Improving Breast Cancer Detection with Pre-trained Models: A CADe and CADx System*

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Abstract

In this research study, we introduce a novel system of two primary modules: (1) Computer-Aided Detection (CADe) and (2) Computer-Aided Diagnosis (CADx). The CADe module is dedicated to the detection and segmentation of potentially anomalous regions within mammograms through the utilization of a pre-trained YOLOv5-seg model. This approach facilitates the early detection of breast cancer. Subsequently, the CADx module leverages the identified and segmented regions for further analysis, employing the VGG 16 classification model to discern the benign or malignant nature of these regions. To gauge the efficacy of our proposed methodology, extensive experiments were conducted on a substantial dataset procured from the Digital Database for Screening Mammography (DDSM). The CADe system yielded robust results in terms of detection and segmentation assessments, with a mean average precision (mAP) of 88%, a precision rate of 93.93%, and a recall rate of 98.02%. Furthermore, the CADx system demonstrated an accuracy rate of 97%.

Keywords

Breast cancer, Computer-aided diagnosis, Deep learning, CNNN, Mammography, DDSM

1. Introduction

Cancer, characterized by uncontrolled cell growth and invasive tendencies into neighboring tissues, constitutes a significant global public health challenge. It ranks as a leading cause of mortality in developed nations, contributing to a substantial number of annual deaths. Among the diverse spectrum of malignancies, breast cancer stands out as a notably prevalent and extensively researched ailment. While encompassing both benign and malignant forms, it's the latter that poses the most severe threat due to its potential for metastasis and spread to distant organs. Age emerges as a prominent risk factor for breast cancer, with its influence growing as individuals age. Notably, in 2020, cancer claimed the lives of 32,802 individuals in Algeria alone [1].

When it comes to existing diagnostic methods, the early detection of breast cancer plays a crucial role in improving patient outcomes. The origins of breast cancer predominantly result from genetic mutations, accounting for only around 10% of cases, while the majority occur spontaneously [2]. Common clinical signs include breast lumps, skin dimpling, and nipple retraction. Healthcare professionals employ various diagnostic tools, including mammography, magnetic resonance imaging (MRI), and biopsy, to diagnose and evaluate breast cancer [2, 3]. Mammography is widely recognized as the gold standard due to its precision and effectiveness.

In addition to tumor detection, accurate diagnosis and appropriate treatment selection are essential aspects of breast cancer management. Computer-Aided Diagnosis (CAD) systems have become indispensable tools in medical imaging, assisting healthcare practitioners in making informed decisions quickly. CAD incorporates technologies like artificial intelligence (AI), computer vision, and medical image processing to analyze and interpret medical images, aiding in the identification and characterization of abnormalities. Within the CAD domain, two primary categories are emerging [4]: CADe, which helps radiologists identify breast cancer indicators on mammograms, and CADx, which aids in distinguishing between different tumor types, encompassing the broader field of computer-aided diagnostics.

Machine learning algorithms have made significant progress in automating the detection, classification, and characterization of breast anomalies in medical images. Traditional machine learning algorithms often require manual feature extraction for these tasks, which involves determining tumor attributes such as size and morphology. However, this approach necessitates domain expertise and prior knowledge.

In contrast, deep learning techniques have revolutionized image analysis, pattern recognition, and computer vision [5]. The Convolutional Neural Network (CNN),

6th International Hybrid Conference On Informatics And Applied Mathematics, December 6-7, 2023 Guelma, Algeria
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a well-established deep learning paradigm, has gained recognition for its exceptional performance in image recognition tasks. This research leverages the capabilities of CNNs to develop and evaluate an innovative model for predicting and identifying breast cancer.

