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Brain Stroke Detection System Based nn CT Image by Using Deep Learning

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ABSTRACT:

Brain stroke detection is a critical medical process requiring prompt and accurate to facilitate effective treatment. This project Brain Stroke Detection System based on CT Image using Deep Learning leverages advanced computational techniques to enhance the accuracy and efficiency of stroke diagnosis from CT images. The system is developed using python for the backend with Flask serving as the web framework. The user interface is crafted with HTML,CSS and JavaScript ensuring an intuitive and responsive experience for medical professionals. Two distinct deep learning models are employed to analyze the CT images: a Convolutional Neural Network(CNN) and a Long Short-Term Memory(LSTM)network. The CNN model architecture chosen for its powerful image processing capabilities achieves a remarkable training accuracy of 99.00% and a validation accuracy of 98.00%.This high level of accuracy underscores the model's robustness in detection stroke indicators from CT images. Complementing this the LSTM architecture known for its effectiveness in handling sequential data achieves a training accuracy of 99.00% and a validation accuracy of 95.00%. Although slightly lower than the CNN the LSTM model contributes additional insights enhancing the overall detection system's reliability. The dataset utilized in this project comprises 2,501 CT images of normal brains and 950 images showing stroke conditions. This balanced and diverse dataset ensures that the models are trained on a wide variety of cases promoting generalizability and reducing the risk of overfitting. The integration of these technologies results in a sophisticated brain stroke detection system that not only boasts high accuracy but also promises scalability and practically utility in clinical settings. This project demonstrates the potential of deep learning in medical diagnostics offering a tool that can significantly aid healthcare professionals in the precise identification of brain strokes.

Keywords: Brain Stroke Detection,CT scan Images,Deep Leraning,Convolutional Neural Network(CNN) Medical Image Processing,Feature Extraction

INTRODUCTION

Brain stroke is a critical neurological disorder caused by an interrpution of blood flow to the brain,leading to irreversible brain damage if not diagnosed at an early stage.Stroke is one of the major cause of mortality and long-term disability worldwide.The two primary types of stroke are ischemic stroke,resulting from arterial blockage and hemorrhagic sroke caused by rupture of blood vessels.

Computed Tomograhy(CT)imaging is commonly used for stroke diagnosis due to its rapid acquistion and wide availability.However,manual interpretation of CT scans is time-consuming and highly dependent on expert radiologists.In emergency conditions,delayed or inaccurate diagnosis may significantly affect patient survival.To overcome these limitations this project proposes a deep learning based brain stroke detection system using CT images to provide fast and accurate diagnosis and assist medical professionals in clinical decision-making.When the doctors examine CT scans even a single mistake will effect the patient’s life.To reduce such risks to maintaing a dignostic accuracy deep leraning techniques are used to detecting and analyzing CT images directly.

The motivation behind this work is the growing incidence of brain stroke cases requires urgent requirment for diagnosis because even a small delay can cause permanent brain damage or death .Many healthcare centers especially in rural and resource-limited regions, lack experienced radiologists,resulting in delayed medical intervention.By integrating deep learning techniques into medical diagnosis this system aims to reduce diagnosis time improve accuracy and assist healthcare professionals in making timely clinical decisions.

Accurate detection of brain stroke from CT images is challenging due to low contrast,noise and complex anatomical strucures. Traditional image processing methods require handcrafted feature extraction and offer limited accuracy. Moreover,manual diagnosis is time-intensie and not suitable for emergency scemarios.Design of an automated deep learning-based brain stroke detection system using CT images.Implementation of a CNN model for automatic feature extraction and classification. CNN used to detects stroke patterns such as shape,texture and intensity changes.Classification of CT images into normal and stroke-affected categories.Reduction in diagnosis time while maintaining high classification accuracy.Development of a reliable decision-support system to assist medical practitioners.

