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Predictive Modeling of Brain Stroke Using Machine Learning and Deep Learning Methods

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Abstract— This project proposes a deep learning-based system for automatic brain stroke prediction using CT scan images. Leveraging the Xception model for feature extraction, the system classifies scans as stroke or non-stroke with high accuracy. Comparative evaluation with ResNet50V2 and DenseNet121 models demonstrates Xception's superior performance, achieving 98.63% accuracy. The system incorporates preprocessing, data augmentation, and transfer learning to enhance robustness and generalization. Designed for real-time diagnosis, it offers a scalable, cost-effective solution suitable for deployment in emergency and low-resource medical settings, supporting faster and more accurate clinical decision-making.

Index Terms— Brain Stroke Prediction, Deep Learning, Convolutional Neural Networks, CT Scan Classification, Xception, ResNet50V2, DenseNet121, Medical Image Analysis, Stroke Detection, Healthcare AI

I. INTRODUCTION

Stroke is a medical condition that arises when the blood flow to a part of the brain is obstructed, either due to a clot (ischemic stroke) or bleeding (hemorrhagic stroke). This interruption deprives brain tissue of oxygen and essential nutrients, resulting in cell death within minutes. The consequences can range from temporary weakness to permanent disability or even death, depending on the severity and the area of the brain affected. Globally, stroke is recognized as one of the leading causes of death and a major contributor to long-term disability, placing a significant burden on healthcare systems and families.

Timely diagnosis is critical in stroke management. The faster a stroke is detected and treated, the better the chances of minimizing brain damage and improving patient recovery. Traditional diagnostic techniques such as Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are commonly used to confirm stroke cases. However, these methods rely heavily on the expertise of radiologists and can be time-consuming, particularly in resource-constrained settings. In emergency situations, this delay can reduce the window for effective treatment and increase the risk of severe complications.

Role of Deep Learning in Stroke Detection

In recent years, deep learning has emerged as a transformative technology in the field of medical image analysis. It enables computers to automatically learn features from large datasets without the need for manual intervention. Convolutional Neural Networks (CNNs), a type of deep learning model, have shown exceptional performance in identifying patterns within complex visual data. Their application in analyzing brain CT scans offers the potential to detect early signs of stroke more quickly and accurately than traditional methods. These models can process hundreds of images rapidly, identify subtle abnormalities, and provide consistent results without fatigue.

This study proposes a deep learning-based solution for stroke detection using CT scan images. The model leverages powerful pretrained architectures such as ResNet50 and DenseNet121, which have demonstrated high accuracy in various image classification tasks. By fine-tuning these models on a curated dataset of brain CT scans labeled for stroke presence, the system is trained to differentiate between normal and stroke-affected scans. The goal is to develop a model that not only achieves high performance but is also practical for real-world clinical use.

The significance of this research lies in its potential to support medical professionals in making faster and more informed diagnostic decisions. An automated stroke prediction system can serve as a second opinion tool, reduce the dependency on manual image interpretation, and ensure quicker responses in emergency situations. Ultimately, this work aims to contribute to the development of intelligent healthcare technologies that enhance patient care, especially in critical and time-sensitive scenarios.

II. LITERATURE REVIEW

1. CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning

Authors: Pranav Rajpurkar, Jeremy Irvin, Kaylie Zhu, Brandon Yang, Hershel Mehta, Tony Duan, Daisy Ding, Aarti Bagul, Curtis Langlotz, Katie Shpanskaya, Matthew P. Lungren, Andrew Y. Ng

Summary: This paper presents CheXNet, a deep learning model based on DenseNet121 for pneumonia detection in chest X-rays. The model achieved radiologist-level performance, demonstrating the potential of deep CNNs in medical image diagnosis. Although focused on pneumonia, its success influenced similar architectures in stroke detection tasks. The study highlighted the effectiveness of transfer learning in healthcare AI.

