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Deep Learning based Counterfeit Nike Shoes Detection using YOLOv8 for Object Detection

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Abstract

The fashion and footwear industries, where brand value and customer trust are paramount, are under constant threat from counterfeit products. This research presents a deep learning-based solution for detecting counterfeit Nike shoes using the YOLOv8 model for object detection. the dataset included four classes: "Nike Fake Air Force," "Nike Fake Jordan 1," "Nike Original Air Force," and "Nike Original Jordan 1," comprising a total of 3,860 images. These were split into training (70%), validation (20%), and testing (10%) sets. The pre-trained, medium-sized YOLOv8 model was used for detection and classification, yielding promising results. The model achieved a mAP of 95.0%, with precision and recall scores of 92.2% and 91.8%, respectively, on the validation set. The images were web scrapped with the Chrome extension called "Download All Images" and then manually filtered so that they would be relevant and of good quality. Each image was then manually labelled using the RoboFlow platform. Nevertheless, the model appears to be promising for implementation in combating counterfeit products, with a high potential accuracy and efficiency.

Keywords: Counterfeit Product Detection, Object Detection, Deep Learning, Nike, YOLOv8.

1. Introduction

The fake or replica products have troubled world markets, and most industries are badly affected by these issues, especially the fashion and footwear industry. Counterfeiting has caused economic loss to real businesses as well as defamed their image in front of buyers,

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which is harming consumers and affecting the quality. The sneaker industry with Nike has taken the heat because of models that are desired and their brand status. The Air Force and Jordan series are the most replicated Nike models, both of which have massive appeal among sneaker heads as well as everyday wearers.

With the increasing level of counterfeit products, many of which look almost identical to genuine goods, traditional methods including manual inspection and authenticating through production elements were not sufficient. Because counterfeiters are getting better and producing ever more sophisticated fake merchandise, there is a strong need for automated solutions that can enable the consumer as well as global brands/retailers to separate real products from fake.

Recent advances in deep learning and computer vision have opened new frontiers with a view to the solution of counterfeit detection. Object-detection models like those in the You Only Look Once (YOLO) series show impressive results in applications from autonomous driving to surveillance in security. Since YOLO is capable of real-time high-accuracy detection, it provides potential for several other tasks, including counterfeit detection.

This research provides a deep learning-based solution for detecting counterfeit Nike shoes using the YOLOv8. The dataset contained 3,860 images from four classes: "Nike Fake Air Force", "Nike Fake Jordan 1", "Nike Original Air Force", and "Nike Original Jordan 1". The current study will use the YOLOv8 model to design an automatic system for identifying counterfeit Nike shoes.

The main contributions of this study lie in the counterfeit detection application using YOLOv8, the development and annotation of an entirely new dataset, and the evaluation of the model performance for the identification of counterfeit and original Nike shoes. Even though there were some problems in collecting and annotating the data, the results showed a model that could be implemented in the fight against counterfeit goods.

2. Related Work

Detecting counterfeits has been a major challenge for the fashion and footwear industries, as counterfeit products can damage brand reputation and cause significant revenue losses. Historically, counterfeit detection relied heavily on manual inspection methods, focusing on product details like stitching quality, material type, and logos. However, these methods are subjective, time-consuming, and impractical for large-scale implementation. With the rise of more sophisticated counterfeit production methods, automated AI-driven solutions are gaining prominence.

Recent studies have introduced automated solutions utilizing deep learning models. YOLOv8 has been particularly effective in real-time counterfeit detection tasks, providing high accuracy and speed for identifying counterfeit products [1]. A two-stage deep learning framework has also been proposed to specifically detect counterfeit luxury handbags, highlighting the role of fine-grained features in distinguishing genuine products from counterfeits [2].

Multi-task learning networks have further enhanced the robustness of counterfeit detection systems, demonstrating improved performance in complex real-world environments [3]. Techniques involving deep metric learning and visual inspection have also proven successful in identifying counterfeit items in various categories [4]. These methods have expanded to address large-scale counterfeit detection challenges, such as those related to sneakers and fashion items, improving accuracy and generalizability across datasets [5].

