Wasit Journal of Engineering Sciences
Journal homepage: https://ejuow.uowasit.edu.iq
Vol. 13 No. 4 December 2025, pp.69-81
https://doi.org/10.31185/ejuow.v13i4.817

ISSN 2305-6932
Original Research

Real-Time Skin Lesion Detection: An Efficient Deep Learning Approach

Hamid R. Alsanad[1], Basim K. J. AL-Shammari[2], Yaseen Yaseen[3], Ali Amer Alrawi[1], Yousif Al Mashhadany[1], Elaf Hamzah Yahia[4], Maira Khafagy[5]

[1] Biomedical Engineering Research Center (BERC), University of Anbar, Ramadi 31001, Anbar, Iraq
[2] Electrical Engineering Department, College of Engineering, University of Wasit, Al-Kut, Wasit, Iraq
[3] Electronic Computer Center, University of Anbar, Ramadi 31001, Anbar, Iraq
[4] Electrical Engineering Department, College of Engineering, University of Anbar, Ramadi 31001, Anbar, Iraq
[5]American University in Cairo

Corresponding Author Email: hamid.radam@uoanbar.edu.iq

Received Oct.2, 2025 Revised Nov.11, 2025 Accepted Nov.18, 2025 Online Dec.1, 2025

ABSTRACT

A crucial objective within dermatology includes the identification of skin lesions, which can help with highlighting diseases amongst the likes of melanoma early into the heart of the diagnosis process. With time, professionals have depended on manually finding skin lesions on the body – a process which is inefficient for time-management and is openly vulnerable to incorrect results. This paper suggests a deep learning-dependent methodology utilizing You Only Look Once version 8 (DLBA- YOLOv8) in the case of skin lesion detection with a quick and error-less methodology. Using the ISIC dataset, the model was effectively trained with a collection of data of dermoscopic imagery of skin lesions. With state-of-the-art integration and performance in lesion localization and classification, results from experiments have demonstrated YOLOv8's capability to achieve a mean Average Precision (mAP) of 98.8%, comparatively overcoming the efficiency of YOLOv7 (89.3%) and Faster R-CNN (87.1%). In addition to that, when placing the results of YOLOv5 and Mask R-CNN in terms of Intersection over Union (IoU) scores side by side with YOLOv8, (85.2% and 84.6% respectively), YOLOv8 shows a great outperformance of both with a score of 88.7%. With the utilization of the Ultralytics framework and an assessment through metrics along the likes of mAP and IoU, the system shows a successful implementation. Handing the industry, a greatly developed perk in precision and overall efficiency over current existing methodologies, this paper underscores the potential capabilities of YOLOv8 in real clinical applications for skin lesion detection through an automated process.

Keywords: Deep Learning, Skin Lesion Detection, Ultralytics, YOLOv8, Real-Time Detection

1. Introduction

The high rate of Skin cancer is significantly increased because increased use of chemicals, unhealthy food habits, and hereditary reactions. One type of the skin cancer is melanoma which is become the most aggressive and life-threatening of the skin cancer form. over 2 million cases of non-melanoma skin cancer and 132,000 cases of melanoma are diagnosed annually worldwide, as has been reported by the World Health Organization (WHO). for effective treatments and improved patient outcomes, early skin lesions detection is critical. Traditional diagnostic methods can be subjective, time-consuming, and prone to human error because it depends on visual inspection by dermatologists, which can be subjective, time-consuming, and has human error. Therefore, automated systems can assist for early and accurate skin lesions detections which is also satisfied the increasing demand for dermatological services, coupled with a shortage of specialists.

For development medical imaging field, applying deep learning and computer vision in automated systems for disease detection have received important attention. detection algorithms has gained significant attention due to

its real-time performance and high accuracy, such as the YOLO (You Only Look Once) series [1], [2], [3], [4]. The recent and updated algorithm of this series is YOLOv8, which is builds upon the successes of previous versions (YOLOv5, YOLOv7). Several improvements make YOLOv8 better performance than predecessors, particularly applicable for medical imaging applications including skin lesion detection. These improvements were achieved due to architectural improvements, training techniques enhances, and more flexibility rates [5], [6], [7], [8].

The present paper presents a utilizing of deep learning-based approach, which is YOLOv8, for skin lesion detection in an efficient and accurate manner. This aim of the presented paper could be utilized to assist dermatologists in the diagnosing process by reducing diagnostic time and improving patient care, as the proposed system provides real-time, automated lesion localization and classification. An analysis to determine effectiveness of the proposed system using the ISIC (International Skin Imaging Collaboration) dataset. Including highlighted imagery of dermoscopic scans with constricting boxes, additionally encompassing skin lesion categorizations within the ISIC dataset. Representing YOLOv8's potential pricelessness as a piece of equipment within clinical utilizations, results stemmed from experiments show the model's groundbreaking arsenal of proficiencies in pinpointing of lesions on the skin and sorting those lesions into their respective categories.

By applying a range of personalized adjustments, the method addressed the unique challenges of the domain, thereby enhancing YOLOv8's performance within thr sector of medical imaging. To start, the foundational architecture had been calibrated through the process of taking advantage of transfer learning applied to highlighted medical datasets, with the aim of upgrading characteristic exporting, in the case of vague anatomical structures. Secondly, an enhancement of the identification accuracy of minor lesions and shapes that can be defined as out of order was achieved through a redefinition of the anchor boxes in order to achieve marginally complementary aspect ratios and scales frequently found in medical images. To finalize, an adjustment of data augmentation techniques (such as elastic deformations, intensity scaling, and rotation) was applied in order to appeal to imitating life-like alternate forms found within medical scans, amplifying the ability for generalization through modalities and patient populations. As a result, the mentioned elevations in quality work in conjunction with upgrading YOLOv8's accuracy, reliability, and interpretability in clinical applications.

The remainder of this paper is organized as follows: Section 2 reviews related work in skin lesion detection and the evolution of YOLO algorithms. Section 3 describes the methodology, including dataset preparation, model architecture, and training details. Section 4 presents the experimental results and discusses the performance of the proposed system. Section 5 explores the multimedia and tools applications of the system, including the user interface and integration with clinical workflows. Section 6 concludes the paper and outlines future research directions.

