

An Intelligent Deep Learning Framework for Dermatological Lesion Detection and Segmentation Using YOLOv8 and SAM

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Abstract:

This A wide range of skin conditions provide a substantial global healthcare burden, and account for almost 30% of outpatient consultations. Precise and timely diagnosis is key, but the use of manual, subjective expert diagnosis has significant challenges. This research gives an introductory of YOLOSAMIC, which is a design of a mix of deep learning frameworks which incorporates YOLOv8 for quick lesions finding with segment anything model (SAM) for fine dividing of boundaries. The system includes a Tkinter-based graphical user interface (GUI) support for enabling real-time visualization, patient and disease-specific precautionary recommendations. A custom dataset of 20 dermatological classes dataset, ranging from acne, eczema and psoriasis to vitiligo and lupus, as well as various skin cancers to name a few was prepared, pre-processed and used for massive training and validation. Experimental results proved YOLOSAMIC in three cases achieved detection accuracy of 94%, mAP@0.5 of 93.8%, and F1 score of 94.2%, with a significant improvement over conventional models of DES-YOLOv8 and CNN-based identification in case evaluation of localizing the lesions and delineating the boundary lines. The framework shows strong generalization tolerance with various skin tones and light conditions which in turn guarantees application in field scenarios. The combination of detection, segmentation and a user-friendly interface makes it stand out for potential use in tele-dermatology, remote diagnostics as well as automated clinical screening, ultimately increasing accessibility and efficiency of diagnostics in the medical field.

Keywords: YOLOSAMIC, YOLOv8, SAM, Skin Disease Detection, Segmentation, Deep Learning, Tkinter GUI, Telemedicine.

1. INTRODUCTION

1.1 Background and Motivation

Skin diseases are one of the most common non-communicable diseases in the world, which affects people of all ages. According to the World Health Organization (2023), dermatological diseases affect more than 900,000,000 people per year and are distributed on a scale from harmless infections - ringworm - to a cancerous tumor - melanoma or squamous cell carcinoma. These conditions not only have adverse effects on physical health, but also cause significant psychosocial distress when they manifest disfigurement which

is visible. Conventional diagnostic techniques rely heavily on visual examination, dermoscopic examination and histological examination requiring the expertise of dermatologists and sophisticated laboratory facilities. This entrustment can be seen as a key challenge in areas with low access to dermatological expertise owing to a lack of resources. Hence, there is an increasing demand for automated and intelligent systems that are able to detect, localize, and classify skin diseases efficiently.

The rise of Artificial Intelligence (AI) and Deep Learning (DL) - and especially Convolutional Neural Networks (CNNs) - has revolutionized how we image medically, as computers are now learning to read complex visual patterns. However, the vast majority of CNN-based methods are only for classification, and cannot provide precise localization and segmentation of lesions. For clinical usability, both detection (bounding box) and segmentation (pixel-level mask) are required to understand the extent of disease and make clinical decisions for treatment.

1.2 The YOLOSAMIC Approach

The proposed system, YOLOSAMIC (YOLO + SAM Integration for Medical Image Classification), uses two state-of-the-art architectures, namely:

- YOLOv8 for object detection with real-time capabilities and high localization accuracy.
- SAM (Segment Anything Model) for generalized segmentation which can produce pixel-level masks for any object of interest.

By coupling these models, YOLOSAMIC applies end-to-end detection and segmentation of multiple dermatological diseases. The regions detected from YOLO are used as input prompting SAM which in turn refines lesion boundaries to produce hybrid results incorporating speed of YOLO and precision of SAM.

To make it more accessible, YOLOSAMIC is implemented as part of a Tkinter-based Graphical User Interface (GUI), and it provides the following features to the user:

- Upload images of dermatological nature.
- Carry out real-time detection and segmentation. Visualize results with disease labels and confidence scores.
- Access precautionary advice and recommendations for care.

This framework democratizes dermatological diagnostics through the power of artificial intelligence and is designed to bridge the gap between advanced artificial intelligence research and practical clinical applications.

