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Leveraging YOLOv8 in Orifake: A Deep learning system for combating counterfeit logos

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Abstract
The proliferation of counterfeit logos necessitates efficient methods for brand protection. The main purpose of this study is to develop Orifake, leveraging YOLOv8 (You Only Look Once), that detects and classifies counterfeit logos. The model analyses logos (Adidas, Nike, Puma) for subtle features like colour, patterns, shapes, and textures. The evaluation demonstrates an average recall of 78.5%. Notably, Orifake identifies fake NIKE logos (recall: 94.9%). However, further refinement is needed for original NIKE logos due to their lower mAP-95 value. This research highlights the potential of Artificial Intelligence (AI) logo detection for brand protection against increasing online fraud.

Keywords: Deep learning, logo detection, YOLOv8, brand authentication

1.0 Introduction

The increased usage of digital media has given businesses fresh opportunities to engage with customers and develop their brands. However, it has also led to the emergence of new challenges, such as the widespread occurrence of counterfeit logos. According to Gunawardhana et al. (2024) and (Goldstein, 2022), the rise of new technologies has brought difficulties and advantages in the fight against counterfeiting and fraud. Criminals are becoming more advanced, which worsens the worldwide consequences. This criminal activity costs up to $4.5 trillion each year, leads to the loss of 2.5 million jobs, and poses significant financial and reputational risks to brands, especially in the retail and luxury industries. Counterfeit logos, crafted to imitate the trademarks of reputable corporations, are employed to deceive consumers and perpetrate fraudulent endeavours. Counterfeit logos have the potential to harm a brand's reputation, impede its revenue generation, and undermine consumer trust.

The Anti-Counterfeiting Intelligence Support Tool (ACIST) reports a 30% annual increase in counterfeit logo instances since 2018, emphasising the problem. Counterfeiters frequently exploit logos to make their products appear genuine, either by exact replication or subtle alterations that go unnoticed. Consumers who do not know how to verify product authenticity risk financial loss by buying fakes

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at real prices (Hyun et al., 2024; Safeer et al., 2023; Nunes et al., 2020; Bombonato et al., 2017). The International Trademark Association believes counterfeiting might cost the world economy $4.2 trillion by 2022, affecting the branded products market.

Traditional practices of detecting counterfeit logos, such as human inspection and barcode scanning, are becoming increasingly inadequate due to the ease with which digital tools allow for their creation and manipulation. This necessitates a shift towards more advanced technologies like machine learning. Therefore, the proposed Orifake branding recognition system aims to address this critical need by providing businesses, consumers, and regulatory organisations with a reliable and efficient tool to combat logo counterfeiting. By leveraging cutting-edge machine learning, Orifake empowers consumers to verify product authenticity and safeguards brand integrity, ultimately fostering greater customer confidence.

The main purpose of this study is to develop Orifake, a deep learning-based system leveraging YOLOv8 that detects and classifies counterfeit logos for Adidas, Nike and Puma and to evaluate the performance of YOLOv8 variants. Hence, this paper introduces Orifake, a deep-learning model for logo authenticity classification using YOLOv8. The paper content is arranged as follows: Literature review examines pertinent prior research; research methodology details the data collection, model architecture, and evaluation; results and discussion showcase analysis and results and conclusion: summaries contributions and outlining future research directions.

2.0 Literature Review

Prior research has been extensively discussed in deep learning endeavours, leading to the development of advanced models. A deep learning system for detecting counterfeit logos and assessing their similarity to genuine had been suggested by Iswarya et al. (2022). The researchers utilised YOLO and the Darknet framework, specifically selecting Darknet-53 due to its advanced structure and exceptional forecast precision. The real-time detection capabilities of YOLO were evaluated on a dataset of copyrighted logos. Training and testing were performed using a CNN model to confirm the accuracy of the system. However, their study focused on a small dataset and did not explore the performance of the latest YOLOv8 architecture.

A study by Vanitha et al. (2024) applied CNN, EfficientNetB1, MobileNetV2, and ResNet50 neural network models to detect the imperfections in detecting the genuineness of the logo. An extensive dataset with real and hard-to-detect logos in a broad range of styles and resolutions was used. Through model validation, the models achieve 67%, 72%, 74%, and 93% accuracy for the EfficientNetB1, CNN, ResNet50, and MobileNetV2, respectively. However, this study focuses on detecting imperfections to determine the genuineness of logos, while our study addresses the challenge of counterfeit logos by providing a tool for logo authenticity classification.

