And., Intl.,J., Appl Sci., Eng., Tech, Vol 06, No 03, November 2026
e-ISSN: 2797-0442

A Mobile App–Based Decision Support System for Counterfeit Product Identification Using Digital Image Analysis

Yunia Ningsih*, Ratna Shofiati, Is Mardianto, Anka Fayiz Rasyad, Tengku Rabih Razzan, Evanda Manggani, Radea Aji Prasojo
Informatics Study Program, Department Informatics Engineering, Faculty of Industrial Technology, Universitas Trisakti, Indonesia

*Corresponding author, e-mail: yunia@trisakti.ac.id

Abstract—The proliferation of counterfeit sportswear makes it difficult for consumers to objectively verify product authenticity. This study proposes an intelligent computer vision–based system to identify the authenticity of sportswear by integrating object detection and deep learning classification within an Android decision support application that also considers user data security. YOLOv8 is employed to detect salient regions in images, including garment fronts and product labels, while EfficientNetB5 classifies authenticity based on extracted visual features. The dataset comprises images of genuine and counterfeit sportswear collected from multiple locations and processed through preprocessing stages: grayscaling, zero centering, histogram equalization, standardization, and Gaussian blur to improve consistency and robustness. Evaluation uses an unseen test set with Precision, Recall, and mean Average Precision as metrics. Results demonstrate that the system effectively detects relevant objects and accurately classifies authenticity, producing bounding boxes, predicted labels, and confidence scores. The mobile application operates reliably in real time, and integrated security mechanisms enhance system resilience. Nevertheless, further dataset expansion and model optimization remain necessary to improve generalization and longterm performance in diverse realworld scenarios. Future work will explore larger datasets and cross domain deployment strategies and validation.

Keywords: Counterfeit Product, Computer vision, YOYO v8, Mobile App, and Verifikasi real-time.

This article *is licensed under the CC–BY-SA license.*

1. Introduction

The rapid advancement of information technology has significantly influenced various sectors, including education, industry, healthcare, and public services. The integration of digital systems enables organizations to improve operational efficiency, enhance decision-making processes, and deliver better service quality [1]. In the field of informatics, the development of intelligent systems and data-driven applications has become a major research focus due to their ability to process large-scale data and generate meaningful insights [2]. Despite these technological advancements, many existing systems still experience challenges related to scalability, data accuracy, usability, and system interoperability. These limitations often reduce system effectiveness and hinder organizational performance. Previous studies highlight that system success is strongly influenced by information quality, system quality, and user satisfaction [3]. Therefore, continuous research is required to design adaptive and efficient technological solutions capable of addressing real-world problems.

Received: May 4, 2026, Revised: June 29, 2026, Accepted: October 9, 2026
https://doi.org/10.25077/aijaset.v6i3.345

This study aims to propose and implement a solution that addresses the identified limitations by applying appropriate computational methods and system design principles. Design-oriented research plays an important role in developing innovative artifacts that improve system performance and usability [4]. The proposed approach is expected to enhance effectiveness, optimize processing time, and improve user experience compared to conventional approaches. The contribution of this research lies in the design, implementation, and evaluation of the proposed system. The findings are expected to provide theoretical contributions to informatics research and practical implications for decision-making and operational processes across various application domains.

2. Method

This research adopts a Research and Development (R&D) approach combined with the Agile Development methodology to design, develop, and evaluate the proposed system. The R&D approach is selected because it enables iterative development of technological artifacts while ensuring validation through testing and evaluation. Agile development supports flexibility, continuous feedback, and incremental system improvement throughout the development lifecycle. The research methodology consists of four main phases: analysis and design, development, implementation and testing, and integration and evaluation.

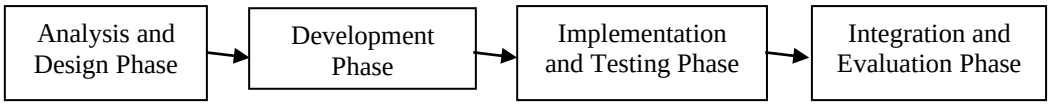


Figure 1. Research Methodology

2.1 Analysis and Design Phase

This phase aims to identify system requirements, define research objectives, and establish the architecture for an Android-based decision support system. Problem identification is conducted through a comprehensive literature review on sportswear counterfeiting, direct observation, and requirement analysis. Functional and non-functional requirements are specified to ensure the system can perform real-time object detection and authenticity classification. System design includes the development of use case diagrams, system workflows, encrypted database schemas, and interface prototypes. During this stage, the computational framework is determined, specifically selecting YOLOv8 for object detection and EfficientNetB5 for image classification [5].