The structure of this paper is organized as follows. Section 2 will delve into existing research and prior work pertaining to the detection and treatment of breast cancer. Following this, Section 3 will address the theoretical and conceptual models employed within this study. Section 4 will center on the datasets utilized in our research endeavors. Furthermore, Section 5 will be dedicated to discussing data preprocessing methods, involving an exploration of techniques implemented for the preparation of data intended for model training. Section 6 will introduce our proposed methodology, outlining the algorithmic approach utilized and emphasizing the innovative facets intrinsic to our breast cancer prediction and identification model. Lastly, Section 7 will be devoted to presenting our findings and undertaking a comprehensive analysis thereof.

2. Related Work

In recent years, significant advancements have been made in the field of breast cancer detection and diagnosis, thanks to notable progress in deep learning techniques. Many studies have explored innovative approaches and frameworks, all aimed at improving the accuracy and efficiency of (CAD) systems for breast lesion analysis. This section provides a comprehensive overview of the most notable contributions in this area.

Yousefi kamal P. [6], presents a novel biphasic algorithm for the classification and segmentation of mammographic images. In the classification phase, the author use a CNN to automatically extract image features, achieving an accuracy of 78% and an AUC of 69%. For tumor segmentation, the author applies the Level-set segmentation method, utilizing spatial fuzzy clustering (LS-SFC), which accurately delineates the tumor region within mammographic images. The combination of segmentation levels with spatial fuzzy clustering enhances the quality of segmentation outcomes, ultimately presenting preprocessed images that unveil the precise tumor region within the image.

M. A. Al-antari et al. [7], introduce a comprehensive computer-aided diagnosis (CAD) system for breast lesion analysis, employing integrated deep learning techniques. This system combines You-Only-Look-Once (YOLO) for lesion detection, a full resolution convolutional network (FrCN) for segmentation, and three distinct deep learning models for classification. Notably, YOLO-based lesion detection achieves impressive accuracy rates of 97.27%, Matthews's correlation coefficient (MCC) of 93.93%, and an F1-score of 98.02%. Additionally, FrCN-based segmentation achieves 92.69% accuracy, 85.36% MCC, a Dice (F1-score) of 92.36%, and a Jaccard similarity coefficient of 85.81%. For classification, CNN, ResNet-50, and InceptionResNet-V2 models exhibit average accuracies of 88.74%, 92.56%, and 95.32%, respectively.

A. Bal et al. [8], propose an innovative deep learning framework for automated breast cancer diagnosis. The framework leverages YOLOv3 as a Region Proposal Network (RPN) to identify significant regions within cytology images. These identified regions are then classified using three distinct CNN classifiers (VGG16, ResNet-50, Inception-v3), resulting in impressive diagnostic accuracy. Notably, Inception-v3 outperforms the other classifiers. The study suggests enhancing the YOLOv3 network and diversifying the dataset to improve region detection. Noteworthy results include the VGG16 model achieving a 96.6% accuracy, 99.6% precision, 94.4% recall, and 99.6% specificity. The ResNet-50 model reaches a 98.8% accuracy, 0.985 precision, 99.4% recall, and 97.9% specificity. Finally, the Inception-v3 model attains a 98.9% accuracy, 1 precision, 98.2% recall, and perfect specificity.

Mefty Zahira Hanan et al. introduced CAD system for breast cancer, employing CNN models [9]. Their approach encompasses two pivotal stages: detection (CADe) and identification (CADx). By meticulously fine-tuning the VGG19 CNN model on the DDSM dataset for CADe and the IDC dataset for CADx, they accomplished remarkable results, attaining a striking accuracy of 99% for CADe and 91% for CADx.

G. H. Aly et al. [10], introduce a breast cancer detection framework utilizing YOLO-V3 and YOLO-V4 models. The framework identifies masses in mammograms and categorizes them as benign or malignant via transfer learning. Notably, YOLO-V4 demonstrates superior detection accuracy, achieving a mean average precision (mAP) of 82.43% in comparison to YOLO-V3's 74.99% after 2 trials. The subsequent classification of masses involves ResNet and Inception V3 classifiers, with Inception V3 yielding more favorable outcomes—an accuracy of 95.00% compared to ResNet's 90.00%.

