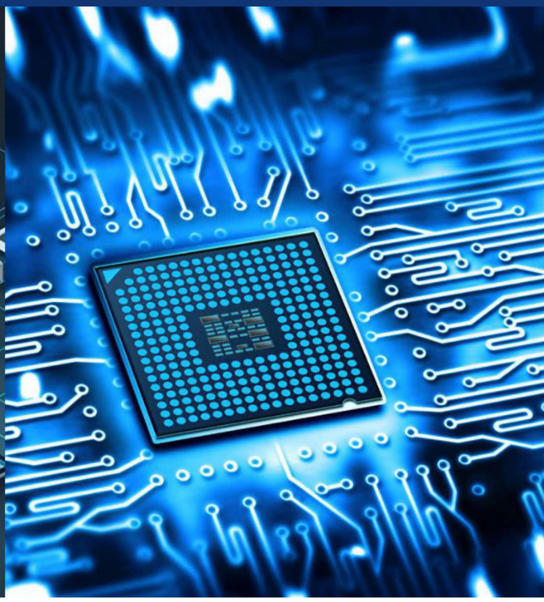
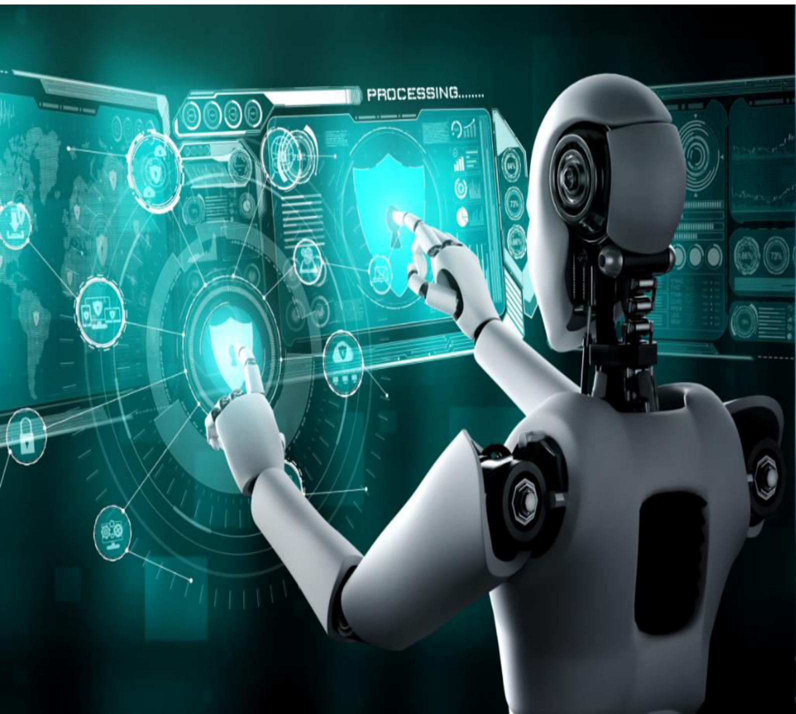
ISSN(O): 2320-9801
ISSN(P): 2320-9798



International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.771

Volume 13, Issue 5, May 2025

© 2025 IJIRCCE | Volume 13, Issue 5, May 2025| DOI:10.15680/IJIRCCE.2025.1305201

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Brain Stroke Detection System Based on MRI Images using YOLO Algorithm

Buvaneswari .M

Assistant professor, Dept. of CSE, Muthayammal Engineering College, Salem, Tamil Nadu, India

G. Kiran Kumar, M. Chaitanya Kumar Reddy, P. Devi Gayathri, K. Mahidhar

UG Students, Dept. of CSE, Muthayammal Engineering College, Salem, Tamil Nadu, India