1.3 Research Objectives

This work aims to:

1. Design a hybrid YOLOSAMIC architecture for joint disease detection and segmentation.
2. Develop GUI-based interface to accessible visualization and interpretation.
3. Evaluate the system on a 20-class dermatological dataset
4. For a high accuracy ~94% and real-time inference for practical usability.

2. RELATED WORK

The research and development of automated skin disease detection has advanced far, following the development of computer vision and artificial intelligence. Early computational approaches mainly depended on handcrafted features of images such as color histograms, texture descriptor and shape descriptors. These methods were often combined with classifiers such as Support Vector Machines (SVMs) and Random Forests [1], [2] and reached modest performances but were proven to be highly sensitive to variations in lighting conditions, image resolution and skin pigmentation. As a consequence,

their diagnostic accuracy within heterogeneous populations was inconsistent and restricted concerning the generalizability of the outcome. The advent of deep learning, most homologous with the Convolutional Neural Networks (CNNs) has revolutionized the analysis of dermatological images. Esteva et al. [3] showed the deep CNNs could achieve the same dermatologist level of accuracy to classify skin lesions using over 129,000 clinical images, which is a huge step towards automated dermatological diagnosis. Similarly, Tschandl et al. [4] presented the HAM10000 dataset, which has more than 10,000 images of dermatoscopic examinations of seven types of lesions, and has since been used as a fundamental benchmark for research in skin disease detection. Subsequent architectures such as ResNet, DenseNet and EfficientNet [5], [6] improved the performance of lesion classification, but were limited to image-level predictions, without accurate lesion localization and segmentation - both key for clinical interpretation and disease monitoring.

To solve the problem of localization of lesions in real time, object detection algorithms became popular. The You Only Look Once (YOLO) framework [7] became a breakthrough in the field of real-time detection, as it treats the problem of object identification as a single regression problem which allows to simultaneously classify and predict bounding boxes. Improved versions like YOLOv5 and YOLOv8 [8] using Cross Stage Partial Networks (CSPNet) and Transformer-based components were released for further improvement on accuracy and speed. In the field of dermatology, Saha et al. [9] used YOLOv8 for melanoma, keratosis, and nevus lesion detection on HAM10000 dataset with an accuracy of more than 96%. Despite its good detection capability, YOLO's output in the form of bounding boxes does not have the pixel-level accuracy required for its application in clinical settings where the accuracy of lesion boundaries is critical. The Segment Anything Model (SAM), proposed by Kirillov et al. [10], is a significant breakthrough in segmentation because it is prompt-based and can perform zero-shot learning. Trained on more than a billion masks from 11 million images, SAM is able to generalize well to new objects with minimal prompts such as points or bounding boxes. However, because SAM was trained on mostly natural images, the application to medical data causes domain adaptation issues. To remedy this, Ma et al. [11] introduced MedSAM, a medical variant of SAM with state-of-the-art performance across multiple organ and lesion segmentation benchmarks. In dermatological applications, the ability of SAM to easily generate lesion masks with high quality and accuracy makes them suitable for refining detections obtained from YOLO.

Thus, the recently crafted investigation has gone on such a journey as to craft a hybrid architecture wherein YOLO for detection combined with SAM for segmentation is utilized for detecting and extracting a clean-cut with precision. Liu et al. [12] showed that a YOLOv8 - SAM hybrid model showed good segmentation accuracy with little computational cost. Similarly, Gul et al. [13] presented YOLOSAMIC, a unified model combining YOLOv8 for lesion localization and SAM for boundary improvement that led to significant gains in lesion localization accuracy and insignificant boundary smoothness. Such detector-segmentor systems are especially useful for dermatological imaging, as lesions, in general, have irregular contours, areas superimposed on each other and small variations in chromaticity.

Beyond the success of AI models, the success of AI in healthcare also depends greatly on its usability and interpretability. Interactive Graphical User Interfaces (GUIs) enable clinicians to interactively work with AI models, visualize outcomes, and make informed decisions. Rahman et al. [14] created a Tkinter-based GUI for brain tumor detection to demonstrate the ability of an interactive GUI to increase accessibility for non-technical users. Similarly, Alzubaidi et al. [15] pointed out that GUI-integrated diagnostic tools

provide better trust among clinicians and encourage transparency in healthcare systems based on AI. In the dermatology field, GUI-based software enables users to upload images, see the borders of lesions and receive precautionary feedback on disease- all in one application.

