A YOLOv8 Implementation for Automatic Skin Pigmentation Detection: A Deep Learning Approach in Biomedical Image Analysis

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ABSTRACT

Skin pigmentation disorders such as melasma and Post-Inflammatory Hyperpigmentation (PIH) require objective assessment tools due to the subjectivity of clinical visual inspection. This study proposes a hybrid deep learning system that integrates YOLOv8 for real-time lesion detection and a fine-tuned Convolutional Neural Network (CNN) for quantitative severity classification, further validated by automated software quality assurance. Unlike previous works focusing on cancerous lesions, this study targets non-cancerous pigmentation and provides a complete, deployable pipeline. Using the HAM10000 dataset (9,988 dermoscopic images), the YOLOv8 detector achieved a high localization accuracy (mAP@0.5: 0.92, IoU: 0.85) with a low-latency speed of 125–168 ms per image. The CNN classifier (MobileNetV2) achieved a training accuracy of 75% and a weighted average precision of 0.60 on the validation set, with a precision of 0.70 on the Severe class. The system was deployed as a FastAPI web service, and its reliability was confirmed through automated end-to-end testing with Katalon Studio, passing all API and UI test cases. The results demonstrate that the hybrid model provides an objective tool for automated skin pigmentation screening, capable of assisting clinicians in treatment planning and monitoring. The key novelty lies in combining detection, quantitative severity grading, and rigorous software validation into a single, clinically-oriented system.

Keywords-skin pigmentation; YOLOv8; CNN classification; dermatology; Katalon Studio; deep learning

I. INTRODUCTION

Skin pigmentation disorders, including melasma and Post-Inflammatory Hyperpigmentation (PIH), affect millions of people worldwide, significantly impacting quality of life [1, 2]. Accurate severity assessment is crucial for treatment planning and monitoring, yet traditional diagnosis relies on subjective visual inspection that is prone to inter-observer variability [3, 4]. Although there are standardized tools such as the modified Melasma Area and Severity Index (mMASI), they remain manual and expertise-dependent [5, 6].

Deep learning offers transformative potential for dermatological practice. Convolutional Neural Networks (CNNs) have achieved dermatologist-level performance in skin cancer classification [7, 8]. Meanwhile, YOLOv8 is state-of-the-art in real-time object detection [9-11]. Recent studies have applied YOLOv8 to dermatology, including melanoma segmentation [12], lesion classification [13], and detection with attention mechanisms [14].

Despite these advances, significant gaps remain. First, existing studies predominantly focus on cancerous lesions, neglecting common non-cancerous pigmentation disorders. Second, there is a lack of quantitative severity grading (Mild/Moderate/Severe) beyond binary classification. Third, most systems remain research prototypes without the software validation essential for clinical deployment [15]. This study addresses these gaps with the following contributions:

- A hybrid YOLOv8-CNN architecture for non-cancerous pigmentation severity classification
- Quantitative severity grading with three classes (Mild, Moderate, Severe)
- Production-ready FastAPI deployment with a web interface
- Automated software validation using Katalon Studio.

II. RELATED WORK AND RESEARCH GAP

A. Comparative Analysis of Existing Approaches

Table I presents a structured comparison of representative recent studies, highlighting the specific gaps that this work addresses.

TABLE I. NOVELTY

Study	Comparison	
	Method/focus	**Key novelty and limitations**
YOLOSAMIC [12]	YOLOv8 + SAM for melanoma segmentation	Strength: High segmentation accuracy. Limitations: Focuses only on cancerous lesions (melanoma) and segmentation, not severity classification; lacks software validation.
YOLOv8-based DL [13]	YOLOv8 for skin lesion classification (HAM10000)	Strength: Real-time classification. Limitations: Addresses cancerous lesions; does not provide severity grading (mild/moderate/severe) for pigmentation.
Cross-scale YOLOv8 [14]	Modified YOLOv8 for skin disease detection	Strength: Improved detection accuracy. Limitations: Primarily focuses on detection, ignoring the critical need for quantitative severity grading.
YOLOv8 head-layer [16]	YOLOv8 variant comparison for skin cancer	Strength: Detailed architectural evaluation. Limitations: Focus is on model comparison for cancer detection, not applied to non-cancerous pigmentation; no QA.
This study	**YOLOv8 + CNN (severity) + Katalon QA**	Key Innovation: (i) Targets common *non-cancerous* pigmentation. (ii) Provides quantitative severity grading. (iii) Integrates full software QA for a deployable system