Zeiser et al. [11], propose a CAD system that leverages deep learning and data augmentation methods to perform mammogram segmentation. They employ a U-Net model and the DDSM dataset, achieving impressive results including an accuracy of 85.95%, sensitivity of 92.32%, and specificity of 80.47%.

In [12], the authors created a CAD system utilizing CNNs, which effectively classified mammography mass lesions as benign or malignant with high accuracy. They improved model performance by using techniques such as transfer learning, fine-tuning, data augmentation, regularization, and dropout. Results indicated that integrating well-engineered deep learning CNNs through transfer learning improved breast cancer classification

accuracy compared to other methods. The fine-tuning approach, focusing on the last two convolutional layers, yielded superior outcomes. The Breast Cancer Screening Framework, developed using Inception v3 model on merged data, achieved remarkable accuracy in classifying mammography mass lesions. This framework even outperformed human assessment, achieving an impressive area under the curve (AUC) of 0.99. The developed framework accurately diagnosed images from various datasets, including Merged Dataset (MD) 98.94%, Digital Database for Screening Mammography (DDSM) 97.35%, Full-field Digital Mammographic Database (INbreast) 95.50% and A Breast Cancer Digital Repository (BCDR) 96.67% [12].

J.Shi. [13], utilizes a YOLO-based computer-aided diagnosis (CAD) system to address the challenges associated with chest cancer detection. Three key issues are discussed and analyzed within the CAD system implementation: the utilization of handcrafted features, the prevalent high false positive rate in clinical settings, and the complexity of detecting irregular nodules in spiral CT scans.

These related works demonstrate the growing interest in utilizing deep learning methods, particularly CNNs, for breast cancer detection and classification. They provide valuable insights into the advancements and potential solutions in this field, contributing to the development of accurate and efficient CAD systems for breast cancer diagnosis.

3. Models

In this research, we propose to use two distinct models, namely VGG16 and YOLOv5-seg, to address the challenges in breast cancer detection and classification.

3.1. VGG16

VGG16, a widely recognized deep CNN architecture introduced by Simonyan and Zisserman. [14], is celebrated for its depth and efficacy in image classification tasks. It comprises 16 convolutional layers organized into blocks, each housing multiple 3x3-sized filter layers. This choice of filter size enables the model to discern intricate image features effectively. VGG16 maintains uniformity by consistently using 3x3 filters, and it simplifies complexity with 2x2 pooling layers, reducing activation map sizes while preserving vital features. After convolution and pooling, the model flattens the features for classification using softmax, making it adept at object recognition. VGG16's extensive depth facilitates the capture of complex patterns, enhancing its classification performance across various computer vision applications, including medical image analysis.A visual representation elucidating the architectural configuration of VGG16 is appended within Figure 1. [14].

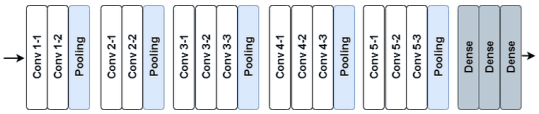

Figure 1: Elucidating the Architectural Configuration of VGG16

3.2. YOLOv5-seg

YOLOv5-seg is a specialized variant of the YOLO (You Only Look Once) [15], algorithm designed for precise instance segmentation tasks. It directly predicts pixel-level masks for objects in images by combining YOLOv5's object detection with ProtoNet, a fully connected network utilizing 2D convolutions with SiLU activation functions to generate mask prototypes. YOLOv5-seg surpasses YOLOv5 in channel outputs, with 351 channels, due to its additional 32 mask outputs. This integration effectively enables instance segmentation by leveraging ProtoNet instance features and object detection information, making it suitable for real-time applications, including medical imaging. Various weight variants (YOLOv5s-seg, YOLOv5m-seg, YOLOv5l-seg, and YOLOv5x-seg) are available to cater to different complexity and accuracy requirements [16].A depiction outlining the architectural arrangement of YOLOv5-sag is provided in Figure 2.[15, 16].