ABSTRACT: Using magnetic resonance imaging to manually segment brain tumors for cancer diagnosis is a complex, tedious and time-consuming task. The accuracy and the robustness of brain tumor segmentation, therefore, are crucial for the diagnosis, treatment planning, and treatment outcome evaluation. Most automated brain tumor segmentation techniques use manually developed functions. Traditional deep learning methods (such as convolutional neural networks) also require a large amount of annotated data for training, which is usually difficult to obtain in the medical field. Here, we describe a new model two-pathway-group CNN architecture for brain tumor segmentation, which exploits local features and global contextual features simultaneously. The model uses the equivalence of the bidirectional CNN model to reduce instability and overfit common parameters. Finally, merge the cascaded architecture into a two-way multicast CNN, where the output of the basic CNN is processed as an auxiliary source and summarized at the final level. YOLO predicts multiple bounding boxes per grid cell. At training time, we only want one bounding box predictor to be responsible for each object. YOLO assigns one predictor to be “responsible” for predicting an object based on which prediction has the highest current IOU with the ground truth. One key technique used in the YOLO models is Non-Maximum Suppression (NMS). NMS is a post-processing step that is used to improve the accuracy and efficiency of object detection. In object detection, it is common for multiple bounding boxes to be generated for a single object in an image. These bounding boxes may overlap or be located at different positions, but they all represent the same object.

KEYWORDS: Artificial Intelligence, Deep Learning, Machine Learning , Convolutional Neural Network, Computed Topography, **M**agnetic **R**esonance **I**mage, **R**ecurrent **N**eural **N**etwork, **Y**ou **O**nly **L**ook **O**nce.

I. INTRODUCTION

An area of machine learning known as "brain-inspired computation" is quite popular. One of the best "machines" we know for learning and problem solving is the human brain. The way the human brain functions is what inspired the brain-inspired method. Neurons are thought to be the primary computing unit of our brain. All judgements made in response to the numerous pieces of information gathered are based on the intricately interconnected network of neurons. The Artificial Neural Network approach does exactly this. There is a subfield of neural networks called Deep Learning (DL), which uses more than three layers more than one hidden layer of neural networks. Deep Neural Networks are the name given to these neural networks utilized in deep learning (DNNs).

The way the nervous system is organized, with one neuron connecting to the others and exchanging information, is comparable to how DL algorithms work. DL models function in layers, and a typical model has at least three layers. Each layer receives data from the one before it and passes it on to the layer after it. While older machine learning models stop improving after reaching a saturation threshold, deep learning models tend to perform well with large amounts of data. A subset of machine learning is deep learning. Deep learning systems can perform better with access to more data, which is the machine equivalent of more experience, in contrast to typical machine learning algorithms, many of which have a finite ability to learn regardless of the amount of data they obtain. Machines can be trained to perform specific activities such as driving a car, spotting weeds in a field of crops, diagnosing diseases, and checking machinery for problems once they have amassed sufficient experience through deep learning.

© 2025 IJIRCCE | Volume 13, Issue 5, May 2025| DOI:10.15680/IJIRCCE.2025.1305201

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

II. PROBLEM STATEMENT

The technique is used to interactive multi label segmentation for N dimensional images. The existing system is mainly focuses on using OzNetv5 models for real-time brain stroke detection in CT and MRI scans. These OzNet algorithm models are known for their efficiency and high accuracy in object detection tasks. The system integrates multi-scale attention mechanisms, which improve the detection of small and critical stroke lesions often missed in traditional methods. The system's ability to process data in real-time makes it particularly valuable for time-sensitive diagnoses. It demonstrates a non- balance between speed and precision, failed to addressing major challenges in medical imaging. It segments the areas which are more difficult to segment. This method is iterative and provides feedback to the user as the segment is calculated.

III.OBJECTIVES

The Brain Stroke Detection System aims to revolutionize stroke diagnosis by leveraging advanced deep learning techniques, such as YOLO-based algorithms, to enable real-time, automated detection of ischemic stroke lesions in CT and MRI scans. By addressing challenges like lesion variability in size, shape, and intensity, the system enhances diagnostic accuracy and speed, providing timely insights for effective treatment. Integrating federated learning ensures patient privacy while utilizing decentralized datasets, and combining imaging data with auxiliary sources offers comprehensive risk assessments. This innovative approach supports healthcare professionals in making informed decisions, ultimately improving patient outcomes and streamlining stroke diagnosis processes.