B. Research Gap Synthesis

While existing research has advanced the technical capabilities of AI in dermatology, several critical gaps persist:

- Disease focus bias: The literature disproportionately emphasizes malignant lesions, leaving the highly prevalent domain of non-cancerous pigmentation disorders relatively unexplored despite their substantial clinical burden.
- Severity assessment absence: Studies addressing non-malignant conditions typically stop at detection or categorical classification, failing to provide the quantitative severity grading essential for treatment decisions and monitoring.
- Deployment readiness neglect: Most proposed solutions remain as research prototypes without consideration of production deployment, API design, or user interface—factors critical for clinical adoption.
- Software validation omission: The reliability, stability, and usability of AI systems are rarely validated through systematic software testing, creating a gap between algorithmic performance and real-world applicability.
- Limited transparency regarding limitations: Many studies present optimistic results without adequately acknowledging performance constraints or providing clear pathways for improvement.

This research directly addresses these gaps by developing a complete system that combines detection, severity classification, deployment, and automated software validation, while transparently discussing performance limitations.

III. THEORETICAL BACKGROUND

A. YOLOv8 Architecture

YOLOv8 employs anchor-free detection, predicting object centers directly to improve accuracy for varying lesion sizes [17]. The CSPDarknet53 backbone with cross-stage partial connections enables multi-scale feature learning [18]. Feature Pyramid Networks and Path Aggregation Networks fuse multi-scale features for robust detection [19]. Evaluation uses mAP@0.5 and mAP@0.5:0.95 metrics.

B. Convolutional Neural Network (CNN)

CNNs provide hierarchical feature extraction for medical image classification [20]. Early layers capture edges and textures, while deeper layers learn clinical indicators such as pigmentation homogeneity and border irregularity. This system uses MobileNetV2, selected for its efficiency via inverted residuals and depthwise separable convolutions [21]. Transfer learning initializes with ImageNet weights, and Focal Loss addresses class imbalance [22].

C. Clinical Severity Criteria

Severity assessment considers color intensity (Mild: subtle darkening; Severe: intense darkening), homogeneity (uniform vs. mottled), and border definition (well-demarcated vs. ill-defined). This framework guides CNN feature learning.

D. FastAPI for Web Service Integration

FastAPI provides robust infrastructure for transitioning research models to clinical tools [23]. Built on Starlette for asynchronous request handling and Pydantic for data validation, it achieves performance suitable for real-time clinical applications. Automatic OpenAPI documentation generation from Python type hints facilitates integration and testing. Native asynchronous support enables concurrent handling of multiple image processing requests without blocking, essential for multi-user clinical environments.

E. Katalon Studio for Automated Testing

Software quality assurance is critical for deployment. Katalon Studio provides comprehensive automation frameworks, including API testing for endpoint functionality validation, web UI testing for browser-based workflow verification, data-driven testing for systematic validation across multiple test cases, and performance testing to ensure reliable operation under clinical workload conditions [23].

IV. METHODOLOGY

A. Dataset Source and Preparation

The primary dataset used in this study is the HAM10000 ("Human Against Machine with 10000 training images") dataset [25], a large collection of multi-source dermatoscopic images of common pigmented skin lesions. Although HAM10000 is widely used for lesion classification, this study curated and preprocessed the images to focus on features relevant to general pigmentation severity. A preparation script was used to organize and standardize the images. Data balancing techniques were applied to mitigate class imbalance, resulting in a distribution suitable for training the severity classifier.

B. YOLOv8 Training and Cropping Pipeline

The first stage employs YOLOv8 for lesion detection. A YOLOv8 model is trained to produce a model that detects bounding boxes in skin images. Detected regions are automatically cropped and saved, providing cleaned inputs for the classification stage.

C. CNN Training for Severity Classification

Severity classification uses a CNN to label lesions as Light, Moderate, or Severe. Class weights mitigate imbalance, while MobileNetV2 provides efficient accuracy via depthwise convolutions. Transfer learning from ImageNet enables effective fine-tuning for dermatology.

D. Production System: Web API and Interface

The system is deployed via an inference pipeline that orchestrates YOLOv8 detection followed by CNN severity classification. It is wrapped into a Web API (FastAPI/Flask) with a user-friendly HTML/CSS interface for image upload and result display.