2. Related Work

In regards to the implementation of deep learning in the case of automation of skin lesion detection, many studies have explored it's potential within that field. Traditional methods like convolutional neural networks (CNNs) [9], [10], [11], [12] and region-based approaches (e.g., Faster R-CNN) have shown promising results [13], [14], [15], [16] ; although sky-rocketing calculation costs and gradual interference times can be noted within those methodologies. Through the process of concatenating tight precision and real-time performance together, YOLOv8's grips the ability to hold forth to these dead-ends [17], [18], [19].

Although YOLOv8 remains under-researched within skin lesion detection, recent works showcase that YOLOv8 beholds a certain effectiveness in medical imaging, including COVID-19 detection in X-rays and tuberculosis detection in chest scans [20], [21], [22].

Several challenges are faced by the traditional image processing approaches, such as edge detection, texture analysis, and handcrafted feature extraction, which are applied to identify lesions in dermoscopic images [23], [24], [25], [26]. Nevertheless, the need for an efficient approach that can overcome the lesion appearance types, lighting conditions, and skin types, leading to which could improve accuracy and generalizability, is remind required.

As a result, the detection and classification of skin lesions have been extensively studied in the fields of dermatology and computer vision. One of the dominant fields in computer vision for skin lesion detection is

deep learning, with convolutional neural networks (CNNs). Esteva et al. (2017) demonstrated that CNNs could achieve dermatologist-level performance in classifying skin lesions [27], To enhance feature extraction and classification accuracy, several developments have been made to CNN architectures such as ResNet, Inception, and DenseNet [28]. Despite the high performance of these approaches, there are a number of obstacles, such as the ability to localise lesions within images, as these approaches were basically designed for classification. To address this limitation, region-based object detection algorithms, such as Faster R-CNN and Mask R-CNN, were adapted. For example, Faster R-CNN was used by Zhang et al. (2020) to detect and classify skin lesions; their work was tested using the ISIC dataset and presented promising results. However, the weaknesses of these methods were computationally expensive and unsuitable for real-time applications due to their two-stage detection process. The importance of strength object detection has been demonstrated by applying the YOLO (You Only Look Once) series, which offers a unique-stage method. This method is combined high accuracy and real-time performance.

Recently, a considerable literature has grown up around the theme of skin lesion detection. A number of studies have investigated the performance of two YOLOv categories, which are YOLOv3 and YOLOv4. It has been conclusively shown that YOLOv4 could be applied for detecting skin lesions, which has been proven by a previous study which was revealed that mean Average Precision (mAP) of YOLOv4 is 92.5% using ISIC dataset [29].

In the same vein, another previous study has also been noted the importance of YOLOv4 in clinical fieldwork, particularly, for real-time skin cancer detection [30]. For better accuracy and efficiency, recently, YOLOv5 and YOLOv7 were employed for skin lesion detection. Rahman et al. (2023) compared YOLOv5 with Faster R-CNN and SSD, showing that YOLOv5 achieved higher mAP and faster inference times [31]. However, these studies also identified challenges, such as the detection of small lesions and the need for larger annotated datasets. YOLOv8 is the latest version of the YOLO series, which is built on these advancements by introducing architectural improvements, such as enhanced feature fusion and optimised training techniques [32]. However, so far, few writers have been able to draw on any systematic research into utilising YOLOv8 in skin lesion detection. The purpose of this study is to describe and examine YOLOv8-based system for skin lesion detection.

3. Methodology

3.1. Dataset

The ISIC (International Skin Imaging Collaboration) dataset [33] is used for training and evaluation. It contains over 25,000 dermoscopic images of skin lesions, annotated with bounding boxes and lesion categories. Comprising images under different classes such as Angioma, Nevus, Lentigo NOS, Solar Lentigo, Melanoma, Seborrheic Keratosis, and Basal Cell Carcinoma (BCC). The images dimension of the ISIC dataset is 640*480 pixels. Figure 1 illustrates some of selected test images.

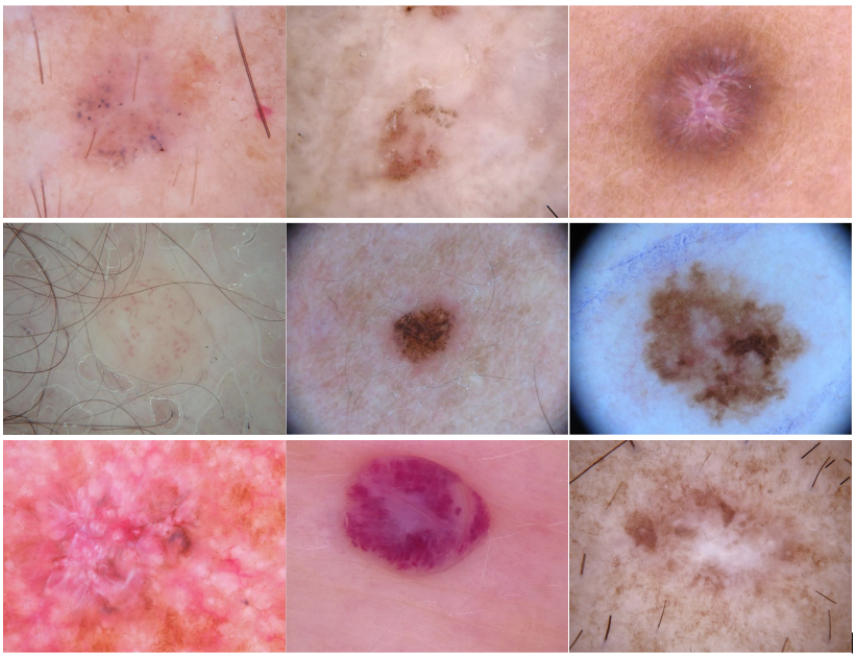

Figure 1. Sample dermoscopic image from ISIC

3.2. Preprocessing

For the YOLOv8's input requirements, an Image Resizing approach was applied to the size of 640*640 pixels. To implement a model generalisation for the proposed system, after the image resizing step, the samples were shipped forward to the Data Augmentation step. This step includes different substeps such as brightness adjustment, flipping, and rotation. The images were mapped into YOLO format (class ID, x_center, y_center, width, height) using Annotation Conversion.