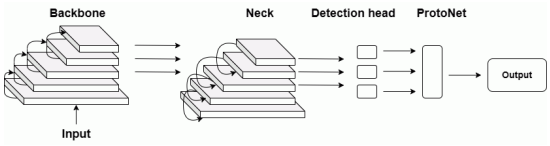

Figure 2: Elucidation of the Comprehensive Structure of YOLOv5l-seg

4. Datasets

In our work, we primarily utilized the Digital Database for Screening Mammography (DDSM) [17], a widely recognized public database extensively employed in breast cancer diagnostic and preventive assistance systems. The DDSM dataset includes 2620 cases, each containing four LJPEG-format images representing two images for each breast (Left_CC, Left_MLO, Right_CC, Right_MLO) from different angles. In total, it comprises 10,480 images depicting various breast conditions, including normal, cancerous, and benign states. For this study, 800 images were

randomly selected from the DDSM dataset, with an equal distribution of 400 normal and 400 abnormal (cancerous and benign) cases.

5. Preprocessing

The preprocessing of all mammograms is accomplished through the following sequential steps:

5.1. Normalization

To optimize the utilization of mammographic images in our CNN model, a normalization process is employed. In this process, the entire images are resized to a standardized dimension of 200×200 pixels [17, 18]. This resizing step ensures uniformity in the input image size, allowing for consistent processing and analysis by the CNN model.

The choice of 200×200 pixels as the target dimension is based on considerations of both computational feasibility and preserving important image information. This dimension strikes a balance between capturing significant details within the breast tissue and maintaining a manageable computational workload.

5.2. Data Partitioning

Data splitting in deep learning involves partitioning the dataset into three subsets: training (70%), validation (10%), and test (20%). The training set is used for model training, the test set assesses performance, and the validation set fine-tunes hyperparameters and guides model optimization.

6. Proposed Method

We propose an innovative method for the classification and segmentation of medical images. This method incorporates state-of-the-art techniques, including CNN YOLOv5-seg for precise region of interest segmentation, and VGG16 for the final classification of results. This approach is designed to enhance the accuracy and efficiency of the Computer-Aided Diagnosis (CAD) system in the medical domain. In the following sections, we will delve into each component of our method and explain how they are integrated to achieve an overall high-performing solution.Figure 3. illustrates a comprehensive depiction of our methodology.

6.1. CADe (Computer-Aided Detection)

To achieve an optimal configuration of the YOLOv5-seg model for our breast cancer detection task, we conducted a series of trials and tests with various versions of the model. After thorough evaluation, we selected

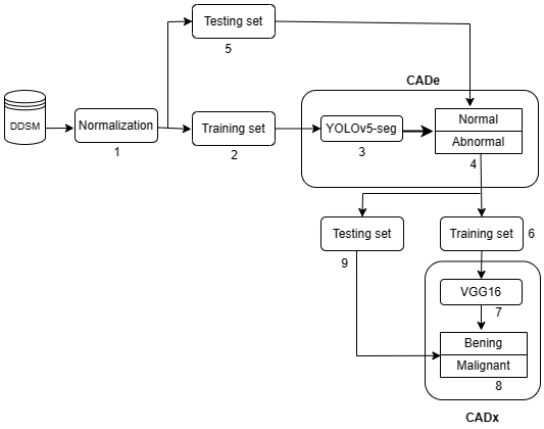

Figure 3: Illustration Elucidates the Fundamental Framework of Our Methodology

the YOLOv5L-seg variant, which exhibited the best performance for our specific database, and we made some changes to it.

6.1.1. Addition of convolutional layers

Given the relatively modest size of the images (200 x 200 pixels), we introduced three additional convolutional layers into the detection head of YOLOv5-seg. This strategic augmentation was undertaken to extract finer-grained information. The specifications of these added layers are depicted in Table 1.

Table 1
Characteristics of New Convolutional Layers: Filters, Kernel, and Activation.