2.2 Development Phase

The development phase focuses on constructing the system based on the predefined design by applying Agile principles through iterative cycles. Core modules are implemented, including data preprocessing (such as grayscaling and Gaussian blur), system logic, and a user interface developed using the Kotlin programming language. Throughout this phase, coding activities are integrated with internal testing to ensure the stability of image scanning and result visualization features. This incremental development approach allows for rapid adaptation to technical changes and enhances the overall quality of the mobile application.

2.3 Implementation and Testing Phase

The implementation phase involves deploying the system in a controlled environment to verify its operational performance. System testing is conducted using multiple approaches: functional testing to ensure features operate according to requirements, usability testing to evaluate user interaction, and performance testing to measure efficiency and response times in a mobile setting [6]. Additionally, security validation is performed—including penetration testing—to confirm the effectiveness of integrated mechanisms such as Host-based Intrusion Detection Systems (HIDS), firewalls, and HTTPS/TLS encryption. These testing results provide the necessary quantitative and qualitative data to assess the system's effectiveness in identifying genuine versus counterfeit products [7].

2.4 Integration and Evaluation Phase

The final phase focuses on integrating all system components—the mobile application, server-side logic, and AI modules—into a unified platform. Integration ensures interoperability between modules, data consistency, and stable operation during authenticity verification. Evaluation is conducted by analyzing testing results using metrics such as Precision, Recall, and mean Average Precision (mAP), as well as gathering user feedback. This phase determines whether the proposed system successfully addresses the research problem and achieves its intended objectives. The findings are then used to identify areas for future optimization and dataset expansion.

3. Result

The study produced an intelligent computer vision–based system for identifying the authenticity of sportswear by integrating the YOLOv8n model as an object detector and EfficientNetB5 as an authenticity classifier. The implementation demonstrates that the model is capable of detecting relevant regions within images, such as the front area of the clothing and product labels, represented through bounding boxes accompanied by confidence values. The classification results indicate that visual features extracted by EfficientNetB5 effectively distinguish between authentic and counterfeit product characteristics, generating prediction labels along with confidence scores [8]. The dataset consists of images of authentic and counterfeit products that underwent preprocessing stages, including grayscaling, zero-centering, histogram equalization, standardization, and Gaussian blur, which improved data consistency during the training process [9].

Evaluation on unseen test data shows the model's ability to generalize across variations in imaging conditions, including differences in lighting, capture angles, and backgrounds. Performance measurement using Precision, Recall, and mean Average Precision (mAP) indicates that the system effectively performs both object detection and authenticity classification. From a system integration perspective, verification confirms that communication between the mobile application, server, and AI module operates as designed [10]. The system consistently produces three main outputs: annotated images with bounding boxes, authenticity classification labels, and confidence scores, which are displayed to users and stored in the database for further analysis and model retraining.

Software testing, including unit testing, integration testing, functional testing, and user acceptance testing, demonstrates that the application satisfies functional requirements and operates stably with acceptable response times in a mobile environment. Regarding information security, the implementation of Host-based Intrusion Detection Systems (HIDS), rule-based firewalls, reverse proxy, encrypted communication, and mutual TLS enhances system resilience [11]. Penetration testing results indicate that the security mechanisms effectively detect and mitigate common attack scenarios, including brute-force authentication, port scanning, and unauthorized administrative access. Overall, the findings suggest that integrating object detection and deep learning–based classification effectively supports automated product authenticity verification. However, improvements in dataset quality and quantity, as well as model parameter optimization, remain necessary to enhance performance in broader real-world deployment scenarios.

AIJASET – Vol. 06, No. 03, November 2026. 331-337
https://doi.org/10.25077/aijaset.v6i3.345



Figure 2. Fake Clothing Photo

Figure 2 shows that the AI system can detect sportswear and verify its authenticity. The image indicates the detected object, while the right side presents the classification results, showing that the product is genuine with an accuracy of 75%. It also displays another classification result indicating that the product is counterfeit with an accuracy of 83.5%.

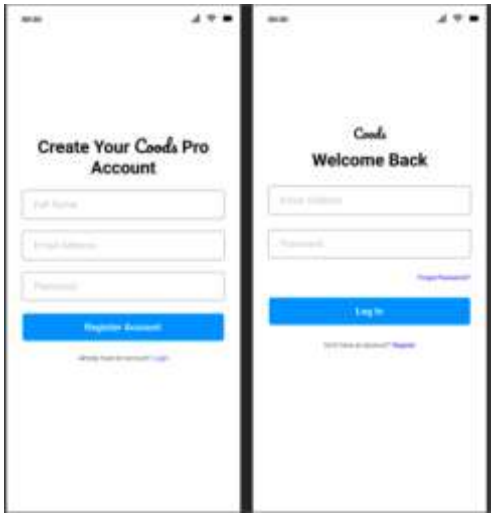


Figure 3. Mobile Apps Display



Figure 4. Dashboard Display

Figure 3 presents the user interface at the initial stage of application access, consisting of the registration (Register) and login (Login) pages. The interface adopts a minimalist design with clear typography to provide easy navigation for users. Figure 4 shows the main dashboard, which serves as the central information hub for users. This page displays a statistical summary of the number of products detected as genuine and counterfeit alerts, as well as a list of recent scan history that presents product details along with their authenticity status.