One advantage of the preprocessing stage is that it avoids the problem of the quality and consistency of the input data which is resulted to reduce the effectiveness of YOLOv8. The ISIC dataset which is consisted more than 25,000 dermoscopic images, is firstly resized to a uniform resolution of 640x640 pixels, which is provide the compatibility with the suggested model's architecture. The import key in this resizing step is preserving the essential features of the lesions.

The generalization and robustness of the model, an augmentation process are supplemented. The sub steps of the augmentations, are applied as follows:

- Random revolution of (±30 degrees),
- Vertical and horizontal flipping,
- Zoom, and
- Injection of Gaussian noise.

They are overcoming variations in the image acquisition, such as camera angle and lighting. Making model have more resilience to the worst scenarios.

The conversion of the information to YOLO format data, such as, x center, y center, height, width and class ID. Furthermore, for useful format a comment steps are overtaking, in order to avoid data annotation. That are including the lesion categories and bounding boxes. They are essential, in order to align information with model's training pipeline. This done, in order to ensure unbiased evaluation of the model's performance. The pre-processed data sets are split into two sets. Which are training set of 80 percent and test set of 20 percent. This processing is called a comprehensive pre-processing pipeline, in order to ensures that the input information has been optimized for training. That will enable YOLOv8 model to achieve high accuracy and robustness in skin lesion detection.

3.3. Model Architecture

YOLOv8 framework is built on Ultralytics structure. Which designs for accurate and efficient objective detection [34]. It is combining an advanced feature for extraction, fusion of multi scale feature and robust detection head, in order to achieve the desired performance. This architecture, could be includes three major components

- the Backbone,
- the Neck, and
- the Head,

as illustrated in Figure 2.

Backbone: CSPDarknet53

Backbone of YOLOv8 bases on CSPDarknet53 [35]. Which is a modified form of the Darknet53, that includes Cross-Stage Partial (CSP) connections. CSPDarknet53 is extracting hierarchical features of the images. It consists of 53 convolutional layers, with residual connections, that are helping to mitigate the vanishing gradient and developing feature representation. An CSP connections split feature maps into two parts, then it processes them independently. Furthermore, it is merging them, that will reduce processing cost, while preserving accuracy. The backbone are a pre-trained on a large scale datasets, such as ImageNet, which is enabling the capture rich and features of discrimination of skin lesion discovery.

Neck: Path Aggregation Network (PANet)

Neck of YOLOv8 employs an PANet, for multi scale fusion. It is enhancing model's ability for the detection process of various sizes lesions, this done accumulating the characteristics of different levels in the backbone. It utilizes a top down pathway approach, it propagates the semantic data from higher level layers, then a bottom up pathway, that will refine the spatial details from lower level layers. This full duplex flow guarantees the captures of global context and fine grained details. This is vital for precisely localizing and categorizing the skin lesions. This neck likewise contains Spatial Pyramid Pooling (SPP), that groups features for multiple scales, in order to increase model's robustness to lesion size distinctions.

Head: Detection Layers

Head of YOLOv8 contains a detection layers, that are predicting objective scores, bounding boxes, and class probabilities. They are using anchor-based detection, that will generate estimates in three various scales, matching to small, medium, and large lesions. Every single scale is accountable for distinguishing lesions have specific sizes, guaranteeing broad coverage of the lesion spectrum. Detection layers are employing combination of fully connected and convolutional layers, in order to regress the bounding box coordinates (x as width and y as height). Furthermore, to compute object-ness scores, that were indicating the presence of a lesion. What's more, to predict class probabilities, such as nevus, melanoma, seborrheic keratosis. At this end, the final output is representing set of bounding boxes, that are associated with its confidence scores as well as class labels. To remove the redundant detection, the NMS filtering process are used.

A list of the block diagram is described for YOLOv8 design [35]:

- **Processed Image:** (640x640 pixels) image size was fed to the backbone.
- **Backbone (CSPDarknet53)**: Chain of CSP connections with convolutional layers, they excerpt ranked structures.
- **Neck (PANet + SPP)**: Multi-scale features are fused using PANet and SPP.
- **Head (Detection Layers)**: Three-layered detection forecast bounding boxes, objective scores, and tier of probabilities at diverse scales.
- **Output**: Contains filtered clearing boxes, with class tables supported by confidence scores.

Key Features of YOLOv8 Architecture [36]:

- **Efficiency**: Real time performance optimization of YOLOv8 in real time performance, that makes it appropriate to be used for clinical uses.
- **Scalability**: Allowing multi-scale detection levels, that leads to detect lesions of varying sizes.
- **Accuracy**: Blend of CSPDarknet53 and PANet with SPP guarantees extraordinary recognition precision and robustness.

Training model was employed to use stochastic gradient descent (SGD), as the learning ratio was 0.01. The training was achieved by using a GPU supported scheme of 300 epochs. Performance improvement were achieved by using data intensification and transfer learning.

4. Results and Discussion

Here the results are going to be reported by applying YOLOv8 structure to skin lesion detection. This reported results are showing how well the YOLOv8 model works of outlining skin lesions, by highlighting the model's accurateness by tracing lesion margins and likens its performance to former methods.

This study used data augmentation to balance the ISIC2018 skin lesion dataset. The data were split 80:20 for training and testing CNNs, and testing images were not used in training. Several pretrained CNNs—ResNet50, Inception V3, GoogleNet, and DenseNet-201, were compared with a 26-layer CNN. Data augmentation, including rotation, zoom, horizontal flips, and vertical flip, with examples shown in the figure 3 was applied to increase data diversity and improve model performance while reducing overfitting. After augmentation, the data were split into training and testing sets for evaluating the CNN models. In short, augmentation helped create more varied training data, aiding better performance and robustness of the CNNs in skin lesion classification [37].