While previous work focused on smaller-scale counterfeit detection, such as luxury handbags and watches, recent research has broadened its scope to encompass industries like footwear and retail, showing the potential for large-scale, real-world applications [6]. This progress has been accelerated using advanced object detection models, such as YOLOv8, which provide the necessary speed and accuracy for real-time detection scenarios [7].

With continuous improvements in deep learning models and training techniques, counterfeit detection systems are becoming increasingly reliable and scalable, making them more viable for practical implementation in retail and other sectors [8, 9, 10]. Recent advancements in visual pattern discovery for image classification and product search have enhanced counterfeit detection, particularly by improving the system's ability to identify subtle design patterns and features in images [11]. Counterfeit product grouping through a cluster ensemble approach has also shown significant promise in improving the efficiency and accuracy of counterfeit detection in diverse product categories [12]. Machine learning techniques have also been successfully applied to identify counterfeit foods, expanding the application of counterfeit detection technologies to other industries [13].

In addition, recent research on structure-aware deep learning models has improved product image classification, providing more accurate counterfeit detection through better understanding of product structures [14]. Other studies have demonstrated the effectiveness of deep learning object detection models in enhancing fake product detection across a range of categories, further expanding the application of these techniques [15].

3. Proposed Work

3.1 Dataset Formulation

Due to the lack of publicly available datasets for detecting counterfeit Nike shoes, a custom dataset of 3,860 images was created for this study. The images were categorized into four classes: “Nike Fake Air Force,” “Nike Fake Jordan 1,” “Nike Original Air Force,” and “Nike Original Jordan 1,” and were divided into training (70%), validation (20%), and testing (10%) subsets. The class-wise dataset split is shown in Table 1. The dataset collection and preparation part led to many challenges. The images were web scrapped with the Chrome extension called "Download All Images" and then manually filtered so that they would be relevant and of good quality. Each image was then manually labelled using the RoboFlow platform, where bounding boxes were drawn around the shoes to indicate their respective class (Counterfeit or Original, Air Force or Jordan 1).

To add more samples to the dataset and make it better, horizontal flip, vertical flip, and -45° to +45° rotation were applied as data augmentation techniques; also, all images were resized to 640x640 pixels. Those steps make the dataset diverse, which helps the model learn and generalize better during training. It also led to an increase in images for training and testing (3,860 vs. 1,497 after augmentation), as shown in Table 2.

Table 1. Dataset Class Split

Nike Fake Air Force	1116 (28.92%)
Nike Fake Jordan 1	935 (24.22%)
Nike Original Air Force	893 (23.13%)
Nike Original Jordan 1	916 (23.73%)
Total	3860 (100%)

Table 2. Dataset Before & After Augmentation

	Before augmentation	**After augmentation**
Images	1497	3860
Classes	4	4
Unannotated	0	0
Training	1051 (70%)	2703 (70%)
Validation	294 (20%)	771 (20%)
Testing	152 (10%)	386 (10%)

3.2 Experimental Setup

Table 3 contains the experimental setup details used to train the model.

Table 3. Experimental Setup

Language	Python 3
Processor	T4 GPU
Ram	16 GB
Storage	120 GB
Operating System	Ubuntu
Environment	Google Colab
Frameworks & Libraries	RoboFlow, Ultralytics, PyTorch

3.3 Object Detection Model

The study utilized the YOLOv8 model for identifying counterfeit Nike shoes. YOLOv8 is recognized for its speed and accuracy, and, for this research, a pre-trained YOLOv8 medium-sized model was employed. Training was done for 100 epochs with an input image size of 640x640 pixels. For better understanding, as shown in (Figure. 2). The YOLOv8 model slices an input image the same way as its previous version into a grid and predicts bounding boxes on objects in different cells specially designed. Convolutional layers are used to detect objects for multiple scales by means of features in this architecture. YOLOv8 medium, which was selected for intermediate performance and the optimization of computational costs, making it suitable for real-time object detection.

Mean average precision (mAP), precision, and recall are used as standard object detection metrics to evaluate the model performance throughout training. Data augmentation was applied to make the model generalize to unseen images better, refer to (Figure. 1A, and Figure. 1B).