Layers	CONV1	CONV2	CONV3
Filters	256	512	1024
Kernel	3x3	3x3	3x3
Activation	PReLU	PReLU	PReLU

6.1.2. Modification of Existing Convolutional Layers

To preserve details across multiple scales, we also introduced alterations to the pre-existing convolutional layers within the YOLOv5-seg detection head. The modifications implemented are as follows:

- Transition from 1x1 to 3x3 kernel size.
- Augmentation of the number of filters for each layer. The specifications of these modified layers are depicted in Table 2.

Table 2
Evolution of Convolutional Layer Characteristics through Filters Modifications.

Layers	CONV'1	CONV'2	CONV'3
Before	125	256	512
After	256	512	1024

These adaptations aim to broaden the receptive field of the filters and enhance the detection head's capability to capture salient features across different spatial scales.The complete modifications are depicted in Figure 4.

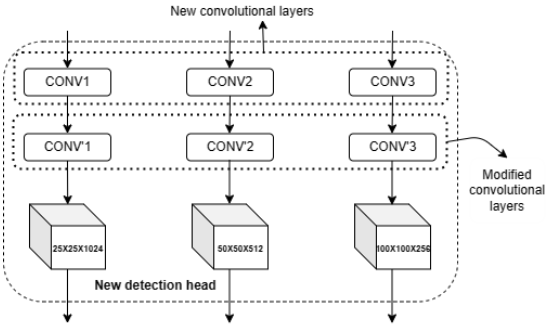

Figure 4: Exploring Configurations and Enhancements in YOLOv5l-seg for Computer-Aided Detection (CADe)

6.2. CADx (Computer-Aided Diagnosis)

After segmenting the mammographic images, a series of steps were undertaken to adapt the VGG16 model to our binary classification task. We present the steps undertaken in the context of this adaptation

Firstly, a resizing layer was judiciously introduced before the initial convolutional layer. This measure was taken to convert monochrome images (1 channel) into RGB images with three channels, thus harmonizing with the input format required by the VGG16 model, which had previously been pre-trained on color images.

In the interest of preserving the features acquired during the preceding training phase, the convolutional layers of the VGG16 model were frozen. Indeed, these layers had captured high-level features from color images of dimensions 512x512 during their pre-training. The freezing of these layers facilitated the retention of these features while permitting task-specific adaptation.

Following the assurance of the stability of convolutional layers, a pivotal step involved the introduction of a flattening layer. This layer facilitated the transformation of three-dimensional feature maps into a one-dimensional vector. This transition was imperative to facilitate the transfer of information extracted by the convolutional layers to the fully connected layers.

Finally, the development of a new classifier represented the ultimate step. Situated above the existing convolutional layers, this classifier was composed of three specific layers. The first layer was a fully connected layer endowed with 256 neurons and activated by a ReLU function. The second layer was also fully connected and comprised 128 neurons activated by ReLU. The final output-oriented layer featured a solitary neuron, its activation governed by a sigmoid function for binary classification.

Consequently, this classifier yields output probabilities through the sigmoid activation function. A value proximate to zero indicates a diminished probability of malignancy, while a value approaching one signifies a substantial probability of malignancy.The new architecture is presented in Figure 5.