A study by Pinitjitsamut et al. (2021) proposed an AI-based logo identification system to recognize and compare product logos. This study intends to replicate and extend their work where the Darknet framework with the YOLO algorithm was employed to detect product logos. OpenCV image classification was utilized to create a Python-based GUI for dataset management and analysis. The YOLO method is the primary variable, and copyright logos serve as sample data. Results indicate a 97% accuracy for fake logos and 99% for 97ine logos. Liu et al. (2020) proposed a dense-block convolutional neural network for apparel brand logo prediction. Multiple dense blocks were incorporated. A large-scale clothing dataset was created, comprising over one million items with detailed attributes. Four dense blocks containing 2-5 convolutional layers were designed. Model parameters were adjusted based on YOLOv3. Experimental results using a 70/10/20 training/validation/test split assessed brand prediction accuracy.

Previous research explored logo detection and recognition methods; for instance, Hu et al. (2020) enhanced accuracy by combining visual and contextual information using YOLOv3. Pimkote and Kangkachit (2018) classified logos using AlexNet, VGG19, and GoogLeNet, advocating for a larger dataset. Li et al. (2022) employed YOLOv2 and Faster R-CNN for large-scale logo recognition. Yang et al. (2022) proposed an attention-net architecture for few-shot brand logo recognition. Based on these prior studies, a notable research gap exists in translating logo detection models into practical, user-friendly systems for real-world authentication. The evolution of YOLO models presents opportunities for YOLOv8 applications because of its high accuracy and efficiency. Therefore, the development of Orifake using YOLOv8 is to fill the research gap.

Overall, the studies demonstrate the effectiveness of deep learning algorithms, particularly YOLO and CNNs within the Darknet framework, for counterfeit trademark recognition. The high accuracy levels suggest their potential for real-world applications in combating online fraud and protecting consumers. This study used YOLOv8 architecture, which gives an advantage in identifying logos accurately and quickly with a high recall rate for fake logos.

3.0 Research Methodology

This research framework outlines a step-by-step process for developing a deep learning system to detect counterfeit trademarks. As shown in Fig. 1, the process begins with data collection that involves gathering a diverse dataset of real and counterfeit logos. This data is then cleaned and preprocessed for model development. After development, the results of the model testing have been demonstrated based on performance metrics (precision, recall, mAP-50) of several YOLOv8 versions. Next, the prototype development and testing were done. The prototype includes image, video, and real-time logo detection, and four buttons corresponding to these functions were created. Finally, the model's effectiveness is evaluated in the prototype testing and evaluation by testing it on untested data to assess its accuracy in identifying counterfeit trademarks.

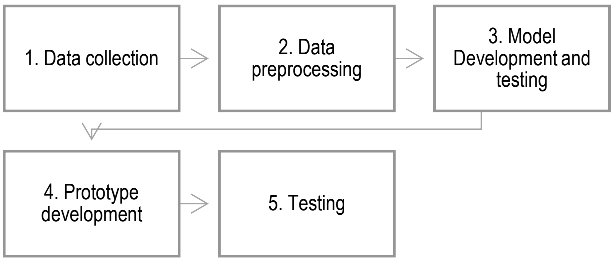

Fig. 1 Research Framework

3.1 Data Collection
This study utilized official company websites with downloadable logos. A rich and representative dataset of real and counterfeit logos from RoboFlow was needed to train and assess the detection system. The collected genuine logos represented many industries, businesses, and design variances to guarantee the model could generalise. The dataset has three sizes. Dataset 1 had 279 brand logos. To improve precision, 540 photos from Google, Pinterest, and RoboFlow were added to Dataset 2, which had 819 branding logo images. The model's performance was improved by adding 371 photos to the dataset. Dataset 3 was the largest at 1,190 images. Logos from counterfeit or modified logo sites were used. Such sources included internet platforms, websites, and marketplaces that marketed counterfeit goods. Taking legal and ethical precautions when collecting bogus logos was vital. Fig. 2 illustrates the logos used in this study.