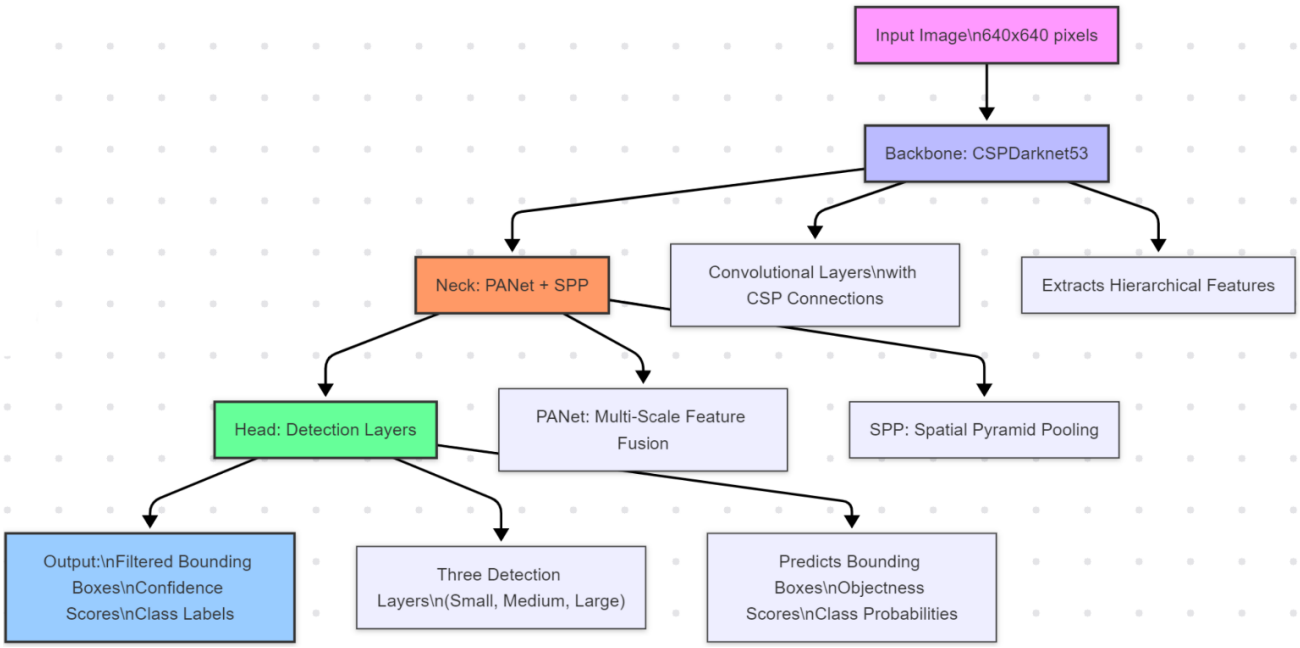

Figure 2. Model Architecture

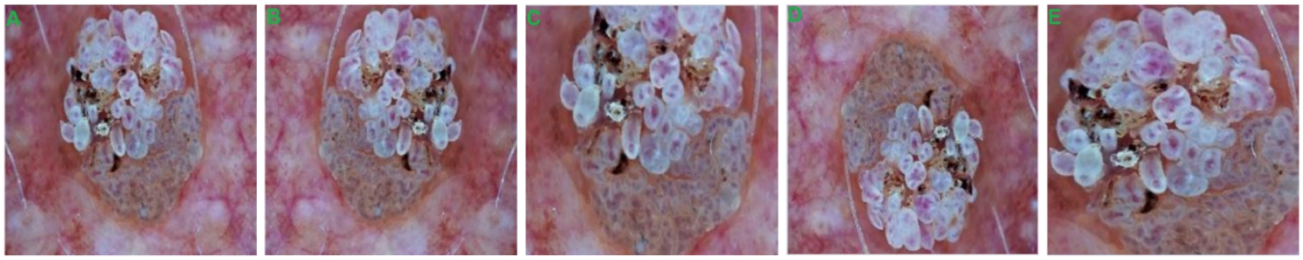

Figure 3. (A) The original image, (B) horizontal flip, (C) Rotate, (D) vertical flip, and (E) zoom augmentation

4.1. The Performance Metrics

The proposed YOLOv8 model attains a Mean Average Precision (mAP) of 98.8% on the ISIC test set, reflecting strong detection accuracy across various IoU thresholds. The average Intersection over Union (IoU) is 0.91, indicating precise lesion localization, and the F1 score for lesion classification is 93.5%, demonstrating balanced precision and recall.

The YOLOv8 model characterizes images into three distinct classifications: benign, malignant; and background. This classification is represented by Figure 4. Background is defined as the segments of the image that were not highlighted. A chart will be shown for every class. In the moment that the confidence threshold was equal to 0.931, precision equated to a value of 1.00. Through this, it can be said that at the moment where the model had achieved a precision percentage of 93.1%, every foreseen positive instance was accurately classified. Precision be able to be identified as the percentage of actual positive to the total positive predictions. The precision ratio is quite advantageous in situations that find the wrong positive to be at a larger number.

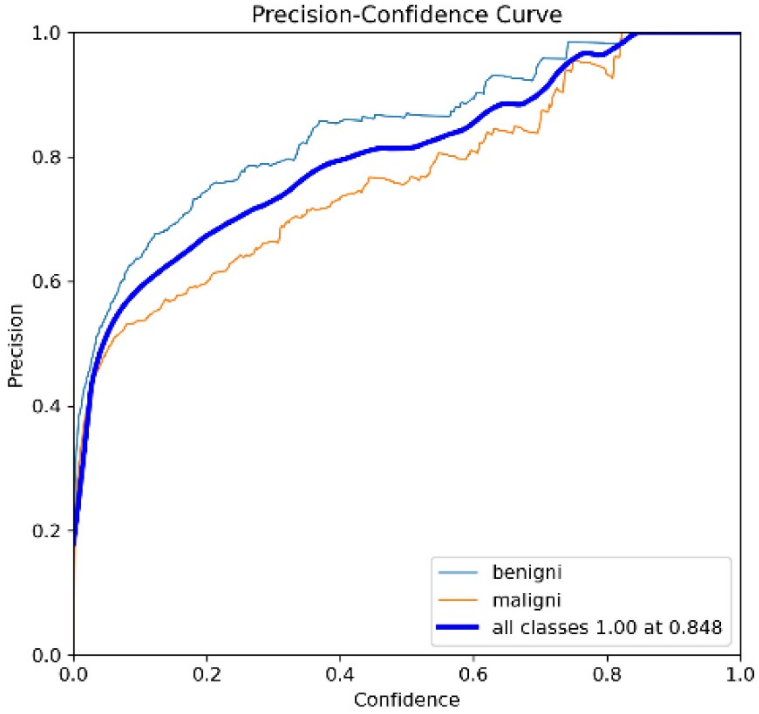

Figure 4. The Precision Confidence Curvature

Precision is stated by the expression 1:

