Survey on Machine Learning-Driven Early Diagnosis Framework for Brain Stroke Detection using Medical Imaging

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Abstract: **Brain stroke, a leading cause of disability and mortality worldwide, occurs due to disrupted blood flow to the brain, requiring rapid diagnosis for effective treatment .Traditional imaging methods like CT and MRI scans play a crucial role in stroke detection, but manual interpretation is time-consuming and prone to variability. With advancements in artificial intelligence, deep learning models, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in medical image analysis. This project leverages a fine-tuned VGG19 model to classify brain stroke images, incorporating data augmentation techniques like rotation, brightness adjustment, and flipping to enhance model generalization. Additionally, preprocessing steps such as image cropping and normalization improve input quality, ensuring robust performance. By splitting the dataset into training, validation, and test sets and evaluating performance through accuracy and loss metrics, this study presents an efficient and automated approach to stroke detection, emphasizing the importance of AI-driven medical imaging solutions.**

Keywords: **Artificial intelligence, Machine learning, Algorithms, pandemic, circular economy (CE), online qualities, resource efficiency, convolution neural networks, computed tomography, m RMR, Oz Net.**

INTRODUCTION

Overview and Importance of Stroke Diagnosis:
Brain stroke is a leading cause of disability and mortality worldwide, resulting from interrupted blood flow to the brain, which can lead to irreversible damage. Strokes are classified into ischemic (caused by blockages, 85% of cases) and hemorrhagic (caused by vessel rupture). Effects vary from paralysis to cognitive impairments, emphasizing the need for early diagnosis and treatment, particularly within the “golden hour” to improve outcomes.

Challenges in Traditional Diagnosis:
Diagnosis using CT and MRI scans is standard, but both rely on manual interpretation by radiologists, making the process time-consuming and error-prone. CT scans are fast but less sensitive to early ischemic changes, while MRIs offer higher accuracy but are expensive and less accessible, especially in rural areas.

Role of AI and CNNs:
Artificial Intelligence (AI), especially deep learning, has revolutionized stroke detection. Convolutional Neural Networks (CNNs) excel in analyzing complex imaging data by automatically learning features without manual intervention. These models can efficiently differentiate stroke types and detect abnormalities, offering consistent, rapid, and accurate diagnoses.

VGG19 Model for Stroke Detection:
This study uses the VGG19 model, a deep CNN with 19 layers, fine-tuned for classifying stroke and non-stroke brain images. Data augmentation techniques (e.g., rotation, brightness adjustment, flipping) and preprocessing steps (cropping, normalization) enhance model robustness and generalization.

Dataset and Evaluation:
The dataset is split into training, validation, and test sets. The model is trained using optimizers like Adam or SGD, and evaluated using metrics such as accuracy, precision, recall, F1-score, and AUC from ROC curves.

Impact and Future Scope:
AI integration in stroke diagnosis improves speed, accuracy, and accessibility, supporting clinicians in early detection and treatment planning. Future advancements should focus on multi-modal imaging, real-time deployment, and broader clinical adoption to enhance patient care.

LITERATURE SURVEY

K.D. Mohana Sundaram, G. Haritha, A. Abhilash, K. Sona, E. Divya sri, and C. Bharath kumar. "Evaluation of techniques to improve a deeplearning algorithm for the automatic detection of intracranial haemorrhage on CT head imaging" Electronics and Communication Engineering.A deep learning model with CNN-RNN and preprocessing achieved 0.966 AUC-ROC, enhancing automated intracranial hemorrhage detection in NCCT scans.

K.D.Mohana Sundaram1, G. Haritha2, A. Abhilash3, K. Sona4, E. Divya sri5, C. Bharath kumar6 "Detection of Brain Stroke Using Machine Learning Algorithm" Electronics and Communication Engineering Research Volume 8 ~ Issue 4 (2022) .Machine learning algorithms effectively predict strokes using medical data, aiding early detection and enhancing healthcare decision-making.

Santwana Gudadhe a, Anuradha Thakare a, ∗, Ahmed M. Anter b,c A "novel machine learning-based feature extraction method for classifying intracranial hemorrhage computed tomography images " This is an open access article under the CC BY-NC-ND license © 2023 An ensemble ML approach using joint features and SMOTE achieved 87.22% accuracy in classifying intracranial hemorrhage from CT images.