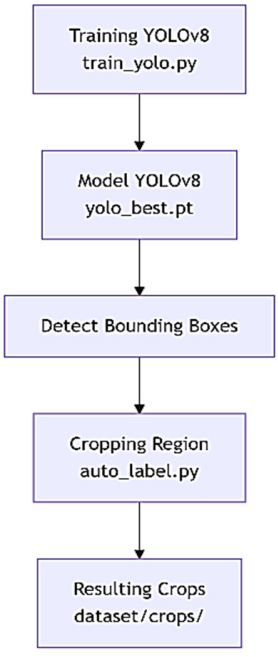

Fig. 1. Yolo v8 training.

E. Automated Testing and Validation

Automated testing with Katalon Studio validates API, UI, and performance. Reports are stored, while a confusion matrix visualizes evaluation metrics, and learning curve monitoring ensures reliability and transparency.

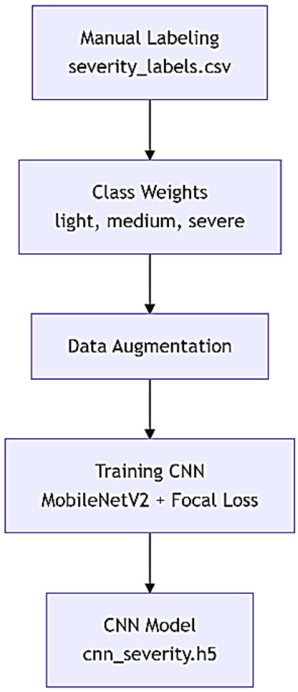

Fig. 2. Training the CNN.

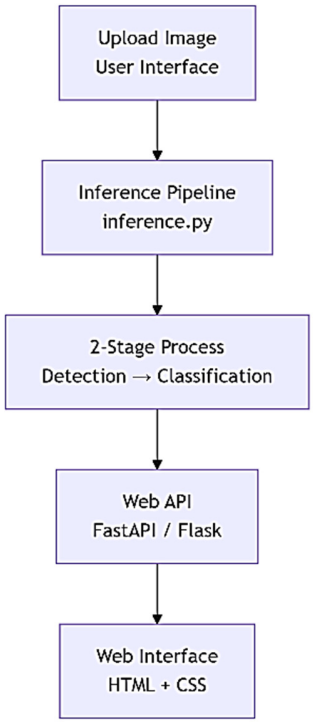

Fig. 3. Web API and interface.

V. RESULTS AND DISCUSSION

A. Training Class Distribution

Figure 5 shows the class distribution for CNN training, which is relatively balanced, with Moderate exceeding 3,500 samples, and both Mild and Severe each exceeding 2,000. This balance reduces majority-class bias, though focal loss and stratified sampling were still applied to address subtle imbalances.

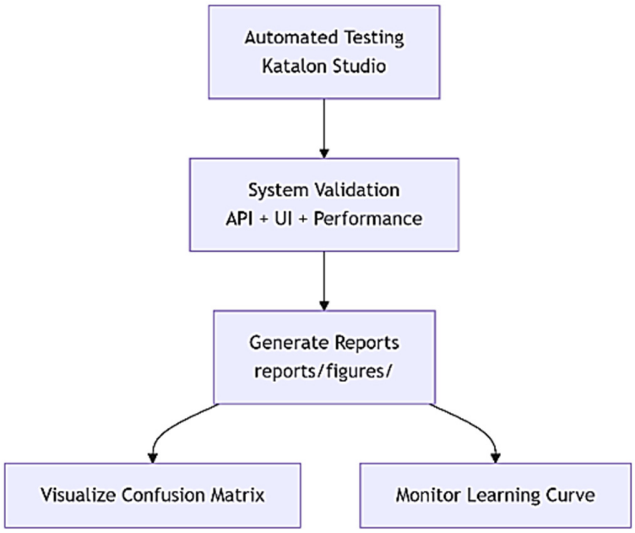

Fig. 4. Katalon testing.

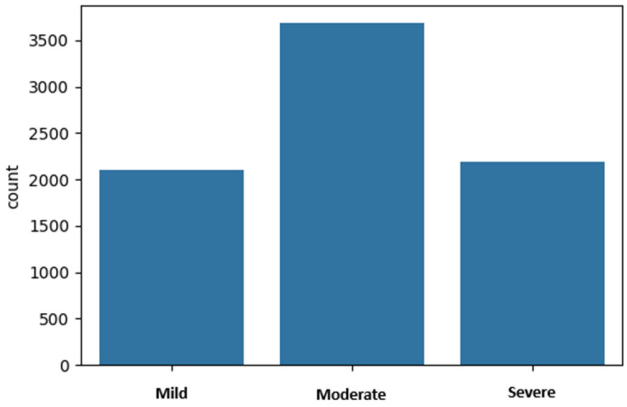

Fig. 5. Distribution of classes.