Convolutional Neural Networks (CNNs) are a class of deep learning algorithms that are particularly effective for processing structured grid data, such as images. They are widely used in various applications, including image recognition, object detection, and medical image analysis, including brain stroke detection. Here's an overview of CNNs, their architecture, and how they can be applied to brain stroke detection Apply convolution operations to the input, using filters (kernels) to detect patterns such as edges, textures, and shapes. Each filter produces a feature map that highlights specific features in the input image. Traditional methods often underperform in identifying these complex features, leading to suboptimal diagnoses. The novel framework utilizes advanced deep learning techniques like EnigmaNet to enhance segmentation accuracy. By focusing on attention mechanisms, the model prioritizes critical lesion features. It demonstrates robust performance across varied datasets, improving lesion detection while maintaining computational efficiency. This advancement is crucial for timely and accurate stroke diagnosis. The study underscores the importance of handling data imbalances to ensure smaller lesions are not overlooked. Integration of this method into medical imaging workflows could significantly improve patient outcomes.

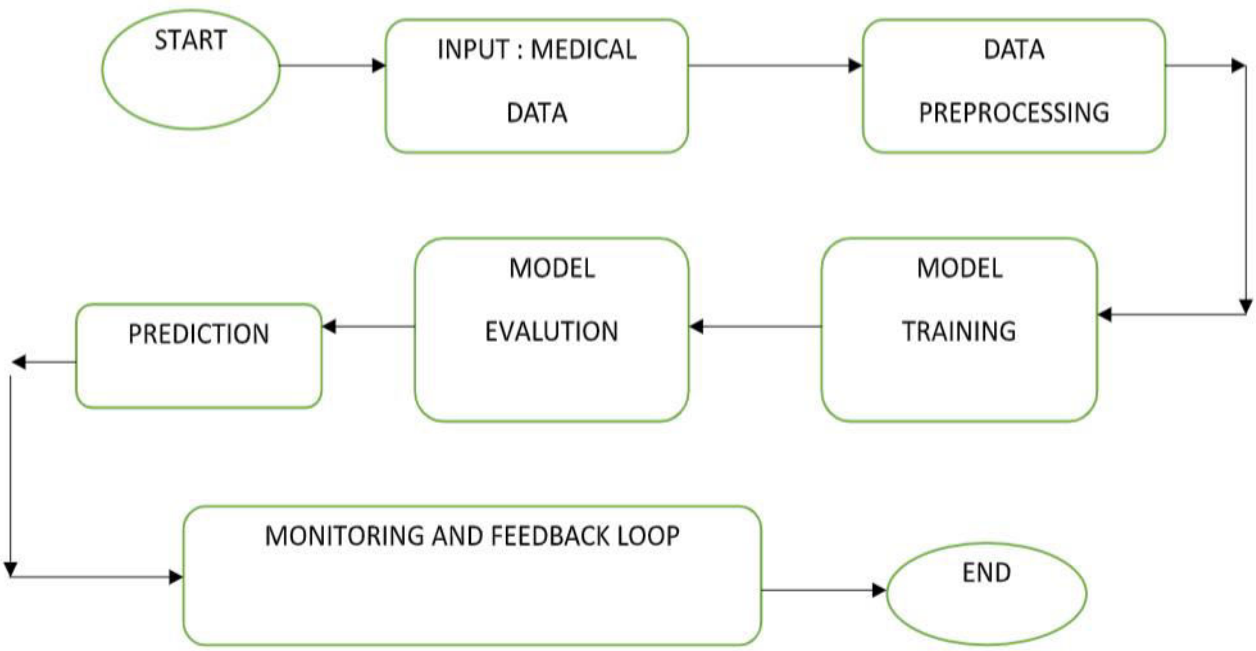
This can be integrated with advanced object detection algorithms like YOLOv8 to identify stroke indicators in imaging data. This research focuses on using YOLOv8 models for real-time brain stroke detection in CT and MRI scans. These YOLO models are known for their efficiency and high accuracy in object detection tasks. The system integrates multi-scale attention mechanisms, which improve the detection of small and critical stroke lesions often missed in traditional methods. With reported accuracies exceeding 96%, the study highlights the potential of YOLO models to transform clinical workflows. The system's ability to process data in real-time makes it particularly valuable for time- sensitive diagnoses. It demonstrates a balance between speed and precision, addressing major challenges in medical imaging. Implement a computer-aided diagnostic system that utilizes unsupervised feature perception enhancement methods to improve the detection of ischemic strokes. This system can analyze electronic health records alongside imaging data to provide comprehensive risk assessments.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

IV. SEQUENTIAL DIAGRAM



Creating a dataset for brain stroke detection using machine learning algorithms is a critical step in developing accurate and reliable models for automated diagnosis. This dataset comprises brain imaging data collected from various sources, including medical institutions, research databases, and publicly available datasets. It encompasses various modes of imaging such as magnetic resonance imaging (MRI), computed tomography (CT), and angiography.