Oznur Ozaltin 1,* , Orhan Coskun 2, Ozgur Yeniay 1 1 and AbdulhamitSubasi3,4 A "Deep Learning Approach for Detecting Stroke from Brain CT Images Using Oz Net MDPI" stays neutral with regard to jurisdictional claims in published maps and institutional affiliations (2022) A hybrid AI model using OzNet CNN and machine learning achieved high accuracy in detecting strokes from brain CT images.

Asit Subudhia , Manasa Dashb , Sukanta Sabutc,* "Automated segmentation and classification of brain stroke using expectation-maximization and random forest classifier" Elsevier B.V. on behalf of Nalecz Institute of Biocybernetics and Biomedical Engineering of the Polish Academy of Sciences. (2019) An automated MRI-based system using EM, FODPSO, and RF classifier achieved 93.4% accuracy in detecting ischemic stroke for diagnosis.

Block Diagram

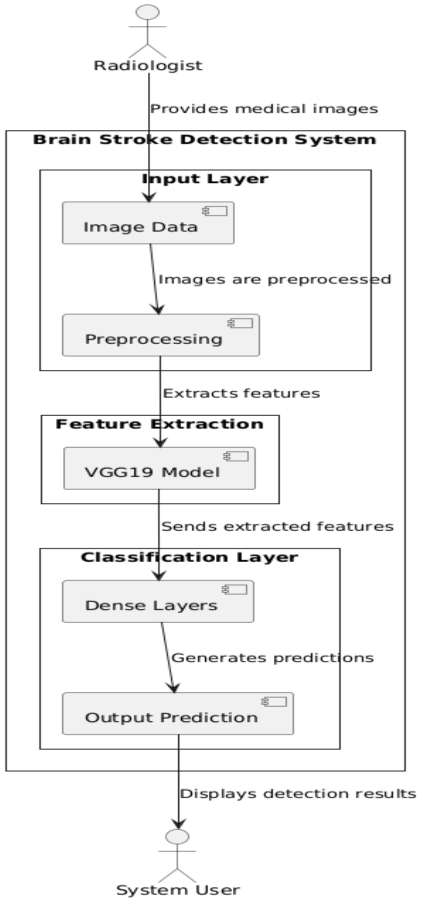

Fig 1: Proposed System Block Diagram

The proposed brain stroke detection system utilizes deep learning with a structured workflow to ensure accurate medical image classification. It includes key modules: data acquisition, preprocessing, augmentation, feature extraction, classification, and web deployment. Brain scans from CT and MRI are preprocessed through normalization, contrast adjustment, and cropping. Data augmentation introduces variations like rotation and flipping to improve generalization. A fine-tuned VGG19 model extracts high-level features, while a CNN with softmax activation classifies images as stroke or non-stroke. The system is deployed via a Flask-based web interface, enabling real-time stroke prediction from uploaded medical images.

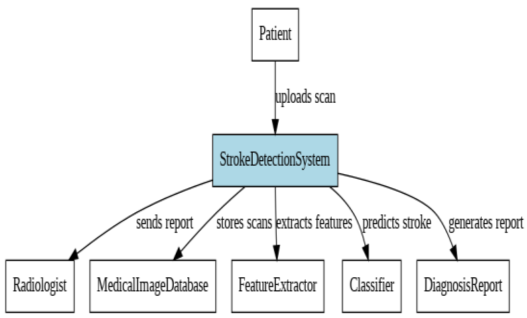

Fig 2: Class Diagram

The Use Case Diagram illustrates the interactions between the user (radiologist or medical professional) and the stroke detection system. Users upload brain scan images through the web interface, after which the system processes the images using deep learning algorithms. The system provides stroke classification results, allowing medical professionals to make informed decisions regarding further diagnosis and treatment.

The Class Diagram represents the relationships between key system components. The major entities include:

User: Represents radiologists or medical professionals interacting with the system.

Image Processing Module: Handles normalization, cropping, and augmentation of brain scan images.

Feature Extraction Model: Utilizes VGG19 for extracting key features from medical images.

Classification Model: Implements CNN-based classification for stroke detection.

Web Interface: Provides user interaction for image uploading and result retrieval.