Fig. 2 Example of images for every class

3.2 Data Preprocessing
The dataset was properly formatted, annotated, and enhanced for efficient training and use in Orifake tasks using the YOLOv8 model. Various data preprocessing methods were applied to ensure compatibility and effectiveness. The results of the data preparation are displayed in Tables 1 and 2. Table 1 breaks down each dataset into specific classes based on brand and authenticity. Meanwhile, Table 3 shows the impact of data augmentation, which increased the number of samples in each dataset to enhance dataset size and potentially improve the model's performance during training. All images were auto-oriented and resized to 640 by 640 pixels. Data augmentations included horizontal and vertical flips, rotations between -15° and +15° to desensitize the model to orientation variations, and shearing between ±15° horizontally and vertically to add variability and improve the model's response to image distortions and different viewing angles.

Table 1 Dataset of every class

Dataset	Class	Annotated Class
Dataset 1	ADIDAS_fake	42
	ADIDAS_original	45
	NIKE_fake	38
	NIKE_original	57
	PUMA_fake	43
	PUMA_original	54

Dataset 2	ADIDAS_fake	137
	ADIDAS_original	137
	NIKE_fake	136
	NIKE_original	136
	PUMA_fake	136
	PUMA_original	137
Dataset 3	ADIDAS_fake	198
	ADIDAS_original	227
	NIKE_fake	182
	NIKE_original	228
	PUMA_fake	169
	PUMA_original	203

Table 2 Data augmentation results

Dataset	Dataset size	Augmented data
Dataset 1	279	535
Dataset 2	819	1475
Dataset 3	1190	2138

3.3. Model Development and Testing

The YOLOv8 model for object detection is developed in stages, with three main components: the Backbone, Neck, and Head. In order to extract hierarchical characteristics, the Darknet architecture is improved by the Backbone, CSPDarknet53. Feature learning and representation are both improved by the Neck, which is built on CSPNet and enhances information flow between network stages. To accommodate objects of varied sizes, the Detection Head uses predefined anchor boxes to make a multi-scale bounding box and class probability predictions.

After running the dataset through Visual Studio Code for verification, we switch to Google Colab to drastically reduce runtimes. The YOLOv8 Large (yolov8l.pt) architecture is utilised to train the model. Its parameters include a learning rate of 0.001, input photos with 640x640 pixels, and 60 epochs of stochastic gradient descent (SGD) optimisation. With the model weights saved in 'best.pt' and validation data supplied in 'data.yaml', the YOLO framework is used to evaluate the model. This procedure evaluates the model's capability to detect objects, revealing its efficacy and precision.

In order to determine the best training configuration, three experiments were run to evaluate and analyse the performance of different YOLOv8 model variations. The dataset sizes and data splitting ratios used in each experiment varied. The model was tested in Experiment 1 with 50, 60, and 100 epochs. The optimal number of epochs was 60, which produced the best results with an average Precision (mAP-50) of 0.64. The 80:20 data splitting ratio provided the optimal blend of recall (70.3%) and precision (78.0%) in Experiment 2. Of the four YOLOv8 variations tested in Experiment 3, YOLOv8-L achieved the best accuracy (78.1%), followed by mAP-50 (86.7%). The results of Experiment 3 are detailed in the Results and Discussion section.

3.4 Prototype Development and Testing

The Orifake prototype utilizes YOLOv8 to accurately and efficiently detect logos across media formats. This tool identifies authentic and counterfeit logos in images, videos, and real-time feeds. Core functions include image, video, and real-time logo detection. The interface in Fig. 3 features four buttons corresponding to these functions: "Insert Image" for selecting images, "Insert Video" for selecting videos, "Open Camera" for capturing real-time images, and "Close Camera" for ending the camera preview. Detection results, including confidence scores, potential matches, and bounding boxes, are displayed. An example (Fig. 3) shows a counterfeit Nike logo detected with 93% confidence. The app enables easy media upload, analysis, and real-time detection, providing clear authenticity results. YOLOv8 integration ensures high-performance logo verification.

Fig. 3 Orifake Logo Detection prototype interface

4. Results and Discussion

4.1 Model Experiment 3 Results

Different model configurations suited for handling small, medium, and large items in the input image make up the size variants in YOLOv8. The size of the anchor boxes used during training can be changed to create these variations. The test results presented in Table 3 demonstrate that the performance metrics of several YOLOv8 versions exhibit variability. With a precision of 0.781%, recall of 0.79%, mAP-50 of 0.867%, and mAP-95 of 0.608%, YOLOv8-L shows the highest results. With a precision of 0.788%, recall of 0.756%, mAP-50 of 0.828%, and mAP-95 of 0.589%, YOLOv8-S trails closely behind. The results show that YOLOv8-N obtains 0.783% precision, 0.703% recall, 0.775% mAP-50, and 0.512% mAP-95. Meanwhile, YOLOv8-M achieves 0.773% precision, 0.774% recall, 0.83% mAP-50, and 0.586% mAP-95. YOLOv8-L is the model with the highest precision and mAP values, making it the best-performing model overall according to these measures.