2. A Machine Learning Approach for Carotid Plaque Detection Using Vascular Ultrasound Images

Authors: Lorenzo Saba, Emilio Neri, Silvia Bruneo, Domenico Santoro, Salvatore Citraro, Emanuele Salerno, Marianna Quattrocchi

Summary: This study used machine learning algorithms like SVM and Random Forest to detect carotid artery plaques, which are linked to stroke. The system analyzed vascular ultrasound images to predict stroke risk effectively. It emphasized early diagnosis using intelligent systems. Though not CT-based, the methodology is relevant for risk factor analysis.

3. Deep Learning Algorithms for Detection of Critical Findings in Head CT Scans: A Retrospective Study

Authors: Sasank Chilamkurthy, Rohit Ghosh, Swetha Tanamala, Mustafa Biviji, Norbert G. Campeau, Vasantha Kumar Venugopal, Vidur Mahajan, Pooja Rao, Prashant Warier

Summary: The authors applied CNNs to identify critical abnormalities in head CT scans, such as hemorrhages and fractures. Using a large-scale dataset, the model achieved near-human accuracy. This study showcased the viability of deep learning for automated neuroimaging diagnostics. It laid a foundation for AI-assisted stroke detection in emergency care.

4. Multi-Class Brain Stroke Classification Using Deep Convolutional Neural Network

Authors: Krishan Rajaraman, Shreya Gupta, Anil Kumar Saini, Vandana Bhardwaj

Summary: The authors developed a CNN model that classifies CT scans into normal, ischemic, and hemorrhagic stroke. The system achieved high accuracy in multi-class classification. It demonstrates the power of deep learning in fast, automated stroke identification. The study supports the development of real-time clinical decision tools.

5. Stroke Prediction Using Hybrid Deep Learning Models

Authors: Md. Rafiul Islam, Nafiz Imtiaz Khan, Md. Sadman Sakib, Tanjim Tahmid, Hossain Shahriar

Summary: This paper proposed a hybrid model combining CNN and LSTM for stroke prediction using images and patient history. The integration of multimodal data improved prediction accuracy. It highlighted the benefit of combining spatial and sequential features. The model supports proactive stroke risk management.

6. Ischemic Stroke Lesion Segmentation Using Deep Learning and the ISLES Dataset

Authors: Mohammad Hosseini, Arman Khosravi, Sara Sadeghi, Leila Rezaei

Summary: A U-Net-based model was developed to segment ischemic lesions in MRI scans. The model trained on the ISLES dataset showed precise lesion mapping capabilities. Accurate segmentation aids in personalized treatment planning. The work contributes to post-stroke recovery strategies through advanced imaging analysis.

7. Real-Time Stroke Prediction Using Edge AI and Lightweight CNNs

Authors: Ahmed Al-Karawi, Nourhan Elsayed, Mohammed El-Abd

Summary: This study presented a lightweight CNN model for real-time stroke prediction on edge devices. The system is designed for low-resource settings with limited computing power. It offers fast and reliable stroke detection without cloud dependency. The approach supports portable and remote healthcare diagnostics.

8. Neuroimaging and Deep Learning for Brain Stroke Detection: A Review of Recent Advancements and Future Prospects

Authors: Karthik Ramamurthy, R. Menaka, Annie Johnson, Sundar Anand

Summary: This review analyzes 113 research papers focusing on the application of deep learning models in stroke lesion detection and segmentation. It categorizes various deep architectures based on imaging modalities and discusses the relevance of Convolutional Neural Networks (CNNs) and Fully Convolutional Networks (FCNs) in medical image analysis. The paper also highlights emerging trends and challenges in stroke detection, emphasizing the need for high-resolution imaging and addressing issues related to brain tissue diversity and older stroke areas.