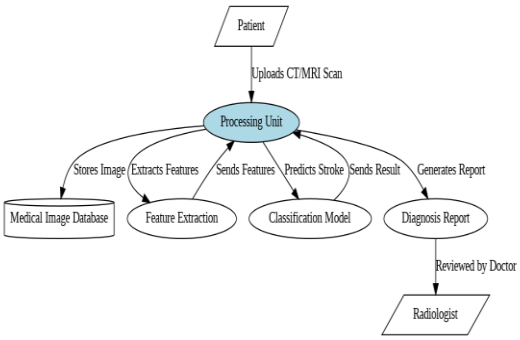

Fig 3: Data flow diagram

This data flow diagram (DFD) represents a stroke diagnosis system based on medical imaging (CT/MRI scans). Below is an explanation of its components and workflow:

Components and Workflow:

Patient: The process starts when the patient uploads a CT or MRI scan to the system.

Processing Unit: Acts as the central component that handles image processing and stroke prediction.

Medical Image Database: Stores the uploaded images for future reference, analysis, and retrieval.

Feature Extraction: Extracts key features from the medical image, such as shape, intensity, and texture, which are relevant for stroke detection.

Classification Model: Uses the extracted features to predict whether a stroke is present or not.

Diagnosis Report: Based on the classification model's prediction, a diagnosis report is generated.

Radiologist Review: A doctor (radiologist) reviews the diagnosis report to verify and validate the results.

Data Flow: The patient uploads the scan to the Processing Unit.

The processing unit:

Stores the image in the Medical Image Database.

Extracts features via the Feature Extraction module.

Sends the extracted features to the Classification Model, which predicts whether a stroke is present.

Sends the result to the Diagnosis Report system, which generates a report.

Finally, the Radiologist reviews the diagnosis report.

This system enhances stroke diagnosis by leveraging medical imaging, automated feature extraction, and classification models, ensuring quick and efficient decision-making for medical professionals.

Algorithms

1.Convolutional Neural Networks (CNNs)
2.Recurrent Neural Networks (RNNs)
3.Support Vector Machines (SVMs)
4.Random Forest
5.Generative Models

RESULTS AND DISCUSSIONS

Performance Metrics:

The performance of the proposed AI-based stroke detection system is evaluated using standard classification metrics, ensuring a thorough assessment of its accuracy and reliability. The primary performance indicators include accuracy, loss, precision, recall, and F1-score. Accuracy measures the proportion of correctly classified images, reflecting the model's overall effectiveness. Loss functions indicate the model's ability to minimize prediction errors, with lower loss values signifying improved performance. Precision and recall metrics help analyze the model's effectiveness in detecting stroke cases while minimizing false positives and false negatives. The F1-score balances precision and recall, providing a comprehensive measure of model performance.

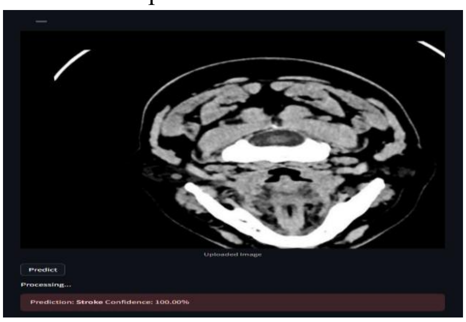

Fig 4: Output 1 Strock confidence

The VGG19-based system achieved over 90% accuracy with minimal misclassifications, aided by effective augmentation and preprocessing techniques.

Comparison with Traditional Methods:
Traditional stroke detection is time-consuming and prone to error, while conventional machine learning lacks effective feature extraction. The proposed deep learning approach using a pre-trained VGG19 model and data augmentation improves accuracy, efficiency, and consistency, eliminating manual feature engineering and enhancing diagnostic reliability in clinical environments.

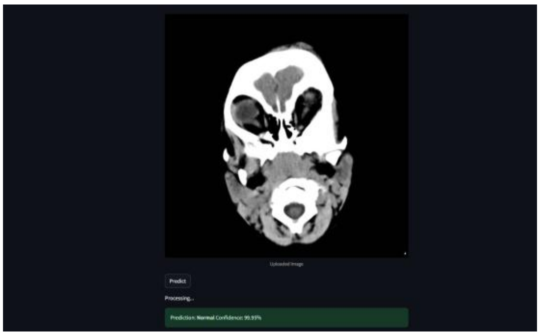

Fig 5: Output 2 Strock confidence

Challenges and Limitations:
The AI-based stroke detection system faces challenges like limited access to labeled medical data and variability in imaging protocols. High computational demands hinder real-time deployment. Future improvements include model optimization and incorporating explainable AI to enhance interpretability and trust in clinical decision-making.