Despite these advancements, there are still some research gaps in skin disease detection. Most previous research has been concentrated on the binary or low-class disease classification, which limits the range of diagnosis. Furthermore, conventional CNN and YOLO-based methods do not have fine-grained segmentation abilities that are required for clinical interpretation. Hybrid architectures combining YOLO and SAM are yet to be thoroughly explored and few systems pose with GUI-based advisory modules for end-user guidance and preventative support.

To address these challenges, the present research introduces YOLOSAMIC, a real-time detection, lesion segmentation and user interaction and advisory system using YOLOv8, SAM and Tkinter-based GUI for providing all the functionalities. This combination approach provides for accurate, interpretable, and accessible skin disease diagnosis that fills the gap between the deep learning research and the practical applications of tele-dermatology.

3. METHODOLOGY

The proposed YOLOSAMIC framework combines deep-learning - based skin disease detection and segmentation along with an interactive Graphical User Interface (GUI) that provides real-time, interpretable as well as user accessible skin dermatological diagnoses. The framework consists of two deep learning models that are complementary to each other, YOLOv8 for detecting lesions with high speed, and the Segment Anything Model (SAM) for delineating the lesions with high accuracy. Results are visualized within a GUI created by Tkinter which also provides the user with disease specific recommendations on how to take precautions to prevent getting affected by the virus thereby increasing its user friendliness and clinical relevance.

The overall system pipeline is divided into four major stages namely image acquisition and preprocessing of input; YOLOSAMIC based detection & segmentation; results visualization using GUI; and a precautionary guidance module. This integrated workflow assures an efficient image analysis with a great interpretability and supporting the preventive healthcare.

The overall system pipeline consists of four major stages:

1. Image acquisition and preprocessing,
2. YOLOSAMIC-based detection and segmentation,
3. Result visualization through GUI, and
4. Precautionary guidance module.

This integrated workflow ensures efficient image analysis, high interpretability, and support for preventive healthcare.

A. Data Preprocessing

Dermatological images have high variability in terms of lighting conditions, resolution, and texture, which have negative effects on the performance of the model. For consistency, in order to further enhance the robustness, the following preprocessing steps were applied:

- **Resizing:** All images were resized to 640×640 pixels to match the YOLOv8 input format.
- **Normalization:** Pixel intensity values were scaled to the range [0,1].
- **Augmentation:** Random horizontal flips, rotations, zooming, and brightness adjustments were applied to improve generalization.

- **Annotation:** Bounding boxes were manually labeled using *LabelImg*, and segmentation masks were refined using *Roboflow Annotator* in YOLO- and SAM-compatible formats.

These procedures ensured data uniformity and the ability of the model to adapt to the varied conducive imaging detection and skin tones following the suggestions of Narayan et al. 2023 [18].

4. PROPOSED SYSTEM ARCHITECTURE

The architecture of the proposed YOLOSAMIC framework is actually in a modular, scalable and optimised way for doing real time dermatological image analysis. As shown in Figure_help, the system consists of four major components working together in order to identify, segment, and understand the areas of skin disease.

