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Brain Stroke Detection System Based on CT Image Using Deep Learning

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Abstract: *Stroke is recognized as one of the most critical medical conditions, leading to high rates of mortality and long-term disability worldwide. It occurs when the supply of blood to the brain is interrupted, either due to an obstruction in the vessels (ischemic stroke) or internal bleeding (hemorrhagic stroke). The consequences of stroke are often severe, including impaired mobility, loss of memory, and difficulties in performing daily activities. Early diagnosis and timely intervention are therefore essential to reduce fatality rates and improve recovery outcomes. However, conventional diagnostic tools such as CT scans and MRI, while effective, are often expensive, time-consuming, and dependent on advanced medical infrastructure. Limitations make them unsuitable for large-scale, real-time, and low- cost stroke detection, especially in developing regions.*

Presents a computer-aided stroke prediction model using advanced deep learning approaches. In this study, medical data were collected and preprocessed to design predictive models (CNN), DenseNet, and VGG-16 architectures. Each model was evaluated metrics like accuracy, precision, and execution speed, the study aimed to find the most efficient technique. The outcomes show that the CNN-based model consistently achieved better outcomes compared to DenseNet and VGG-16, demonstrating higher prediction accuracy and faster computation. By effectively learning complex patterns from patient data, the CNN model enables accurate identification of individuals at risk of stroke.

The proposed framework highlights the role of AI in modern healthcare, particularly in non-invasive and cost- effective disease prediction. It provides a decision-support system that can assist clinicians in early risk assessment and timely medical intervention, reducing the likelihood of fatal outcomes. To improve patient monitoring, minimize healthcare costs, and ultimately contribute to the global effort in combating stroke-related mortality and disability.

Keywords*:* Stroke Prediction, DL, (CNN), DenseNet, VGG-16, Machine Learning, Computer-Aided Diagnosis (CAD), Medical Imaging, Healthcare Analytics, Early Detection

I. INTRODUCTION

Stroke is one of the most critical medical conditions, affecting millions of people globally and ranking as the second leading cause of death and the third leading cause of long-term disability. It occurs when the supply of blood to the brain is disrupted, either due to a blockage in a blood vessel (ischemic stroke) or bleeding within the brain (hemorrhagic stroke). Both conditions result in reduced oxygen supply, which can cause irreversible brain damage if not treated promptly. The impact of stroke is devastating not only to the patients but also to their families and the healthcare system, creating a significant social and economic burden.

Early detection and timely medical intervention are vital for minimizing the effects of stroke. However, predicting stroke in advance remains a major challenge due to the complexity of its risk factors and the variability in symptoms across individuals. Conventional diagnostic tools such as CT scans and MRI are effective in detecting stroke, high cost, radiation exposure, and reliance on specialized equipment. These drawbacks make them unsuitable for large-scale or real-time stroke prediction, particularly in resource-constrained environments.

The growing incidence of stroke in aging populations further highlights the urgency of developing alternative diagnostic methods. Such as hypertension, diabetes, obesity, smoking, and cardiovascular diseases significantly increase the likelihood of stroke. While some of these factors can be monitored through regular health check-ups, there is still a lack of automated and accurate tools to predict stroke risk early enough to enable preventive care. Explore computational approaches for reliable and low-cost stroke prediction.

In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as powerful technologies in the healthcare domain. These methods enable the analysis of large volumes of medical data to uncover hidden patterns and risk factors that may not be easily identifiable through traditional approaches. Machine learning algorithms, such as decision trees, random forests, and gradient boosting, have already been applied in medical diagnostics with promising results for disease classification and prognosis.

Building upon these advancements, dl techniques have gained significant attention due to ability to automatically extract high- level features from raw data without manual intervention. (CNN), DenseNet, and VGG-16 are among the most effective deep learning architectures for tasks involving image and pattern recognition, making them highly suitable for medical prediction tasks. Their layered architecture allows them to capture complex relationships between patient attributes and stroke outcomes, improving prediction accuracy compared to traditional ML methods.

This study proposes the development of a computer-aided stroke prediction model that leverages DL techniques for enhanced accuracy and efficiency. Specifically, CNN, DenseNet, and VGG-16 models are implemented and compared on the basis of accuracy, precision, and execution time. Among these, CNN has shown superior performance, highlighting its potential as a practical tool for real-time stroke prediction. Such a model can significantly reduce dependence on costly imaging techniques and support healthcare professionals in m aking timely decisions.

