

CNN-Based Fake Brand Logo Recognition and Authentication

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Abstract— Counterfeit logos have become a major concern for businesses as they can damage brand reputation and mislead customers. This project presents a deep learning-based approach for detecting fake and original logos using a Convolutional Neural Network (CNN). A dataset containing genuine and fake logo images is collected and pre-processed through image resizing, normalization, and data shuffling to improve the quality of training data. The processed dataset is divided into training and testing sets in an 80:20 ratio. The CNN model automatically learns important visual features from the images and classifies logos with high accuracy. The developed system provides a simple graphical user interface that allows users to upload logo images and instantly verify their authenticity. Experimental results show that the proposed model achieves reliable classification performance while reducing manual verification effort. This system can support organizations in identifying counterfeit logos and protecting brand identity through an efficient and automated detection process.

Keywords — Counterfeit Logo Detection, Convolutional Neural Network (CNN), Deep Learning, Image Classification, Computer Vision, Logo Authentication, Brand Protection, Image Processing, Feature Extraction, Fake Logo Recognition.

I. INTRODUCTION

The rapid expansion of e-commerce platforms and online shopping has increased the availability of counterfeit products worldwide. One of the primary methods used by counterfeit manufacturers is the replication of well-known brand logos to make fake products appear genuine. These counterfeit logos can mislead consumers, reduce customer trust, and cause significant financial losses to brand owners. As a result, developing an automated system capable of accurately distinguishing fake logos from genuine ones has become an important research area in computer vision and image processing. Early research in content-based image retrieval

demonstrated the importance of extracting visual features from images for efficient recognition and comparison, providing the foundation for many modern logo recognition systems [1].

Logo detection and recognition involve identifying the presence of a logo in an image and verifying its authenticity. Traditional approaches mainly depended on handcrafted image features such as color, texture, and shape descriptors. Although these methods performed reasonably well under controlled conditions, they often failed when images contained complex backgrounds, changes in illumination, different viewing angles, or partial occlusions. Advances in image retrieval and visual feature extraction have significantly improved the robustness of image recognition systems, enabling more reliable detection of visual objects in real-world environments [2].

Recent developments in deep learning have transformed image classification by enabling models to learn meaningful visual features directly from training data. Convolutional Neural Networks (CNNs) have shown excellent performance in image recognition tasks because they automatically extract hierarchical features without requiring manual feature engineering. Research on event detection and semantic annotation has also highlighted the importance of deep visual representations for recognizing objects under varying environmental conditions, making deep learning a suitable choice for logo authentication applications [3].

Several studies have focused on detecting logos and trademarks in multimedia content. Product image search techniques have demonstrated that ranking visually similar images can improve the retrieval of authentic products and support logo verification systems [4]. Similarly, automatic trademark detection in sports videos has shown that computer vision algorithms can successfully recognize logos even under challenging viewing conditions such as scale variation, rotation, and partial visibility [5]. Advertisement billboard detection methods have further confirmed that combining local and global visual information improves logo localization and recognition accuracy in practical applications [6].

In this project, a Convolutional Neural Network (CNN) is employed to classify logo images as either genuine or fake. The collected dataset is preprocessed through image resizing, normalization, and random shuffling before being divided into training and testing sets using an 80:20 ratio. The trained CNN model automatically learns discriminative visual features and performs accurate logo classification. A graphical user interface is also developed to enable users to upload logo images and obtain instant authenticity predictions. The proposed system provides an efficient, reliable, and automated solution for counterfeit logo detection, helping organizations protect their brand identity and improve consumer confidence [5].

II. RELATED WORK

[1] A. Smeulders, M. Worring, S. Santini, A. Gupta, and R. Jain, "Content Based Image Retrieval at the End of the Early Years," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2000.

