Online-Journals.org

iJOE International Journal of Online and Biomedical Engineering

iJOE | eISSN: 2626-8493 | Vol. 19 No. 14 (2023) | OPEN ACCESS

https://doi.org/10.3991/ijoe.v19i14.41065

PAPER

Effective Brain Stroke Prediction with Deep Learning Model by Incorporating YOLO_5 and SSD

Yanda Sailaja(✉),
Velmurugan Pattani

SRM Institute of Science and Technology, Kattankulathur, Chennai, Tamil Nadu, India

ys2059@srmist.edu.in

ABSTRACT

Ischemic stroke is a life-threatening disorder that significantly reduces a person's lifespan. The timely diagnosis of stroke heavily relies on medical imaging techniques such as magnetic resonance imaging (MRI), computerized tomography (CT), and x-ray imaging. However, the manual localization and analysis of these images can be time-consuming and yield less accurate results. To address this challenge, we propose the implementation of deep-learning object detection techniques for computerized lesion identification in medical images. In this study, we employ three categories of deep learning object identification networks: deep convolutional neural network (DCNN), you only look once (YOLO) 5, and single-shot detector (SSD). By leveraging these advanced deep learning models, we aim to reduce the effort and time required for screening and analyzing a significant number of daily medical images, including MRI, CT, and x-ray images. With the addition of YOLO5 and SSD among these networks, the accuracy achieved was 96.43%, demonstrating their effectiveness in accurately identifying lesions associated with ischemic stroke.

KEYWORDS

computerized tomography (CT), deep convolutional neural network (DCNN), magnetic resonance imaging (MRI), single-shot detector (SSD), you only look once (YOLO) 5

1 INTRODUCTION

Currently, brain stroke is one of the leading causes of death, ranking second in terms of the frequency. In 2019, cerebral strokes alone claimed the lives of 700,000 individuals [1]. Blood flow will be disrupted as brain cells become constrict. When the brain's blood supply is cut off, it fails to receive oxygen. Due to a lack of oxygen and nutrition, all cells start to weaken. All cells will start to die within a minute, leading to stroke. Hypertension is a contributing factor to brain stroke, but it is not the sole cause. There are several other factors that can lead to a brain stroke, including diabetes, lack of sleep, i.e., insomnia, high cholesterol, cigarette smoking, a family history of stroke, and even COVID-19 infection. Stroke is classified

Sailaja, Y., Pattani, V. (2023). Effective Brain Stroke Prediction with Deep Learning Model by Incorporating YOLO_5 and SSD. *International Journal of Online and Biomedical Engineering (iJOE)*, 19(14), pp. 63–75. https://doi.org/10.3991/ijoe.v19i14.41065

Article submitted 2023-05-03. Revision uploaded 2023-07-10. Final acceptance 2023-07-17.

mainly into three types: ischemic stroke, transient ischemic attack (TIA), and hemorrhagic stroke. Ischemic stroke occurs when blood clots form in a blood vessel, causing an immediate interruption of blood flow. TIA is also called a mild stroke. Hemorrhagic means that blood vessels leak and cause bleeding. We can identify a stroke by using a computerized tomography (CT) scan or a magnetic resonance imaging (MRI) scan [2].

A magnetic field and radio pulses are used in an MRI scan. It is safer to conduct x-ray inspections than CT scans [3]. MRI provides a detailed description of the state of each part of the brain despite being noisier, more expensive, and more time-consuming than CT scans. Anatomical images of the tissue are not the only images it takes; it also takes functional images of how the tissues function in the body [4]. MRI has emerged as a key diagnostic tool for the diagnosis of medical images, serving as the foundation for the diagnosis and management of stroke, particularly ischemic stroke, which is the most common type of stroke and is hardly characterized by CT scans, especially in comparison with hemorrhagic stroke [5]. "This research aims to use deep learning algorithms to analyze and localize MRI images to get the best accuracy." Traditional methods such as manual analyzing and localizing can be time-consuming, and the results may be inaccurate.

Recent advances in image processing have enabled computer-aided diagnosis (CAD) systems that utilize quantitative image features and machine learning techniques to achieve higher effectiveness and precision [6]. The use of deep convolutional neural networks (DCNNs) is a recommended method for automatically creating and combining image information [7]. Images are processed using various types of filters, and the use of deep convolutional neural networks with multiple layers enables the thorough extraction of information from images [8]. Through this approach, the network is capable of identifying distinguishing features at different spatial levels, ensuring a thorough analysis [9].