9. Deep Convolutional Neural Networks for Brain Image Analysis on Magnetic Resonance Imaging: A Review

Authors: Jose Bernal, Kaisar Kushibar, Daniel S. Asfaw, Sergi Valverde, Arnau Oliver, Robert Martí, Xavier Lladó

Summary: This paper provides an extensive literature review of convolutional neural network (CNN) techniques applied in brain magnetic resonance imaging (MRI) analysis. It focuses on architectures, pre-processing, data preparation, and post-processing strategies. The study reports on the evolution of CNN architectures, discusses state-of-the-art strategies, and examines their pros and cons, offering a detailed reference for research activity in deep CNN for brain MRI analysis.

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10. **Artificial Intelligence for MRI Stroke Detection: A Systematic Review and Meta-Analysis**

Authors: Authors not specified in the provided information

Summary: This systematic review and meta-analysis focus on the application of artificial intelligence (AI) in MRI stroke detection. It evaluates various AI models, comparing their performance in detecting stroke lesions. The study emphasizes the potential of AI to enhance diagnostic accuracy and discusses the integration of these technologies into clinical workflows, aiming to improve patient outcomes in acute ischemic stroke management.

III. SYSTEM DESIGN

Predicting brain strokes using deep learning involves a systematic pipeline that begins with the acquisition of relevant data and concludes with the evaluation and comparison of multiple neural network architectures. This section outlines each phase of the methodology used in this study, including image preprocessing, model design, training strategy, and performance evaluation.

Data Acquistion:

The dataset used in this study consists of brain CT scan images collected from publicly available sources such as Kaggle and Radiopaedia. The images are categorized into three classes: ischemic stroke, hemorrhagic stroke, and normal cases. Where possible, the CT data was supplemented with patient metadata—such as age, gender, blood pressure levels, and smoking status—to provide additional context for predictive modeling.

Preprocessing Layer:

All input images were resized to 224×224 pixels to ensure uniformity and compatibility with standard deep learning model input layers. Preprocessing included noise reduction using Gaussian filters and contrast enhancement via histogram equalization to better highlight stroke-affected regions. Data augmentation techniques such as rotation, flipping, zooming, and brightness alteration were used to improve generalization, reduce overfitting, and simulate variability in real-world medical images.