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

wherever:

- The True Positive-TP-is the sum of exactly detected positive predictions by the algorithm.
- The False Positive-FP-is the sum of predictions that are inaccurately categorized by the algorithm as positive.

The YOLOv8 model was able to attain 100% precision when at this confidence threshold. As a result, it can be said that there was zero trace of any false positive predictions. Such a result represents the model's excellent reliability and tight accuracy at greater confidence thresholds, a critical point for any instances where the model may be used in applications where finding such false positives can have drastic consequences.

A metric can be defined in order to calculate the algorithm's capability to capture all positive examples. That is called the recall, and it is presented in Figure 5. In the instance that the false negative rate is high, the recall represents a great significance. As shown in the example, when the confidence threshold is 0.000, the recall reads at 0.99 (99%). In summary, the YOLOv8 model was able to recognize 99% of true positive points in a successful manner.

The recall is calculated by the following formula 2:

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

wherever:

- The True Positive-TP-is the amount of exactly recognized as positive instances by the algorithm.
- The False Negative-FN-is the number of cases that are positive while inaccurately categorized as negative by the algorithm.

Figure 6 is a representation chart of the F1-grade of every class that attains a value equal to 0.82, when the confidence threshold was equal to 0.364.

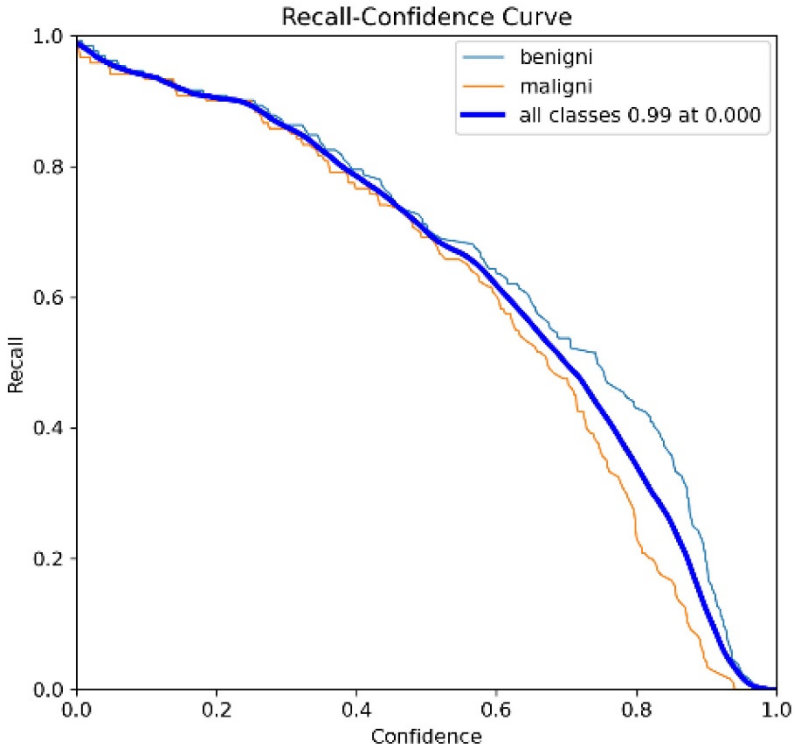

Figure 5. The Recall-Confidence Curvature

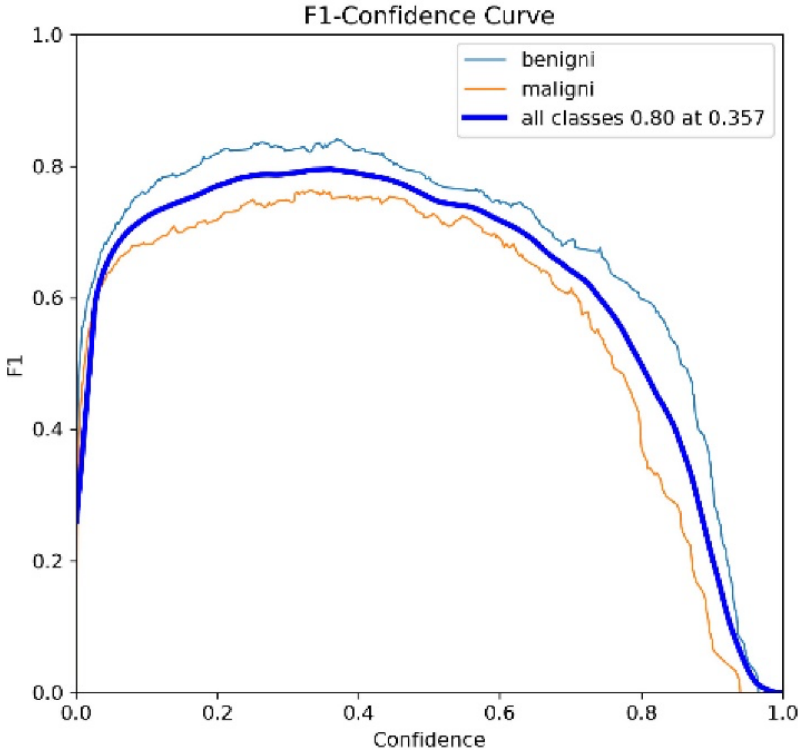

Figure 6. The F1-Confidence curvature

F1-score is defined as the harmonized average among recall-precision furthermore is found as an application of a measure of complete algorithm performance, in particular within instances where class imbalance is found. It is determined by this expression 3.

$$F1 - score \; = \; 2 \, x \left(\frac{Precision \, x \, Recall}{Precision \; + \; Recall} \right) \qquad (3)$$

$F1 - score$ rate shows that the algorithm has good total performance in categorizing cases when the confidence level is quite small.