This paper presents a comprehensive review of Content-Based Image Retrieval (CBIR), which retrieves images by analyzing their visual characteristics rather than relying on text descriptions. The authors discuss important image features such as color, texture, shape, and local geometric patterns that are widely used for image matching and retrieval. They also explain different similarity measurement techniques and user feedback mechanisms that improve retrieval performance. The survey highlights the challenges of bridging the semantic gap between low-level image features and high-level human understanding. In addition, it discusses database indexing methods and system architectures for large-scale image retrieval applications. The concepts presented in this work provide a strong foundation for image recognition tasks, including logo detection. The feature extraction and similarity analysis techniques described in this paper have significantly influenced the development of modern computer vision systems used for authenticating logos and detecting counterfeit products.

[2] R. Datta, D. Joshi, J. Li, and J. Z. Wang, "Image Retrieval: Ideas, Influences, and Trends of the New Age," *ACM Computing Surveys*, 2008.

This survey reviews the major developments in image retrieval technologies and explains how the field has evolved with advances in machine learning and multimedia analysis. The authors discuss various feature extraction methods, image

annotation techniques, semantic image understanding, and visual similarity measurements. The paper also examines the growing importance of combining visual information with learning algorithms to improve retrieval accuracy in practical applications. It highlights several real-world challenges, including large-scale image databases, computational efficiency, and the semantic interpretation of visual content. The survey emphasizes that modern image retrieval systems should automatically learn meaningful representations from images instead of depending only on handcrafted features. These concepts have influenced many computer vision applications, including logo recognition, counterfeit detection, and brand authentication. The paper provides valuable insights into designing efficient and reliable image-based recognition systems for commercial and industrial applications.

[3] L. Ballan, M. Bertini, A. Del Bimbo, L. Seidenari, and G. Serra, "Event Detection and Recognition for Semantic Annotation of Video," *Multimedia Tools and Applications*, 2011.

The authors present a detailed survey of event detection and recognition techniques for semantic video analysis. The paper explains how visual features extracted from image sequences can be used to recognize objects, actions, and events automatically. It discusses interest point detection, feature descriptors, temporal modeling, and machine learning methods for identifying meaningful patterns in videos. The study categorizes different recognition techniques based on application domains and video characteristics while addressing challenges such as camera movement, object occlusion, and varying lighting conditions. The authors also emphasize the importance of semantic annotation for improving multimedia search and retrieval systems. Although the primary focus is video analysis, the object recognition techniques discussed are highly relevant to image classification tasks such as logo detection. The research demonstrates how robust feature extraction and deep visual representations contribute to accurate object recognition under real-world conditions.

[4] Y. Jing and S. Baluja, "PageRank for Product Image Search," *Proceedings of the WWW Conference*, 2008.

This paper introduces a novel image ranking approach for product image retrieval by applying the PageRank algorithm to visual similarity graphs. Instead of relying only on textual information associated with images, the proposed method analyzes visual relationships among product images

to identify the most representative and relevant results. The authors construct a graph based on image similarity and assign importance scores using an iterative ranking process. Experimental results demonstrate that incorporating visual content significantly improves retrieval quality and user satisfaction compared with traditional text-based search methods. The proposed ranking strategy helps identify authentic product images more effectively, making it valuable for commercial image search applications. The concepts presented in this research are applicable to counterfeit logo detection because they improve the retrieval of visually similar brand logos. The study highlights the importance of visual similarity analysis for developing accurate logo verification and authentication systems.

[5] L. Ballan, M. Bertini, and A. Jain, "A System for Automatic Detection and Recognition of Advertising Trademarks in Sports Videos," *Proceedings of ACM Multimedia*, 2008.

This paper proposes an automated system for detecting and recognizing advertising trademarks that appear in sports videos. The authors combine logo localization and recognition techniques to identify trademarks under different viewing conditions, including scale variation, camera movement, and partial occlusion. The proposed framework reduces manual effort by automatically detecting candidate logo regions while allowing human supervisors to verify the final results. The study demonstrates that computer vision algorithms can effectively recognize logos in complex video scenes despite challenges such as changing backgrounds and image distortions. The research highlights the importance of robust feature extraction, efficient matching algorithms, and accurate logo localization for real-world trademark recognition. The techniques presented in this work have influenced modern logo detection systems that employ deep learning for improved recognition accuracy. This research provides valuable guidance for developing automated counterfeit logo detection systems capable of distinguishing genuine logos from fake ones in practical applications.