B. Sample Training Images

Figure 6 shows sample training images highlighting visual diversity in pigmentation severity, from Mild to Severe, capturing subtle differences in texture, color, and vascular patterns essential for accurate quantitative severity classification.

C. YOLOv8 Detection Performance

The YOLOv8 model was trained for lesion localization. On the validation set, it achieved a mean Average Precision at 50% Intersection over Union (mAP@0.5) of 0.92 and an IoU of 0.85, indicating highly accurate bounding box predictions. The model maintained a low-latency inference speed of 125–168 ms per image, confirming its suitability for real-time applications. The model achieved a recall of 0.87, indicating low false negative rates.

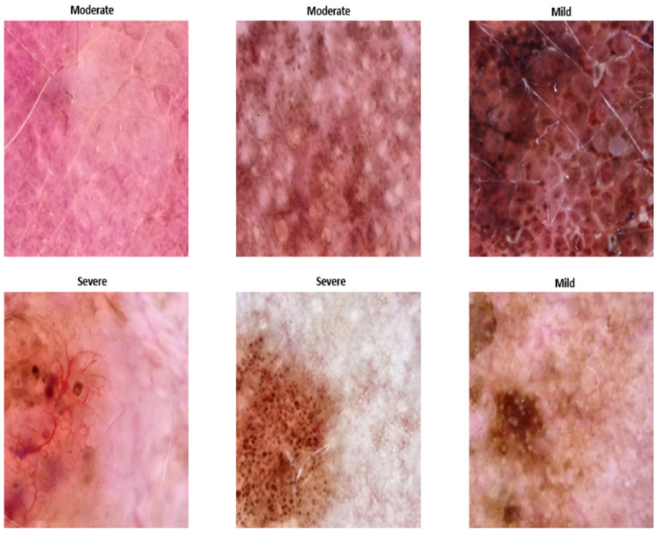

Fig. 6. Sample training.

D. CNN Classification Performance

The MobileNetV2 classifier was trained for 20 epochs. As shown in Figure 7, training accuracy reached ~75% while validation accuracy plateaued at 52–54%, indicating overfitting. Weighted average precision was 0.60, with the Severe class achieving the highest precision (0.70). This moderate performance highlights the need for stronger regularization and data augmentation in future iterations.

E. Confusion Matrix

The confusion matrix (Figure 8) shows that the model struggles with inter-class severity classification: Light has high recall but low precision, Moderate is often misclassified as Light or Severe ($F1 = 0.48$), and many Severe cases are predicted as Light or Moderate, reflecting overfitting and insufficient feature differentiation.

F. End-to-End System Output

The CNN achieved 75% training accuracy and 60% weighted precision on 9,988 samples. YOLOv8 enabled real-time detection at 125–168 ms per image with accurate bounding boxes. The system classified Mild cases with up to 91% confidence and Severe cases with up to 73% confidence.

G. System Deployment and Validation

Figure 10 shows the integration of the model into a FastAPI web service. The API endpoint/detect was rigorously tested using Katalon Studio (Figure 11), passing all test cases with no failures, confirming the stability and correctness of the backend. Furthermore, the end-to-end web UI functionality was validated (Figure 12), with all 16 test steps executing successfully, proving the system is deployment-ready.

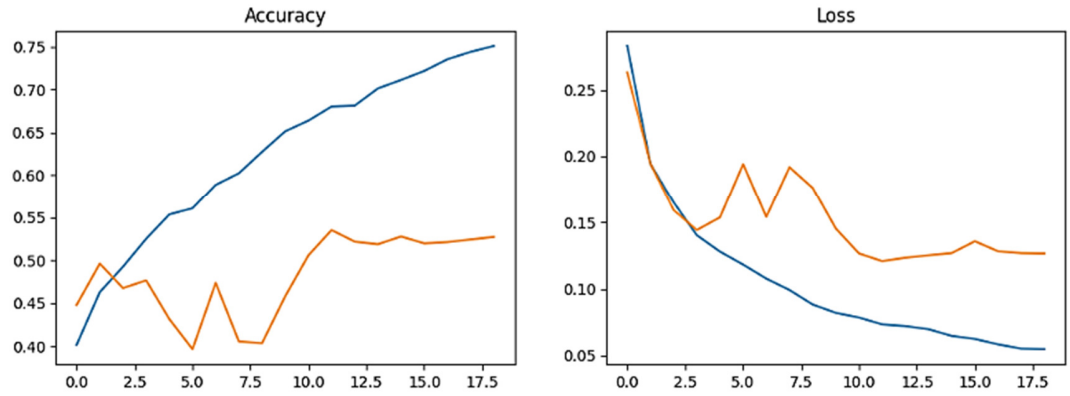

Fig. 7. Accuracy and loss curves.