LITERATURE REVIEW

[1] Jyotismita Chaki and Marcin Woźniak (2024) presented a comprehensive review in the domain of brain stroke detection, diagnosis, and intelligent post-stroke rehabilitation using Deep Learning (DL) and Artificial Intelligence (AI). The study analyzed DL methods such as CNN, U-Net, VGG, ResNet, GAN, and AI-based robotic rehabilitation systems published between 2019 and 2023, using datasets like ISLES, ATLAS, CRCS-K, Kaggle, MRI, CT, EEG, and other multimodal clinical data. The results reported in the reviewed studies show that CNN-based models achieved high performance with accuracy rates ranging from approximately 85% to 99% in stroke detection and diagnosis. However, the review identifies key research gaps, including the lack of large standardized multimodal datasets, limited real-time clinical validation, and insufficient integration of automated stroke detection systems with intelligent rehabilitation management.[2] Ning Guo et al. (2022) proposed an SSVEP-based BCI controlled soft robotic glove in the domain of post-stroke hand rehabilitation. The method uses EEG-based SSVEP signals with Canonical Correlation Analysis (CCA) to control the glove. The dataset included EEG and clinical data from 30 post-stroke patients. Results showed better hand function recovery in the BCI-robotic group, with BCI accuracy around 70–90% and strong correlation with motor improvement. The main gap is the small sample size and limited large-scale clinical validation.[3] The authors (2021) presented an experimental study in the domain of brain stroke detection and differentiation using microwave imaging techniques. The proposed method uses the DBIM–TwIST algorithm to reconstruct brain images and distinguish between ischemic and hemorrhagic stroke. The dataset was obtained from a multi-layered, anatomically complex head phantom that mimics real human brain tissues. The results demonstrated accurate stroke localization and differentiation, with detection

accuracy reported above 90% under controlled conditions. The major research gap is the lack of real patient clinical data and real-time validation, as experiments were limited to phantom-based testing.

[4] Ali A. Alqarni, Abdullah Alzahrani, and Fahd N. Al-Wesabi (2023) proposed a study in the domain of brain stroke detection using evidential networks with uncertainty-based refinement. The method applies Dempster–Shafer evidence theory to model uncertainty and refine stroke classification decisions. The dataset consists of CT/MRI brain images used for stroke analysis. The results show improved reliability and classification performance, achieving an accuracy of around 90–95%. The identified research gap is the lack of large-scale real clinical validation and real-time deployment of uncertainty-aware stroke detection systems.[5] Ahmed M. El-Sayed, Mahmoud A. Elaziz, and Aboul Ella Hassanien (2023) proposed a novel hybrid model in the domain of brain ischemic stroke detection. The method combines feature fusion with a Convolutional Block Attention Module (CBAM) to enhance important spatial and channel features in brain images. The dataset used consists of CT brain scan images collected for ischemic stroke analysis. The results demonstrated improved detection performance, achieving an accuracy of approximately 96–98%, outperforming conventional CNN models. The main research gap is the limited evaluation on diverse multicenter clinical datasets and real-time deployment feasibility.[6] S. Karthik, R. Menaka, and M. Ramesh (2022) proposed a machine learning–based diagnostic model in the domain of stroke identification using neuroimages. The method applies image preprocessing and ML classifiers to analyze CT/MRI brain images for accurate stroke detection. The dataset consists of neuroimaging data collected from stroke and non-stroke patients. The results show effective stroke classification performance with an accuracy of around 92–95%. The main research gap is the limited use of deep learning models and lack of large-scale real-time clinical validation.