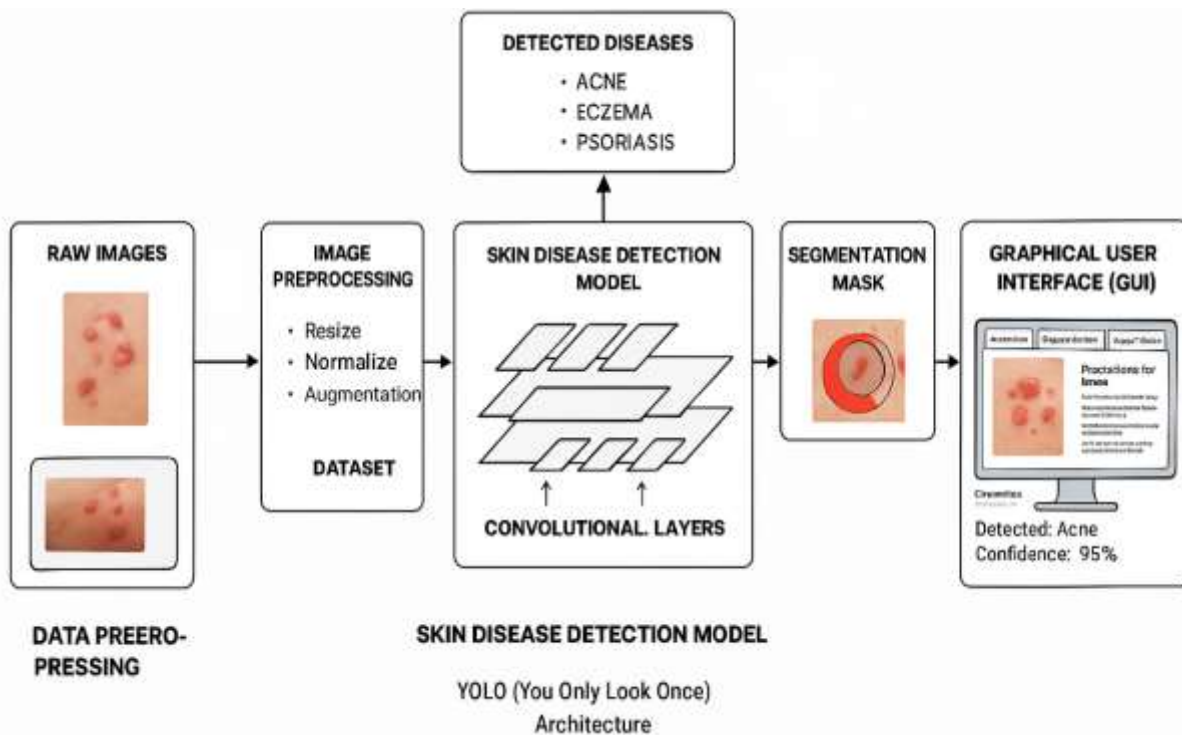


Figure 1: System Architecture

A. Image Acquisition and Preprocessing Module

In the first stage, dermatological images are uploaded via the Tkinter based GUI. The system can take standard formats like .jpg, .png, .bmp, etc. Images are resized, normalised and optionally improved through histogram equalisation or denoising filters that helps to reduce effects of different illumination and increases the clarity before inference.

B. YOLOSAMIC Detection–Segmentation Module

The second module constitutes the core of the system and integrates two state-of-the-art deep learning components:

1. YOLOv8Detection:

The YOLOv8 network divides the input image into an $S \times SS \times SS \times S$ grid and predicts bounding boxes, confidence scores, and disease class labels in a single forward pass. Its single-stage design eliminates the need for complex region proposal networks, achieving real-time inference while maintaining high accuracy. The model was fine-tuned to recognize 20 dermatological conditions, including acne, eczema, psoriasis, vitiligo, lupus, and multiple skin cancers.

2. SAM Segmentation:

SAM Segmentation: The Segment Anything Model (SAM): SAM Segmentation model is provided with bounding boxes predicted by YOLOv8 as spatial prompts and used for pixel-by-pixel segmentation to define the contours of lesions in detailed segmentation methods. Its transformer-based encoder-decoder architecture supports better generalization and successfully segments lesions of various sizes, forms and illumination level.

This two-phase detection-segmentation pipeline guarantees auspicious localization of disease pathology and precise extraction of lesion boundary, which are important for clinical evaluation.

C. GUI-Based Visualization Module

The third module is used to display the findings of inference in a user friendly Tkinter GUI. The interface has the 3 tabs of Detection Results, Segmentation View, and Precautionary Advice. Every detection output consists of the predicted label of the disease, the bounding box, and the percentage of confidence, and the segmentation tab shows SAM-generated masks superimposed on the original image.