Figure 1A. Horizontal & Vertical Flip

Figure 1B. Rotation within the Range of -45° to +45°

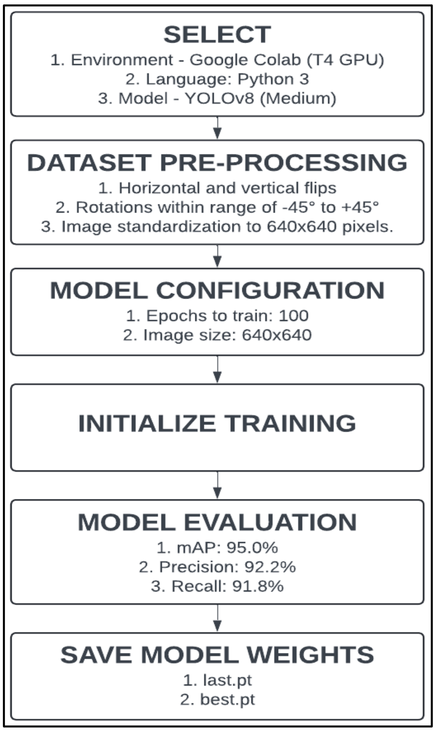

Figure 2. Training & Detection Flowchart of Pretrained Network YOLOv8

3.4 YOLOv8 Architecture

Backbone: The backbone is a convolutional neural network (CNN), which extracts features from the input image. Cross-stage partial connections are employed between layers with the encoding layer for information flow so that YOLOv8 using a custom CSPDarknet53 backbone can achieve ever higher accuracy with 53 convolutional layers.

Neck: The neck fuses feature maps from the different stages of the backbone to allow information at different scales. Since a banner sheet network is introduced in the YOLOv8 architecture, which is a novel module referred to as C2f directly without following the generally used FPN operations. This asset integrates high-level semantic features and low-level spatial information of small objects, which greatly improves its detection accuracy.

Head: The head makes predictions. Multiscale detection consists of modules that are responsible for predicting bounding boxes, objectness scores, and class probabilities for all grid cells in the feature map. From these predictions, final detections are aggregated.

The Figure 3 visualizes YOLOv8 architecture and Table 4 provides detailed information on the network's depth and width scaling factor.