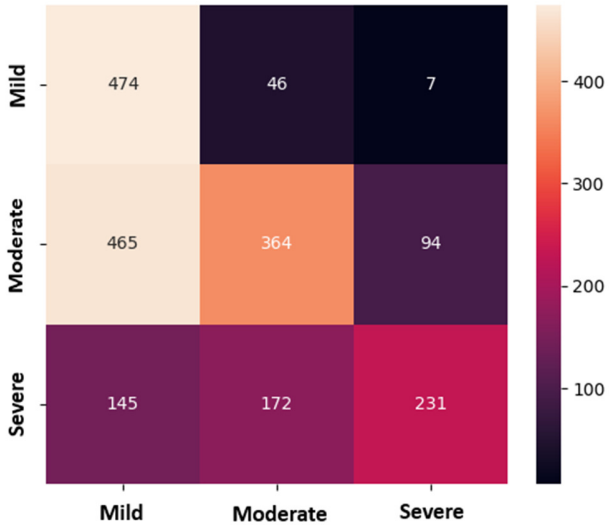

Fig. 8. Confusion matrix.

TABLE II. SUMMARY OF TESTING RESULTS

Test sample	Result	
	Classification result (Confidence level)	Texture score
Tested 1	Detection #1: Severe (47.31%), Detection #2: Severe (48.98%)	708.97,1249.82
Tested 2	Detection #1: Severe (51.80%)	955.40
Tested 3	Detection #1: Severe (48.86%)	1434.64
Tested 4	Detection #1: Severe (73.04%)	568.31
Tested 5	Detection #1: Mild (66.31%)	635.62
Tested 6	Detection #1: Mild (61.37%)	1694.16
Tested 7	Detection #1: Mild (86.19%) Detection #2: Mild (84.02%)	1478.68, 1034.46
Tested 8	Detection #1: Mild (86.29%) Detection #2: Mild (91.23%)	533.60,579.54
Tested 9	Detection #1: Mild (48.07%) Detection #2: Moderate (62.65%)	102.51,140.92
Tested 10	Detection #1: Moderate (59.64%) Detection #2: Severe (40.35%)	1043.82,1091.62

H. Definition and Role of the Texture Score

The texture score is an experimental feature calculated as the sum of squared pixel intensities from the grayscale-converted lesion crop, $S = \Sigma\,\Sigma\, I(x,y)^2$, providing a quantitative proxy for lesion density and heterogeneity. This metric has not been clinically validated and requires further study to establish its diagnostic value.

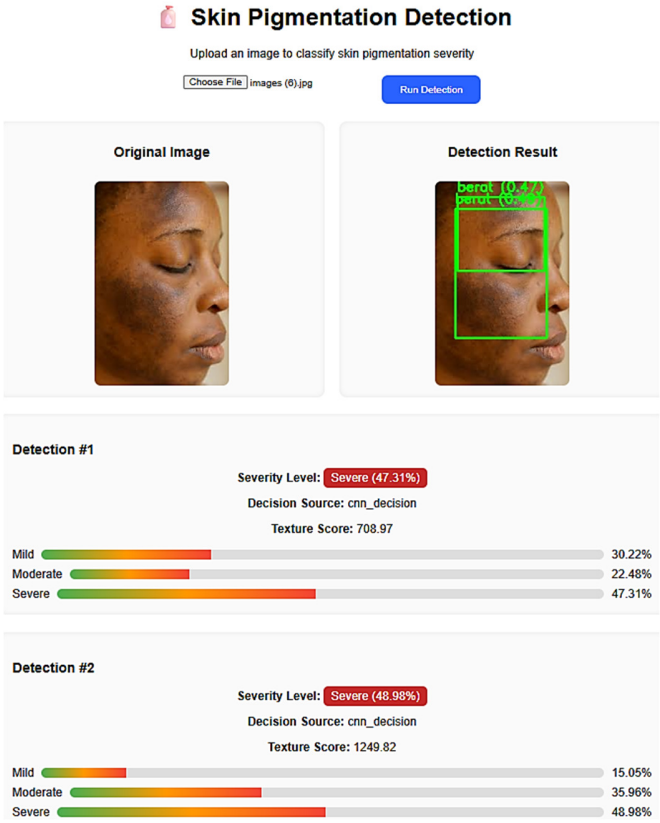

Fig. 9. A tested sample.