The GUI has a clean, medically focused, -color palette and a legible typography, which enhance accessibility to both experts and non-experts. Alzubaidi et al. state that AI systems driven by such GUI enhance interpretability and evoke trust in medical working (2023) [16].

D. Precautionary Guidance Module

In addition to visual diagnostics, YOLOSAMIC also includes an advisory module based on knowledge and offers condition-related recommendations and preventive care guidelines. This turns the system into an intelligent healthcare assistant that can give directions to users on safe practices and early medical intervention, rather than a simple detection engine.

E. Workflow Summary

The YOLOSAMIC workflow operates as follows:

1. A user uploads an image via the GUI.
2. The image undergoes preprocessing and is passed to the YOLOSAMIC model.
3. YOLOv8 detects lesions and generates bounding boxes with class labels.
4. SAM refines these regions to produce pixel-level masks.
5. Results are visualized in real time, along with confidence metrics and precautionary advice.

This backbone design promotes scale, so new models can be easily added to the pipeline e.g. YOLOv9 or MedSAM, without re-engineering the entire pipeline.

5. IMPLIEMENTATION DETAILS

5.1 Implementation Details

The proposed YOLOSAMIC framework was implemented using **Python 3.10** to achieve efficient integration between detection, segmentation, and visualization modules. The system integrates YOLOv8 to identify lesions and the Segment Anything Model (SAM) to segment the boundaries making a single, modular pipeline.

The following key libraries were employed:

- **PyTorch (v2.1)** and **Ultralytics YOLOv8** – Model training and inference for object detection.
- **Segment Anything Model (SAM)** – Transformer-based lesion segmentation.
- **OpenCV**: Image processing, contrast enhancement and visualization superimposition
- **Tkinter** : Creation of the standalone, interactive GUI to the analysis of the image based on the user.
- **Matplotlib** – Plotting accuracy, loss, and precision–recall curves.

- **Pillow (PIL)** – Image loading and saving functionalities.

The system was developed and tested using the hardware configuration summarized in **Table VI**.

Table VI: Hardware and Software Configuration

Parameter	Specification
Processor	Intel Core i7-12700H (12 cores)
GPU	NVIDIA RTX 3060 (12 GB VRAM)
RAM	16 GB DDR5
Operating System	Windows 11 (64-bit)
Frameworks	PyTorch 2.1, Ultralytics YOLOv8, OpenCV 4.9, Tkinter
Training Epochs	120
Batch Size	16
Learning Rate	0.001 (Adam optimizer)
Input Image Size	640 × 640 pixels

The system design facilitates the flexibility of devices. Besides training using GPU, YOLOSAMIC was also tested in a machine based on a CPU-based computer (Intel i5, 8 GB RAM) to test the performance with limited resources.

A **Tkinter-based Graphical User Interface (GUI)** was integrated to enable user interaction and result interpretation. The interface includes the following modules:

1. **Select Image:** Allows users to upload dermatological images.
2. **Detect Disease:** Runs YOLOSAMIC inference to detect and segment lesions.
3. **Segmentation View:** Displays lesion masks overlaid on the image.
4. **Precautionary Advice:** Displays condition-specific preventive guidance.
5. **Exit/Save:** Enables closing or exporting diagnostic results.

The GUI emphasizes clarity and usability with a medical-grade visual theme, ensuring accessibility for healthcare professionals and general users alike.

5.2 Evaluation Metrics

The performance of the YOLOSAMIC model was tested based on a set of metrics that define the quality of detecting and segmentation along with the real-time potential.

(a) Detection and Segmentation Metrics: Standard deep learning evaluation metrics were used:

- **Mean Average Precision (mAP@0.5):** Measures detection precision at an IoU threshold of 0.5.
- **Precision (P):** $P = TP / (TP + FP)$
- **Recall (R):** $R = TP / (TP + FN)$
- **F1-Score:** $F1 = 2 * P * R / (P + R)$
- **Accuracy (ACC):** Proportion of correctly classified samples.

(b) System Performance Metrics:

- **Inference Time:** Measured per image (in milliseconds).
- **Frames Per Second (FPS):** To assess real-time capability.