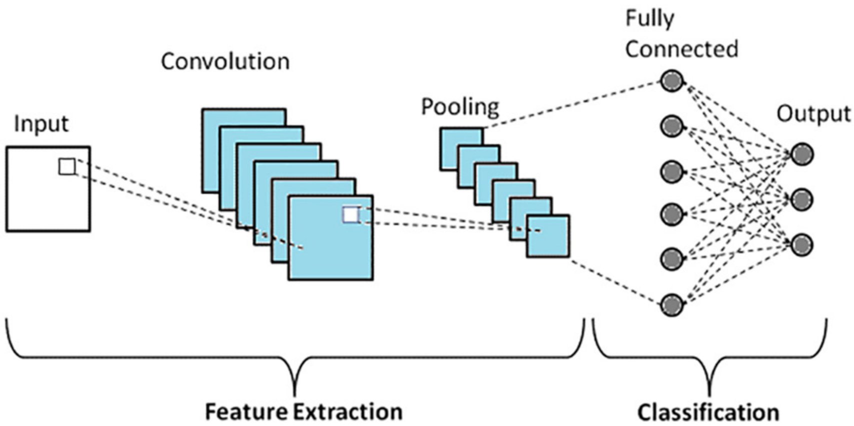

Fig. 1. Architecture of deep convolutional neural network (DCNN)

Region-Based Convolutional Neural Network (RCNN) and CNN has two stage object detection methods [10]. In two-stage detection, the model will first identify the detection region's features and provide a region proposal, and in the second step, it will classify the samples using CNN [11].

A CNN is utilized by the famous YOLOv5 technique, which is highly regarded for its ability to recognize objects in a single stage. This approach improves the accuracy of localization, object identification, and inference speed [12]. You only look once (YOLO) series is a deep learning approach that was first introduced in 2016.

It revolutionized object detection algorithms by employing a single-stage architecture. Over the years, the YOLO series has undergone significant advancements, culminating in the development of YOLOv5, the latest iteration of the YOLO algorithm for computer vision tasks. YOLOv5 stands as one of the most state-of-the-art algorithms within the YOLO family. It has gained immense popularity and is widely utilized for target detection and recognition tasks [13] [14] [15].

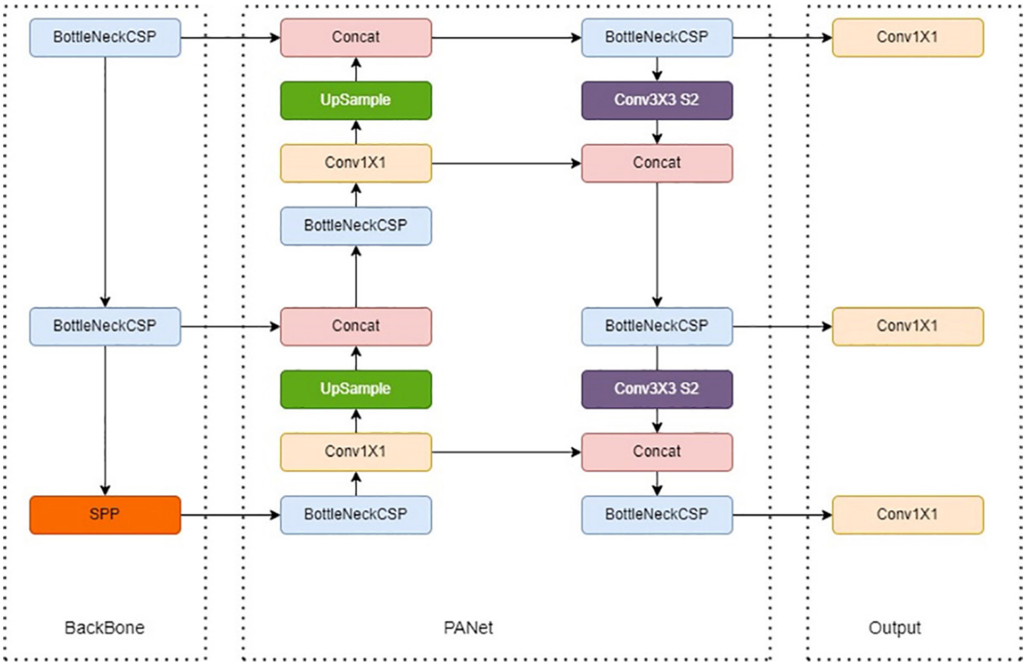

Fig. 2. Architecture of YOLOv5

Another well-known method is a single-shot detector (SSD) which is the process of creating a feature map by simultaneously running a neural network on all of the input images. Single-shot multi-box detection only needs one shot to identify numerous objects in the image [16]. SSD learns the classification and placement of object regions simultaneously, resulting in great detection speed and accuracy [17] [18].

