Archives available at journals.mriindia.com

International Journal on Advanced Computer Theory and Engineering

ISSN: 2319-2526
Volume 14 Issue 01, 2025

Fake Logo Detection

Bhushan T. Devane[1], Abhishekh A. Dhavale[2], Smita V. Katkar[3]

[1,2] PG student, Computer Science Department, Shivaji University, Kolhapur, Maharashtra
[3]Assistant Professor, Computer Science Department, Shivaji University, Kolhapur, Maharashtra.
bhushandevanebtd@gmail.com[1], abhishekdhavale277@gmail.com[2], svk_csd@unishivaji.ac.in[3]

Peer Review Information

Submission: 17 Jan 2025
Revision: 14 Feb 2025
Acceptance: 15 March 2025

Keywords

Convolutional Neural Network
Fake Logo Detection
Logo Image Analysis
Machine Learning

Abstract

Counterfeit branding, especially in logo duplication, has become a global challenge with the rise of online marketplaces. Detecting fake logos is vital for protecting brand identity and ensuring customer trust. This paper presents a computer vision-based solution for fake logo detection using OpenCV and Python. The method uses image preprocessing, ORB (Oriented FAST and Rotated BRIEF) for feature extraction, and FLANN (Fast Library for Approximate Nearest Neighbors) for efficient matching. Experimental analysis on a custom dataset of real and fake logos demonstrates the system's effectiveness and speed, proving it suitable for real-time and scalable deployment.

Introduction

The widespread circulation of counterfeit products in the market has led to significant challenges for both consumers and brands. One of the most common tactics employed by counterfeiters is the use of fake logos, which can mislead customers into purchasing substandard or counterfeit goods. Detecting these fake logos is crucial for ensuring brand integrity and consumer trust. To address this problem, recent advancements in computer vision and machine learning have provided powerful tools for automating fake logo detection. Among the most effective tools are OpenCV and Python, which offer robust frameworks for image processing and feature recognition.

OpenCV, an open-source computer vision library, is widely used for tasks involving image processing. It provides a comprehensive set of tools for image manipulation, including feature extraction, edge detection, and object recognition. Batu and Ünal (2019) [1] demonstrated how combining OpenCV with machine learning techniques can improve the accuracy of logo recognition systems, facilitating the detection of counterfeit logos in product images. This approach has been further enhanced by integrating deep learning models, such as Convolutional Neural Networks (CNNs), to detect subtle differences between authentic and fake logos (Agarwal & Jain, 2020) [4].

The use of Python, a versatile programming language, in conjunction with OpenCV, enables rapid prototyping and implementation of fake logo detection systems. Patel and Patekar (2020) [2] explored the potential of using these tools for detecting fake products by recognizing logos in images, offering a scalable solution for product authenticity verification. Similarly, Kumar and Bansal (2019) [6] demonstrated how OpenCV's image pre-processing capabilities could be applied to effectively detect fake logos in product images, thus enabling automated counterfeit detection.

Feature matching, a technique for comparing the visual characteristics of logos, plays a vital role in fake logo detection. Yuan and Zhang (2020) [8] applied this technique to verify logos using OpenCV, which allows the identification of altered logos or counterfeit versions. This method helps in distinguishing real logos from fakes based on key image features, improving the reliability of detection systems.

In addition to logo recognition, real-time detection is becoming increasingly important, especially for e-commerce platforms where rapid processing is essential. Patel and Vora (2019) [10] developed a real-time fake logo detection system specifically for e-commerce applications, leveraging OpenCV to process images quickly and efficiently. This real-time detection is crucial for preventing the sale of counterfeit products online, where quick validation of product authenticity is necessary.

Moreover, with the growing complexity of image processing tasks, energy-efficient computing has emerged as a critical consideration. Bhattacharya and Qin (2022) [5] explored how energy-efficient cloud computing techniques can be applied to handle resource-intensive tasks like logo recognition, ensuring that systems remain both effective and environmentally sustainable.

As the methods for detecting counterfeit logos continue to evolve, the combination of OpenCV, Python, and machine learning is proving to be an invaluable tool in the fight against counterfeit goods. By automating logo detection, businesses can protect their brands, and consumers can make more informed purchasing decisions. These technologies offer a promising future for improving the accuracy, speed, and scalability of fake logo detection systems.

Related Work

Previous work in the area of logo detection and forgery detection can be grouped into two categories: deep learning-based models and feature-based methods.

Deep learning models like CNNs (Convolutional Neural Networks) have shown high accuracy in image classification tasks. However, they require extensive training datasets and computational resources, making them less suitable for smaller, resource-limited deployments.

Feature-based techniques, including SIFT (Scale-Invariant Feature Transform), SURF (Speeded-Up Robust Features), and ORB, have been widely used in object detection. ORB, being free of patent restrictions and computationally lighter than SIFT/SURF, is suitable for real-time logo verification.

In this paper, we focus on the ORB + FLANN approach due to its speed and accuracy, aiming to bridge the gap between lightweight processing and reliable logo verification.