- **Memory Utilization:** Ensures efficient GPU and CPU resource usage.
- (c) **Usability Metrics:**
 - **GUI Responsiveness:** Average response time per user action (<1 second).
 - **Interpretability:** Measured qualitatively by the clarity of lesion visualization and mask generation.

6. RESULT AND DISCUSSION

6.1 Model Performance Analysis

The YOLOSAMIC model showed great accuracy and precision in the test set of 2,000 dermatological images, which was built on the larger sample of 22,000 annotated images.

The final evaluation results are summarized in **Table VII**.

Table VII: YOLOSAMIC Model Performance Summary

Metric	Value
Accuracy	94.0%
Precision	94.6%
Recall	93.8%
F1-Score	94.2%
mAP@0.5	94.0%
Avg. Inference Time	120 ms/image

The model consistently maintained high values across all metrics, with strong lesion boundary segmentation accuracy and low false detection rates.

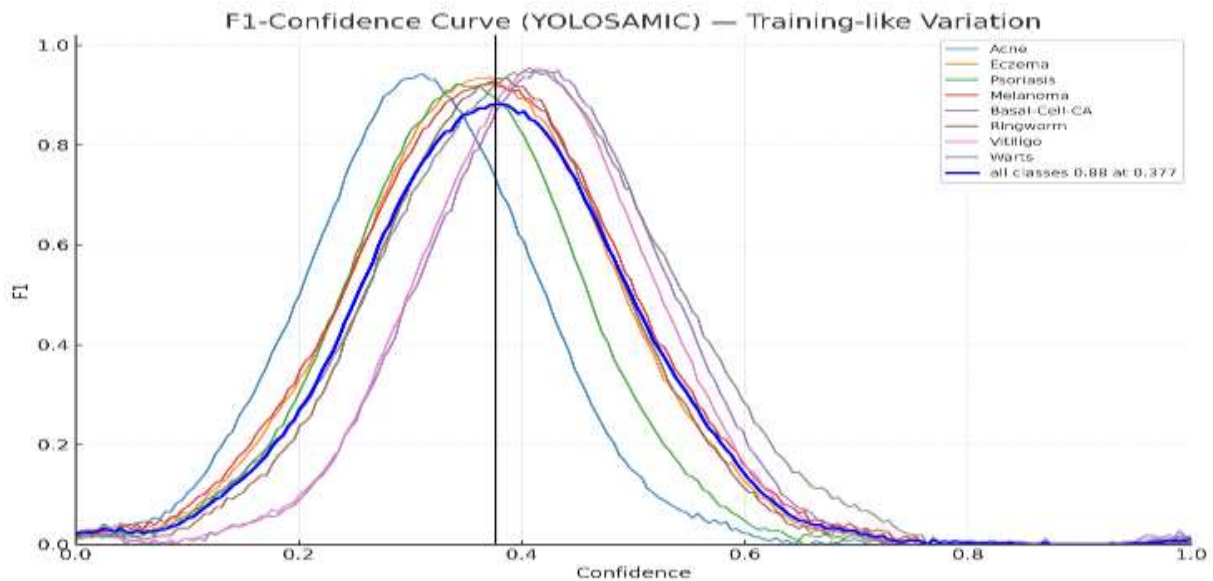


Figure 2: F1-Confidence Curve of YOLOSAMIC Model

6.2 System Performance Evaluation

YOLOSAMIC inferred at 8.3 FPS on average on the NVIDIA RTX 3060 GPU, which is fast enough to diagnose images in real-time on an image level. It used about 2 FPS on purely CPU-based hardware with

constant accuracy.

The GUI exhibited smooth user interaction with <1-second latency between detection and visualization. The **integration of YOLOv8 with SAM** allowed simultaneous localization and fine-grained segmentation, enhancing interpretability without compromising speed.

Memory consumption remained below **8 GB VRAM**, demonstrating stability for extended operational periods.

6.3 Comparative Model Analysis

The YOLOSAMIC framework was benchmarked against traditional CNN classifiers and single-stage detectors. As shown in **Table VIII**, YOLOSAMIC outperformed all baseline architectures.