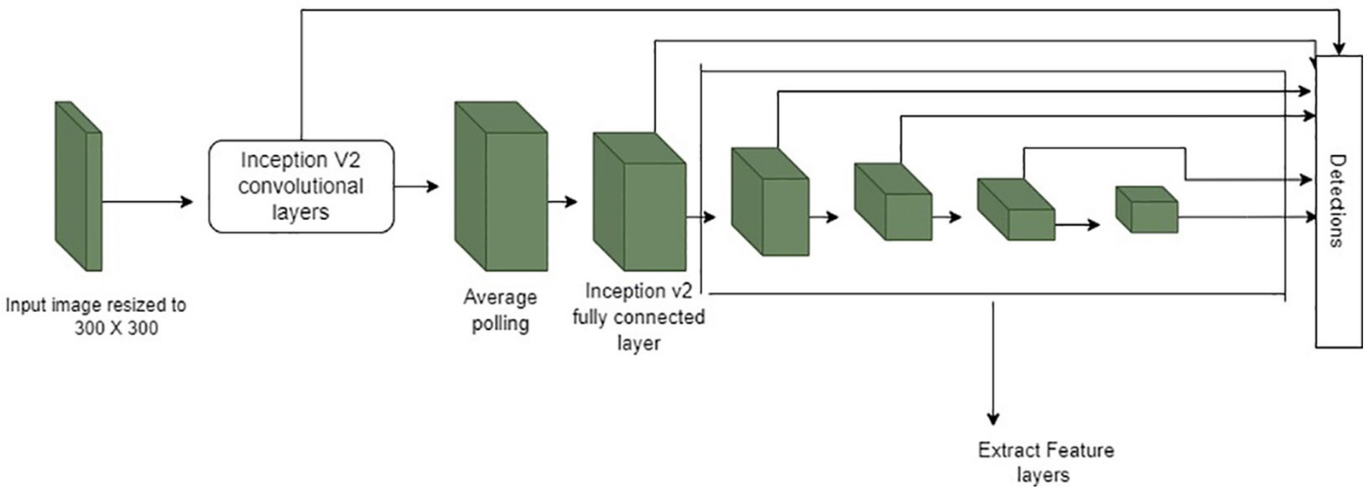

Fig. 3. Architecture of SSD

2 RELATED WORKS

Brain stroke prediction has been a topic of much discussion in the literature, with various approaches being explored. In this segment, we will delve into a specific set of methods that are related to this issue.

Shujun Zhang et al. [19] gathered data in the form of images from two nearby Grade III-A hospitals and carried out expert labeling for a later open study on the disease of ischemic stroke. Five indicators are the focus of statistical analysis, and important conclusions and recommendations are made for ischemic stroke prevention and therapy. YOLOv3 networks, SSDs, and faster R-CNN networks are used in deep learning techniques with a precision of 89.77% for automatic lesion detection.

Yu-Liang Lai et al. [20] proposed that the deep-learning technique not only assists physicians in evaluating the functional consequences of stroke victims in clinical settings but also empowers patients to anticipate their prognosis beforehand. Furthermore, it provides a computerized support system for individualized recommendations and treatments, thus enhancing the overall quality of care.

Chung-Ming Lo et al. [21] argue that an AUC of > 0.98 can be achieved in recognizing acute ischemic stroke in NCCT images using DCNN architecture for a specific scanner. The study also revealed the differences in accuracy between a customized model and a general model. Customized models are more significant in therapeutic applications compared to general models. With computer-aided diagnosis (CAD) providing suggestions to radiologists, emergency situations can be dealt with promptly, resulting in better patient care and treatment outcomes.

Yi-Zeng Hsieh et al. [22] proposed a model that was excellent concerning the output image according to the CNN deep neural network model structure. The lesion may be difficult to see if the block is too small. However, this study revealed that the estimated block position can be utilized to train the CNN model for more accurate lesion detection. This can be achieved by integrating the elimination of the skull with MRI brain segmentation using the patch CNN approach.