The data collection phase in the brain stroke detection project involves gathering medical imaging data essential for developing and testing the machine learning model. This data is sourced from hospitals and clinics, where CT and MRI scans of stroke patients are often annotated by radiologists, as well as from publicly available research databases such as BRATS (Brain Tumor Segmentation) and other stroke-specific repositories. Additionally, medical imaging archives like PACS (Picture Archiving and Communication Systems) are utilized to ensure a diverse and comprehensive dataset. These datasets encompass various imaging modalities, including CT, MRI, and angiography, to address different diagnostic scenarios. Diversity in patient demographics, lesion characteristics, and imaging resolutions is critical to ensure the model's robustness. Metadata accompanying the scans, such as patient history and imaging parameters, enhances the contextual understanding of the model. Ethical considerations, including anonymization of patient data and obtaining informed consent, are prioritized during this phase.

V.SYSTEM MODEL AND ASSUMPTIONS

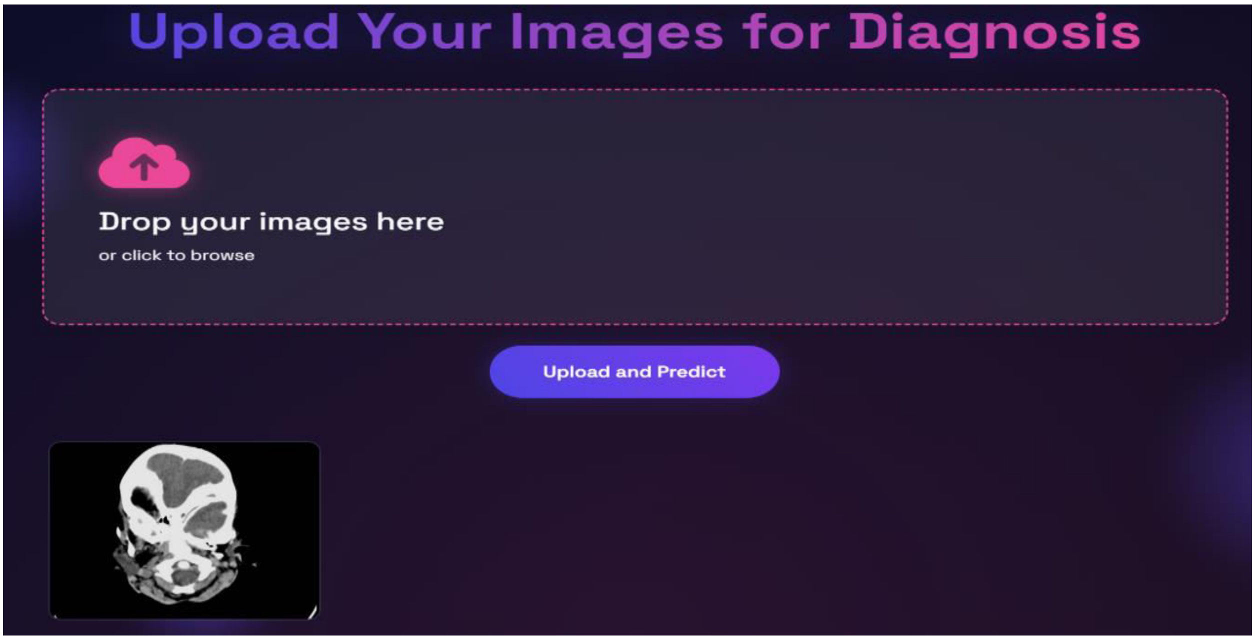
Feature extraction for brain stroke detection involves identifying and selecting relevant characteristics from imaging or clinical data to improve model performance. Techniques such as Principal Component Analysis (PCA) and Factor Analysis (FA) are commonly used to reduce dimensionality and highlight significant features. YOLO models are designed for fast processing, allowing for real-time analysis of medical images. This capability is crucial in clinical settings where timely diagnosis can significantly impact patient outcomes.YOLOv8 An advanced version that incorporates improvements for better accuracy and speed, particularly in identifying stroke indicators from facial features.