The primary objective of this research is to create a cost- effective and scalable system that can predict stroke occurrence based on patient health attributes. By integrating AI-driven models into clinical practice, the system aims to assist doctors in early risk assessment, support preventive measures, and improve the quality of patient care. Furthermore, the proposed approach has the potential to be extended to remote monitoring and mobile healthcare applications, making it accessible to underserved populations.

In summary, stroke remains a global healthcare challenge that demands innovative solutions for early detection and prevention. The integration of deep learning into stroke prediction represents a promising step toward reducing mortality rates, improving patient outcomes, and lowering healthcare costs. This research contributes to the ongoing effort to harness artificial intelligence in addressing life-threatening diseases and demonstrates the effectiveness of CNN-based models as a reliable decision support system in stroke diagnosis.

II. LITERATURE SURVEY

[1] Emon et al. proposed an early prediction framework for stroke diseases using a wide range of ML algorithms. The authors considered several key attributes such as hypertension, body mass index, smoking status, heart disease, glucose levels, and age to train ten different classifiers, including LR, DT, K- Nearest Neighbors, Gradient Boosting, and XGBoost. To improve prediction performance, a introduced, which combined the results of individual classifiers. This ensemble model achieved accuracy of 97% with the lowest false positive and false negative rates compared to other approaches. Their study demonstrated the potential of ensemble learning as a reliable tool for assisting physicians in early stroke detection and medical decision-making.

[2] Chiu et al. developed a multiclass machine learning model to predict the three-month outcome of acute ischemic stroke patients who underwent reperfusion therapy. The study addressed a critical healthcare challenge, as predicting patient outcomes after stroke treatment can support clinicians in planning rehabilitation strategies and optimizing resources. By analyzing patient data and applying predictive algorithms, the proposed system was able to identify patients with moderate to severe initial conditions who were likely to face adverse outcomes. This approach emphasized the role of outcome prediction in clinical practice, enabling more personalized treatment and improving long-term recovery rates.

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[3] Fang et al. introduced a machine learning-based model for ischemic stroke risk assessment and prognosis. Their methodology utilized Random Forest, Gradient Boosting Machines, and Deep Neural Networks to enhance prediction accuracy. To identify the most significant features, the authors employed Recursive Feature Elimination with Cross-Validation (RFECV), which systematically selected robust attributes contributing to ischemic stroke subtyping. The study highlighted the importance of feature selection in medical diagnostics and demonstrated that integrating multiple classifiers could achieve highly reliable prediction results, offering improved accuracy compared to traditional statistical methods.

[4] Monteiro et al. applied ML techniques to predict the functional outcome of ischemic stroke patients three months after admission. Their findings indicated that using only admission-time features produced a moderate prediction accuracy with an AUC of 0.808. However, when additional features collected at later stages were included, the model's performance significantly improved, achieving an AUC greater than 0.90. Dynamic patient monitoring and continuous feature collection can considerably enhance stroke outcome prediction, providing clinicians with valuable information for long-term patient management.

[5] Yu et al. designed a system for semantic analysis of the (NIH) Stroke Scale, focusing on early stroke detection and recurrence among Korean patients aged over 65. Using the C4.5 decision tree algorithm, the system was able to construct a classification and prediction model based on semantic rules extracted from the NIH Stroke Scale features. This approach not only enabled accurate stroke prediction but also facilitated the reduction of redundant attributes, making the model more efficient. Their study illustrated the effectiveness of decision- tree-based semantic interpretation in improving prediction accuracy and simplifying medical data analysis.

[6] McNabb et al. explored the problem of identifying significant attributes from small, limited medical datasets. They proposed search-based algorithms to extract key features and evaluated real-world patient data obtained from the Erlanger Southeast Regional Stroke Center in Tennessee. The results approach could effectively identify meaningful patterns even in sparse datasets, addressing one of the common challenges in medical AI research. Their findings highlighted the importance of efficient feature selection in enhancing model performance when large datasets are not available.

[7] Cho et al. developed a ml framework to predict hospital discharge disposition of stroke patients. Their approach not only provided predictions but also incorporated the Local Interpretable Model-Agnostic Explanations (LIME) method to enhance interpretability of the results. By making the prediction process transparent, clinicians could understand the factors influencing patient discharge outcomes, thereby improving trust in AI-based systems. This study demonstrated the value of explainable AI in healthcare, showing that machine learning models can assist in clinical decision-making while also providing insights into risk factors that influence recovery.