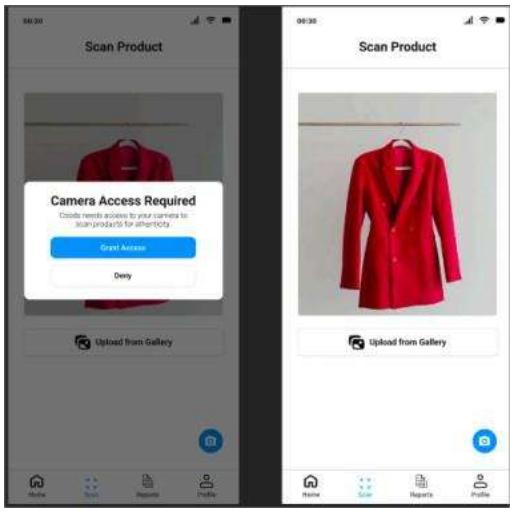


Figure 5. Take Picture



Figure 6. Counterfeit Product Detection Results

Figure 5 shows the process of capturing product images to be identified by the application. This stage begins with the application requesting camera access permission from the user, followed by the camera interface that allows users to either take a photo of the product directly or upload an existing image from the device gallery. Figure 6 presents the final result of the product identification process performed by the application. This page provides detailed information about the scanned product, such as the brand name and category, and displays the detection outcome in the form of status labels such as “Genuine” and “Counterfeit,” along with an action button to save the detection report.

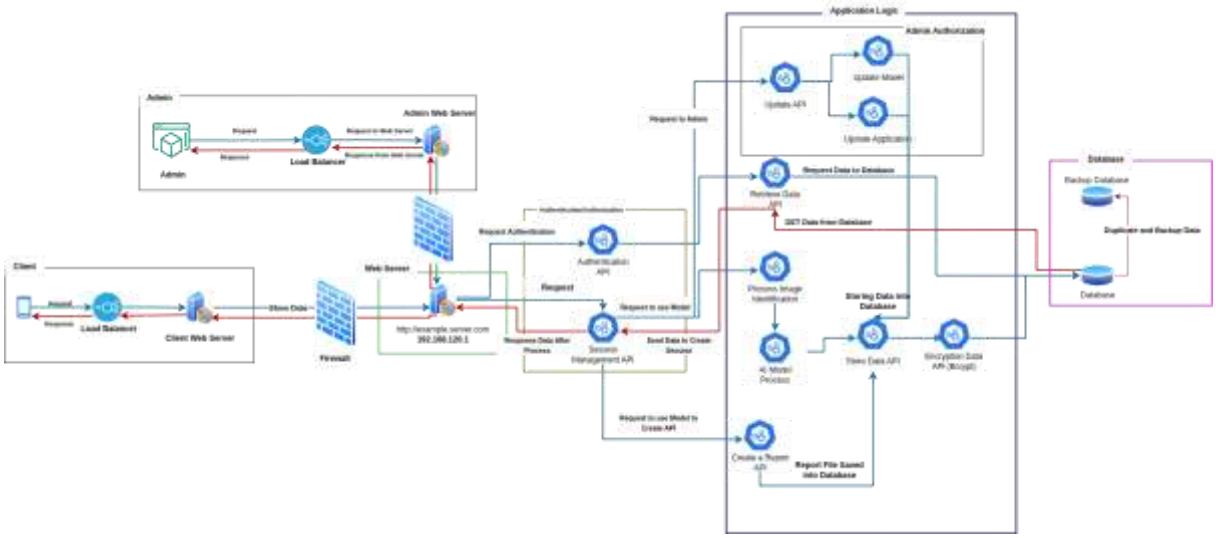


Figure 7. System Design Diagram

Figure 7 illustrates the system architecture and design, which describe the data flow from the user side (Client & Admin) to the storage layer (Database). The system employs a Load Balancer and Firewall to ensure secure and stable access before requests are forwarded to the Web Server. At the core of the system, the application logic manages various essential functions, ranging from authentication processes and image identification using Artificial Intelligence models to data storage in an encrypted database equipped with a backup mechanism.