YOLO models have been employed to automatically detect and classify brain abnormalities, such as tumors and ischemic strokes, from MRI and CT scans. The models utilize bounding boxes and scores to provide precise localization of detected feature Some studies have integrated federated learning with YOLO models to enhance privacy and data security while training on distributed datasets .This approach allows for collaborative learning without sharing

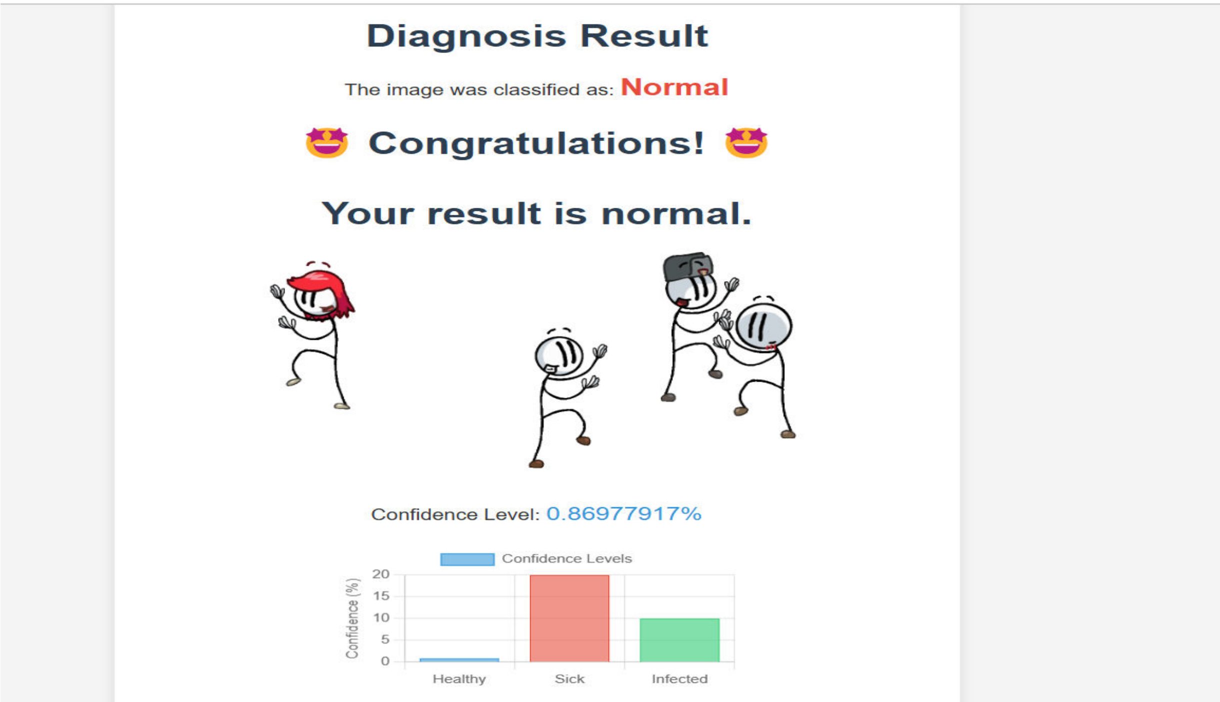
© 2025 IJIRCCE | Volume 13, Issue 5, May 2025| DOI:10.15680/IJIRCCE.2025.1305201
www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|
International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)
(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

sensitive patient data. Recent implementations have reported high accuracy rates, with some models achieving over 96% in identifying lesions associated with strokes .The use of multi-scale attention mechanisms in YOLOv8 has further improved detection capabilities, especially for small lesions.