III. DATASET DETAILS

The dataset used in this study consists of logo images collected from various brands and organized into two categories: Original and Fake logos. The original logo images represent authentic brand trademarks, while the fake logo images include counterfeit, modified, or duplicated versions that closely resemble the genuine logos. The dataset contains images with different sizes, colors,

orientations, backgrounds, and lighting conditions to simulate real-world scenarios. Each image is labeled according to its corresponding class, enabling supervised learning for logo classification. Since the collected images may vary in quality and resolution, some samples contain background noise, distortions, or slight visual differences that require preprocessing before model training. The availability of labeled logo images allows the development of an automated deep learning model capable of distinguishing genuine logos from counterfeit ones. This dataset provides valuable visual information for studying logo characteristics and learning discriminative patterns that differentiate authentic brand logos from fake imitations. By utilizing these labeled images, the proposed system aims to improve brand protection and support automatic counterfeit logo detection with high accuracy.

Before training the classification model, the dataset undergoes several preprocessing operations to improve image quality and ensure consistency across all samples. Initially, all logo images are resized to a fixed resolution of 64×64 pixels, normalized by scaling pixel values between 0 and 1, and shuffled randomly to eliminate data bias. These preprocessing steps help the model learn meaningful visual features while reducing computational complexity. After preprocessing, the dataset is divided into 80% training data and 20% testing data, where the training images are used to learn the distinguishing characteristics of original and fake logos, and the testing images are used to evaluate the performance of the trained model. The processed dataset is then provided to the Convolutional Neural Network (CNN) for feature learning and classification. Through systematic training and testing, the dataset enables accurate logo recognition and supports the development of an efficient automated system for counterfeit logo detection.

IV. PROPOSED METHODOLOGY

The proposed methodology utilizes a Convolutional Neural Network (CNN) to automatically classify logo images as either Original or Fake. Initially, the logo image dataset is uploaded into the system, where the images are organized into two separate classes representing genuine and counterfeit logos. The uploaded dataset undergoes preprocessing to improve image quality and ensure consistency across all samples. During preprocessing, all logo images are resized to 64×64 pixels, normalized by scaling pixel values, and randomly shuffled to eliminate data bias. These preprocessing operations

help improve the learning capability of the CNN model and reduce computational complexity. After preprocessing, the dataset is divided into 80% training data and 20% testing data. This data preparation stage provides the CNN model with high-quality input for learning the distinguishing visual characteristics of original and fake logos.

Following dataset preparation, the processed logo images are supplied to the proposed CNN model for training and classification. The CNN automatically extracts important visual features such as edges, shapes, textures, and logo patterns through multiple convolution and pooling layers, eliminating the need for manual feature engineering. During training, the model continuously updates its weights to minimize classification errors and improve prediction performance. Once training is completed, the CNN model is evaluated using the testing dataset. Various performance measures, including accuracy, precision, recall, F1-score, and the confusion matrix, are calculated to evaluate the effectiveness of the proposed model. The system also generates training accuracy and loss graphs to visualize the learning behavior of the CNN throughout the training process. Finally, the trained model is used to classify newly uploaded logo images as either genuine or fake with high prediction accuracy.

The system architecture illustrates the complete workflow of the proposed fake logo detection system. It consists of logo dataset uploading, image preprocessing, CNN model training, performance evaluation, training graph generation, and logo classification. After successful model training, users can upload any logo image through the graphical user interface, and the trained CNN model predicts whether the uploaded logo is Original or Fake. The system also displays evaluation metrics, confusion matrix, prediction results, and training graphs to analyze the overall classification performance.



Figure 1. System Architecture for Fake Logo Detection Using Convolutional Neural Network (CNN)

The proposed methodology is designed to provide an efficient and automated solution for counterfeit logo detection using deep learning techniques. Initially, the logo image dataset containing original and fake logos is uploaded into the application. Since the collected images may vary in size, resolution, and quality, preprocessing is performed to resize the images, normalize pixel values, and shuffle the dataset before training. The processed dataset is then divided into training and testing sets using an 80:20 ratio, ensuring reliable model evaluation on unseen data.