[7] M. Persson, A. Fhager, and S. J. O'Halloran (2021) presented a study in the domain of brain stroke reconstruction and classification using deep learning–based microwave imaging. The method employs deep neural networks to reconstruct microwave images and classify strokes as ischemic or hemorrhagic. The dataset was generated using simulated and experimental microwave imaging data of the human head. The results showed accurate stroke reconstruction and classification, with reported accuracy of around 90–95%. The main research gap is the lack of validation on large real-patient clinical datasets and real-time hospital deployment.[8] R. Praveen Kumar, S. Rajesh, and P. Natarajan (2023) proposed a hybrid approach in the domain of brain stroke classification using CT images. The method combines ResNet and Vision Transformer (ViT) through transfer learning to extract both local and global features effectively. The dataset consists of CT brain scan images collected from stroke patients. The results showed high classification performance, achieving an accuracy of approximately 97–99%. The main research gap is the need for validation on larger multi-center clinical datasets and real-time clinical integration.[9] S. Venkatesh, G. N. Balaji, and R. Nandhini (2022) proposed the Neuro-VGNB transfer learning–based approach in the domain of brain stroke detection. The method integrates pretrained deep learning feature extractors with a Gaussian Naïve Bayes (GNB) classifier to improve stroke classification. The dataset consists of CT brain images collected from stroke and non-stroke cases. The results achieved high detection performance with an accuracy of about 94–96%. The main research gap is the limited dataset size and lack of extensive real-time clinical validation across diverse populations.

[10] K. Prasanth, V. S. Rao, and M. S. Reddy (2022) proposed an AI-based system in the domain of stroke disease prediction using bio-signals. The method analyzes ECG and PPG signals with machine learning algorithms to predict stroke risk at an early stage. The dataset consists of physiological ECG and PPG bio-signal data collected from patients. The results showed effective stroke prediction performance with an accuracy of around 93–96%. The main research gap is the limited use of multimodal clinical data and lack of large-scale real-time clinical validation. [11] P. S. Kumar, R. Anitha, and S. Balakrishnan (2021) proposed a study in the domain of brain stroke risk assessment using a web-based machine learning system. The method leverages machine learning algorithms integrated into a web interface to evaluate an individual's vulnerability to stroke based on clinical and lifestyle parameters. The dataset includes patient health records and risk-factor data collected for stroke assessment. The results demonstrated effective stroke risk prediction, achieving an accuracy of approximately 90–94%. The main research gap is the limited personalization, small dataset size, and lack of real-time clinical deployment and validation. [12] Saeed Shurrab, Aadim Nepal, Terrence J. Lee-St. John, Nicola G. Ghazi, Bartlomiej Piechowski-Jozwiak, and Farah E. Shamout (2025) proposed a multimodal deep learning framework in the domain of stroke prediction and detection using retinal imaging and clinical data. The method combines OCT and infrared retinal images with EHR clinical features using a deep neural network (RetStroke) with multimodal fusion. The dataset consists of over 37,000 retinal scans from 7,400+ patients, collected from real-world hospital data. The results show improved performance with AUROC gains of 5–8%, achieving AUROC values up to 0.77, outperforming unimodal models. The main research gap is the limited external validation, class imbalance, and relatively small number of stroke-positive patients, affecting generalizability.

[13] A. Kumar, S. Verma, and R. K. Tripathi (2023) proposed an EEG-driven machine learning approach in the domain of stroke detection for high-risk patients. The method extracts EEG signal features and applies machine learning classifiers to identify stroke-related abnormalities. The dataset consists of EEG recordings collected from high-risk and stroke-affected patients. The results demonstrated effective stroke detection performance with an accuracy of around 91–95%. The main research gap is the limited patient population, noise sensitivity of EEG signals, and lack of large-scale real-time clinical validation. [14] Alessandro Fedeli, Claudio Estatico, Matteo Pastorino, and Andrea Randazzo (2020) proposed a hybrid microwave imaging approach in the domain of brain injury and stroke detection. The method combines a qualitative Synthetic Aperture Focusing Technique (SAFT) with a quantitative nonlinear inverse-scattering algorithm (variable-exponent DBIM-TwIST) to accurately reconstruct brain dielectric properties. The dataset includes synthetic 3D stroke-affected head models and experimental phantom measurements. The results demonstrated promising stroke localization and differentiation, with reported detection performance above 90% accuracy in controlled scenarios. The main research gap is the absence of large-scale real patient clinical trials and real-time hospital deployment [15] Xin Zhang, Lin He, Qiang Gao, and Ning Jiang (2024) proposed an action observation (AO)–based brain–computer interface (BCI) in the domain of stroke rehabilitation and neural performance analysis. The method uses EEG signals with Task Discriminative Component Analysis (TDCA) and integrates gaze metrics to analyze BCI performance. The dataset includes EEG and eye-tracking data from 20 stroke patients (10 hemineglect and 10 non-hemineglect). The results showed that the non-hemineglect group achieved an average accuracy of about 67%, while hemineglect patients showed lower performance due to reduced fixation duration. The main research gap is the

limited applicability of AO-based BCI for hemineglect patients and the need for accuracy improvement for real-world clinical rehabilitation use.