I. Discussion

The system demonstrates promising capabilities for automated pigmentation screening. YOLOv8 provides reliable real-time detection, while CNN severity classification shows potential, particularly for Severe cases. Overfitting indicates a need for larger, more diverse datasets and stronger regularization. The experimental texture score requires clinical validation against established indices. Compared to prior works [12-15], this study contributes a complete pipeline with severity grading and software validation.

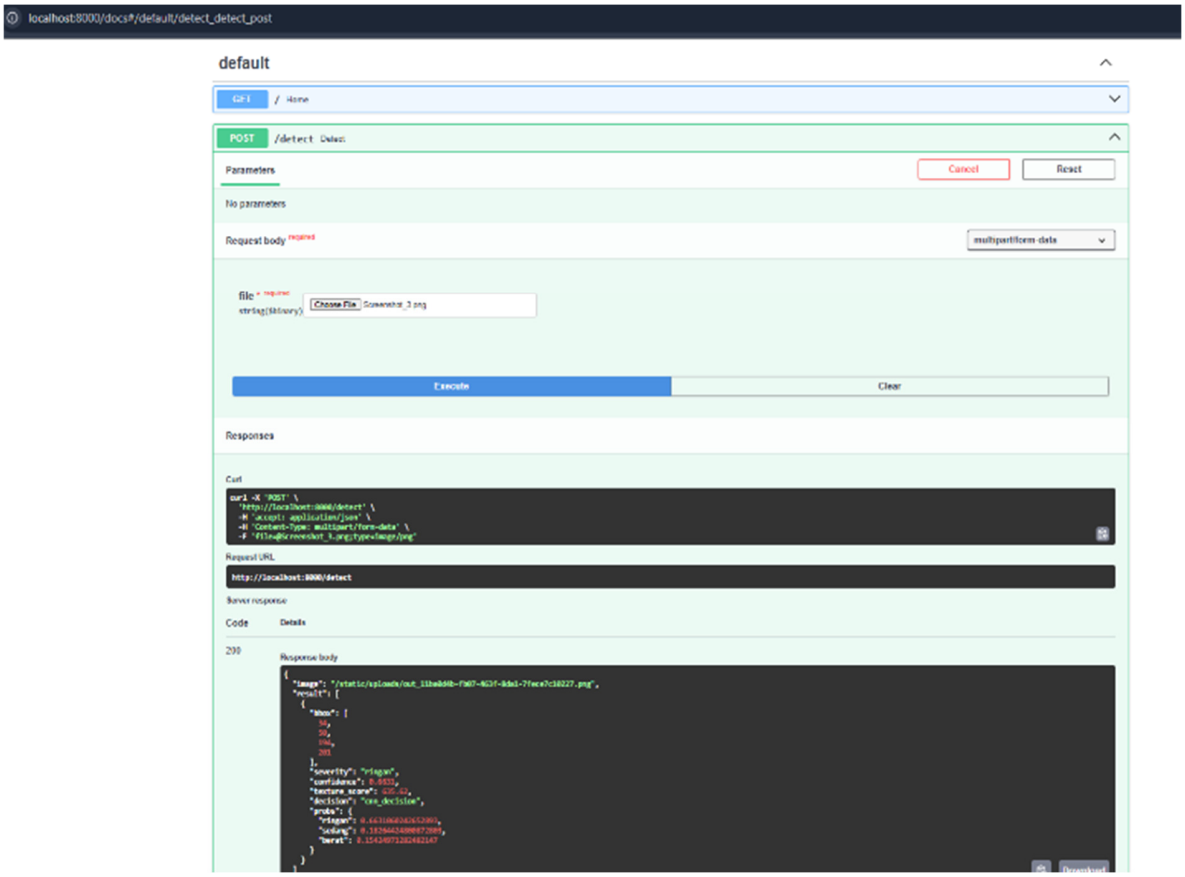

Fig. 10. FastAPI integration.