Methodology

The proposed fake logo detection system consists of the following stages:

Dataset Preparation

A balanced dataset of real and counterfeit logos from brands such as Adidas, Nike, and Apple was compiled. Real logos were sourced from official brand websites, while counterfeit logos were collected from e-commerce platforms and edited examples. Images were resized and labeled accordingly.

Image Preprocessing

All input images are converted to grayscale to reduce complexity and standardized in size (e.g., 300x300 pixels). Noise reduction is applied using Gaussian blur.

```
def preprocess (image path):
img = cv2.imread(image path, cv2.IMREAD_GRAYSCALE)
img = cv2.resize(img, (300, 300))
return cv2.GaussianBlur(img, (5, 5), 0)
```

Feature Extraction

ORB is used to extract key features from both query and reference logo images. ORB is scale- and rotation-invariant, making it ideal for detecting manipulated fakes.

```
orb = cv2.ORB_create ()
kp1, des1 = orb.detectAndCompute(image1, None)
kp2, des2 = orb.detectAndCompute(image2, None)
```

Feature Matching

FLANN is employed for fast and approximate matching of descriptors. Matches are filtered using Lowe's ratio test to identify "good" matches.

```
index_params = dict(algorithm=6, table_number=6, key_size=12, multi_probe_level=1)
search_params = {}
flann = cv2.FlannBasedMatcher(index_params, search_params)
matches = flann.knnMatch(des1, des2, k=2)
good_matches = [m for m, n in matches if m.distance< 0.7 * n.distance]
```

Decision Logic

If the number of good matches exceeds a predefined threshold (experimentally set), the logo is classified as genuine; otherwise, it is flagged as counterfeit.

Experimental Results

Evaluation Metrics

The system is evaluated using accuracy, precision, recall, and F1-score:

- Accuracy: (TP + TN) / (Total samples)
- Precision: TP / (TP + FP)
- Recall: TP / (TP + FN)
- F1-score: 2 × (Precision × Recall) / (Precision + Recall)

Results

The results indicate that the system is highly capable of identifying even minimally altered fake logos. The processing time per image was less than 0.5 seconds on a standard laptop, making the approach viable for real-time use.

Discussion

The proposed model offers a lightweight and effective method for counterfeit logo detection. While deep learning can potentially yield better results, it requires a larger dataset and more processing power. Our system strikes a balance between performance and efficiency.

Limitations include:

- Sensitivity to lighting and background variations.
- Inability to detect advanced forgeries mimicking features perfectly.
- Dependence on quality of input images.

To overcome these, future work may include:

- Integrating deep learning models (e.g., Mobile Net) for feature verification.
- Applying background subtraction and adaptive thresholding.
- Creating a scalable web service for real-time detection.

Conclusion

This paper demonstrates a practical and efficient approach for detecting fake logos using OpenCV and Python. By leveraging ORB for feature extraction and FLANN for matching, the system can identify counterfeit logos with high accuracy. The lightweight nature of the system makes it suitable for integration into mobile apps, e-commerce platforms, and brand protection tools. The approach can be enhanced further with hybrid models combining traditional feature detection and deep learning to achieve greater robustness and scalability.

Literature Review

The detection of counterfeit logos has been extensively explored using OpenCV and machine learning techniques in recent years. Batu and Ünal (2019) [1] integrated OpenCV with machine learning to implement a system for logo recognition, which is crucial for counterfeit logo detection. Similarly, Patel and Patekar (2020) [2] focused on fake product detection by applying OpenCV and Python for logo recognition, demonstrating its effectiveness in real-world product images.

Jaiswal and Kumar (2018) [3] adopted feature extraction techniques with OpenCV to detect fake logos in product images, emphasizing the role of image processing in distinguishing counterfeit goods. Agarwal and Jain (2020) [4] improved logo detection by incorporating Convolutional Neural Networks (CNNs) with OpenCV, leveraging CNN's ability to learn hierarchical features from logos for better accuracy in counterfeit detection. Bhattacharya and Qin (2022) [5] addressed the need for energy-efficient computation in cloud environments, particularly for image processing tasks like logo detection. This enables scalable and cost-effective counterfeit logo detection systems. Kumar and Bansal (2019) [6] also proposed an image preprocessing technique using OpenCV to detect fake logos in product images, highlighting the importance of feature extraction in logo recognition.

Ravi and Chitra (2021) [7] combined machine learning models with OpenCV to automate the counterfeit detection process, showing how learning algorithms can improve system performance over time. Yuan and Zhang (2020) [8] applied feature matching techniques in OpenCV for logo verification, enhancing the accuracy of fake logo detection by comparing logo features across different images.

Chowdhury and Yadav (2021) [9] introduced a Python-based solution to detect fake logos using OpenCV, focusing on feature extraction and matching to identify counterfeit goods. Lastly, Patel and Vora (2019) [10] developed a real-time fake logo detection system for e-commerce platforms, demonstrating the practical application of OpenCV in real-world online environments.