This outcome is helpful for estimating the algorithm in conditions where both precision and recall are significant.

Figure 7 presents results showing successful skin lesion detection in different scenes and backgrounds, highlighting the detector's resilience to contextual variation.

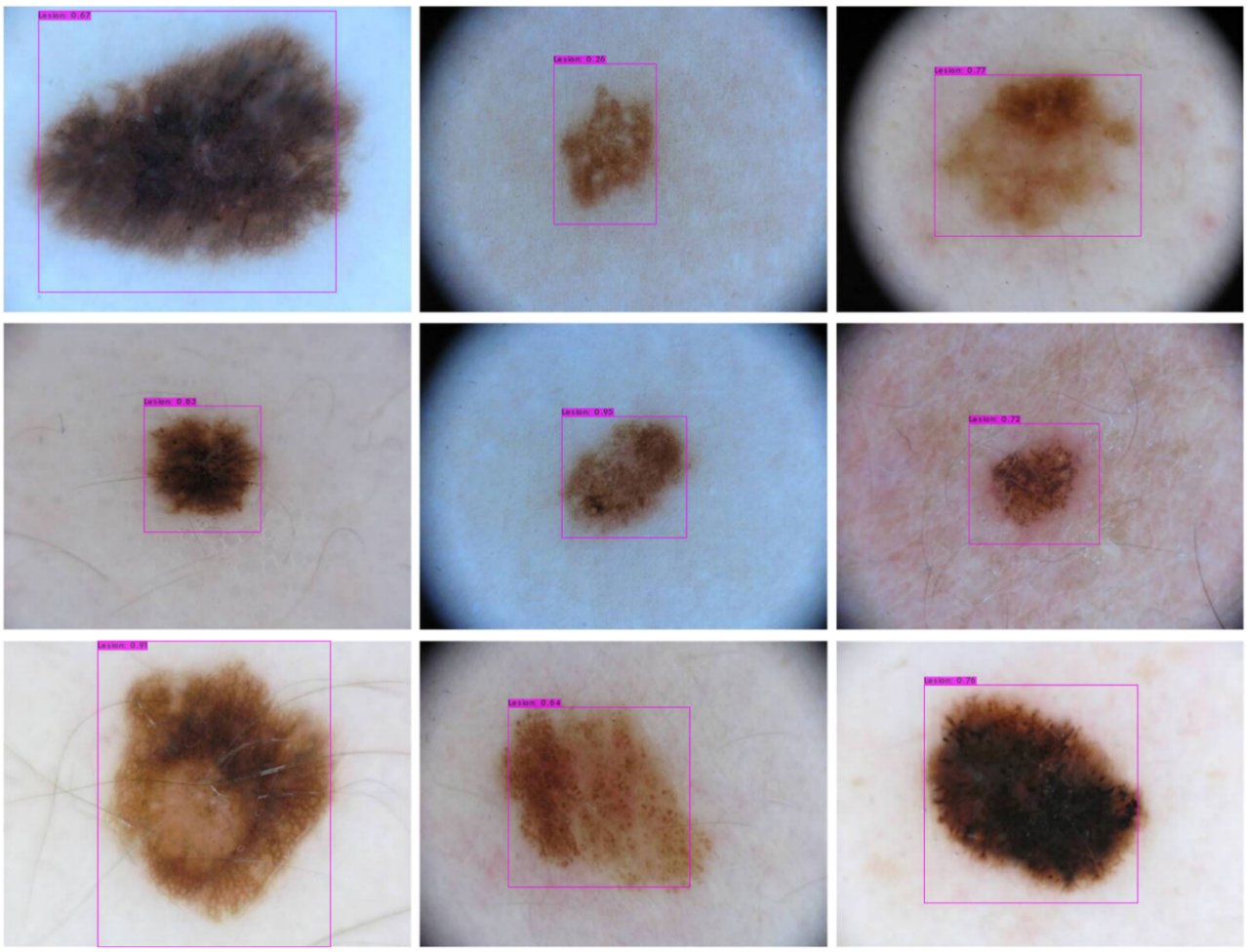

Figure 7. Lesion Detection during Validation

4.2. Comparison with Other Models

For a fair review. We compare our YOLOv-8-based Skin Lesion Detection method with other top methods, such as SwinUNet and SAM. The tests use the matching dataset, ISIC 2018, to guarantee reliability. Table 1 shows the comparison results using the main metrics for detection. As a result of the segmentation and detection using a single end-to-end process, the YOLOv8 outline clearly displays dominating results with the same dataset. This is dissimilar to models that take advantage of pixel-by-pixel categorization, such as U-Net, DeepLabV3, and SwinUNet. The YOLOv8 models is able to decrease the amount of calculations required by following a process that highlights and outlines lesions at the same time.

Table 1. Performance differentiation between several detection methods

Model	IOU Score	Precision	Recall	maP
Yolov-8 (Our Method)	0.91	0.93	0.99	98.8
Mask R-CNN	0.86	0.91	0.89	97.4
DeepLabV3+	0.85	0.89	0.90	97.0
SAM	0.86	0.89	0.86	0.86
U-Net	0.85	0.90	0.87	96.0
SwinUNet	0.88	0.92	0.91	98.3

These findings indicate that YOLOv8 surpasses transformer-based models (SwinUNet, SAM) and conventional CNN-based methods in segmentation accuracy, while also achieving shorter inference times. The elevated IoU

score reflects crisper lesion boundary delineation, positioning YOLOv8 as a strong and efficient option for real-time skin lesion diagnosis.