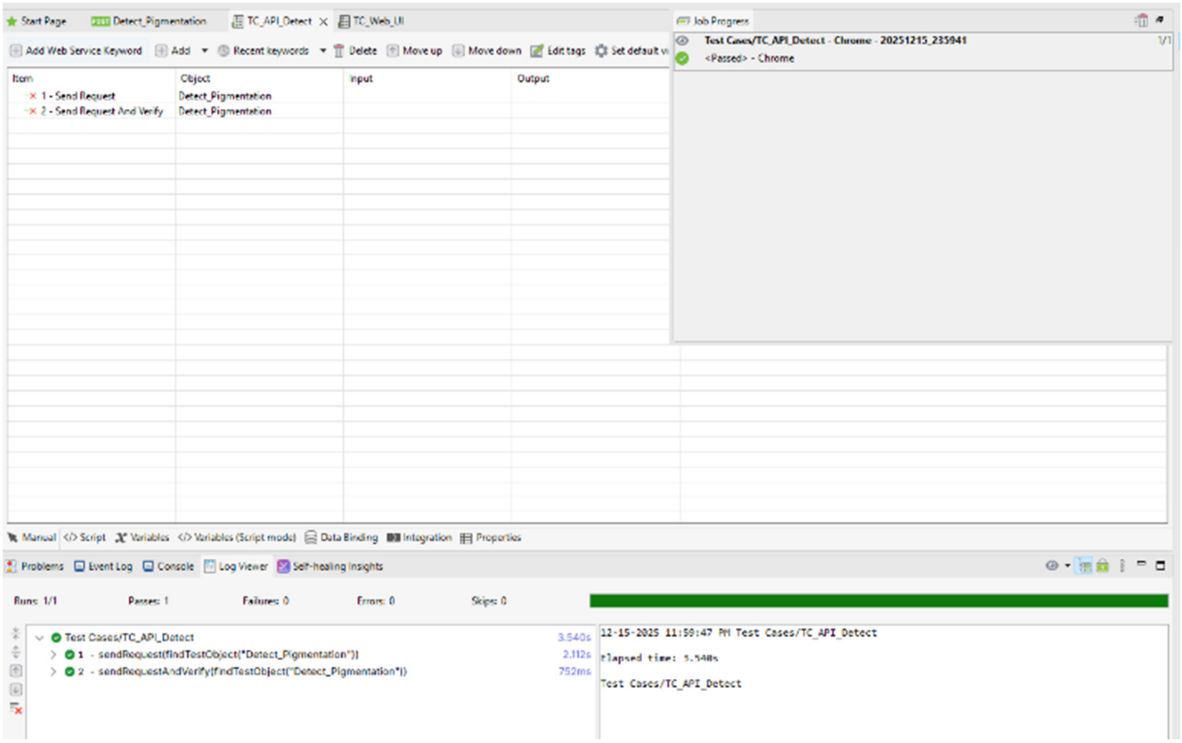

Fig. 11. Katalon API test case.