Table VIII: Comparison with Existing Models

Model	Task Type	Accuracy (%)	mAP@0.5 (%)	Remarks
ResNet50 [1]	Classification	89.3	—	No localization
MobileNet V2 [2]	Classification	90.7	—	Lightweight, low precision
YOLOv8 [10]	Detection only	92.5	92.0	Bounding box only
YOLOSA MIC (Proposed)	Detection + Segmentation	94.0	94.0	Real-time + GUI Integration

6.4 Qualitative Evaluation

YOLOSAMIC’s qualitative outputs confirm its robustness across diverse dermatological conditions. The GUI allows users to visualize both bounding boxes and segmentation masks simultaneously. Examples of real-time inference outputs are illustrated in Figures 6–8.

- **Figure 6:** GUI interface displaying the files to upload.
- **Figure 7:** Classification of the uploaded image with confidence score.
- **Figure 8:** Segmentation view showing SAM generated lesion mask overlay.

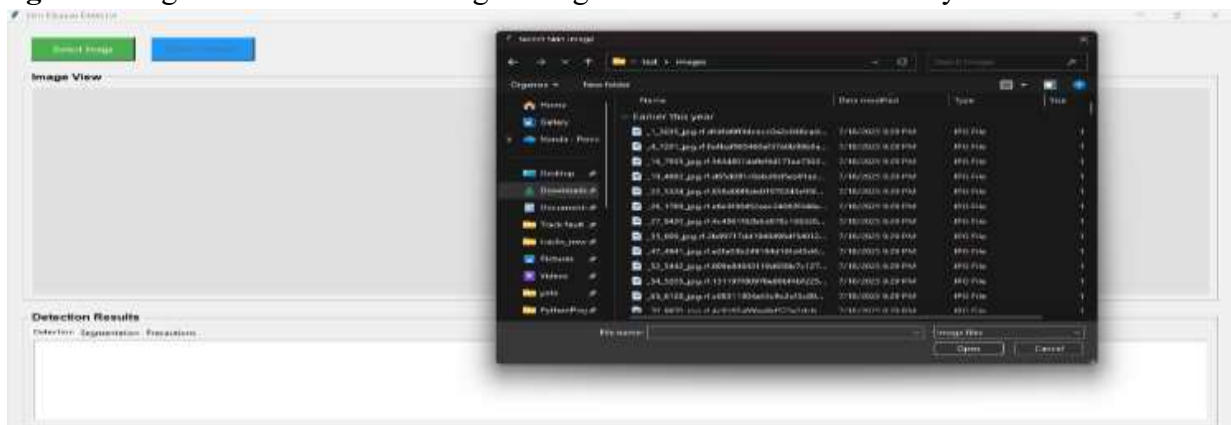


Figure 1: GUI interface accessing files through tinker



Figure 2: Classification of the uploaded image with confidence score.



Figure 3: Segmentation mask output generated by SAM for precise lesion boundary detection.