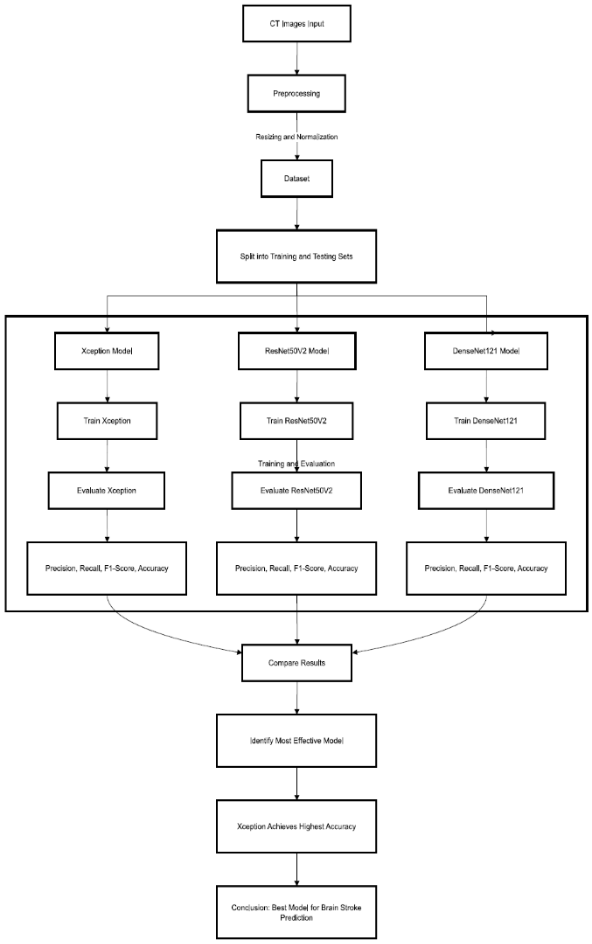

Fig 1: Flow Diagram

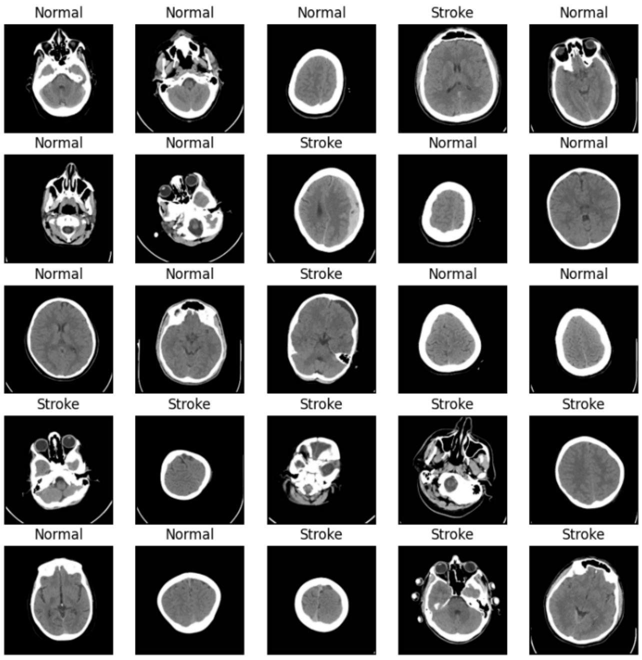

Fig 2: Stroke and Normal Brain Images

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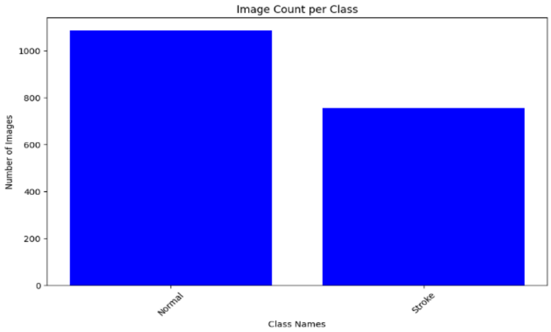

Fig 3: Image Count per Class

Deep Learning Model Development:

To identify the most efficient model for stroke prediction, three deep learning architectures were selected: ResNet50, DenseNet121, and a custom Convolutional Neural Network (CNN).

ResNet50V2 incorporates residual blocks to mitigate vanishing gradient issues, allowing deeper networks to learn complex patterns.

DenseNet121 connects each layer to every other layer to maximize feature reuse and strengthen gradient propagation, resulting in efficient training with fewer parameters.

Xception, a high-performing architecture based on depthwise separable convolutions, offers an optimized balance between accuracy and computational efficiency. It leverages channel-wise filtering, making it particularly powerful for fine-grained image classification tasks like stroke detection.

All models were implemented with ReLU activation, Softmax for final classification, Batch Normalization to stabilize training, and Dropout to prevent overfitting. Transfer learning was applied by initializing weights from ImageNet, followed by fine-tuning on the stroke dataset.

Model Training Strategy:

The dataset was divided into training (70%), validation (15%), and testing (15%) sets. Training was conducted using the Adam optimizer and categorical cross-entropy loss function. Early stopping and learning rate reduction were used to avoid overfitting and improve convergence. The models were implemented using TensorFlow and Keras in Python and trained on GPU-accelerated hardware for faster performance.

Evaluation Metrics:

To thoroughly assess each model's performance, various evaluation metrics were used. Accuracy was measured to determine the overall correctness of predictions. Precision quantified the proportion of correctly predicted stroke cases among all positive predictions, while recall (sensitivity) assessed how effectively the model identified actual stroke cases. The F1-score, a harmonic mean of precision and recall, provided a balanced metric for performance evaluation.

Specificity was calculated to ensure the correct identification of non-stroke cases, and AUC (Area Under the ROC Curve) served as a measure of the model's ability to differentiate between stroke and non-stroke classes. In addition, confusion matrices were analyzed to provide a clear view of classification performance, showing true positives, false positives, false negatives, and true negatives for each model.