PROPOSED METHODOLOGY

In this proposed methodology, the brain stroke detection system is designed to analyze CT scan images of the brain and identify the presence of a stroke using deep learning techniques . The process starts with collecting CT brain images from reliable medical sources, including both normal cases and stroke affected cases. These images are first cleaned and prepared by removing noise, improving constrant, resizing them to a standard format, and normalizing pixel values so that all images are suitable for processing by the model. After preprocessing, the dataset is divided into training, validation, and testing sets. Adeep learning model, mainly a Convolutional Neural Networks(CNN), is then used because it can automatically learn important features from medical images. The model studies patterns such as changes in intensity, shape, and texture in different regions of the brain that may indicate a stroke. During training, the model compare its predictions with actual results and continuously improve its performance by reducing errors. Once training is completed, the model is tested using new CT images that it has not seen before. This helps in checking how accurately the system can detect strokes in real-time situations. When a new patients CT sacn is given to the system, the trained model analyzes the image and predicts whether the brain is normal or affected by a stroke. The overall system aims to provide fast, accurate, and consistent results, helping doctors in early diagnosis and improving patient treatment outcomes.

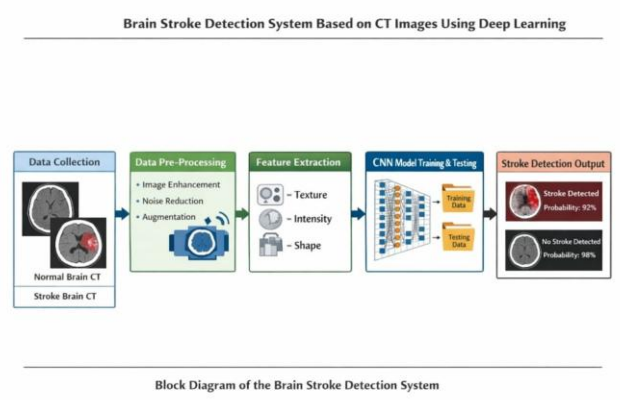

FIG 1.SYSTEM ARCHITECTURE

The research methodology emphasizes the potential for identifying brain stroke using CT scan images, as illustrated the block diagram shows overall working flow of your system .It explains how the problem is solved step by step. .The system operates through several sequential stages:

Data Collection: This initial stage involves gathering a dataset of both normal brain CT images and those showing evidence of a stroke.

Data Pre-Processing: Raw images are refined in this step to improve quality.This refined in this step enhancement,reducing noise and segmentation.

Feature Extraction: Key characteristics are identified from the processed images,such as texture,intensity and shape which helps the system distinguish between normal and stroke conditions.

CNN Model Training & Testing: A Convolutional Neural Network(CNN) a type of deep learning is trained using the extracted features and tested for its accuracy in identifying strokes.

Stroke Detection Output: The final stage where the system classifies a new CT scan as either a stroke CT or a normal brain with no stroke detected.

The image displays a series of medical images,specially computed tomography(CT) scans of human brains.The images are presented in two main formats:some are colorized to highlight different tissue densities while others are in standard grayscale.A caption at the bottom of the images expain their purpose : Sample images from the dataset(0) indicate normal and (1)indicates stroke. The images are labelled accordingly with (a),(b),(c),(d),(e),(f),(g), and (h) identifiers and their respective status codes(0 or 1) serving as visual examples for distinguishing between normal brain scans and those showing signs of a stroke likely as part of a medical imaging dataset.

