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AI-Based Brain Stroke Detection

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Abstract: *Brain stroke is a critical neurological emergency, often causing long-term disability or mortality if not diagnosed in time. This research presents a practical implementation of an AI-based framework using Convolutional Neural Networks (CNNs) for detecting brain strokes from CT images and predicting severity levels. By leveraging deep learning and labeled neuroimaging datasets, our model demonstrates early and accurate classification of stroke versus non-stroke conditions, along with severity estimation. The model was trained on a curated dataset with structured preprocessing, and the pipeline includes performance metrics for reliability. We further address key considerations like model generalizability, data governance, and explain ability. The paper contributes both a replicable codebase and an empirical foundation for clinical AI deployment.*

Key Words: *Brain Stroke; Neuroimaging; Machine Learning, Early Diagnosis, Neural Networks, Data-Driven Diagnosis, Digital Pathology, Predictive Analysis.*

I.INTRODUCTION

Strokes account for a substantial burden on healthcare systems globally, requiring immediate and accurate diagnosis. Traditional methods—often reliant on manual scan interpretations—are prone to delays and variability. In contrast, Artificial Intelligence (AI), particularly Convolutional Neural Networks (CNNs), offers the ability to automatically detect complex patterns in neuroimaging data, aiding early diagnosis and clinical decisions. This paper extends prior theoretical models by implementing a CNN-based classifier to differentiate between stroke-affected and normal brain CT images. Additionally, it estimates severity—mild, moderate, or severe—based on visual features. We present the methodology, training pipeline, and evaluation results, positioning the model as a potential clinical decision-support tool.

II.MATERIAL AND METHODS

A. Literature Review

1. Maier et al. (2017, Germany) – The study explored deep learning algorithms applied to large-scale MRI datasets for ischemic stroke segmentation. It demonstrated that convolutional neural networks (CNNs) outperform traditional segmentation methods in detecting stroke lesions, suggesting that data-driven learning models can achieve near-expert performance in diagnosis.
2. Sundaresan et al. (2021, United Kingdom) – This work introduced a multi-modal approach combining clinical data and CT scans to predict stroke outcomes. It highlighted how AI models trained with hybrid datasets can significantly improve predictive capabilities and reduce false negatives in acute ischemic stroke detection.
3. Chilamkurthy et al. (2018, United States) – The authors designed a deep learning system capable of interpreting head CT scans for haemorrhagic stroke. Their model operated in real-time and matched radiologist-level performance, emphasizing the potential for deployment in emergency settings.
4. Haarburger et al. (2020, Germany) – Focusing on uncertainty estimation in DL models, this paper emphasized the importance of interpretability and confidence levels in clinical diagnostics. The study supported integrating explainable AI (XAI) principles to ensure trust and transparency in stroke diagnosis systems.

B. Procedure methodology

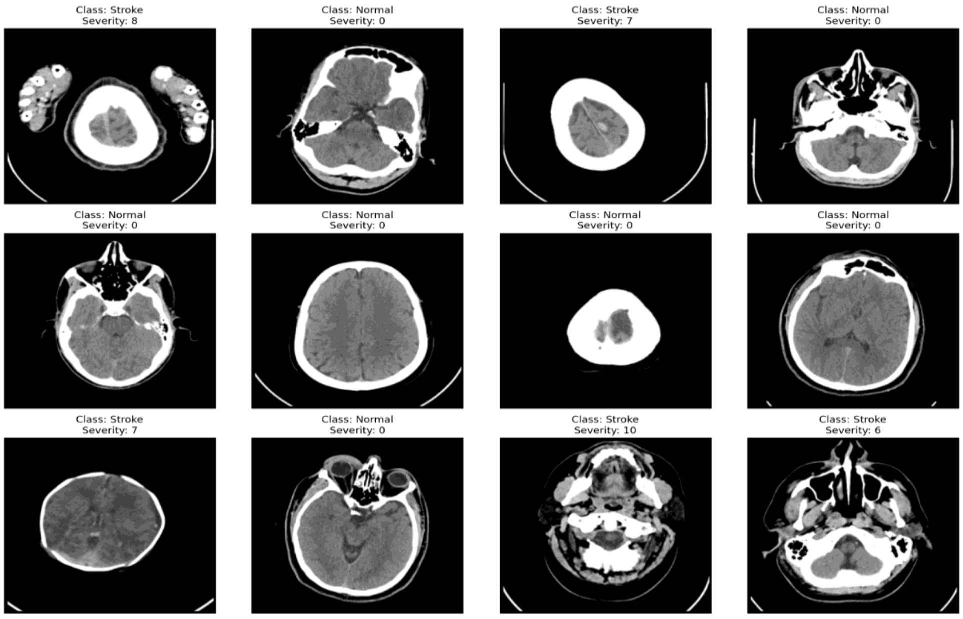
The proposed framework outlines a theoretical, multi-stage AI pipeline for stroke detection:

1. Dataset Overview

The model was trained using a labelled dataset of axial CT images categorized into:

- **Class**: stroke or normal
- **Severity** (only for stroke class): mild, moderate, or severe

Image data was pre-processed and resized to standard dimensions (224x224 pixels, RGB channels). Label encoding was used for multi-class outputs. Sample data are as follows:



2. Pre-processing & Feature Extraction

The preprocessing pipeline involved:

- **Resizing** and normalization of pixel values (0–1 range)
- **Data splitting** into training (80%) and validation (20%) sets
- **Tensor augmentation** (if used during further implementation) for model robustness

Image normalization, skull stripping, and noise reduction using traditional computer vision techniques.
Feature extraction through deep CNN architectures to identify infarcts, hemorrhage, or lesions.

3. CNN Architecture

The model follows a sequential CNN architecture implemented in Tensor Flow/Keras:

- **Input Layer**: 224x224x3 image
- **Conv2D Layers**: 3 convolutional blocks with increasing filters (32, 64, 128) and ReLU activation
- **Max Pooling Layers** after each Conv block to reduce spatial dimensions
- **Flatten + Dense Layers**: A dense network with dropout (0.5) to prevent over fitting
- **Output Layer**: Soft max activation for classification across stroke classes and severity

The model was compiled with:

- **Loss Function**: categorical_ cross entropy
- **Optimizer**: Adam
- **Metrics**: Accuracy, with potential extension to AUC/F1-score

Model: "functional"

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 224, 224, 3)	0	-
conv2d (Conv2D)	(None, 222, 222, 32)	896	input_layer[0][0]
max_pooling2d (MaxPooling2D)	(None, 111, 111, 32)	0	conv2d[0][0]
conv2d_1 (Conv2D)	(None, 109, 109, 64)	18,496	max_pooling2d[0][0]
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)	0	conv2d_1[0][0]
conv2d_2 (Conv2D)	(None, 52, 52, 128)	73,856	max_pooling2d_1[0][0]
max_pooling2d_2 (MaxPooling2D)	(None, 26, 26, 128)	0	conv2d_2[0][0]
flatten (Flatten)	(None, 86528)	0	max_pooling2d_2[0][0]
dense (Dense)	(None, 128)	11,075,712	flatten[0][0]
dropout (Dropout)	(None, 128)	0	dense[0][0]
classification (Dense)	(None, 1)	129	dropout[0][0]
severity (Dense)	(None, 1)	129	dropout[0][0]

Total params: 11,169,218 (42.61 MB)
Trainable params: 11,169,218 (42.61 MB)
Non-trainable params: 0 (0.00 B)