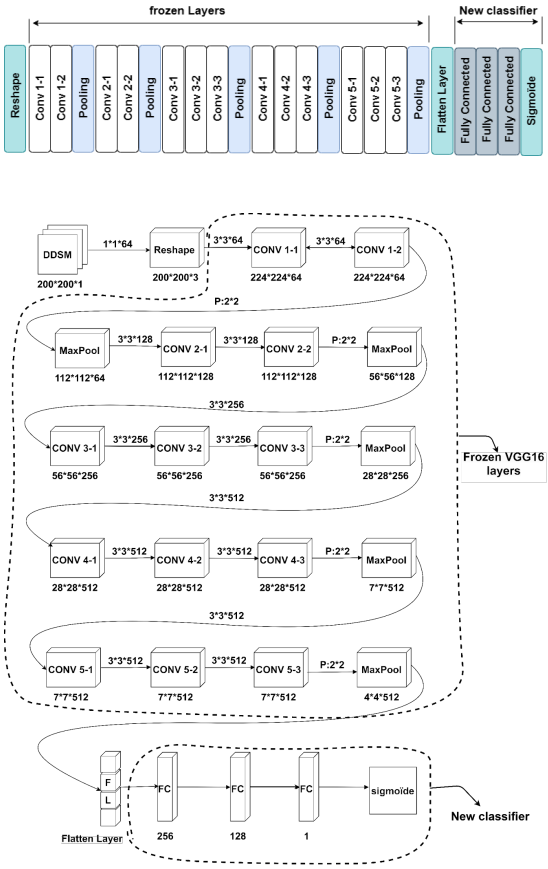

Figure 5: Exploring Variants and Enhancements of VGG16 Architecture for Computer-Aided Diagnosis (CADx)

7. Findings and Analysis

7.1. Assessment Criteria

In this section, we discuss the evaluation metrics used to assess the performance of our proposed method, specifically for the YOLO model and the VGG16 model. We focus on key metrics such as mean Average Precision (mAP), precision, recall, and accuracy to provide a comprehensive evaluation of the models' performance.

- `True Positives (TP)` : It represents the number of positive instances correctly identified or classified as positive by a model or test.
- `True Negatives (TN)` : It represents the number of negative instances correctly identified or classified as negative by a model or test.
- `False Positives (FP)` : cIt represents the number of negative instances incorrectly identified or classified as positive by a model or test. In other words, it is the number of instances that are actually negative but were mistakenly classified as positive.
- `False Negatives (FN)` : It represents the number of positive instances incorrectly identified or classified as negative by a model or test. In other words, it is the number of instances that are actually positive but were mistakenly classified as negative.
- `Accuracy` : It is a common evaluation metric that measures the overall correctness of the predictions made by the model.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

- `Precision` : Precision measures the accuracy of positive predictions made by the models.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

- `Recall` : Recall, also known as sensitivity or true positive rate, measures the model's ability to correctly detect positive instances.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

- `Mean Average Precision (mAP)` : The computer vision research community relies on the Mean Average Precision (mAP) as a standard metric to assess the reliability of object detection models. It quantifies the performance of these models by calculating the mean of average precision (AP) values across recall values ranging from 0 to 1.

$$\text{AP} = \int_0^1 P(r)\,\mathrm{d}r \quad \text{mAP} = \frac{1}{N}\sum_{i=1}^{N} \text{AP}_i \quad (4)$$

Noticed

For the YOLO model, we evaluate its performance by using mAP, precision, and recall. These metrics assess the model's ability to accurately detect and classify objects in the given dataset.

For the VGG16 model, we focus on accuracy as the primary evaluation metric. Accuracy provides a comprehensive measure of the model's correctness in classifying images into their respective categories.

7.2. Outcome Summary

In this section, we present the outcomes of our research study, which focuses on the combined use of CADe and CADx techniques. Our experimental setup involved utilizing a 10th generation Intel Core i7 processor coupled with an NVIDIA GeForce MX150 graphics card for training and evaluation purposes.

7.2.1. CADe Results

For CADe, we employed the YOLOv5-seg model, conducting extensive experiments to achieve improved performances. Over 100 iterations were conducted using various YOLOv5-seg models, each with different hyperparameters, aiming to enhance the results. The obtained results are presented in Figure 6. and Table 3.

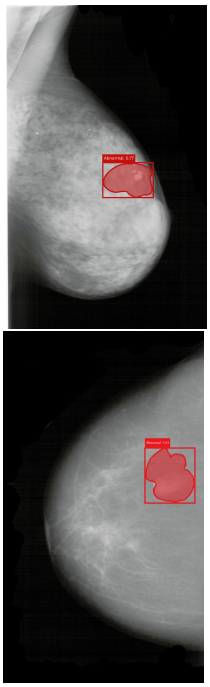

Figure 6: The Result of Mammography Segmentation Using YOLOv5-SEG

Table 3
Performance Evaluation of YOLOv5l-seg Through Multiple Training Iterations: A Comparative Analysis.