Hossain et al. [23] examined that the YOLOv5l model outperformed YOLOv5s, YOLOv5m, and cutting-edge object identification algorithms, according to the research. The YOLOv5l model has demonstrated exceptional accuracy, exhibiting outstanding results across a wide range of metrics. Its remarkable precision, sensitivity, specificity, F1-score, mean average precision (mAP), and classification loss were observed to be 96.32%, 95.17%, 95.28%, 95.53%, 96.12%, and 0.0130, respectively. Notably, this model was used to identify tumors in RMW images, where it successfully classified them as either benign or malignant based on a predicted bounding box and objectness score. The YOLOv5l model is a trustworthy tool that can automatically identify and classify tumors in a portable microwave brain imaging device. It can operate in real time, making it an effective application for medical professionals.

Syed Anwar Hussainy et al. [24] examined the data collected by the model from several Internet of Medical Things (IoMT) devices. Here, both signals and data are used to extract the heart's characteristics. All of these components were sent to the diagnostic system via the DCNN. In order to guarantee the confidentiality of shared patient statistics over the cloud, a hash-based integrity-checking mechanism is employed. The features are analyzed, followed by classification using the DCNN to distinguish between normal and pathological heartbeats. The UCI dataset is used to assess the performance of the suggested model. The newly created DCNN classifier outperforms current models in terms of accuracy as well.

The findings demonstrate that, in terms of accuracy, the suggested methodology performs better than the other options. As a result, the Internet of Things (IoT)-based, secure cloud computing model for smart health care has produced effective outcomes.

Hussain et al., [25] examined different data sets, including diabetic, pulmonary, and clinical data sets, which are used in the proposed integrated DL model-based heart disease prediction scheme. The approach extracts a variety of variables from diverse data sets, including texture, heart rate, blood sugar, after-meal sugar, body mass index (BMI), smoking habits, degree of physical activity, and other features. The retrieved features are fed into an NN for training, which applies convolution to the texture feature as it impacts the extracted features.

3 INTEGRATED DEEP LEARNING WITH YOLO5 AND SSD-BASED BRAIN STROKE PREDICTION MODEL

In the proposed work, we took the sample dataset with 459 MRI stroke-attacked images and trained those images in the DCNN to extract the features. Once we got the resultant feature-extracted image, we took those images as input to the proposed algorithm.

The resultant proposed algorithm is a combination of YOLO5 and SSD. Both algorithms are very popular in object detection. SSD always gives a better result in tiny object detection, which is most useful for small clot identification in the brain vessels. YOLO also has a faster inference speed.

Load the pre-trained YOLOv5 and SSD models and their corresponding configurations.

Read in an input image or video frame, represented as a matrix X with dimensions (H, W, C), where H is the height, W is the width, and C is the number of channels (e.g., 3 for RGB images).

Apply image preprocessing techniques such as resizing, normalization, and padding to match the input size of the YOLOv5 and SSD models. Let YOLOv5 take an input image X′ with dimensions (H′, W′, C′) and SSD take an input image X″ with dimensions (H″, W″, C″).

Step1:

Run the input image or frame through the YOLOv5 model to obtain a set of bounding box predictions and confidence scores for each detected object. The output of YOLOv5 is a set of bounding box coordinates (bx, by, bw, bh) and class probabilities (p) for each detected object. Let B_YOLOv5 be the set of bounding boxes and C_YOLOv5 be the set of class probabilities obtained from YOLOv5.

$$bx = \Sigma(tx) + cx \tag{1}$$

$$by = \Sigma(ty) + cy \tag{2}$$

$$bw = pw * \exp(tw) \tag{3}$$

$$bh = ph * \exp(th) \tag{4}$$

$$p = \Sigma(tp) * cp \tag{5}$$

$$B\_YOLOv5, C\_YOLOv5 = YOLOv5(X') \tag{6}$$

Step 2:

Filter out the bounding boxes with low confidence scores. Let T be a threshold for the confidence score below which bounding boxes are filtered out.

$$\text{B\_YOLOv5}' = \{\text{b} \mid \text{b in B\_YOLOv5 and p\_b} >= \text{T}\} \tag{7}$$

Step 3:

For each remaining bounding box b in B_YOLOv5′, extract the region of interest (ROI) from the input image or frame and resize it to the input size of the SSD model.

$$\text{ROI\_b} = \text{X}[\text{bx} - \text{bw} / 2\text{:bx} + \text{bw} / 2,\ \text{by} - \text{bh} / 2\text{:by} + \text{bh} / 2] \tag{8}$$

$$\text{ROI\_b}' = \text{resize}(\text{ROI\_b}, (\text{H}'', \text{W}'', \text{C}'')) \tag{9}$$

Step 4:

Run ROI_b′ through the SSD model to obtain a set of class predictions and confidence scores. The output of SSD is a set of class probabilities (p′) and bounding box coordinates (bx′, by′, bw′, bh′) for each detected object within the ROI. Let B_SSD be the set of bounding boxes, and C_SSD be the set of class probabilities obtained from SSD.

$$\text{bx}' = \sum(\text{tx}') + \text{cx}' \tag{10}$$

$$\text{by}' = \sum(\text{ty}') + \text{cy}' \tag{11}$$

$$\text{bw}' = \text{pw}' * \exp(\text{tw}') \tag{12}$$

$$\text{bh}' = \text{ph}' * \exp(\text{th}') \tag{13}$$

$$\text{p}' = \sum(\text{tp}') * \text{cp}' \tag{14}$$

$$\text{B\_SSD, C\_SSD} = \text{SSD}(\text{ROI\_b}') \tag{15}$$

Step 5:

Filter out the class predictions with low confidence scores. Let T′ be a threshold for the confidence score below which class predictions are filtered out.

$$\text{B\_SSD}'' = \{\text{b}' + (\text{bx} - \text{bw} / 2, \text{by} - \text{bh} / 2, \text{bw}, \text{bh}) \mid \text{b}' \text{ in B\_SSD and p\_b}' >= \text{T}'\} \tag{16}$$

$$\text{C\_SSD}'' = \{\text{c} \mid \text{c in C\_SSD and p\_c} >= \text{T}'\} \tag{17}$$

Assign each remaining class prediction to the corresponding bounding box from **step 5**.

Step 6:

```
B_final = B_YOLOv5', C_final = {}
  for b in B_YOLOv5':
    for b' in B_SSD'':
      if(b interested b')and (class(b')in C_SSD''):
        C_final[b] = class(b')
```

Output the final set of bounding boxes and class labels as the detected objects in the input image/frame.

Return B_final and C_final.

Architecture:

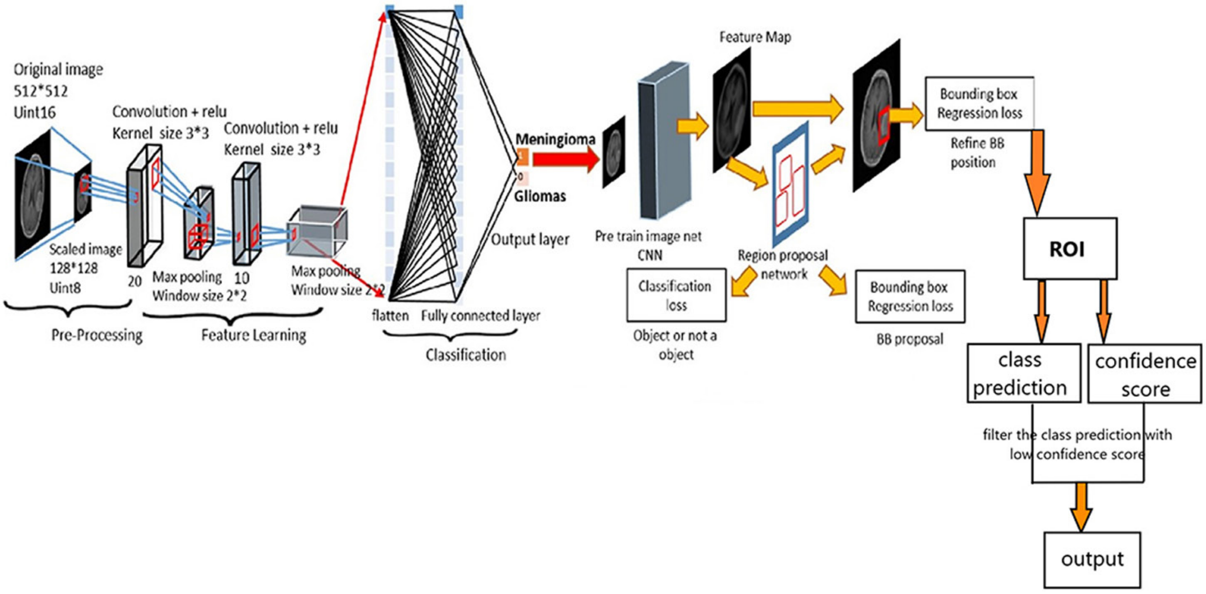

Fig. 4. Architecture of proposed Yolo5_SSD prediction model

In practical situations, the accuracy and speed of object recognition can be increased by combining the YOLOv5 and SSD models. While SSD excels at detecting small things within regions of interest, YOLOv5 offers quick and accurate object detection for a variety of item sizes and types. These two models can be combined to improve performance by combining their individual capabilities. The suggested approach makes use of YOLOv5 and SSD's complementary capabilities to recognize objects in an image or video frame more precisely and effectively.