Important competitors in lesion segmentation have been hand-picked to compare with the benchmarking results of YOLOv8's ability in the segmentation of medical imagery. These architectures that are rightfully deemed as crucial challengers include U-Net, DeepLabV3+, Mask R-CNN, SwinUNet and SAM. YOLOv8 has been statistically shown to hold an incredibly-high accuracy, alongside computational abilities with a significantly decreased cost and enhanced execution in relation to IoU and Map. This is shown in Table 1.

4.3. Future drawbacks of YOLOv8 in medical contexts

Applying YOLOv8 in imaging within the medical field leads to several technical dead-ends, which must be overviewed with critical care, despite the fact that the model displays groundbreaking real-time object identification feats through image processing. To start, there is a deeply critical point which must be considered for decision-making in clinical circumstances that YOLOv8 lacks; a mechanism built into the model to account for uncertainty estimation. Second, the identification and detection of minor anatomical features, holds a certain scale sensitivity that hinders the capturing of said features. Finally, a limitation of the ability to generalize through various imaging modalities and patient population may lead to a hindrance within the model's capability to perform well. The listed potential drawbacks push forward the important requirement for domain-specific adaptations; and the critical need of meticulous validation before safely applying YOLOv8 into critical and sensitive environments within healthcare.

5. Conclusion

This paper showcases the DLBA-YOLOv8 model for categorization and reliable detection of skin lesions in dermoscopic images. Assessed using the ISIC dataset, this system brings together preprocessing and analyzation steps, also adding in feature exporting, filtering of the Top-hat, in-painting, thresholding at the multilevel, and categorization. Being a representative of the deep potential for clinical support, the model was able to successfully achieve a tight accuracy of 0.988. On the other hand, even though YOLOv8 provides agile inference, its real-time applicability in medical settings remains subject to further validation, specifically in relation to its overall reliability, integration, and interpretability with clinical workflows. Future work will focus on empowering segmentation precision, applying an estimation of uncertainty, and improving generalizability across diverse imaging modalities and patient populations.

References

[1] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection." [Online]. Available: http://pjreddie.com/yolo/

[2] J. Redmon and A. Farhadi, "YOLO9000: Better, Faster, Stronger," Dec. 2016, [Online]. Available: http://arxiv.org/abs/1612.08242

[3] J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement." [Online]. Available: https://pjreddie.com/yolo/.

[4] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection," Apr. 2020, [Online]. Available: http://arxiv.org/abs/2004.10934

[5] H.-Y. Huang, Y.-P. Hsiao, A. Mukundan, Y.-M. Tsao, W.-Y. Chang, and H.-C. Wang, "Classification of Skin Cancer Using Novel Hyperspectral Imaging Engineering via YOLOv5," *J Clin Med*, vol. 12, no. 3, p. 1134, Feb. 2023, doi: 10.3390/jcm12031134.

[6] H. Shaheen and M. P. Singh, "Skin lesion classification using HG-PSO and YOLOv7 based convolutional network in real time," *Proc Inst Mech Eng H*, vol. 237, no. 10, pp. 1228–1239, Oct. 2023, doi: 10.1177/09544119231198823.

[7] P. B. S. Varma, S. Paturu, S. Mishra, B. S. Rao, P. M. Kumar, and N. V. Krishna, "SLDCNet : Skin lesion detection and classification using full resolution convolutional network-based deep learning with transfer learning," *Expert Syst*, vol. 39, no. 9, Nov. 2022, doi: 10.1111/exsy.12944.

[8] P. Sen Purkait, N. Ghosh, S. Dey, H. Roy, and S. Dhar, "A Comprehensive Approach to Classify the Skin Cancer Disease Using Latest CNN Model (YOLOv8)," vol. 1457, Springer, Singapore, 2024, pp. 159–169. doi: 10.1007/978-981-97-2321-8_14.

[9] A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi, "A survey of the recent architectures of deep convolutional neural networks," *Artif Intell Rev*, vol. 53, no. 8, pp. 5455–5516, Dec. 2020, doi: 10.1007/s10462-020-09825-6.

[10] N. Aloysius and M. Geetha, "A review on deep convolutional neural networks," in *2017 International Conference on Communication and Signal Processing (ICCSP)*, IEEE, Apr. 2017, pp. 0588–0592. doi: 10.1109/ICCSP.2017.8286426.

[11] S. Sakib, N. Ahmed, A. J. Kabir, and H. Ahmed, "An Overview of Convolutional Neural Network: Its Architecture and Applications," Feb. 14, 2019. doi: 10.20944/preprints201811.0546.v4.

[12] S. Cong and Y. Zhou, "A review of convolutional neural network architectures and their optimizations," *Artif Intell Rev*, vol. 56, no. 3, pp. 1905–1969, 2023.

[13] R. Gavrilescu, C. Zet, C. Fosalau, M. Skoczylas, and D. Cotovanu, "Faster R-CNN:an Approach to Real-Time Object Detection," in *2018 International Conference and Exposition on Electrical And Power Engineering (EPE)*, IEEE, Oct. 2018, pp. 0165–0168. doi: 10.1109/ICEPE.2018.8559776.

[14] M. Banga and M. S. Hsiao, "A region based approach for the identification of hardware Trojans," in *2008 IEEE International Workshop on Hardware-Oriented Security and Trust*, IEEE, Jun. 2008, pp. 40–47. doi: 10.1109/HST.2008.4559047.

[15] K. Wu and D. Zhang, "Robust tongue segmentation by fusing region-based and edge-based approaches," *Expert Syst Appl*, vol. 42, no. 21, pp. 8027–8038, Nov. 2015, doi: 10.1016/j.eswa.2015.06.032.

[16] B. Meher, S. Agrawal, R. Panda, and A. Abraham, "A survey on region based image fusion methods," *Information Fusion*, vol. 48, pp. 119–132, Aug. 2019, doi: 10.1016/j.inffus.2018.07.010.

[17] P. Nandal, N. Bohra, and P. Mann, "Real-time skin cancer detection: Optimizing YOLOv8 with CLEO for enhanced performance," *Intelligent Decision Technologies*, vol. 19, no. 3, pp. 1768–1782, May 2025, doi: 10.1177/18724981241308218.