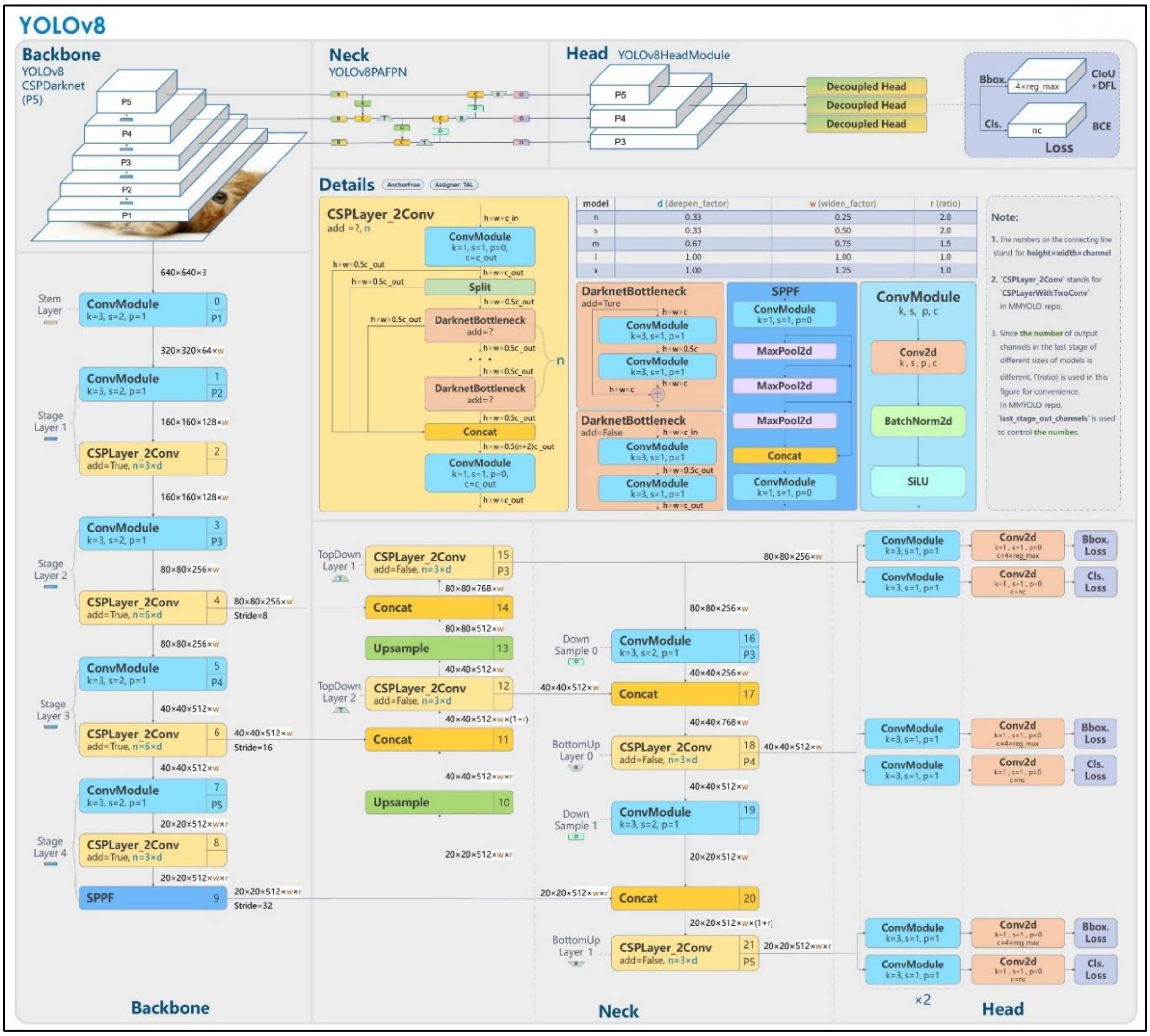

Figure 3. YOLOv8 Architecture [16]

Table 4. YOLOv8 Depth and Width Scaling Factors

Model	Depth	Width
YOLOv8 Nano	0.33	0.25
YOLOv8 Small	0.33	0.50
YOLOv8 Medium	0.67	0.75
YOLOv8 Large	1.00	1.00
YOLOv8 Extra Large	1.00	1.25

3.5 Hyperparameter Tuning

Table 5 details the hyperparameters used during model training.

Table 5. Hyperparameter Tuning

Batch Size	16
Initial Learning Rate	0.01
Weight Decay	0.0005
Momentum	0.937
Early Stopping Patience	100 Epochs
Final Learning Rate	0.01 (Linearly Reduced)
Automatic Mixed Precision (AMP)	Enabled
Loss Function Weights – Bounding Box Regression	7.5
Loss Function Weights – Classification Loss	0.5
IoU Threshold	0.7
Max Detections per Image	300

4. Results and Discussion

4.1 Confusion Matrix

The confusion matrix (Figure. 4) is a simple tabular layout to display the performance of classification across all categories. This matrix says how well the model separates between real shoes and fake ones, also for classes that are often confused. This provides information about how accurate the model is with each class and can help give insight into where the classifier might have difficulty discriminating between similar classes.

For instance, the model does a good job at identifying fake Air Force shoes from Nike with 370 true positives. There are still some misclassification incidents, with 22 pairs of fake Nike Air Force being classified as real Nike Air Forces, which shows the limitation where the distance between counterfeit and original categories is very close. While the model is strong at identifying original Nike Jordan 1 shoes, it struggles slightly more with distinguishing them from the fake counterparts, as reflected in the confusion between original and fake classes.

