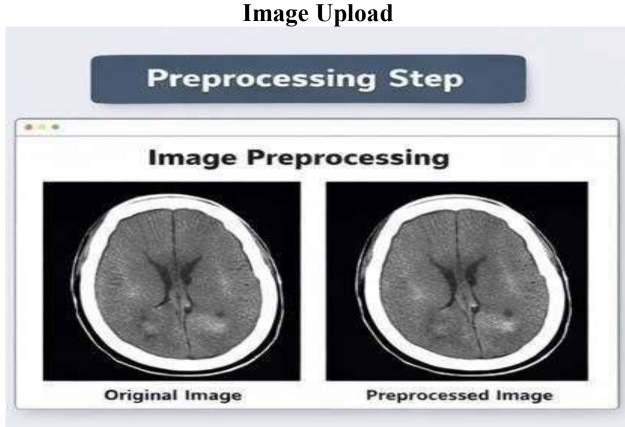


Image Upload



System Interface and Experimental Results

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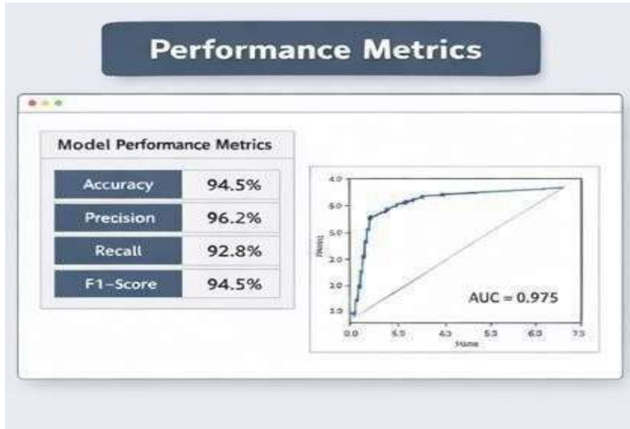

Performanc

System Interface
The developed system includes a graphical web interface that allows users to interact with the brain hemorrhage detection model. The interface contains several modules including the home page, image upload module, preprocessing visualization module, feature extraction stage, classification module, and result display section.The home screen provides an overview of the system and allows users to navigate through different sections of the application. The image upload module enables users to select CT scan images from their local devices. Once uploaded, the system processes the image and performs automated preprocessing. During preprocessing, the image is resized, normalized, and prepared for deep learning analysis.The feature extraction stage utilizes the VGG16 deep learning architecture to identify relevant patterns such as edges, textures, and structural abnormalities that may indicate intracranial bleeding. These extracted features are then forwarded to the XGBoost classifier, which performs the final classification of the CT scan.After classification, the result page displays whether the CT image corresponds to a hemorrhagic or non-hemorrhagic condition. In addition, the performance section of the interface provides visualization tools to analyze model accuracy and other evaluation metrics.

Confusion Matrix and Performance Evaluation
The performance of the classification model is evaluated using a confusion matrix, which measures how accurately the system predicts the presence or absence of brain hemorrhage. The confusion matrix contains four possible outcomes: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).A True Positive occurs when the model correctly identifies a hemorrhagic brain condition. A True Negative represents a correct prediction of a normal brain condition. A False Positive occurs when the model predicts hemorrhage even though the brain is normal. A False Negative indicates that the model fails to detect an existing hemorrhage.

For example, when evaluating 100 CT scan images, the system produced the following results:

- True Positives (TP) = 42
- False Negatives (FN) = 3
- False Positives (FP) = 5
- True Negatives (TN) = 50

Using these values, several performance metrics can be calculated.

Accuracy measures the overall correctness of the model. The system achieved an accuracy of approximately 92%, indicating that most CT images were classified correctly.Precision evaluates how many of the predicted hemorrhage cases were actually correct. The model achieved a precision value of approximately 0.893, demonstrating reliable detection of hemorrhage cases.Recall (Sensitivity) measures the ability of the model to correctly detect actual hemorrhage cases. The recall value of 0.933 indicates that the model successfully identifies most hemorrhage instances.F1-Score combines precision and recall into a single metric that balances both measures, providing a comprehensive evaluation of the classifier’s performance.These performance metrics demonstrate that the proposed hybrid system can effectively classify brain CT scans and assist medical professionals in identifying hemorrhage cases.

Software Testing
Software testing was conducted to verify the reliability and correctness of the developed system. Several test scenarios were executed to ensure that each component of the system performed as expected.Initially, the dataset loading process was tested to confirm that CT scan images could be successfully read and analyzed by the system. Preprocessing operations were then evaluated to ensure that noise removal, normalization, and image

transformation procedures were correctly applied.Subsequently, the classification module was tested to verify that the machine learning model could accurately analyze the processed images and generate predictions. The trained model was successfully loaded and executed within the system environment. User input through the web interface was also tested to confirm that images could be uploaded and processed without errors.Finally, the prediction module was evaluated to ensure that the classification results were displayed correctly to the user. The testing results indicated that all system components functioned successfully and produced the expected outputs.

Future Enhancements

Although the proposed system demonstrates promising results in detecting brain hemorrhage, several improvements can be considered in future research. One possible enhancement is the use of larger and more diverse medical datasets to improve model generalization and robustness. Incorporating additional imaging modalities such as MRI or multi-modal imaging data may also enhance diagnostic accuracy.Another important area for improvement involves addressing ethical considerations associated with artificial intelligence in healthcare. Ensuring patient data privacy, reducing potential bias in training datasets, and improving model transparency are critical factors for the responsible deployment of AI-based diagnostic systems.Future systems may also integrate advanced deep learning architectures such as EfficientNet, Vision Transformers, or attention-based models to further improve feature extraction and classification performance. Additionally, real-time integration with hospital information systems could allow automated diagnosis to assist clinicians in emergency medical situations.

Conclusion

This study presented a hybrid approach for detecting brain hemorrhage in CT scan images using deep learning and machine learning techniques. The proposed system combines the VGG16 convolutional neural network for feature extraction with the XGBoost algorithm for classification. By leveraging the strengths of both approaches, the model achieves improved diagnostic accuracy compared to traditional methods.The automated detection framework reduces the need for manual feature engineering and supports faster analysis of CT images. This capability can significantly assist radiologists in identifying hemorrhage cases, particularly in emergency situations where rapid diagnosis is essential. Experimental results demonstrate that the proposed model achieves high accuracy and reliable performance when evaluated using standard classification metrics.Overall, the integration of deep learning and machine learning techniques provides a powerful tool for medical image analysis. The proposed system has the potential to enhance diagnostic efficiency and contribute to improved patient outcomes in the field of neurological healthcare.

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