Table 3 Experiment 3 Model Training Results

Model	Precision	Recall	mAP-50
YOLOv8-N	0.783%	0.703%	0.775%
YOLOv8-S	0.788%	0.756%	0.828%
YOLOv8-M	0.773%	0.774%	0.83%
YOLOv8-L	0.781%	0.79%	0.867%

Table 4 Validation results for Experiment 3

Validation	242				
Class	Instances	Precision	Recall	mAP-50	mAP-95
All	292	0.781%	0.785%	0.867%	0.607%
ADIDAS_fake	73	0.764%	0.753%	0.841%	0.684%
ADIDAS_original	82	0.728%	0.793%	0.821%	0.657%
NIKE_fake	33	0.740%	0.949%	0.955%	0.725%
NIKE_original	61	0.928%	0.637%	0.824%	0.392%
PUMA_fake	13	0.763%	0.746%	0.858%	0.565%
PUMA_original	30	0.764%	0.833%	0.905%	0.62%

Table 4 presents a comprehensive assessment of the object detection model, revealing encouraging outcomes across all categories. Overall, the model obtains a recall of 0.785%, mAP-50 of 0.867%, mAP-95 of 0.607%, and precision of 0.781%. The model identifies ADIDAS_fake for particular classes with a precision of 0.764%, recall of 0.753%, mAP-50 of 0.841%, and mAP-95 of 0.684%. With a precision of 0.728%, recall of 0.793%, mAP-50 of 0.821%, and mAP-95 of 0.657%, ADIDAS_original exhibits impressive results. With a precision of 0.740%, a high recall of 0.949%, an exceptional mAP-50 of 0.955%, and a mAP-95 of 0.725%, the model performs exceptionally well in identifying NIKE_fake. The results for NIKE_original are as follows: mAP-50 of 0.824%, mAP-95 of 0.392%, recall of 0.637%, and precision of 0.928%.The model obtains 0.763% precision, 0.746% recall, 0.858% mAP- 50, and 0.565% mAP-95 for PUMA_fake. Finally, PUMA_original shows remarkable mAP-50 of 0.905%, mAP-95 of 0.62%, recall of 0.833%, and precision of 0.764%. The model's overall performance indicates that it is effective in identifying and categorizing cases across various classes, with significant exceptions like PUMA_original and NIKE_fake.