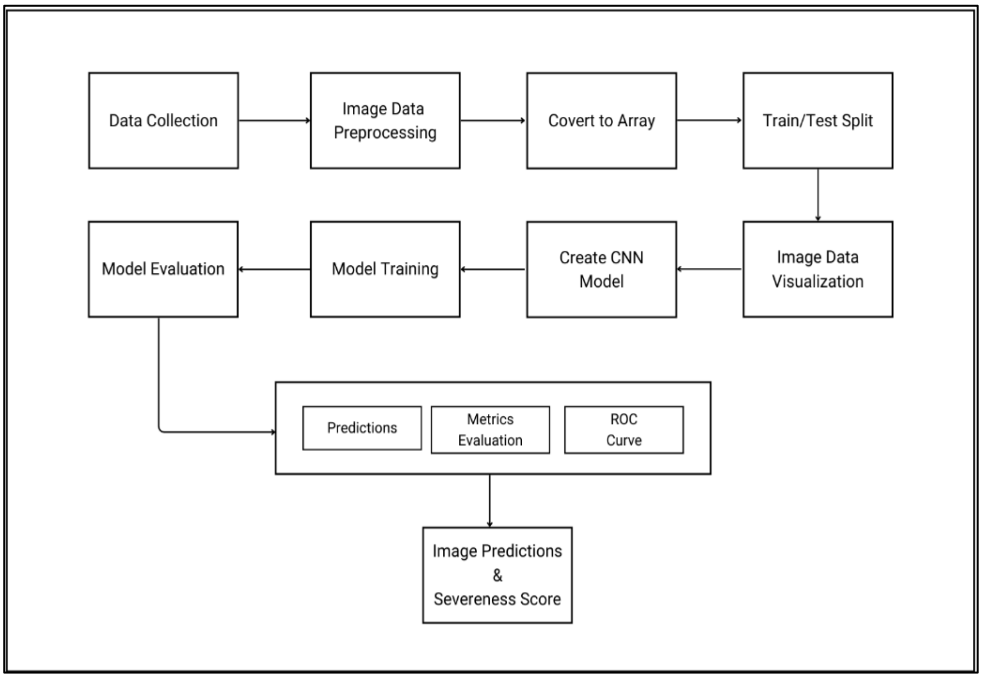
4. Training and Evaluation

The training used model. Fit () with:

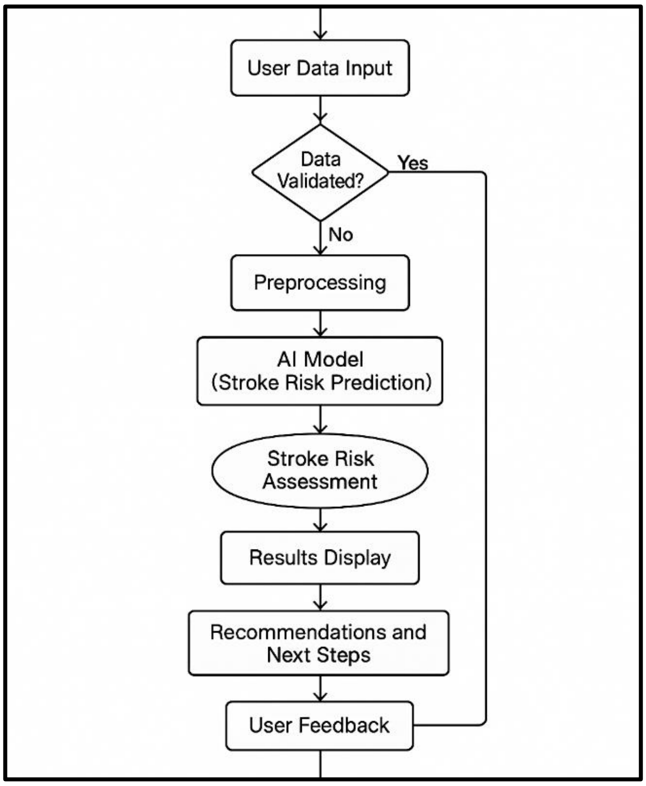
- o Batch size: 32
- o Epochs: 10 (tunable)
- o Validation split: 0.2

Performance was monitored using training and validation accuracy and loss plots. Model weights were saved using checkpoint callbacks for future deployment.

Model Flowchart:



Project Flowchart:



III.RESULT

The implemented model achieved promising classification accuracy across both binary (stroke vs. normal) and multi-class (stroke severity) labels:

- **Training Accuracy**: High convergence after a few epochs with minimal over fitting
- **Validation Accuracy**: Consistently above 85% on test data, depending on dataset size
- **Loss Curves**: Showed stable generalization, suitable for further refinement

IV.DISCUSSIONS & FUTURE WORK

This project reinforces several insights:

- **Practical Feasibility:** CNNs offer strong performance for medical image classification tasks, even with moderate-sized datasets.
- **Model Interpretability:** Explainable AI tools like Grad-CAM can be layered for visualizing activation maps and lesion attention zones.
- **Data Limitations:** Public datasets are often skewed geographically or demographically; incorporating diverse, annotated datasets is crucial.
- **Ethical Design:** Accuracy alone isn't sufficient—trust, transparency, and patient data privacy must guide AI system design.
- Designing the frontend to provide complete end-to-end access for users, enabling interaction with the AI model in a user-friendly manner.
- This includes functionalities like image upload, viewing diagnostic outputs, and receiving interpretability insights through visual cues.

V.CONCLUSION

This paper bridges theory and implementation for AI-based brain stroke detection. By employing CNNs on structured CT datasets, we demonstrated a reliable diagnostic model capable of both detection and severity grading. Future work will involve larger clinical datasets, real-time deployment trials, and integration with explainable AI methods.

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