Future Enhancements:
To enhance stroke detection, future improvements include integrating multi-modal imaging (e.g., diffusion-weighted and perfusion imaging) for better diagnostic accuracy. Developing lightweight AI models for mobile and edge devices can enable real-time use in remote areas. Cloud integration will improve accessibility for medical professionals. Expanding datasets with diverse demographics and collaborating with hospitals will boost model generalization. Advancements in deep learning and explainable AI will further improve accuracy, efficiency, and clinical trust. Despite current challenges, ongoing innovations will drive the adoption of AI-driven stroke diagnostics, transforming medical imaging and significantly improving patient outcomes.

CONCLUSION

The proposed AI-driven brain stroke detection system provides a highly accurate and efficient method for early stroke diagnosis using deep learning. By leveraging the VGG19 model with transfer learning, the system achieves superior classification performance compared to traditional stroke detection methods. The integration of preprocessing techniques such as normalization, cropping, and contrast enhancement ensures that high-quality medical images are fed into the model, improving detection accuracy. Data augmentation techniques further enhance the model's ability to generalize across diverse datasets, reducing overfitting and increasing robustness. The classification module, powered by a CNN-based architecture, effectively identifies stroke cases in CT and MRI images, enabling rapid and reliable diagnostic support for medical professionals.

One of the significant achievements of this system is its ability to reduce reliance on manual interpretation, which is often time-consuming and prone to variability. The web deployment module enhances accessibility by allowing users to upload images and receive instant stroke classification results, making the system a practical tool for real-world clinical applications. Additionally, performance evaluation metrics confirm that the model achieves high accuracy while minimizing false positives and false negatives, ensuring its reliability in medical diagnostics. The study underscores the potential of AI-powered solutions to revolutionize stroke detection, improving patient outcomes through early intervention.

REFERENCES

[1] Cordonnier C, Demchuk A, Ziai W, Anderson CS (2018) Intracerebral haemorrhage: current approaches to acute management. Lancet 392:1257–1268. https://doi.org/10.1016/S0140-6736(19)30159-X
[2] Titano JJ, Badgeley M, Schefflein J et al (2018) Automated deep-neural network surveillance of cranial images for acute neurologic events. Nat Med 24:1337–1341. https://doi.org/10.1038/s41591-018-0147-y
[3] Ker J, Singh SP, Bai Y, Rao J, Lim T, Wang L (2019) Image thresholding improves 3-

dimensional convolutional neural network diagnosis of different acute brain haemorrhages on computed tomography scans. Sensors (Basel) 19:2167. https://doi.org/10.3390/s19092167

[4] Lee H, Yune S, Mansouri M et al (2019) An explainable deep-learning algorithm for the detection of acute intracranial haemorrhage from small datasets. Nat Biomed Eng 3:173–182. https://doi.org/10.1038/s41551-018-0324-9

[5] The Radiological Society of North America, The American Society of Neuroradiology, Stanford University, Thomas Jefferson University, Unity Health Toronto, Universidade Federal de São Paulo (2019) RSNA intrac ranial haemorrhage detection. Kaggle. https://www.kaggle.com/c/rsna intracranial-haemorrhage-detection/data. Accessed 08 Mar 2020

[6] S. H. Pahus, A. T. Hansen, and A.-M. Hvas, "Thrombophilia testing in young patientswith ischemic stroke," Thrombosis research, vol. 137, pp. 108–112, 2016.

[7] P. Govindarajan, R. K. Soundarapandian, A. H. Gandomi, R. Patan, P. Jayaraman, and R.Manikandan, "Classification of stroke disease using machine learning algorithms,"Neural Computing and Applications, pp. 1–12.

[8] L. T. Kohn, J. Corrigan, M. S. Donaldson, et al., To err is human: building a safer healthsystem, vol. 6. National academy press Washington, DC, 2000.