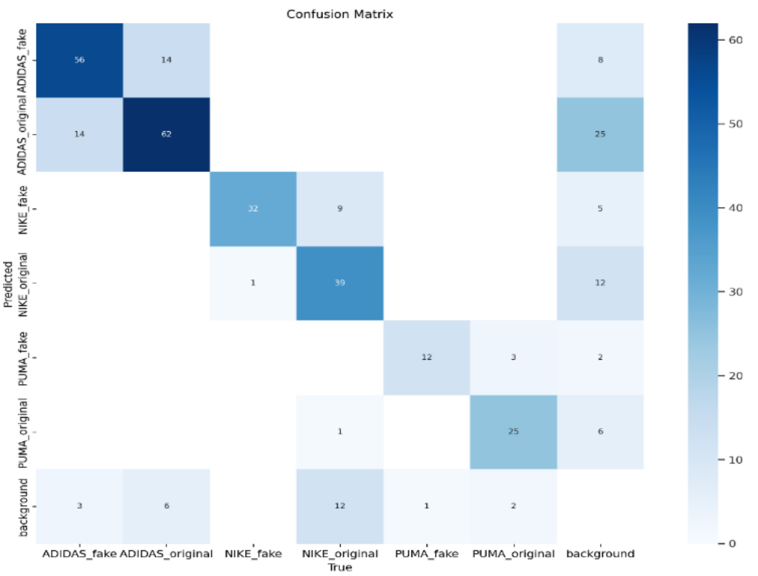

Fig. 4 Yolov8-L confusion matrix

Significant outcomes are revealed by looking at the object detection model's performance over a range of classes, as shown in Fig. 4. With 60 correct identifications, ADIDAS_fake has the highest accuracy, which is consistent with the visual depiction. Nonetheless, there are a number of misclassifications: eight as the background, one as NIKE_fake, two as PUMA_fake, and 14 as ADIDAS_original. With 16 accurate identifications, ADIDAS_original is challenged by 14 cases incorrectly labelled as ADIDAS_fake and 25 instances classified as the background. Although NIKE_fake has been accurately detected 16 times, it has been misclassified 32 times as the background and three times as PUMA_fake. Specific misclassifications for NIKE_original are not physically apparent, although they are probably confused with other brands or backgrounds. PUMA_fake observes misclassifications of three instances as PUMA_original and six as the background out of 20 valid identifications. PUMA_original is misclassified as the background 15 times and as PUMA_fake 12 times, although having the second-highest right identification rate at 40 instances. The visually suggested background class is misclassified as PUMA_original at least once, even though it is not expressly shown in the image. The model shows general effectiveness in recognizing occurrences across many classes despite the misclassifications; some classes, such as PUMA_original and ADIDAS_fake, stand out in terms of accurate identifications.

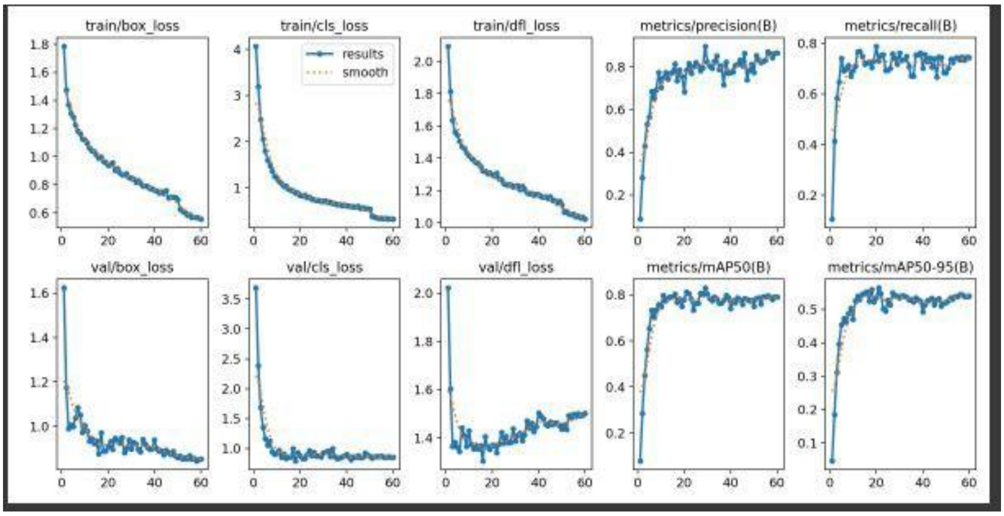

Fig.5 Yolov8-L Model Results

Based on Fig. 5 above, the performance characteristics of a model training using the Stochastic Gradient Descent (SGD) optimizer across 60 epochs on Dataset 3 are shown in the graphs with a precision of 86.7% and a recall of 78.5%. The model's performance for exact object localization significantly increased, as evidenced by the mean Average Precision (mAP) scores, which showed 86.7% at an Intersection over Union (IoU) threshold of 0.5 (mAP-50) and only 60.7% at closer IoU thresholds from 0.5 to 0.95 (mAP-95).

Overall, the experiments identified the most effective configurations and model sizes for accurate object detection and classification, particularly for distinguishing between fake and original branded items. The experiments concluded that 60 epochs are optimal for training the YOLOv8-N model. An 80:20 data splitting ratio provides the best balance between precision and recall, and the YOLOv8-L variant delivers the highest performance in terms of precision and mAP, making it the best model for accurate object detection and classification of branded items.

4.2 Prototype testing result

The Orifake underwent rigorous testing to ensure functionality, accuracy, and reliability. Unit, integration, and system testing were conducted. Unit testing verified individual components, while integration testing assessed component interactions. System testing evaluated the entire app using diverse media, including edge cases. Performance metrics (accuracy, confidence, speed) were recorded. User acceptance testing will be conducted upon completion. Figure 6 illustrates preliminary testing results.