4 CLASSIFIER'S PERFORMANCE

The suggested integrated deep learning model for predicting brain strokes has been developed in Python, and its effectiveness has been evaluated across a number of variables. The effectiveness of the suggested model, Yolo5 SSD, is evaluated using a variety of factors.

A variety of criteria were required in order to evaluate the brain stroke classifier's performance. Accuracy, precision, recall, and F1-score are the classification techniques that are most commonly produced.

a) Precision (P) = TP/(TP + FP)

The percentage of true positives (TP) versus all predicted positives (TP + FP) is known as precision (P). It determines how often the model is accurate in predicting that an observation falls into the positive class, or how accurate positive predictions are:

Table 1. Analysis on precision

Method	Precision
DCCN	0.961
SSD	0.968
Yolo5	0.973
Proposed	0.986

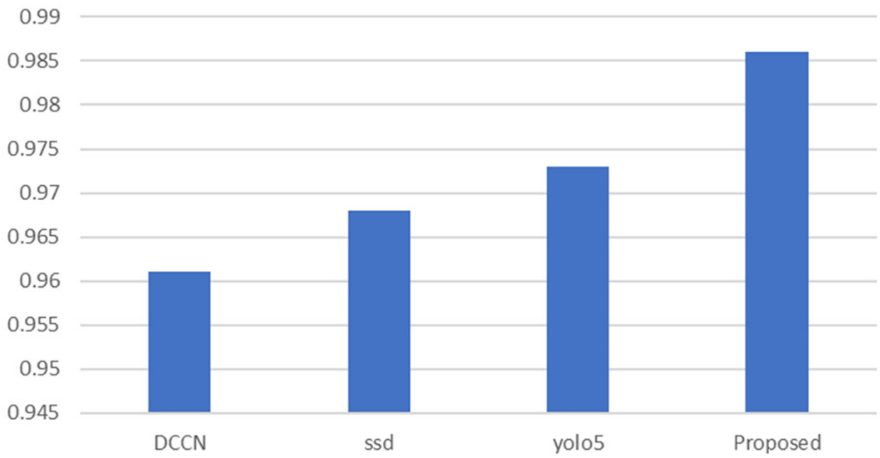

Fig. 5. Analysis on precision

b) Sensitivity / Recall (R) = TP/(TP + FN)

Sensitivity, commonly referred to as recall, is a performance indicator used to assess how well a binary classification model performs. It gauges the percentage of actual positive cases that the model accurately classifies as positive. The values listed below must be known in order to compute sensitivity.

True positive: The proportion of genuine positive cases that the model accurately detected.

False negative: Instances are those that were mistakenly labeled as negative despite actually being positive.

Table 2. Analysis on recall

Method	Recall
DCCN	0.949
SSD	0.955
Yolo5	0.964
Proposed	0.985

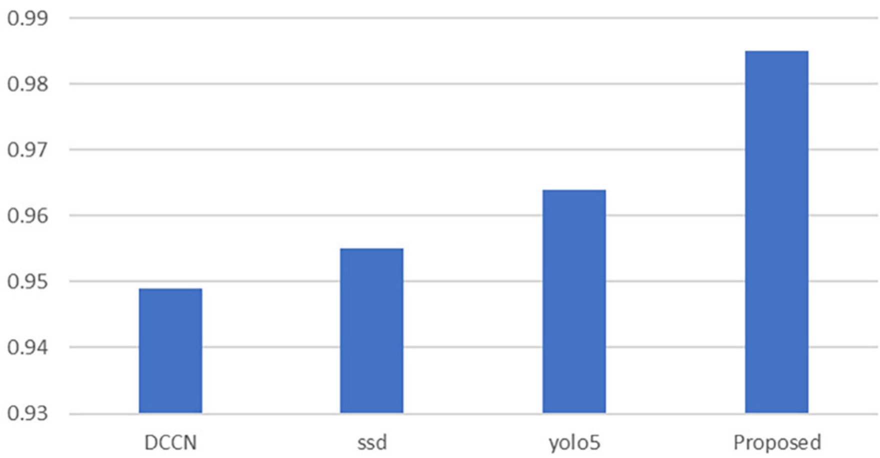

Fig. 6. Analysis on recall

c) Specificity (S) = TN/(TN + FP)

Where FP is the number of false positives and TN is the number of true negatives (individuals without the condition who were correctly classified as negative) (people without the condition who are incorrectly identified as positive). A statistical metric called specificity is used to assess how well a diagnostic test or screening tool identifies people who do not have a given ailment or disease. It gauges the test's capacity to avoid false positives by showing the percentage of true negatives among all people who do not have the condition. The lower the number of false positives and the more accurately it can identify people who are actually negative, the greater the specificity of a test.