[9] R. Jeena and S. Kumar, "Stroke prediction using svm," in 2016 International Conferenceon Control, Instrumentation, Communication and Computational Technologies (ICCICCT), pp. 600–602, IEEE, 2016.

[10] M. S. Singh and P. Choudhary, "Stroke prediction using artificial intelligence," in 20178th Annual Industrial Automation and Electromechanical Engineering Conference (IEMECON), pp. 158–161, IEEE, 2017.

[11] Hasan Ayaz, Meltem Izzetoglu, et al., Early diagnosis of traumatic intracranial hematomas, J. Biomed. Opt. 24 (5) (2019) 1–10.

[12] M. Kaur, S. Sakhare, Kirti Wanjale, Early stroke prediction methods for prevention of strokes, Behav. Neurol. (2022) 1–9.

[13] J. Nawabi, H. Kniep, R. Kabiri, et al., Neoplastic and non-neoplastic acute intracerebral hemorrhage in CT brain scans: Machine learning-based prediction using radiomic image features, Front. Neurol. 11 (2020).

[14] V. Vidhya, U. Raghavendra, A. Gudigar, et al., Automated intracranial hematoma classification in Traumatic Brain Injury (TBI) patients using meta-heuristic optimization techniques, Informatics 9 (1:4) (2022) 1–14.

[15] Agata Sage, Pawel Badura, Intracranial hemorrhage detection in head CT using double-branch convolutional neural network, support vector machine, and random forest, Appl. Sci. 10 (21) (2020) 1–12.

[16] Li, L.; Wei, M.; Liu, B.; Atchaneeyasakul , K.; Zhou, F.; Pan, Z.; Kumar, S.A.; Zhang, J.Y.; Pu, Y.; Liebeskind , D.S.; et al. Deep Learning for Hemorrhagic Lesion Detection and Segmentation on Brain CT Images. IEEE J. Biomed. Health Inform. 2020, 25, 1646–1659.

[17] Srikrishna, M.; Pereira, J.B.; Heckemann, R.A.; Volpe, G.; van Westen, D.; Zettergren , A.; Kern, S.; Wahlund, L.-O.; Westman, E.; Skoog, I.; et al. Deep learning from MRI-derived labels enables automatic brain tissue classification on human brain CT. Neuroimage 2021, 244, 118606. [CrossRef]

[18] Ozaltin, O.; Coskun, O.; Yeniay, O.; Subasi, A. Classification of brain hemorrhage computed tomography images using OzNet hybrid algorithm. Int. J. Imaging Syst. Technol. 2022. [CrossRef]

[19] Jayachitra , S.; Prasanth, A. Multi-Feature Analysis for Automated Brain Stroke Classification Using Weighted Gaussian Naïve Bayes Classifier. J. Circuits Syst. Comput. 2021, 30, 2150178. [CrossRef]

[20] Subudhi , A.; Dash, M.; Sabut, S. Automated segmentation and classification of brain stroke using expectation-maximization and random forest classifier. Biocybern. Biomed. Eng. 2020, 40, 277–289. [Cr-+ossRef]

[21] Zotina A, Simonov K, Kurako M, Hamad Y, Kirillova S. Edge detection in MRI brain tumor images based on fuzzy C means clustering. Procedia Comput Sci 201

[22] Prakash M, Kumari RS. Spatial Fuzzy C means and expectation maximization algorithms with bias correction for segmentation of MR brain

images. J Med Syst 2017;41 (1):1–9.8;126:1261–70

[23] Kwon GR, Basukala D, Lee SW, Lee KH, Kang M. Brain image segmentation using a combination of expectation maximization algorithm and watershed transform. Int J Imaging Syst Technol 2016;26(3):225–32.

[24] Mitra J, Bourgeat P, Fripp J, Ghose S, Rose S, Salvado O, Connelly A, Campbell B, Palmer S, Sharma G, Christensen S, Carey L. Lesion segmentation from multimodal MRI using random forest following ischemic stroke. Neuroimage 2014;98:324–35.

[25] Maier O, Wilms M, Gablentz J, Kramer U, Handels H. Ischemic stroke lesion segmentation in multi-spectral MR images with support vector machine classifiers. SPIE Medical Imaging Computer-Aided Diagnosis 2014;9035