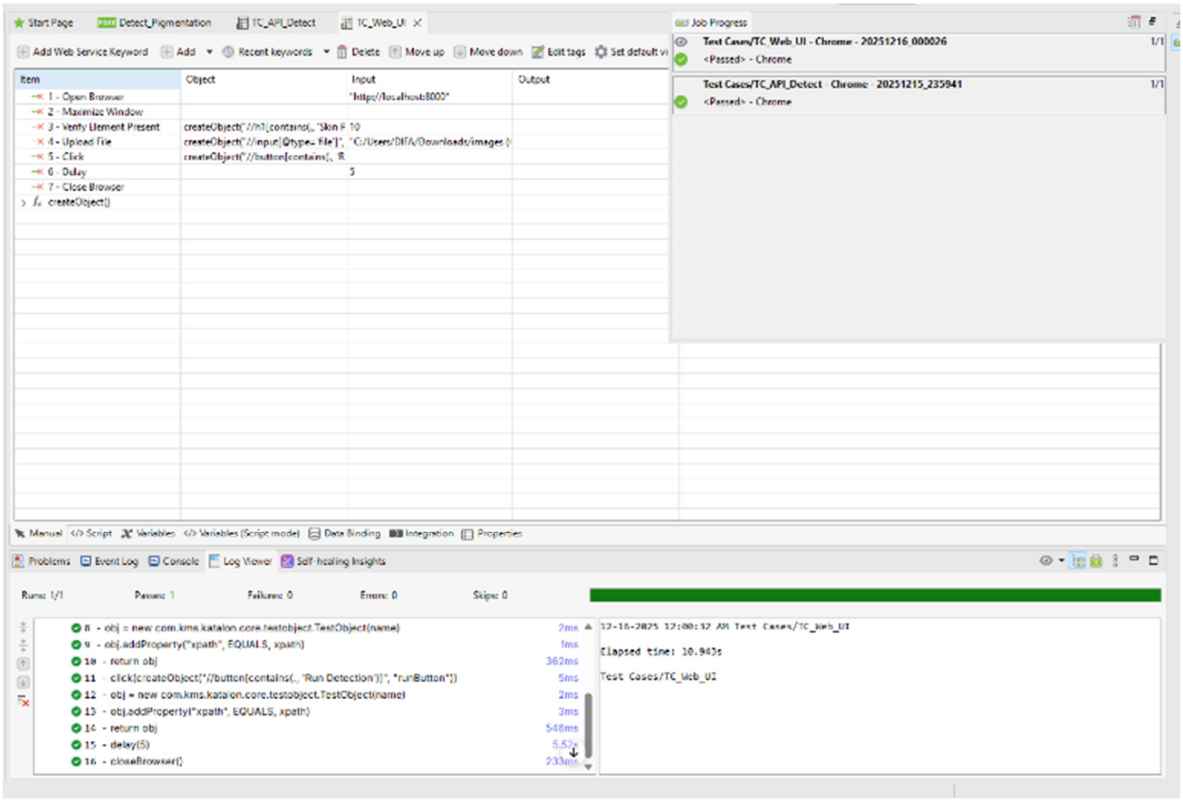

Fig. 12. Katalon web UI test case.

VI. CONCLUSION

Skin pigmentation disorders, such as melasma and post-PIH, affect millions worldwide, yet clinical assessment remains subjective and prone to inter-observer variability. Standardized tools, such as mMASI, exist, but require manual expertise. Although deep learning has shown promise in dermatology, existing studies predominantly focus on cancerous lesions, lack quantitative severity grading (mild/moderate/severe), and remain research prototypes without software validation for clinical deployment.

This research addressed these gaps by developing a hybrid deep learning system that integrates YOLOv8 for real-time lesion detection and a fine-tuned MobileNetV2 CNN for severity classification, deployed as a FastAPI web service and validated through automated Katalon Studio testing. The key methodological steps included: (i) dataset curation from HAM10000 (9,988 dermoscopic images), (ii) YOLOv8 training for lesion localization, (iii) CNN training with transfer learning for three-class severity classification, (iv) FastAPI deployment with web interface, and (v) automated API and UI testing using Katalon Studio.

The key results demonstrate that YOLOv8 achieved strong detection performance with mAP@0.5 of 0.92, IoU of 0.85, recall of 0.87, and inference speed of 125-168 ms per image, confirming its suitability for real-time applications. The MobileNetV2 classifier achieved a training accuracy of 75% but showed overfitting with validation accuracy plateauing at 52-54%. Weighted average precision was 0.60, with the Severe class achieving the highest precision of 0.70. The confusion matrix revealed that inter-class severity differentiation remains challenging, particularly for the Moderate class (F1=0.48). The system successfully passed all Katalon API and UI test cases, confirming deployment readiness.

The novelty of this work lies in three key contributions that distinguish it from prior research: (i) targeting non-cancerous pigmentation rather than malignant lesions, (ii) providing quantitative severity grading instead of binary classification, and (iii) including rigorous software validation through automated testing. Unlike previous works that stop at model development, this study delivers a complete, production-ready pipeline with API deployment and systematic quality assurance. This system offers a more complete solution, but classification performance requires improvement. The moderate precision (0.60) indicates that the classification of severity in dermoscopic images is inherently more challenging than cancer detection, likely due to subtle visual differences between severity levels. This finding contributes to the field by identifying the difficulty of this task.

This study has several limitations. First, while large, the HAM10000 dataset was not specifically designed for severity grading. Second, overfitting indicates the need for stronger regularization and data augmentation. Third, the experimental texture score ($S = \Sigma\,\Sigma\, I(x,y)^2$) requires clinical validation against established indices such as mMASI. Fourth, the system has not been tested in real clinical settings.

Future work will focus on: (i) collecting a dedicated severity-graded dataset with expert annotations [25], (ii) implementing advanced regularization techniques (dropout, batch normalization, data augmentation), (iii) conducting clinical validation studies comparing AI predictions with dermatologist assessments, and (iv) exploring ensemble methods or vision transformers to improve classification accuracy. These enhancements will move toward a clinically deployable AI system for objective pigmentation assessment, ultimately assisting dermatologists in treatment planning and monitoring.

DECLARATION OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

ACKNOWLEDGMENT

Not applicable in this work.

DATA AVAILABILITY

The HAM10000 dataset used in this study is publicly available [25]. The code and trained models are available from the corresponding author upon reasonable request.

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