4. Conclusion

The intelligent system developed in this study demonstrates that the integration of YOLOv8 for object detection and EfficientNetB5 for classification effectively identifies sportswear authenticity with high accuracy and optimized inference speeds. This performance is significantly bolstered by rigorous data engineering, where preprocessing techniques—including grayscaling, histogram equalization, zero-centering, and Gaussian blur—ensure data consistency and precise feature extraction. Furthermore, the software engineering implementation using the Kotlin programming language has resulted in a scalable, maintainable, and user-friendly mobile application, with testing confirming that core functionalities such as real-time image scanning and result visualization operate in strict accordance with the system design.

Beyond functional performance, the system incorporates robust information security through a combination of rule-based firewalls (iptables), HIDS/IPS (Fail2Ban), and encrypted communications via HTTPS and mutual TLS, effectively mitigating unauthorized access and common cyber threats. The comprehensive verification and validation phase confirms that all integrated components, from the AI models to the security infrastructure, operate as a unified and technically feasible solution for real-world deployment. Ultimately, this mobile-based identification system provides a rapid and efficient means of product verification, offering significant potential for evolution into a comprehensive integrated decision-support platform for broader anti-counterfeiting applications.

Acknowledgment

We would like to express our sincere gratitude to the Informatics Study Program, Department of Informatics Engineering, Faculty of Industrial Technology, Universitas Trisakti for their guidance to the supervising lecturers and for the financial support for research equipment, which enabled this research to be completed successfully.

References

[1] R. Hamzeh, L. Thomas, J. Polzer, X. W. Xu, and H. Heinzel, “A Sensor Based Monitoring System for Real-Time Quality Control: Semi-Automatic Arc Welding Case Study,” *Procedia Manuf.*, vol. 51, pp. 201–206, Jan. 2020, doi: 10.1016/j.promfg.2020.10.029.

[2] J. Zhang, J. Cao, J. Chang, X. Li, H. Liu, and Z. Li, “Research on the Application of Computer Vision Based on Deep Learning in Autonomous Driving Technology,” Jun. 04, 2024, *arXiv*: arXiv:2406.00490. doi: 10.48550/arXiv.2406.00490.

[3] R. Katageri, R. Bhushi, and D. S. S. Padmannavar, “Transfer Learning in Computer Vision,” vol. 6, no. 4, 2023.

[4] M. Palla and R. Karra, “A Comparative Study of Pre-Trained CNN Models with Transfer Learning for Content-Based Image Retrieval,” *Eng. Technol. Appl. Sci. Res.*, vol. 15, no. 4, pp. 25820–25826, Aug. 2025, doi: 10.48084/etasr.11496.

[5] N. A. Megantara and E. Utami, “Object Detection using YOLOv8 : A Systematic Review,” *SISTEMASI*, vol. 14, no. 3, pp. 1186–1193, May 2025, doi: 10.32520/stmsi.v14i3.5081.

[6] Y. Alashban, “Breast cancer detection and classification with digital breast tomosynthesis: a two-stage deep learning approach,” *Diagn. Interv. Radiol.*, Apr. 2025, doi: 10.4274/dir.2024.242923.

[7] I. Arifin, R. F. Haidi, and M. Dzalhaqi, “Penerapan Computer Vision Menggunakan Metode Deep Learning pada Perspektif Generasi Ulul Albab,” *J. Teknol. Terpadu*, vol. 7, no. 2, pp. 98–107, Dec. 2021, doi: 10.54914/jtt.v7i2.436.

[8] A. Wang *et al.*, “YOLOv10: Real-Time End-to-End Object Detection,” Oct. 30, 2024, *arXiv*: arXiv:2405.14458. doi: 10.48550/arXiv.2405.14458.

[9] W. He, T. Zhou, Y. Xiang, Y. Lin, J. Hu, and R. Bao, “Deep Learning in Image Classification: Evaluating VGG19’s Performance on Complex Visual Data,” Dec. 29, 2024, *arXiv*: arXiv:2412.20345. doi: 10.48550/arXiv.2412.20345.

[10] A. Ponraj *et al.*, "A multi-patch-based deep learning model with VGG19 for breast cancer classifications in the pathology images," *Digit. Health*, vol. 11, p. 20552076241313161, Jan. 2025, doi: 10.1177/20552076241313161.

[11] A. W. Maulana, S. A. Wibowo, U. Sunarya, R. Rahmania, and A. Insani, "Performance Improvement of YOLOv8-RTDETR Method Based Retail Product Detection," *J. Image Graph.*, vol. 12, no. 3, pp. 292–301, 2024, doi: 10.18178/joig.12.3.292-301.