After preprocessing, the training images are provided to the proposed CNN model, which automatically learns discriminative visual features from the logo images. Unlike traditional image recognition techniques that depend on manually designed features, CNN extracts meaningful representations directly from the training data through deep convolutional layers. Once the training process is completed, the model is tested using the remaining testing images to evaluate its performance. Finally, the trained CNN model classifies new logo images as Original or Fake. The overall performance is analyzed using accuracy, precision, recall, F1-score, confusion matrix, and training accuracy-loss graphs, demonstrating the effectiveness of the proposed deep learning approach for counterfeit logo detection.

V. RESULT AND DISCUSSION

The experimental results demonstrate the effectiveness of the proposed Convolutional Neural Network (CNN) model for automated fake logo detection. Initially, the logo image dataset containing Original and Fake logo images was uploaded into the system. The dataset was then preprocessed by resizing all images to 64×64 pixels, normalizing pixel values, and randomly shuffling the samples to improve the learning capability of the CNN model. After preprocessing, the dataset was divided into 80% training images (248 images) and 20% testing images (62 images) to ensure reliable model evaluation. The CNN model was then trained using the prepared dataset to automatically learn distinguishing visual features from logo images. During training, the network extracted important characteristics such as edges, textures, shapes, and structural patterns, enabling accurate differentiation between genuine and

counterfeit logos. Experimental results show that the trained CNN model achieved an accuracy of 94.84%, precision of 95.21%, recall of 94.84%, and F1-score of 94.83%, demonstrating excellent classification performance for fake logo detection.

The confusion matrix generated by the CNN classifier further validates the effectiveness of the proposed model. Most logo images were classified correctly, while only a small number of images were misclassified, indicating that the CNN successfully learned the discriminative visual features required for logo authentication. The system also generated a CNN Training Accuracy and Loss Graph, where the accuracy continuously increased while the loss gradually decreased with each training epoch. This learning behavior confirms that the proposed CNN model converged successfully without significant overfitting. Finally, the trained model was tested using unseen logo images through the Logo Classification module. The prediction module accurately classified uploaded test images as either Original or Fake, providing instant prediction results through the graphical user interface. Overall, the obtained results demonstrate that the proposed CNN-based framework provides a reliable, accurate, and automated solution for counterfeit logo detection, making it suitable for real-world brand authentication applications.



Figure [2] Confusion Matrix of the Proposed CNN Classifier

Figure 2 presents the confusion matrix generated by the proposed CNN classifier after evaluating the testing dataset. The confusion matrix compares the actual logo classes with the predicted classes, where the vertical axis represents the True Class and the horizontal axis represents the Predicted Class. Most logo images were correctly classified as either Original or Fake, while only a few samples were incorrectly predicted. The low number of misclassified images demonstrates that the CNN model successfully learned the distinguishing visual characteristics of genuine and counterfeit logos, resulting in high classification reliability.

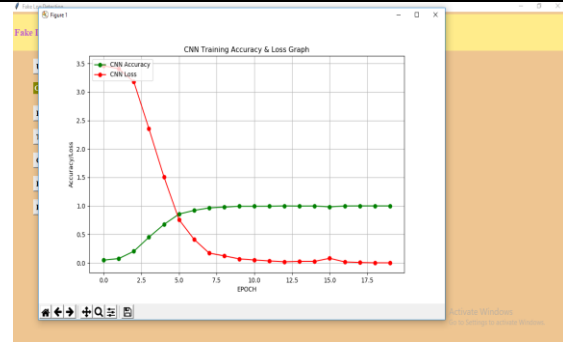
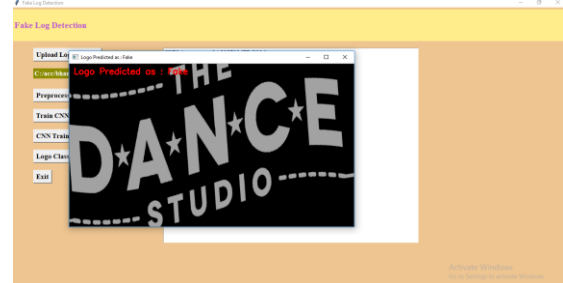
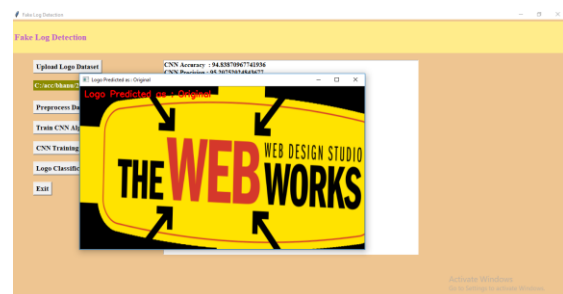