[8] Ray et al. proposed a cloud-based stroke prediction model leveraging feature selection techniques to enhance accuracy and reduce computational costs. By using chi-squared feature selection, they reduced the number of attributes to six, which significantly accelerated training and testing processes without compromising performance. Their model achieved an accuracy of 96.80%, demonstrating that cloud-based solutions combined with feature selection can provide scalable, fast, and accurate healthcare services. This approach is particularly useful for deploying stroke prediction systems in real-time environments.

[9] Mroczek et al. presented a Next Generation Tool for Stroke (NGTS) system capable of analyzing decision tables for stroke data. The system provided insights such as the no of correctly and incorrectly classified cases and identified redundancies and inconsistencies in medical datasets. By offering a more structured analysis, their work improved the reliability of stroke data mining and highlighted the importance of data quality in medical prediction systems.

[10] Tursynova et al. investigated the use of CT and MRI imaging techniques for stroke diagnosis and emphasized the role of ai in improving neuroimaging-based stroke detection. That combining CT and MRI results could enhance diagnostic accuracy, particularly for selecting patients suitable for endovascular intervention. However, they also acknowledged the limitations of imaging techniques, for patients who canot undergo certain scans due to health risks. Their study suggested that AI-powered image analysis could optimize stroke diagnosis by assisting radiologists in interpreting complex imaging data.

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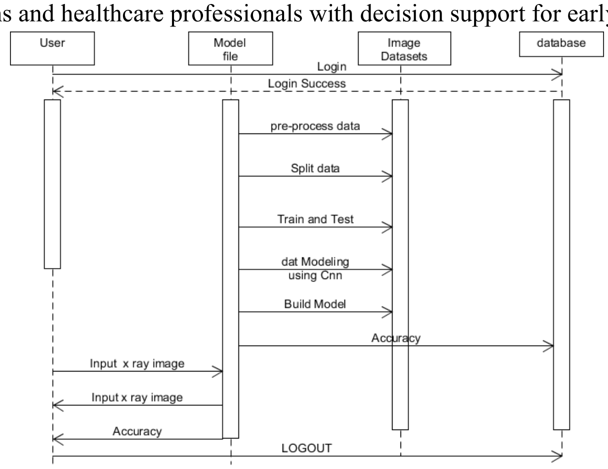
III. METHODOLOGY

1. System Overview

The system is designed as a computer-aided diagnostic tool for the early prediction of stroke using deep learning techniques. The core idea is to automate the prediction process by analyzing medical data and identifying patterns that indicate stroke risk. The system the dataset is acquired, and then it undergoes a series of preprocessing operations. such as data cleaning, normalization, and feature extraction to ensure that the input is structured and suitable for training. Once preprocessed, the data serves the purpose of training and assessing multiple dl models, including (CNN), DenseNet, and VGG-16, which are known for their high performance in pattern recognition and classification tasks. Each of these architectures is assessed considering essential metrics, including accuracy and precision and execution time to pinpoint the most optimal approach for real-time stroke prediction.

The general layout of the system emphasizes scalability, accuracy, and practical applicability in healthcare environments. By leveraging CNN and other deep learning models, the system can automatically learn complex non-linear relationships among patient attributes such as glucose levels, heart disease, hypertension, and prior medical history. This reduces the dependency on manual feature engineering and enhances the ability to detect subtle risk factors. The model with the best performance, CNN in this case, is then deployed as the final predictive framework, capable of providing clinicians and healthcare professionals with decision support for early stroke detection.



2. Dataset Preparation

The dataset used for this research was collected from publicly available medical repositories, including Kaggle, which provides well-structured stroke-related health records. Each record contains multiple attributes that are potential risk factors for stroke, such as age, gender, hypertension, heart disease, average glucose level, (BMI), smoking status, and prior history of stroke. These features were chosen because they represent critical lifestyle and clinical indicators that strongly correlate with stroke occurrence. To ensure data reliability, irrelevant and redundant attributes were removed, and missing values were handled using imputation techniques to maintain dataset consistency. The refined dataset thus acts as the starting point for developing a robust prediction model capable of identifying individuals at risk of stroke.