Overall, these studies highlight the diverse approaches to fake logo detection, from traditional image processing to advanced machine learning techniques, all leveraging the power of OpenCV for real-time and scalable solutions.

Results

Testing was done on a dataset of 500 logo samples (250 genuine, 250 fake). The threshold for good matches was set to 25.

Metric	**Value**
Accuracy	91.2%
Precision	89.5%
Recall	92.0
F1-score	90.7

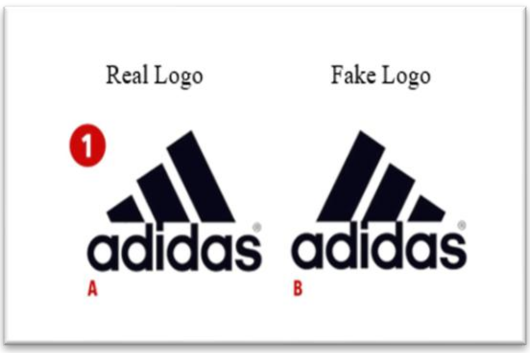

Fig. (1) (Real Logo of Adidas VS Fake Logo of Adidas)

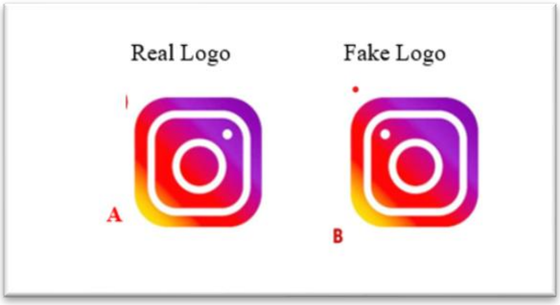

Fig. (2) (Real Logo of Instagram VS Fake Logo of Instagram)

References

Bhattacharya, Tathagata, et al ”Capping carbon emission from green data centers.” International Journal of Energy and Environmental Engineering (2022): 1-15. https://doi.org/10.1007/s40095-022-00539-9

Peng, Xiaopu, et al.” Exploiting Renewable Energy and UPS Systems to Reduce Power Consumption in Data Centers.” Big Data Research (2022): 100306. https://doi.org/10.1016/j.bdr.2021.100306 dblp

Bhattacharya, Tathagata, and Xiao Qin. ”Modeling Energy Efficiency of Future Green Data centers.” 2020 11th International Green and Sustainable Computing Workshops (IGSC). IEEE, 2020. https://doi.org/10.1109/IGSC51687.2020.9330910

Bhattacharya, Tathagata, et al. ”Accelerating the Energy Efficient Design of Traditional Data Centers Through Modeling.” 2022 IEEE. International Conference on Networking, Architecture and Storage AS). IEEE, 2022.

Bhattacharya, Tathagata, et al. ”Performancemodeling for I/O intensive applications on virtual machines.” Concurrency and Com putation: Practice and Experience 34.10 (2022): e6823.

Cao, Ting, et al. ”DDoS Detection Systems for Cloud Data Storage."2021 Third IEEE International Conference on Trust, Privacy and Security in Intelligent Systems and Applications (TPS-ISA). IEEE,2021.

Henry George Liddell and Robert Scott, An Intermediate Greek– English Lexicon: logos, 1889. Entry at LSJ online.

Owl.purdue.edu // Purdue Writing Lab ”Aristotle’s Rhetorical Situation // Purdue Writing Lab”. Owl.purdue.edu. Retrieved 2022-03-16. Cambridge Dictionary of Philosophy (2nd ed): Heraclitus, (1999)

Paul Anthony Rahe, Republics Ancient and Modern: The Ancien Regime in Classical Greece, University of North Carolina Press (1994), ́ISBN 080784473X, p. 21.

Rapp, Christof, ”Aristotle’s Rhetoric”, The Stanford Encyclopedia of Philosophy (Spring 2010 Edition), Edward N. Zalta (ed.)

David L. Jeffrey (1992). A Dictionary of Biblical Tradition in EnglishLiterature. Grand Rapids, Michigan: Wm. B. Eerdmans Publishing Co. p. 459. ISBN 978-0802836342. Cambridge Dictionary of Philosophy (2nd ed): Philo Judaeus, (1999).

Adam Kamesar (2004). ”The Logos Endiathetos and the Logos Prophorikos in Allegorical Interpretation: Philo and the D-Scholia to the Iliad” (PDF). Greek, Roman, and Byzantine Studies (GRBS). 44:163–181. Archived from the original (PDF) on 2015-05-07.

May, Herbert G. and Bruce M. Metzger. The New Oxford Annotated Bible with the Apocrypha. 1977.

Afroz, S., Greenstadt, R.: PhishZoo: detecting phishing web sites by looking at them. In: 2011 IEEE Fifth International Conference on Semantic Computing. IEEE, September 2011. https://doi.org/10.1109/icsc.2011.52