Fig. 6 Example of Orifake Logo Detection prototype testing

The results of the Orifake system testing and evaluation have demonstrated significant insights into the performance and accuracy of the model. Initially, the dataset used in the experiments consisted of three progressively larger sets of images, each contributing to improved training and validation outcomes. Three datasets were used: Dataset 1 (279 images) served as a baseline but was limited. Dataset 2 (819 images) expanded data sources to Google, Pinterest, and Roboflow. Dataset 3 (1,190 images) provided the most comprehensive dataset for robust model training.

The experimentation involved various phases, starting with preprocessing the dataset to ensure compatibility and effective training using the YOLOv8 model. The results from different model configurations and training epochs highlighted the variations in precision, recall, and mean Average Precision (mAP) at different IoU thresholds. Model variations (YOLOv8-L, N, S) were tested, with YOLOv8-L achieving the highest precision (0.781%) and mAP-50 (0.867%) compared to YOLOv8-N and YOLOv8-S. Validation results showed varying logo classification and detection accuracy across classes. While some classes reached high performance (e.g., NIKE_fake: precision 0.745%, recall 0.74%, mAP-50 0.799%), others (e.g., ADIDAS_original, PUMA_fake) required optimization. The confusion matrix (Figure 3) identified misclassification patterns (e.g., ADIDAS_fake classified as other logos). These insights, alongside training results, inform future model improvements for enhanced real-world performance. Iterative testing, analysis, and refinement demonstrate the model's potential, necessitating ongoing development for reliable logo authentication.

The findings connect with the theoretical frameworks that are related to deep learning. The high recall achieved for fake Nike logos (94.9%), for example, aligns with the theory of hierarchical features learning in CNNs related to variations in shape and colour. YOLOv8's CNN component learns increasingly complex features, from basic visual elements to high-level logo attributes, enabling it to discern subtle counterfeit manipulations. Furthermore, the model simultaneously localizes and classifies logos as “authentic” or “fake” based on object detection as a classification problem. Orifake's ability to detect deviations in visual authenticity highlights the models capacity of counterfeit detection concepts, to capture nuanced perceptual differences between authentics and fake logos. Finally, the utilization of pre-trained weight in YOLOv8 reflects the principle of transfer learning, allowing the model to efficiently adapt to the specific task of logo authentication.

This study has several limitations regarding of diversity of datasets and lack sufficient variations within the “original” logo class such as differences in product context, lighting or design iterations. Other than that, model biases in the training data or architecture could contribute to misclassifications. For example, if the training set inadvertently correlates certain subtle features with authenticity, the model might struggle to generalize to original logos that deviate from these learned patterns.

5. Conclusion and Future Work

The study on Orifake has demonstrated promising results in accurately detecting authentic and counterfeit logos using the YOLOv8 model. Through rigorous testing with progressively larger datasets and various model configurations, the system achieved commendable precision and recall rates, particularly with Dataset 3, which provided a comprehensive training set of 1,190 images. The detailed analysis of precision, recall, and mAP metrics across different classes revealed the model's strengths and areas needing improvement. Despite the challenges of misclassification in certain logo classes, the overall performance underscores the system's potential for real-world applications.

Future work should focus on further optimizing the model to address identified weaknesses, particularly in the detection accuracy of specific logo classes like ADIDAS and PUMA. Enhancing the dataset with more diverse and high-quality images, exploring advanced augmentation techniques, and implementing more sophisticated preprocessing steps could contribute to improved model performance. Additionally, incorporating feedback mechanisms from user acceptance testing will be vital in refining the user interface and overall usability of the app. Expanding the scope to include more logotypes and real-time detection scenarios will further enhance the system's robustness and applicability. Continuous iteration and evaluation will be essential to achieving a reliable and effective logo detection solution. Integrating with brand databases, supporting more platforms, and leveraging hardware acceleration are key steps toward a more precise, efficient, and user-friendly application. Orifake can also be applied with real-world application such as integrated into e-commerce platform to verify the authenticity of logos automatically, and can be extended to authenticate other visual elements like packaging. A mobile application is also a good smartphone app that can scan logos for instant authenticity verification. Customs and border control agencies can also benefit Orifake by identifying counterfeit goods, and companies could monitor online marketplaces for unauthorized logo use.

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Paper Contribution to Related Field of Study

This study significantly contributes to the body of knowledge in deep learning system focusing on the image processing. It introduces the development of prototype name Orifkae that used for counterfeit logo detection. It provides empirical data on YOLOv8's performance in logo classification, offering practical insights of AI-driven brand protection.

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