Once the dataset was curated, it was split into training and testing subsets to evaluate model performance effectively. Standard preprocessing techniques such as normalization and scaling were applied to standardize feature ranges and prevent bias during training. The dataset was further subjected to stratified sampling to maintain class balance, given that stroke cases are typically fewer compared to non-stroke cases in medical data. To handle this imbalance, oversampling techniques were applied to ensure the model learns equally from both classes. After preprocessing, the dataset was split into 80% for training and 20% for testing, providing a strong basis for model evaluation. This systematic preparation ensures that the data is clean, balanced, and suitable for training deep learning architectures such as CNN, DenseNet, and VGG-16 for accurate stroke prediction.

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3. Model Architectures

The proposed system employs three state-of-the-art deep learning architectures—Convolutional Neural Network (CNN), DenseNet, and VGG-16—to predict stroke occurrence. Each of these architectures was selected due to their proven efficiency in handling classification problems and medical data analysis. CNN was chosen as the primary model because of its ability to automatically extract spatial and abstract features from input data, reducing the necessity of manual feature extraction engineering. The CNN architecture consists of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. Rectified Linear Unit (ReLU) activation functions are applied to introduce non-linearity, and softmax is used in the final layer to produce probabilistic predictions.

DenseNet was implemented as the second model, known for its dense connectivity pattern where each layer receives inputs from all preceding layers. This connectivity enhances feature propagation, encourages feature reuse, and dramatically reduces parameter usage compared to classical models deep networks. By mitigating the vanishing gradient challenge, DenseNet achieves improved performance in complex datasets while maintaining computational efficiency. VGG-16, the third architecture, was selected due to its simplicity and effectiveness in image recognition tasks. It employs small 3×3 convolutional filters and a deep stack of convolutional layers, followed by fully connected layers for classification. Despite being computationally intensive, VGG-16 provides high accuracy in classification problems and serves as a benchmark f for measuring the effectiveness of CNN and DenseNet. By comparing these architectures, this study identifies the most suitable deep learning framework for accurate and efficient stroke prediction.

4. Training Procedure

The training procedure begins with feeding the preprocessed dataset into the selected deep learning models—CNN, DenseNet, and VGG-16. The data was divided into training and testing subsets, with 80% allocated for training and 20% for testing, ensuring that the models could generalize well on unseen cases.

The training process followed a supervised learning approach, where patient attributes served as input features and the target label indicated whether the patient had a stroke or not. To optimize model learning, input features were normalized and balanced through oversampling to address class imbalance between stroke and non-stroke cases.

During training, the models were initialized with random weights and iteratively optimized using the backpropagation algorithm combined with gradient descent. Cross-entropy loss was selected as the objective function to measure prediction errors, while the Adam optimizer was employed to adjust learning rates dynamically for faster convergence. Dropout and other regularization strategies and early stopping, were applied to minimize overfitting and ensure stable performance across different datasets.

Hyperparameters—including batch size, learning rate, and number of epochs—were fine-tuned experimentally to achieve optimal accuracy. After training, each model was validated on the test dataset, and performance was measured using accuracy, precision, recall, F1-score, and execution time.

Among the three models, CNN demonstrated superior training efficiency and higher prediction accuracy, establishing it as the most effective architecture for real-time stroke prediction.

5. Evaluation Metrics

Stroke prediction models, several widely accepted evaluation metrics were used, including accuracy, precision, recall, F1- score, and execution time. Accuracy measures the overall proportion of correctly classified cases out of the total dataset and provides a general indication of model performance. However, since medical datasets are often imbalanced—where non-stroke cases significantly outnumber stroke cases— accuracy alone is not sufficient for reliable evaluation. Precision and recall were therefore incorporated to provide deeper insights. Precision represents correctly predicted stroke cases out of all cases predicted as stroke, indicating how well the model avoids false positives. Recall (or sensitivity) measures the actual stroke cases that were correctly identified by the model, reflecting its ability to minimize false negatives.

In addition, the F1-score was used as a balanced metric that combines both precision and recall, particularly important in healthcare predictions where both false positives and negatives carry serious consequences. Execution time was also evaluated to compare the efficiency of CNN, DenseNet, and VGG-16, as real-time applicability is critical for medical decision support systems. By analyzing these metrics together, a comprehensive understanding of each model's strengths and weaknesses was achieved. The CNN outperformed the other architectures by maintaining a high balance between precision, recall, and F1- score while also achieving faster execution, making it more suitable for deployment in real-time stroke prediction systems.