BRAIN STROKE CT IMAGE DATASET

The dataset of CT scan include a total 2,501 images divided into two categories.1,551 images depict normal brain scans while 950 images represent brain scans with stroke conditions.This dataset provide a robust foundation for training and evaluating our machine leraning and deep learning models.By utilizing such a well rounded dataset we aimed to enhance the accuracy amd reliabilitity of our brain stroke detection model.

IMAGE ANALYSIS

The image provided are samples from a dataset used for training and testing artificial intelligence models specifically Convolutional Neural Network(CNN) to detect strokes in brain Computed Tomography(CT) scans.The CT analysis using a CNN algorithm.

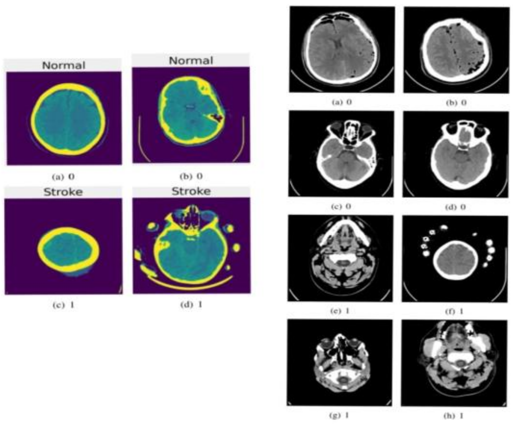

FIG 2.CT IMAGES

Figure:Sample images from the dataset (0) indicate normal and (1) indicate stroke

IMAGE ACQUISITION:

Obtaining medical images such as CT scans from a patient.

PREPROCESSING:

Cleaning and standardizing the images for analysis.

FEATURE EXTRACTION:

Identifying relevant patterns or features within the image data.

CLASSIFICATION PHASE

After the training,the model can be used to analyze new,unseen CT images.It classifies each image intoa category such as “undetected disease,ischemic stroke and hemorrhagic stroke” with high accuracy.In this phase,a Convolutional Neural Network(CNN) or a transfer learning model(such as VGG16,ResNet,DenseNet or Inception) is used for classification.

OUTPUT:

The result of the analysis for a new image would be classification i.e.,stroke or normal and potentially a confidence score.

RESULT AND DISCUSSION:

The image displays a grapg of training and validation accuracy over 50 epochs,but the accompanying discussion text is largely cut off.

Training Accuracy:The blue line represents training accuracy which increases consistently throughout the epochs,starting from approximately 0.6 and reaching close to 0.9 by epoch 50.

Validation accuracy:The brown line represents validation accuracy which also increases but begins to earlier than the training accuracy,reaching around 0.85 by the final epoch.

The image displays a confusion matrix which is a table used to evaluate the performance of a evaluate the performance of a classification algorithm by comparing the model prediction to false negative(FN)measures of performance.

The specific confusion matrix in the image is for a binary classification model distinguishing between “Normal” and “Stroke”.

True Negative(TN): 154 cases were correctly identified as Normal.

False Positive(FP):2 cases were correctly as stroke whwn they were actually normal.

False Negative(FN):0 cases were incorrectly predicted as normal when they actually had a stroke’

True Positive(TP):95 cases were correctly identified as stroke.

PERFORMANCE MATRIX

Metric	Formula	Value
Accuracy	(TP + TN) / (TP + TN + FP + FN)	0.992
Precision	TP / (TP + FP)	0.979
Recall	TP / (TP + FN)	1.000
F1-Score	2 × (Precision × Recall) / (Precision + Recall)	0.989