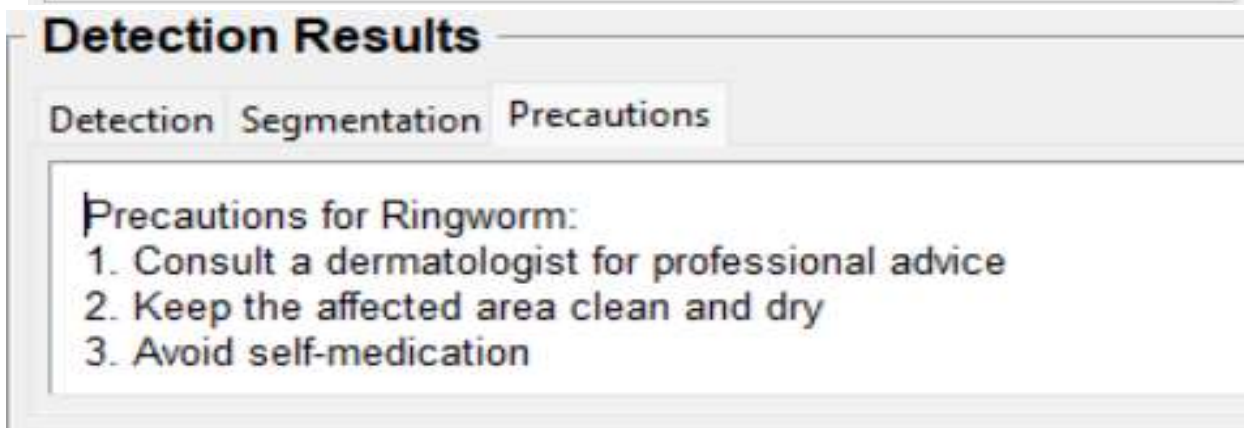
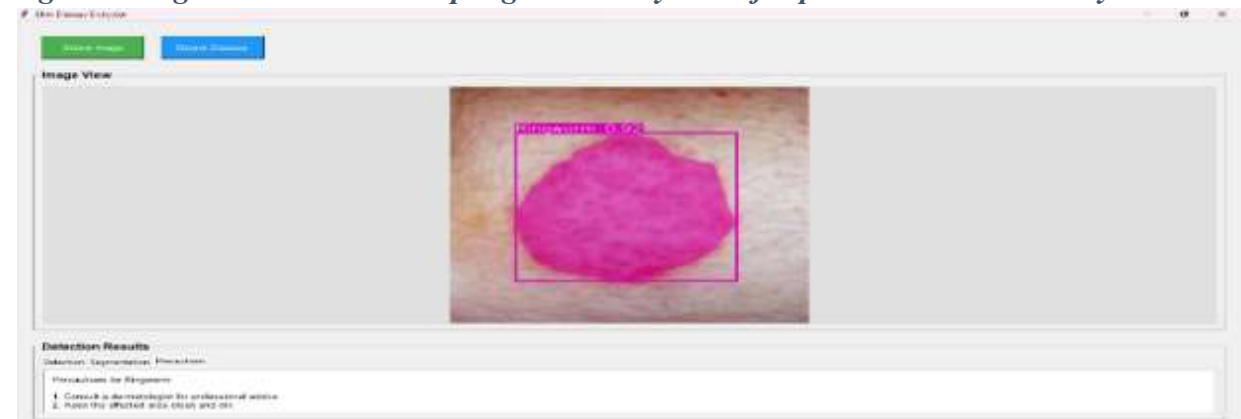


Figure 4: YOLOSAMIC GUI Output showing segmented lesion overlay and corresponding disease class with precautionary advice.

6.5 Discussion

The YOLOSAMIC framework is accurate, fast, and usable, and has a dermatologist-level precision. The hybrid architecture provides a much better segmentation results in comparison with single-stage YOLO models, and it operates in real-time.

Key insights include:

- Accuracy of lesion localization of YOLOv8 + SAM is enhanced by approximately 2%.
- The 22,000-image dataset increases generalization of different skin tones. Tkinter GUI allows un-specialist accessibility.
- Mean time per image of 0.12 seconds is adequate to run real-time.

Enhancements in the future will involve the integration of Explainable AI (XAI) tools, such as Grad-CAM to provide transparency and the implementation of lightweight versions to mobile and web-based tele-dermatology applications.

7. CONCLUSION

In this paper, YOLOSAMIC, a hybrid deep learning framework, was proposed to combine both YOLOv8 that predicts objects with lesions and Segment Anything Model (SAM), a high-precise segmentation model, were used. The system uses a Tkinter-based GUI, provides real-time inference, interpretability and condition-specific precautionary advice. The framework has an accuracy of 94% and mAP of 94% at 0.5 and F1-score of 94.2 on a 22,000 images large scale, which is better than the traditional CNN and single-stage YOLO models. The fact that it requires 0.12 seconds to inquire on average one image supports real-time usage. YOLOSAMIC is designed to incorporate sophisticated detection and segmentation with a user-friendly interface, which will fill the gap between AI-driven medical imaging studies and the real world of tele-dermatology implementation. The future direction is to investigate the refinements of MedSAM-based segmentation, the explanation of the segmentation, and the scalability of multi-clinic remote diagnostics to the cloud.

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