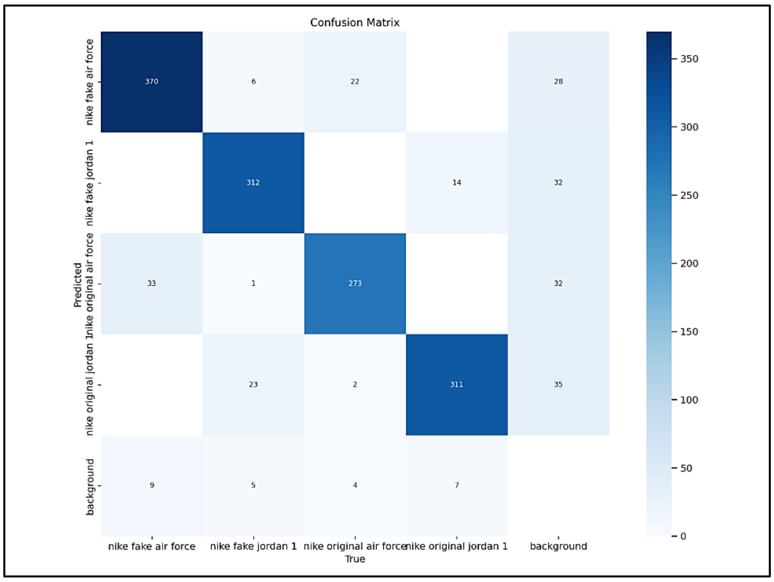

Figure 4. Confusion Matrix

4.2 F-1 Confidence Curve

The F1-Confidence Curve (Figure. 5) displays the F1 score (y-axis) against confidence thresholds (x-axis) for different Nike shoe categories. All curves show high F1 scores (above 0.8) for most confidence levels, indicating good overall performance in balancing precision and recall. The curves remain relatively stable until very high confidence thresholds, where they sharply decline.

The "all classes" curve (in blue) shows the model achieves an F1 score of 0.92 at a confidence threshold of 0.555, representing strong overall performance across categories. Fake Jordan 1 shoes consistently show the highest F1 scores, while original Air Force shoes have slightly lower scores.

This demonstrates the model's effectiveness in classifying both fake and original Nike shoes across different confidence levels, with performance dropping only at extremely high thresholds.

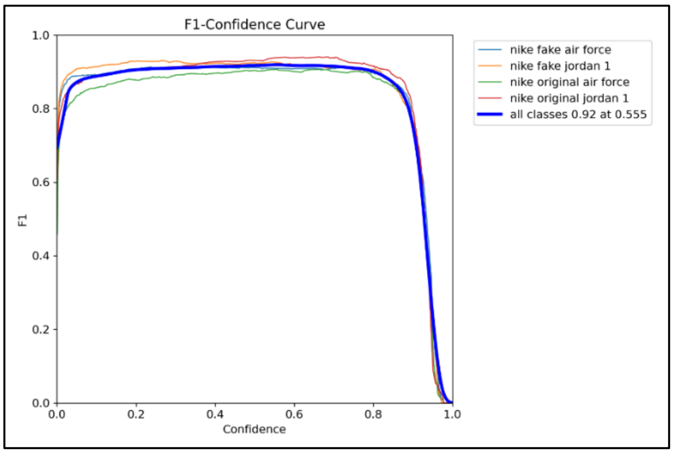

Figure 5. F-1 Curve (F-1 Confidence Curve)

4.3 Precision-Recall Curve

The Precision-Recall Curve (Figure. 6) graph shows the model's strong ability to distinguish between original and counterfeit Nike shoes across different categories. All curves maintain high precision (above 0.9) over a wide range of recall values, indicating excellent performance. The "Nike Fake Jordan 1" has the highest area under the curve (AUC) at 0.967, followed closely by the "Nike Original Jordan 1" at 0.965. "Nike Original Air Force" and "Nike Fake Air Force" also perform well with AUCs of 0.937 and 0.930, respectively.