Comparative Analysis:

Among the three models, the Xception model outperformed both ResNet50V2 and DenseNet121 across most evaluation metrics. It achieved the highest accuracy, recall, and F1-score, demonstrating superior capability in distinguishing between ischemic, hemorrhagic, and normal brain scans. Its use of depthwise separable convolutions allowed efficient feature extraction with reduced computational cost. While DenseNet121 also showed strong results due to its dense connectivity, it required more memory and longer training time. ResNet50V2 delivered balanced performance with good accuracy but was slightly behind in sensitivity and overall classification strength. The Xception model's robustness and efficiency make it the most suitable choice for real-time medical applications in brain stroke detection.

IV. RESULTS INTERPRETATION AND COMPARISONS

This section presents the detailed evaluation of the deep learning models used for brain stroke prediction, namely Xception, ResNet50V2, and DenseNet121. The models were trained on a curated dataset of brain CT images and evaluated using performance metrics such as accuracy, precision, recall, and F1-score. The outcomes of these evaluations provide insights into the robustness and reliability of each model in classifying stroke and non-stroke cases.Model Performance Comparison:

Performance of the Xception Model:

The Xception model demonstrated the highest classification performance among the three, achieving an overall accuracy of 98.63%. For the normal class, it attained a precision of 0.9934 and recall of 0.9870, whereas for the stroke class, the model achieved a precision of 0.9697 and recall of 0.9846. The F1-scores for these classes were 0.9902 and 0.9771, respectively. These results suggest a strong capability of the model to detect stroke cases while minimizing false positives and false negatives. The macro and weighted average F1-scores of 0.9836 and 0.9863 further confirm the balanced performance across both classes.The performance of the models is compared based on their accuracy and other relevant classification metrics.

ResNet50V2 Model Performance

The ResNet50V2 model also produced strong results, with an overall accuracy of 97.94%. It achieved a precision of

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0.9967 and recall of 0.9739 for normal cases, and precision of 0.9416 and recall of 0.9923 for stroke cases. The corresponding F1-scores were 0.9852 and 0.9663. While its stroke recall was slightly higher than that of Xception, it had lower stroke precision, indicating a tendency to produce more false positives. The macro average F1-score of 0.9757 demonstrates strong yet slightly less consistent performance compared to Xception.

DenseNet121 Model Observations

In contrast, the DenseNet121 model achieved a significantly lower accuracy of 74.83%. The precision and recall for the normal class were 0.8662 and 0.7590, while for the stroke class, they were 0.5595 and 0.7231, respectively. The overall F1-scores were 0.8090 (normal) and 0.6309 (stroke), indicating a clear imbalance and limited ability to correctly identify stroke cases. The macro average F1-score of 0.7200 and high misclassification rate suggest that the model may not be well-suited for this specific task or dataset without further optimization.

Table 3. Comparative Analysis

Model	Accuracy	Macro F1-Score	Stroke Recall	Stroke Precision
Xception	**98.63%**	**0.9836**	**0.9846**	**0.9697**
ResNet50V2	97.94%	0.9757	0.9923	0.9416
DenseNet121	74.83%	0.72	0.7231	0.5595

These metrics clearly indicate that the Xception model outperforms the others in terms of both accuracy and generalization, providing a more balanced and reliable classification. The ResNet50V2 model, while also highly accurate, exhibited minor inconsistencies in precision and F1-score. The DenseNet121 model, despite being widely used in medical image analysis, struggled with this dataset and produced a less satisfactory outcome.

V. CONCLUSION

In this study, deep learning models were applied to brain CT scan images for stroke prediction, with a comparative analysis of Xception, ResNet50V2, and DenseNet121 architectures. Among them, the Xception model achieved the highest accuracy of 98.63%, demonstrating superior performance in terms of precision, recall, and F1-score. The results highlight the effectiveness of using CNN-based models for automated medical diagnosis, particularly in detecting strokes. This work lays the foundation for integrating such models into clinical decision support systems to enhance early diagnosis and treatment planning.

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