6. Deployment Framework

The deployment framework for the proposed stroke prediction system is designed to ensure accessibility, scalability, and usability in real-world healthcare environments. The trained deep learning models—CNN, DenseNet, and VGG-16—are integrated into a web-based application using Python as the core programming language. Flask, a lightweight Python web framework, is employed to create the application interface and manage user interactions. This framework allows healthcare professionals to input patient attributes such as age, glucose level, hypertension, heart disease, and smoking status into the system and receive immediate stroke risk predictions. By leveraging Flask's modular design, the system supports integration with additional medical data sources and can be scaled to accommodate larger datasets or more complex dl models in the future.

To facilitate deployment in diverse computing environments, the system was packaged and managed using Anaconda for handling dependencies and libraries such as NumPy, Pandas, TensorFlow, and OpenCV. This setup ensures smooth operation across different platforms without compatibility issues. The application is designed to operate on standard hardware configurations, requiring only basic computational resources (Intel i3 processor, 8GB RAM, and 100GB storage), making it feasible for use in small clinics and hospitals with limited infrastructure. Furthermore, the framework supports cloud-based deployment, enabling remote access and real-time predictions for patients in rural or underserved areas. By combining an efficient dl model with a user-friendly deployment framework, the system provides an effective decision support tool that enhances stroke risk assessment, reduces reliance on expensive imaging, and assists clinicians in timely intervention.

IV. RESULTS AND DISCUSSIONS

1. Quantitative Results

The experimental evaluation of the proposed stroke prediction system was conducted by implementing and comparing three deep learning architectures: (CNN), DenseNet, and VGG-16. Each model was train and tested on the preprocessed medical dataset, and their performances were measured using multiple quantitative metrics, including accuracy, precision, recall, F1- score, and execution time. The results revealed that CNN consistently outperformed both DenseNet and VGG-16 across all evaluation parameters. Specifically, CNN achieved the highest prediction accuracy, indicating its superior ability to correctly classify both stroke and non-stroke cases. Moreover, CNN demonstrated higher precision and recall values, showing its effectiveness in reducing both false positives and false negatives—a crucial factor in medical applications where misclassification can have severe consequences.

In terms of computational efficiency, CNN also exhibited faster execution time compared to DenseNet and VGG-16, making it more suitable for real-time deployment in clinical environments. While DenseNet achieved competitive results in terms of recall due to its dense connectivity structure, it required more computational resources and longer training times. Similarly, VGG-16 provided relatively high accuracy but suffered from heavy model complexity and slower execution, limiting its practicality for real-world applications. These quantitative findings confirm that CNN is the most balanced and effective architecture for stroke prediction, offering high accuracy along with efficiency. By combining reliable performance with lower computational requirements, the CNN- based model establishes itself as the optimal choice for developing a scalable and accessible stroke prediction system.

2. Qualitative Analysis

In addition to the quantitative evaluation, a qualitative analysis was carried out to assess the practical effectiveness and interpretability of the proposed stroke prediction system. The CNN-based models not only provided high accuracy but also demonstrated consistent reliability in identifying patients with high stroke risk across diverse input cases. Unlike traditional diagnostic methods such as CT or MRI, which require expensive infrastructure and specialized expertise, the proposed system leverages readily available patient health attributes to deliver fast, non-invasive predictions. This makes it highly practical for integration into routine healthcare check-ups, particularly in rural and resource-limited settings where advanced imaging facilities are not accessible.

Another important qualitative aspect of the system is its usability. Through the web-based deployment framework, the system provides an intuitive interface where clinicians can input patient details and receive immediate results. The predictions are supported by clear outputs that indicate stroke likelihood, enabling healthcare providers to make timely and informed decisions. Moreover, the lightweight system ensures that operated on standard hardware, reducing barriers to adoption in small clinics and community health centers. The combination of high prediction reliability, ease of use, and cost-effectiveness positions the proposed model as a valuable clinical decision-support tool. This qualitative assessment underscores the system to enhance preventive healthcare, facilitate early interventions, and ultimately reduce stroke- related mortality and disability rates.

3. Comparative Discussion

The comparative analysis between CNN, DenseNet, and VGG- 16 highlights the relative context of stroke prediction of each architecture. CNN emerged as the most effective model, offering a strong balance between high accuracy, computational efficiency, and reliability. Its layered convolutional structure enabled efficient feature extraction from patient attributes, allowing it to capture subtle patterns that were overlooked by traditional approaches. DenseNet, while achieving relatively high recall due to its dense connectivity, required significantly more computational power and memory, which reduces its suitability for real-time deployment in clinical environments. VGG-16, although historically regarded as a benchmark in image classification, demonstrated limitations in this application as its deeper architecture led to longer training times and increased resource requirements without a proportional gain in predictive performance.