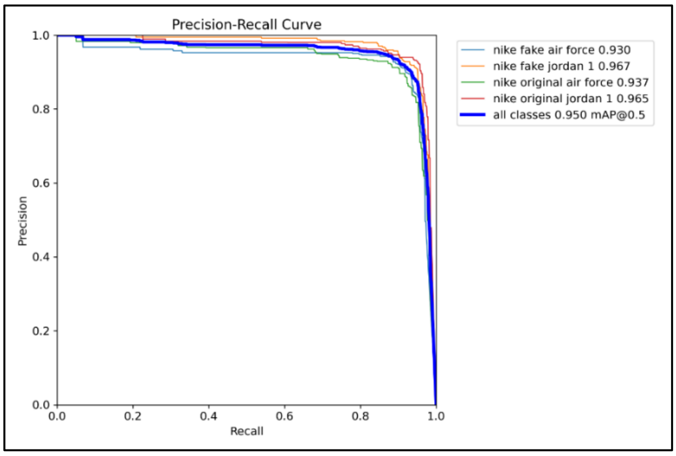

Figure 6. PR-Curve (Precision-Recall Curve)

4.4 Precision-Confidence Curve

The Precision-Confidence Curve (Figure. 7) illustrates the model's performance in identifying original and counterfeit Nike shoes. It shows high precision across different confidence levels for various shoe categories, with "Nike Fake Jordan 1" shoes being the most accurately detected. The model demonstrates strong overall performance, reaching perfect precision at a 0.983 confidence threshold. While it excels in most categories, there's a slight dip in precision for "Nike Original Air Force" shoes in the mid-confidence range. This effectively showcases the model's capability to distinguish between original and fake Nike shoes, maintaining high precision even at lower confidence levels for most categories.

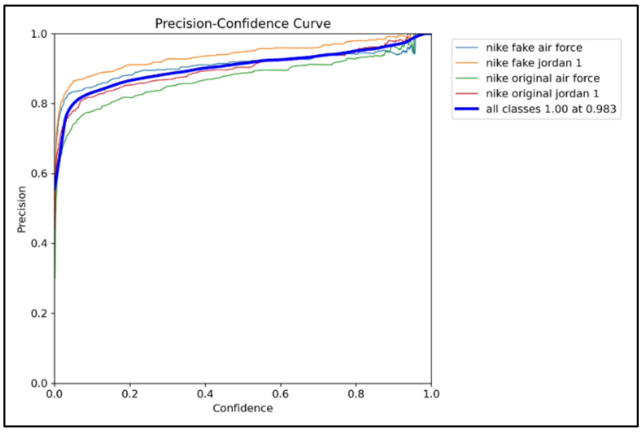

Figure 7. P-Curve (Precision-Confidence Curve)

4.5 Overall Results

Table 6 contains the overall results of the model.

Table 6. Overall results

Class	Precision	Recall	mAP50	mAP50-95
All	92%	91%	95%	84%
Nike Fake Air Force	91%	91%	92%	82%

Nike Fake Jordan 1	94%	90%	96%	86%
Nike Original Air Force	90%	90%	93%	81%
Nike Original Jordan 1	91%	95%	96%	85%

5. Conclusion

In this study, a deep learning model, YOLOv8, was designed to detect fake Nike sneakers. A total of 3,860 images were constructed as a custom dataset from four categories to train the model to properly differentiate between original and counterfeit shoes. The model performed very well with precision, recall, and mAP of 92.2%, 91.8%, and 95%, respectively.

Class separation was good, and while some misclassification persisted as shown on confusion matrices or precision-recall curves, the model did well in distinguishing between classes. Finally, YOLOv8 proved to be an effective approach for counterfeit detection, with the scope of accuracy enhanced further by adding more images into datasets and advanced feature extraction in the future.

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Author's biography

Aniket Panchal holds a bachelor's degree in information technology (BSc.IT) with a CGPA of 9.82 and is currently pursuing his master's in information technology (MSc.IT). He is a mobile app developer with knowledge of integrating machine learning models into mobile applications and creating REST APIs to enable the use of larger models on mobile devices. His work focuses on applying AI and machine learning to create innovative mobile solutions.

Neha Vora is currently pursuing her Ph.D. in Computer Science and holds a master's in computer applications (MCA). She is qualified in NET, SET, and GATE, and brings over 9 years of teaching experience, along with 1 year of industry experience. Her primary research areas include computer vision, image processing, machine learning, object detection, and artificial intelligence.