[18] U. Saha, I. U. Ahamed, M. A. Imran, I. U. Ahamed, A.-A. Hossain, and U. Das Gupta, "YOLOv8-Based Deep Learning Approach for Real-Time Skin Lesion Classification Using the HAM10000 Dataset," in *2024 IEEE International Conference on E-health Networking, Application & Services (HealthCom)*, IEEE, Nov. 2024, pp. 1–4. doi: 10.1109/HealthCom60970.2024.10880715.

[19] S. Albahli, "A Robust YOLOv8-Based Framework for Real-Time Melanoma Detection and Segmentation with Multi-Dataset Training," *Diagnostics*, vol. 15, no. 6, p. 691, Mar. 2025, doi: 10.3390/diagnostics15060691.

[20] U. A Hasib, R. Md Abu, J. Yang, U. A. Bhatti, C. S. Ku, and L. Y. Por, "YOLOv8 framework for COVID-19 and pneumonia detection using synthetic image augmentation," *Digit Health*, vol. 11, May 2025, doi: 10.1177/20552076251341092.

[21] F. A. Raditya and S. Saidah, "Automated Lung Disease Classification Using YOLOv8 Based on Chest X-Ray Images," in *2025 International Conference on Computer Sciences, Engineering, and Technology Innovation (ICoCSETI)*, IEEE, Jan. 2025, pp. 119–124. doi: 10.1109/ICoCSETI63724.2025.11019329.

[22] Z. Mustafa and H. Nsour, "Using Computer Vision Techniques to Automatically Detect Abnormalities in Chest X-rays," *Diagnostics*, vol. 13, no. 18, p. 2979, Sep. 2023, doi: 10.3390/diagnostics13182979.

[23] P. Bansal, R. Garg, and P. Soni, "Detection of melanoma in dermoscopic images by integrating features extracted using handcrafted and deep learning models," *Comput Ind Eng*, vol. 168, p. 108060, Jun. 2022, doi: 10.1016/J.CIE.2022.108060.

[24] A. Naeem, T. Anees, M. Khalil, K. Zahra, R. A. Naqvi, and S.-W. Lee, "SNC_Net: Skin Cancer Detection by Integrating Handcrafted and Deep Learning-Based Features Using Dermoscopy Images," *Mathematics*, vol. 12, no. 7, p. 1030, Mar. 2024, doi: 10.3390/math12071030.

[25] T. Saba, "Computer vision for microscopic skin cancer diagnosis using handcrafted and non-handcrafted features," *Microsc Res Tech*, vol. 84, no. 6, pp. 1272–1283, Jun. 2021, doi: 10.1002/jemt.23686.

[26] K. A. Ogudo, R. Surendran, and O. Ibrahim Khalaf, "Optimal Artificial Intelligence Based Automated Skin Lesion Detection and Classification Model," *Computer Systems Science and Engineering*, vol. 44, no. 1, pp. 693–707, 2023, doi: 10.32604/csse.2023.024154.

[27] A. Esteva *et al.*, "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, vol. 542, no. 7639, pp. 115–118, Feb. 2017, doi: 10.1038/nature21056.

[28] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, IEEE, Jun. 2016, pp. 770–778. doi: 10.1109/CVPR.2016.90.

[29] T. G. Debelee, "Skin Lesion Classification and Detection Using Machine Learning Techniques: A Systematic Review," *Diagnostics*, vol. 13, no. 19, p. 3147, Oct. 2023, doi: 10.3390/diagnostics13193147.

[30] N. Aishwarya, K. Manoj Prabhakaran, F. T. Debebe, M. S. S. A. Reddy, and P. Pranavee, "Skin Cancer diagnosis with Yolo Deep Neural Network," *Procedia Comput Sci*, vol. 220, pp. 651–658, Jan. 2023, doi: 10.1016/J.PROCS.2023.03.083.

[31] D. D. Aboyomi and C. Daniel, "A Comparative Analysis of Modern Object Detection Algorithms: YOLO vs. SSD vs. Faster R-CNN," *ITEJ (Information Technology Engineering Journals)*, vol. 8, no. 2, pp. 96–106, Dec. 2023, doi: 10.24235/itej.v8i2.123.

[32] M. Sohan, T. Sai Ram, and Ch. V. Rami Reddy, "A Review on YOLOv8 and Its Advancements," Springer, Singapore, 2024, pp. 529–545. doi: 10.1007/978-981-99-7962-2_39.

[33] S. Neelakandan, S. Divyabharathi, S. Rahini, and G. Vijayalakshmi, "Large scale optimization to minimize network traffic using MapReduce in big data applications," in *2016 International Conference on Computation of Power, Energy Information and Commuincation (ICCPEIC)*, IEEE, Apr. 2016, pp. 193–199. doi: 10.1109/ICCPEIC.2016.7557196.

[34] J. Ye *et al.*, "YOLOv8 Architectural Scene Section Recognition Method Based on SimAM-EMA Hybrid Attention Mechanism," *Sensors*, vol. 25, no. 10, p. 3060, May 2025, doi: 10.3390/s25103060.

[35] M. Mahasin and I. A. Dewi, "Comparison of CSPDarkNet53, CSPResNeXt-50, and EfficientNet-B0 Backbones on YOLO V4 as Object Detector," *International Journal of Engineering, Science & Information Technology (IJESTY)*, vol. 2, no. 3, pp. 64–72, Jul. 2022, doi: https://doi.org/10.52088/ijesty.v1i4.291.

[36] R. Varghese and S. M., "YOLOv8: A Novel Object Detection Algorithm with Enhanced Performance and Robustness," in *2024 International Conference on Advances in Data Engineering and Intelligent Computing Systems (ADICS)*, IEEE, Apr. 2024, pp. 1–6. doi: 10.1109/ADICS58448.2024.10533619.

[37] G. Dhiman *et al.*, "A Novel Machine-Learning-Based Hybrid CNN Model for Tumor Identification in Medical Image Processing," *Sustainability*, vol. 14, no. 3, p. 1447, Jan. 2022, doi: 10.3390/su14031447.