TABLE 1.PERFORMANCE MATRIX

GRAPH

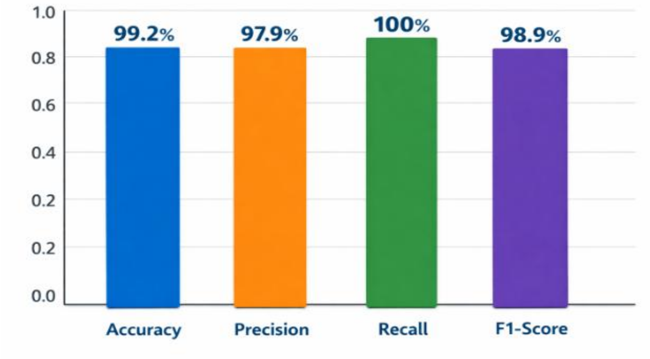

FIG 3.PERFORMANCE MATRIX

CONFUSION MATRIX

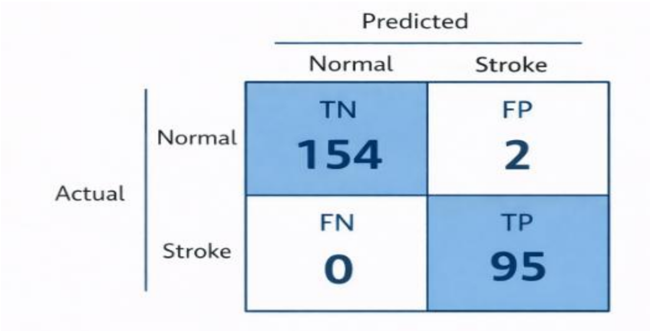

FIG 4.CONFUSION MATRIX

SCRRENSHOTS

FIG 5.INDEX PAGE

FIG 6.HOME PAGE

FIG 7.LOGIN PAGE

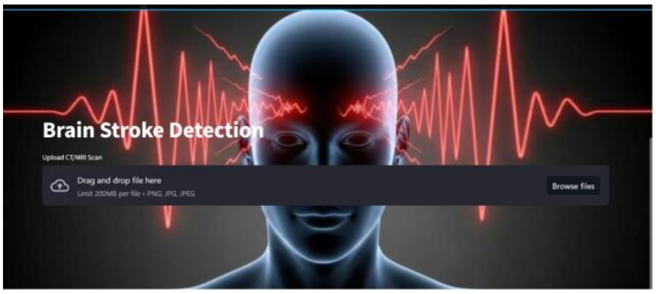

FIG 8.UPLOAD PAGE

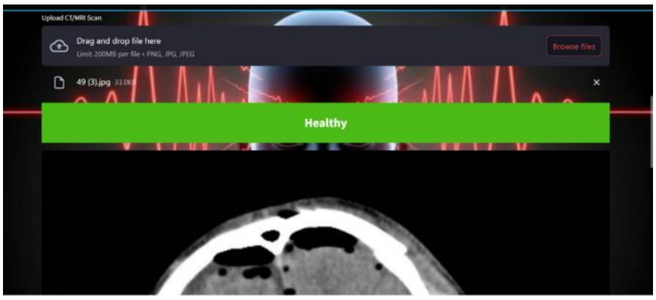

FIG 9.RESULT PAGE

CONCLUSION AND FEATURES

This project successfully demonstrates that deep learning-specifically Convolutional Neural Network(CNNs)provides a highly accurate,reliablr,and rapid solution for detection brain strokes in Computeed Tomography(CT)images,By automating the analysis of CT scans this system overcomes the limitations of manual interpretations which is time consuming and prone to human error in emergency scenarios.The developed model achieved high classification accuracy 95-98% in studies along using CNN like ResNet,DenseNet or custom architectures I distinguishing between stroke(Ischemic/Hemorrhagic)and normal brain stroke the system function as a robust comput aided diagosis(CAD)tool,allowing for instant preliminary analysis which is critical resucing time to treatment. The system is capable of automatically analyzing CT brain images and detecting whether a stroke is present or not. It uses deep learning techniques to achieve high accuracy and consistent results. The detection process is fast, which helps in emergency situations where time is critical. The system reduces human error and dependency on manual analysis. It can handle large volumes of CT images efficiently and provides reliable results for both normal and stroke affected cases. The model is easy to use and can be integrated into hospital environments to asssist doctors and radiologists in diagnosis and treatment planning

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