Table 3. Analysis on specificity

Method	FPR
DCCN	0.038
SSD	0.032
Yolo5	0.027
Proposed	0.013

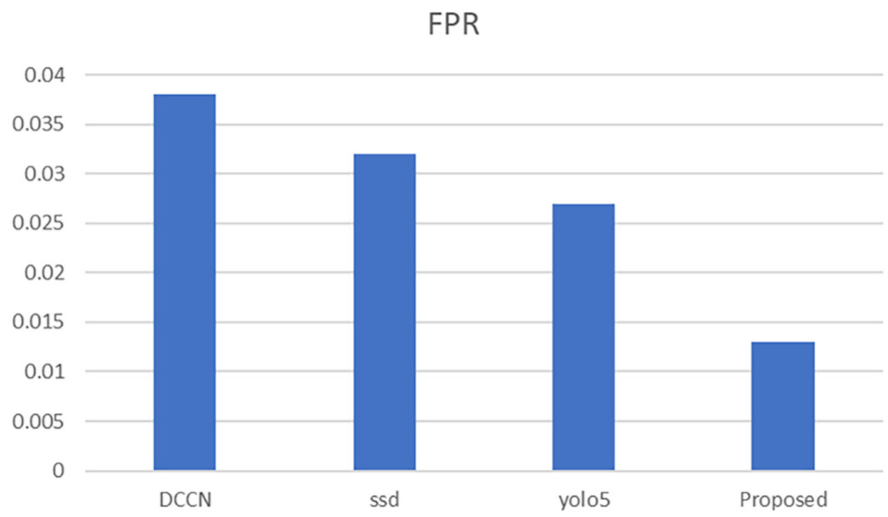

Fig. 7. Analysis on specificity

d) F1-score (Fs) = 2 * TP / (2 * TP + FP + FN)

The harmonic mean of recall and precision is named the F1score. By taking into account both precision and recall, it offers a fair assessment of the model's performance.

Table 4. Analysis on F1-score

Method	F-Score
DCCN	0.954
SSD	0.961
Yolo5	0.968
Proposed	0.985

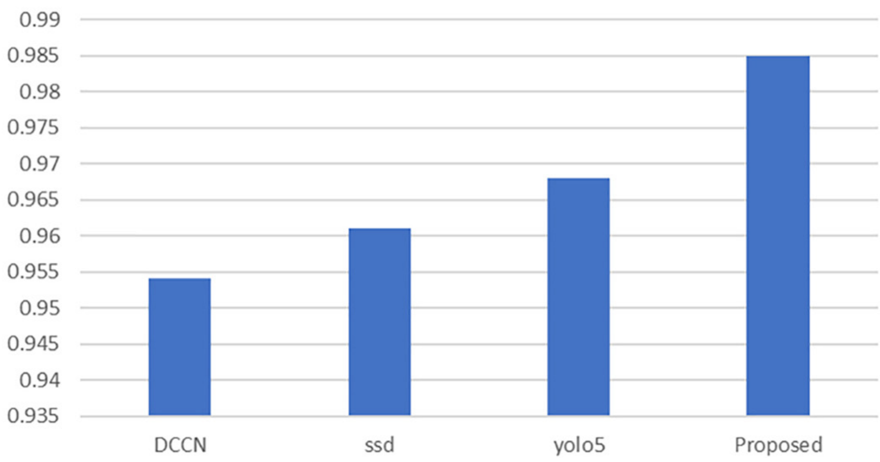

Fig. 8. Analysis on F1-score

e) Mean average precision (mAP) = (1/n) * Σ (i = 1 to n) Precision (i) * Recall (i)

An often-used measure in object detection tasks is mAP. It Figures out the average precision across various recall levels. The precision and recall at various thresholds are computed, and the mean of the precision values for each recall threshold is taken.