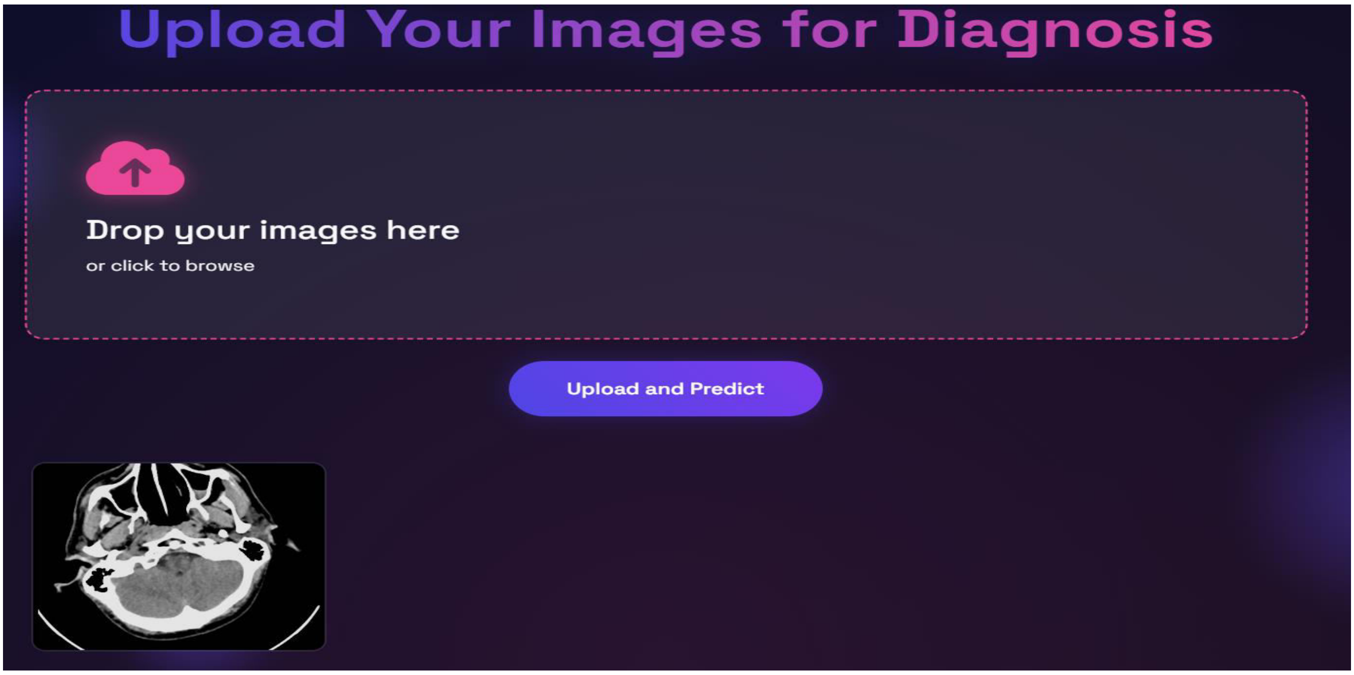
Sample Input



Sample Output

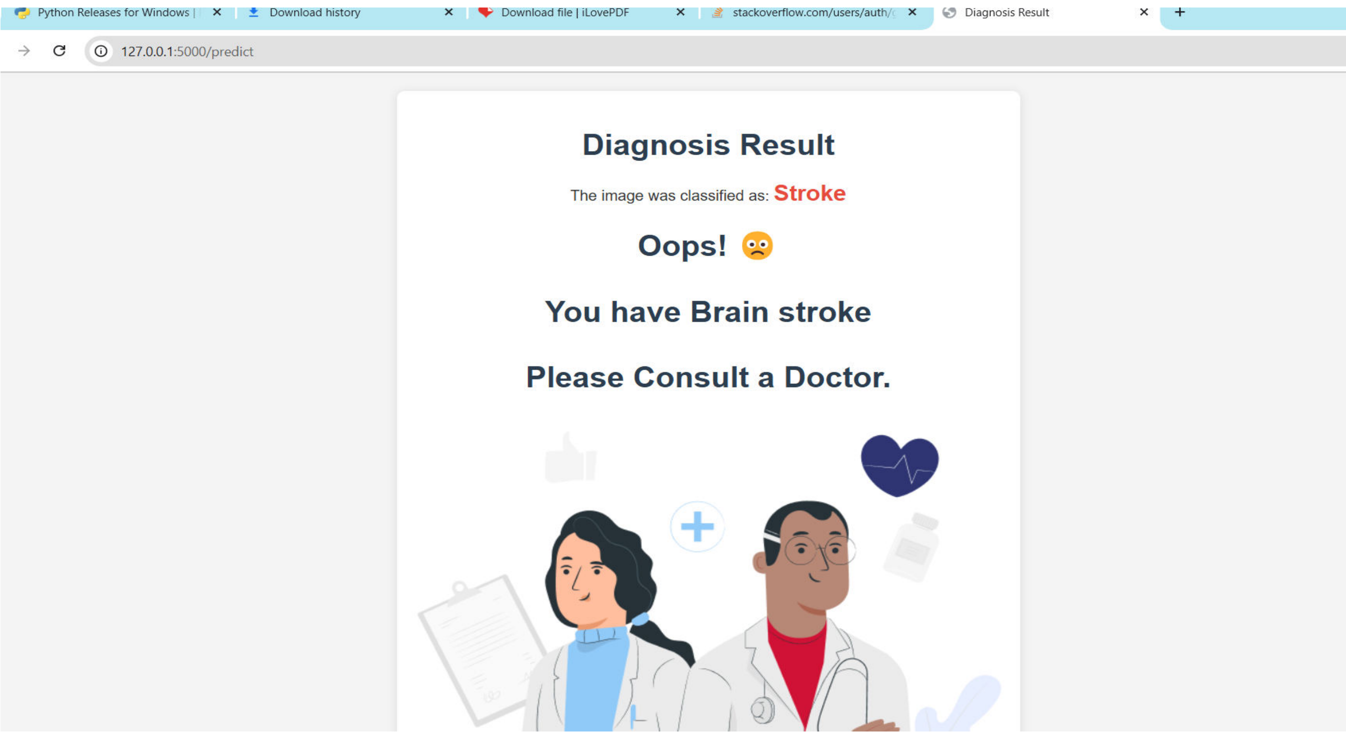


Sample input



Upload Image Processing for Brain Stroke

Sample Output



Diagnosis Result for Brain Stroke

V. IMPLEMENTATION

Feature extraction for brain stroke detection involves identifying and selecting relevant characteristics from imaging or clinical data to improve model performance. Techniques such as Principal Component Analysis (PCA) and Factor Analysis (FA) are commonly used to reduce dimensionality and highlight significant features. YOLO models are designed for fast processing, allowing for real-time analysis of medical images. This capability is crucial in clinical settings where timely diagnosis can significantly impact patient outcomes.YOLOv8 An advanced version that incorporates improvements for better accuracy and speed, particularly in identifying stroke indicators from facial features.

YOLO models have been employed to automatically detect and classify brain abnormalities, such as tumors and ischemic strokes, from MRI and CT scans. The models utilize bounding boxes and scores to provide precise localization of detected feature Some studies have integrated federated learning with YOLO models to enhance privacy and data security while training on distributed datasets .This approach allows for collaborative learning without sharing sensitive patient data. Recent implementations have reported high accuracy rates, with some models achieving over 96% in identifying lesions associated with strokes .The use of multi-scale attention mechanisms in YOLOv8 has further improved detection capabilities, especially for small lesions.

VI. RESULTS AND DISCUSSION

A brain stroke is a life-threatening medical disorder caused by the inadequate blood supply to the brain. After the stroke, the damaged area of the brain will not operate normally. As a result, early detection is crucial for more effective therapy. Computed tomography (CT) images supply a rapid diagnosis of brain stroke. However, while doctors are analyzing each brain CT image, time is running fast. This circumstance may lead to result in a delay in treatment and making errors. Therefore, we targeted the utilization of an efficient artificial intelligence algorithm in stroke detection. In this paper, we designed hybrid algorithms that include a new convolution neural networks (CNN) architecture called OzNet and various machine learning algorithms for binary classification of real brain stroke CT images. When we classified the dataset with OzNet, we acquired successful performance.