EPOCHS	MODEL	mAP
40	YOLOv5m-seg[1]	22%
40	YOLOv5m-seg[2]	26%
100	YOLOv5l-seg[1]	49%
100	YOLOv5l-seg[2]	68%
300	YOLOv5l-seg[1]	70%
300	YOLOv5l-seg[2]	88%

7.2.2. CADx Results

Moving on to CADx, we employed the VGG116 model and performed over 100 iterations for evaluation. After 100 epochs of training, we achieved an impressive precision of 97%.The obtained results are presented in Figure 7.

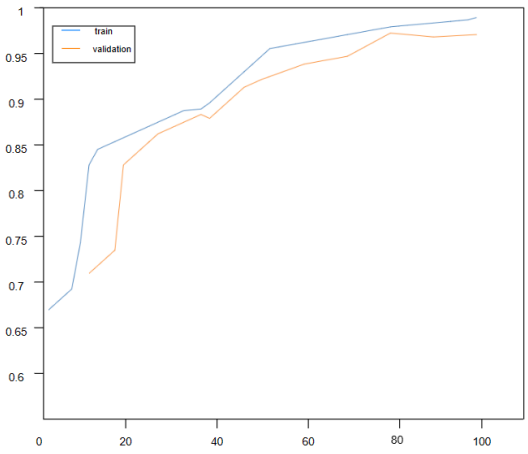

Figure 7: Displaying Training and Validation Accuracies for VGG16

8. CONCLUSION

The principal objective of this research endeavor was to develop a Computer-Aided Diagnosis (CAD) system aimed at augmenting radiologists' diagnostic capabilities, thereby ensuring heightened accuracy in patient assessments. This CAD system was structured into two primary phases: Detection (CADe) and Identification (CADx). Recent years have seen a rapid ascent in the prominence of deep learning as a robust method for predictive analysis, particularly in the realm of image processing. Deep learning Convolutional Neural Network (CNN) models, renowned for their hierarchical architectures, have proven invaluable in extracting intricate features from input images. In the development of our CAD system, a meticulous selection process was employed to identify pre-trained CNN models that exhibited promising outcomes. Specifically, YOLOv5-seg was designated for CADe, while VGG16 emerged as the most suitable choice for CADx.

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While the strides made in developing an advanced Computer-Aided Diagnosis (CAD) system employing deep learning models such as YOLOv5-seg and VGG16 are noteworthy, it is imperative to acknowledge broader implications beyond performance metrics. One significant aspect deserving attention in deploying such systems at scale is the safeguarding of patient data security. Ensuring the integrity and confidentiality of medical information within the CAD system against potential breaches is crucial, aligning with stringent data protection regulations to uphold patient privacy.

Furthermore, the real-world application of these systems necessitates consideration of latency issues, especially in time-sensitive scenarios like medical diagnoses. Minimizing latency between image input and diagnosis output is pivotal for improving clinical workflow efficiency and providing timely insights to healthcare professionals. Achieving low latency in real-time processing without compromising accuracy becomes essential to ensure the practical usability of these systems.

Another critical aspect revolves around the management of extensive datasets in real-world scenarios. As the CAD system operates within clinical environments, seamless handling and storage of vast datasets become

[1] Original YOLOv5-seg
[2] Modified YOLOv5-seg

imperative. Scalability and efficient data management techniques are vital to accommodate the continuous influx of medical imaging data while preserving system performance and responsiveness.

Addressing these challenges—data security, latency optimization, and effective management of extensive real-world datasets—becomes integral for the successful integration and sustainable utilization of CAD systems in clinical settings. While our research demonstrated impressive accuracy and precision, future advancements should focus not only on model performance but also on overcoming these practical hurdles to ensure the seamless and secure deployment of CAD systems in enhancing patient care and diagnosis.

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