Figure 3: CNN Training Accuracy and Loss Graph

Figure 3 illustrates the training performance of the proposed CNN model over multiple training epochs. The green curve represents the training accuracy, while the red curve represents the training loss. It can be observed that the training accuracy steadily increases with each epoch and approaches nearly 100%, whereas the training loss decreases continuously toward zero. This behavior indicates that the CNN model effectively learned meaningful visual features from the training images and achieved stable convergence during the learning process. The graph confirms that the proposed deep learning model provides robust learning performance for fake logo detection.



4(a)



4(b)

Figure 4: Logo Classification Results

Figure 4 demonstrates the prediction capability of the trained CNN model using unseen logo images.

After selecting a test logo image through the graphical interface, the trained model automatically analyzes the image and classifies it as either Fake or Original. Figure 4(a) shows an example where the uploaded logo image is correctly identified as Fake, while Figure 4(b) presents another test image successfully classified as Original. These prediction results confirm that the proposed CNN model generalizes well to previously unseen logo images and provides accurate real-time counterfeit logo detection.

Model	Accuracy score	Precision score	Recall score	f-measure score
CNN	94.84	95.21	94.84	94.83

Table 1: Model Performance Metrics

DISCUSSION

The experimental findings demonstrate that the proposed Convolutional Neural Network (CNN) provides an effective solution for automated fake logo detection. The preprocessing stage, including image resizing, normalization, and random shuffling, improved the quality of the training dataset and enabled the CNN model to learn discriminative visual features effectively. The generated confusion matrix indicates that only a small number of logo images were incorrectly classified, confirming the robustness of the trained model. Furthermore, the CNN Training Accuracy and Loss Graph shows continuous improvement in model accuracy and a gradual reduction in loss throughout the training process, demonstrating successful model convergence. The Logo Classification module accurately predicted unseen logo images as Original or Fake, validating the model's ability to generalize beyond the training dataset. The achieved performance metrics, including 94.84% accuracy, 95.21% precision, 94.84% recall, and 94.83% F1-score, further confirm the reliability of the proposed approach. Overall, the developed CNN-based fake logo detection system provides a fast, accurate, and automated solution for identifying counterfeit logos and can assist organizations in protecting brand identity and reducing the circulation of fake products.

VI. CONCLUSION

This project presented an automated fake logo detection system using a Convolutional Neural Network (CNN) to distinguish between original and counterfeit logo images. The proposed approach involved preprocessing the logo dataset through image resizing, normalization, and dataset shuffling before training the CNN model. The trained network automatically learned important visual features such as edges, shapes, textures, and structural patterns, eliminating the need for manual feature extraction. Experimental results demonstrated that the proposed model achieved high classification performance with an accuracy of 94.84%, effectively identifying both original and fake logos. The confusion matrix and training graphs further confirmed the robustness and stability of the model during the learning process. The developed graphical user interface enables users to upload logo images and obtain instant authenticity predictions, making the system easy to use. Overall, the proposed CNN-based framework provides a reliable, efficient, and automated solution for counterfeit logo detection. The system can assist organizations in protecting brand identity, reducing the circulation of counterfeit products, and improving consumer trust. Future work may focus on expanding the dataset with additional brand logos, incorporating more advanced deep learning architectures such as ResNet or EfficientNet, and developing a real-time mobile or web-based logo authentication system for practical industrial applications.

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