Table 5. Analysis on mAP

Method	mAP
DCCN	0.77
SSD	0.897
Yolo5	0.749
Proposed	0.964

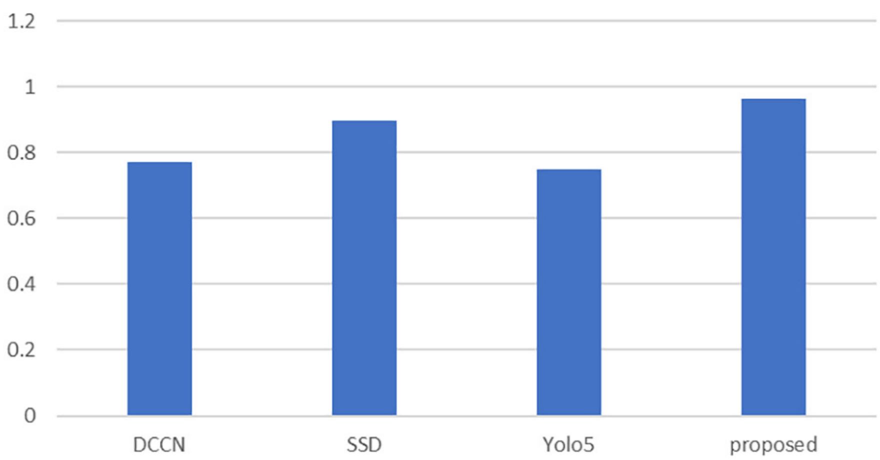

Fig. 9. Analysis on mAP

5 CONCLUSION

Our research shows that deep learning models are capable of properly identifying brain strokes from MRI scans, which can help with early detection and effective treatment of this serious ailment. The good performance metrics show that using the

YOLO5 and SSD models together was successful in achieving high levels of accuracy and precision.

Our proposed algorithm accurately diagnoses stroke lesions, as demonstrated by its high mAP, F1 score, and recall. Additionally, it exhibits a low false positive rate, indicating a high level of specificity. Furthermore, the algorithm's high precision value indicates its capacity to identify actual positive cases and reduce false positives.

Our study makes a contribution to the field of medical image analysis and stroke diagnosis by offering a potential method for deep learning-based automated stroke identification. Our suggested method has a strong performance that points to its potential for inclusion into clinical practice, which could enhance stroke detection and patient outcomes. Additional studies can be conducted to optimize and refine the model for different MRI modalities, populations, and stroke subtypes. Furthermore, it is necessary to validate the algorithm on larger datasets and in a real-world clinical setting.

6 FEATURE WORK

In spite of this, our study shows deep learning's great potential for identifying strokes and promotes future research into this strategy to improve stroke diagnosis and patient care. Using MRI images and deep learning models, our research overall represents a substantial advancement in the development of precise and effective stroke diagnosis tools. The findings of this study highlight the potential of our suggested method for real-world clinical applications and open the door for more development in this area by enabling early and reliable identification of brain strokes. Further research in this field has the potential to greatly enhance patient outcomes and quality of life.

Our study contributes to this expanding body of research by offering a viable method for stroke recognition using MRI images. As technology develops, deep learning algorithms have the potential to play a significant role in medical imaging and diagnosis. The potential of our proposed approach is demonstrated by our findings, which also establish the foundation for further research in this field, with the ultimate goal of improving patient care and outcomes in the diagnosis and treatment of brain strokes.

Our suggested approach may significantly influence clinical practice with future development and validation, which would be advantageous to patients and healthcare professionals alike. As a result, our research has made significant contributions to the fields of medical image analysis and stroke detection. We anticipate more work in this area in the future to further develop stroke diagnosis and patient care.

Overall, our results show the promise of deep learning models for the detection of brain strokes and open the door for additional research in this area with the ultimate aim of enhancing patient outcomes and the standard of care in stroke therapy. Our suggested approach has the potential to be incorporated into clinical practice and has a significant influence on patient care by enabling the early and precise detection of brain strokes using MRI images as technology advances. We are optimistic that our research will lead to new applications for deep learning models in the diagnosis and treatment of strokes, and we look forward to future investigations and the clinical validation of our suggested approach.

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8 AUTHORS

Yanda Sailaja is a Research Scholar at the Department of Computing Technologies, SRM Institute of Science and Technology, Kattankulathur, Tamil Nadu, Chengalpattu District, 603203, India. Doing her research in the area of Deep Learning.

Velmurugan Pattani is working as an Assistant Professor at the Department of Computing Technologies, SRM Institute of Technology, Kattankulathur, Tamil Nadu, India. He completed his doctorate in the year 2017 in published more than 15 papers in the indexed journals. He is an active Reviewer of Concurrency and Computation: Practice and Experience.