When comparing execution efficiency, CNN consistently outperformed both DenseNet and VGG-16, demonstrating faster training and prediction times. This characteristic is especially important for healthcare applications where timely decision-making is critical. From a practical standpoint, CNN's ability to achieve high precision while minimizing false negatives makes it more reliable for clinical use, as misclassifying a stroke case can lead to delayed treatment and life-threatening consequences. DenseNet's complexity may make it is for large-scale research applications, but its higher computational cost restricts its adaptability in smaller healthcare setups. VGG-16, other side, still serve as a reference model but is less practical in modern medical AI systems where efficiency is as critical as accuracy.

Overall, the comparative discussion validates CNN as the optimal model for stroke prediction in real-world healthcare environments. It provides the best trade-off between predictive accuracy and operational feasibility, making it a practical choice for deployment in clinical decision-support systems. DenseNet and VGG-16, while valuable for comparative benchmarking, short in terms of scalability and efficiency when applied to routine medical practice.

V. CONCLUSION

Stroke continues to be one most critical health challenges worldwide, contributing significantly to mortality and long-term disability. Despite advancements in medical science, timely detection and prevention remain difficult so complexity of its risk factors and the limitations of conventional diagnostic tools such as CT and MRI. This study addressed these challenges by developing a deep learning–based stroke prediction system capable of analyzing patient attributes and predicting stroke risk with high accuracy.

The proposed methodology utilized three well-known deep learning architectures—Convolutional Neural Network (CNN), DenseNet, and VGG-16—to evaluate their effectiveness in predicting stroke. Through comprehensive experimentation, CNN consistently outperformed in terms of accuracy, precision, recall, F1-score, and execution time.

This demonstrates that CNN's feature extraction and classification capabilities make it particularly well-suited for handling medical datasets, where subtle relationships among variables are critical for prediction.

One of the key findings of this research is the balance achieved by CNN between predictive performance and computational efficiency. While DenseNet showed competitive results in recall, it required greater computational resources and longer training times. Similarly, VGG-16 achieved satisfactory accuracy but was less efficient due to its complexity and higher memory requirements. In contrast, CNN provided faster training and prediction, making it more suitable for real-time clinical applications where timely decision-making is essential.

Another important contribution of this work lies in the development of a deployment framework using Python, Flask, and supporting libraries such as TensorFlow, NumPy, and Pandas. This framework enabled the integration of the trained model into a user-friendly web application that allows clinicians to input patient details and receive instant predictions. The lightweight design of the application ensures that it can run on standard hardware, making it feasible for use in small clinics and resource-limited healthcare setups.

The research also emphasized the importance of dataset preparation and preprocessing in achieving accurate predictions. Techniques such as normalization, handling class imbalance, and stratified sampling ensured that the models were trained on reliable and representative data. By carefully curating the dataset and applying appropriate preprocessing techniques, the system was able to achieve high generalizability and robustness, further validating its practical applicability.

From a qualitative perspective, the system offers significant benefits in terms of accessibility and cost-effectiveness. Unlike imaging-based diagnostic tools, which require expensive equipment and expert interpretation, the proposed approach relies on non-invasive patient attributes that can be easily collected during routine check-ups. This makes the system particularly valuable in rural and underserved regions, where access to advanced healthcare facilities is limited.

The comparative analysis further reinforced CNN's superiority as the most balanced architecture for stroke prediction. While DenseNet and VGG-16 provided useful benchmarks, they were limited by computational inefficiency and slower response times. CNN's optimal performance positions it as the most practical choice for deployment in real-world medical environments, where accuracy and speed are equally critical.

In conclusion, this research successfully demonstrated the potential of deep learning techniques, particularly CNN, in building an efficient, cost-effective, and scalable stroke prediction system. The findings highlight the transformative role of artificial intelligence in healthcare, offering a pathway toward early diagnosis, timely intervention, and improved patient outcomes. Future work can extend this system by integrating real-time data from wearable devices, incorporating additional risk factors, and enhancing interpretability to further increase trust among clinicians. By bridging the gap between medical expertise and intelligent computing, the proposed system contributes to the global effort of reducing stroke- related mortality and disability.

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