VII. CONCLUSION

The initial steps of Data Collection, Data Preprocessing, and Exploratory Data Analysis (EDA) establish a robust foundation for developing an accurate and reliable brain stroke detection model. By gathering diverse and comprehensive datasets, cleaning and standardizing the imaging data, and deeply analyzing its structure, the workflows ensure that the model is trained on high- quality, unbiased inputs. These processes not only enhance the effectiveness of feature extraction and model training but also address critical challenges like data inconsistency, noise, and biases. This meticulous groundwork is essential for achieving precise and reliable stroke detection outcomes. The future enhancements of the Brain Stroke Detection System focus on refining the workflows for real-time, scalable, and precise diagnostics. Advanced YOLO algorithms, particularly YOLOv8, are employed for efficient feature extraction and accurate localization of stroke indicators, while federated learning ensures data privacy and collaborative utility in healthcare. Enhanced image processing with multi- scale attention mechanisms addresses challenges like noise and small lesion detection, improving accuracy. The integration of an API model streamlines interactions between input data and prediction results, providing timely and actionable insights for clinical use. These advancements position the system as a transformative solution in medical imaging, paving the way for future innovations like YOLOv9 and advanced CNN architectures to handle diverse imaging conditions and further enhance diagnostic precision and efficiency.

REFERENCES

1. Javeed, A. L. Dallora, J. S. Berglund, A. Idrisoglu, L. Ali, H. T. Rauf, and P. Anderberg, "Early prediction of dementia using feature extraction battery (FEB) and optimized support vector machine (SVM) for classification," Biomedicines, vol. 11, no. 2, p. 439, Feb. 2023.
2. L. Dallora, J. S. Berglund, A. Idrisoglu, L. Ali, H. T. Rauf, and P. Anderberg, "Early prediction of dementia using feature extraction battery (FEB) and optimized support vector machine (SVM) for classification," Biomedicines, vol. 11, no. 2, p. 439, Feb. 2023.
3. B. Ghiasi, R. Noori, H. Sheikhian, A. Zeynolabedin, Y. Sun, C. Jun, S. M. Bateni , and S. Abolfathi,

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

"Uncertainty quantification of granular computing-neural network model for predictio pollutant longitudinal dispersion coefficient in aquatic streams," Sci. Rep., vol. 12, no. 1, p. 4610, Mar. 2022.

4. C.-M. Feng, Y. Yan, G. Chen, Y. Xu, Y. Hu, L. Shao, and H. Fu,"Multimodal transformer for accelerated MR imaging," IEEE Trans. Med. Imag., vol. 42, no. 10, pp. 2804–2816, Oct. 2023, doi:10.1109/TMI.2022.3180228.
5. K. Wang, B. Zhan, C. Zu, X. Wu, J. Zhou, L. Zhou, and Y. Wang, "Semi supervised medical image segmentation via a tripled-uncertainty guided meanteacher model with contrastive learning," Med. Image Anal., vol. 79, Jul. 2022, Art. no. 102447, doi: 10.1016/j.media.2022.102447.
6. Wasserthal, H.-C. Breit, M. T. Meyer, M. Pradella, D. Hinck, A. W. Sauter, T. Heye, D.
7. T. Boll, J. Cyriac, S. Yang, M. Bach, and M. Segeroth, ''TotalSegmentator: Robust segmentation of 104 anatomic structures in CT images,'' Radiol., Artif. Intell., vol. 5, no. 5, Sep. 2023, Art. no. e230024, doi: 10.1148/ryai.230024.
8. Pinto, S. Pereira, R. Meier, R. Wiest, V. Alves, M. Reyes, and C. A. Silva, "Combining unsupervised and supervised learning for predicting the final stroke lesion," Med. Image Anal., vol. 69, Apr. 2021, Art. no. 101888.
9. A. Eshmawi, M. Khayyat, A. D. Algarni, and I. Hilali-Jaghdam, "An ensemble of deep learning enabled brain stroke classification model in magnetic resonance images,"
10. J. Healthcare Eng., vol. 2022, pp. 1–11, Nov. 2022.
11. L. Herzog, E. Murina, O. Dürr, S. Wegener, and B. Sick, "Integrating uncertainty in deep neural networks for MRI based stroke analysis," Med. Image Anal., vol. 65, Oct. 2020, Art. no. 101790.
12. Y. C. Kim, J. W. Chung, O. Y. Bang, M. Hong, W. K. Seo, G. M. Kim, E. Y. Kim, J. S.
13. Lee, J. M. Hong, D. S. Liebeskind, and J. L. Saver, ''A deep learning-based automatic collateral assessment in patients with acute ischemic stroke,'' Transl. Stroke Res., vol. 14, no. 1, pp. 66–72, 2023.