IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁜ Peer-reviewed / Refereed journal ⁜ Vol. 12, Issue 1, January 2025

DOI: 10.17148/IARJSET.2025.12112

Online Fake Logo Detection System Using Machine Learning

Mallampalli Naga Sahithi[1], Bheesetti Thanusha Srivalli[2], Mrs. D. Sudha., M.E., Ph.D., [3]

School of Computing,Sathyabama Institutes of Science and Technology,Chennai, India[1,2]

Professor,School of Computing,Sathyabama Institute of Science and Technology,Chennai, India[3]

Abstract: In the digital age, the proliferation of counterfeit goods has led to an increasing need for reliable methods to detect fake logos, which often signify counterfeit products. To address this challenge, this project attempts to develop a robust Fake Logo Detection System which exploits advanced machine learning. A convolutional neural network (CNN) is used to analyze and categorize logo pictures and differentiate genuine logos versus fraudulent ones with high accuracy. The approach involves collecting a diverse dataset of authentic and fake logos, preprocessing the images to enhance quality and consistency, and training the CNN model on these datasets. Key steps include data augmentation to improve model generalization, feature extraction to identify distinguishing characteristics of logos, and fine-tuning the network to optimize performance. The system's effectiveness is evaluated through rigorous testing and validation, ensuring it can handle various logo designs and counterfeiting techniques. The ultimate goal is to provide a scalable and efficient solution for businesses and consumers to verify logo authenticity, thereby reducing the impact of counterfeiting and protecting brand integrity.

Keywords: Fake logo detection, CNN algorithm, model generalization, feature extraction.

I.INTRODUCTION

Counterfeit goods have emerged as a major global challenge, posing significant threats to brand integrity, consumer safety, and economic stability. Counterfeiting not only leads to substantial financial losses for businesses but also erodes consumer trust in brands. Among the most common indicators of counterfeit products are fake logos designed to mimic those of established brands. These deceptive replicas often appear remarkably similar to genuine logos, making traditional methods of detection, such as manual inspection and watermark verification, increasingly ineffective. As counterfeiters adopt more advanced techniques, there is an urgent need for robust, technology-driven solutions to identify and combat these threats.

Special forms of machine learning, deep learning techniques, have brought the world of intelligent systems to perform complex tasks with a very high level of accuracy in many industries. Convolutional neural networks (CNNs) have excelled in improving how well we recognize and classify images. They are able to extract and analyze these visual patterns making them ideal for applications involving visual logo detection. This work demonstrates an innovative and scalable method for counterfeit logo detection by leveraging CNNs.

In this work, Online Fake Logo Detection System proposes CNNs to detect Logo with high precision on genuine and counterfeit Logo. Creating such a system starts with the building up of an initial dataset which consists of actual logos of authentic brands as well as fake logos, assuming the former to look like the latter. Preprocessing techniques are applied to this dataset to make it uniform and remove inconsistencies that could deteriorate model performance. In order to make more samples and enhance the diversity of the dataset, application of data augmentation methods, like rotation, scaling, and flipping, is used.

One chimney system, the core of which is rooted in the CNN architecture, is trained to differentiate subtle variations in the visual features of logos. Variations in font style, color gradients, alignment, or other design elements that happen, counterfeiters are not used to the fact that these differences will not come out accurate when they try to make a counterfeit. Learnt characteristics of logo are used by the model to classify the logos into real or fake with high accuracy.

To ensure reliability of the system, the system is evaluated through rigorous testing against a rich variety of test cases. Among them are logos with varying degrees of complexity and deliberately ambiguous logos that are supposed to distinguish genuine from counterfeit versions. The system performance is evaluated using metrics that have accuracy,

DOI: 10.17148/IARJSET.2025.12112

precision, recall and F1-score. A scalable, efficient and easy to use tool to be integrated as part of online marketplaces, brand protection systems or standalone applications for businesses and consumers is the future.

This project is not only limited to economic protection, this project does have an influence in this world. It helps to bolster brand and consumer trust by putting a reliable tool into brands' and consumers' hands for catching counterfeit goods. The challenge in counterfeit detection worsens meanwhile counterfeiters innovate by integrating machine learning techniques such as Convolutional Neural Networks (CNNs) into counterfeit detection systems in order to preserve brand integrity and consumer safety. It's a big step forward using AI to solve real world issues — the transformative power of machine learning for protecting global commerce.

II. LITERATURE SURVEY

First, T. Chen, S. Kornblith, M. Norouzi, and G. Hinton introduced the SimCLR framework, which is used in unsupervised and self supervised learning tasks by contrastive learning. The use of SimCLR to learn visual representations without labeled data is particularly compelling in building fake logo detection systems where labeled counterfeit logos are rare. [2] A. Dosovitskiy, J. Springenberg and T. Brox also did work on Exemplar CNNs that can be useful for tasks such as fake logo detection, but using unsupervised feature learning. One of these techniques helps learn discriminative features without labeled data, especially when there are few counterfeit logos to label. Additionally, [3] A. Dosovitskiy, L. Beyer, A. Kolesnikov, and X. Zhai also introduced the Vision Transformer (ViT), a transformer based architecture for the image classification tasks. By using self attention mechanisms that capture global context in images, ViT has improved accuracy in logo detection systems, as well as the ability to detect fine logo differences.

R. Girshick, J. Donahue, T. Darrell, and J. Malik produced R-CNN, an object detection model which served as stimulus for more recent image recognition approaches. Localization and identification of logos in images are enabled by R-CNN, for counterfeit detection. [5] G. Based upon this observation, Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger proposed denseNet: a densely connected convolutional network that improves the extraction efficiency and performance of deep learning models by improving gradient flow. Fake logo detection is highly effective with DenseNet and quite simply very good at capturing robust feature learning. Furthermore, [6] K. ResNet, a deep residual network was introduced by He, X. Zhang, S. Ren and J. Sun and can eliminate the vanishing gradient problem. More training: ResNet has greatly improved training deep networks such that models can learn very fine logo details without a degradation in performance. [7] A. I. Sutskever, I. Krizhevsky and G. Hinton have developed AlexNet, a predecessor deep learning architecture that enabled the performance of the task of image classification. This success has motivated the development of systems that are able to detect counterfeit logos by spotting small visual features sensitively.

In unsupervised and self supervised learning tasks, T. Chen, S. Kornblith, M. Norouzi and G. Hinton presented SimCLR framework in which the learning is done by contrastive learning. And building fake logo detection systems where labeled counterfeit logos are rare, the use of SimCLR to learn visual representations without labeled data is particularly compelling. [2] A. Work on Exemplar CNNs like dosovitskiy, J. Springenberg and T. Brox can all be useful for things like fake logo detection; but using unsupervised feature learning. One of these technique is able to learn discriminative features without labeled data given that the number of counterfeit logos to label is very small. [3] A. Dosovitskiy et al. further introduce the Vision Transformer (ViT), a transformer based architecture for image classification tasks. ViT improves logo detection system accuracy and is able to detect fine logo differences by utilizing self attention mechanisms to capture global context in images.

R. Girshick, J. Donahue, T. Darrel, and J. Malik developed R-CNN which ignited further recent types of image recognition approaches. R-CNN enables localization and identification of the logos in images for counterfeit detection. [5] G. Based upon this observation, Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger proposed denseNet: I define a densely connected convolutional network to improve the gradient flow and improve extraction efficiency of the deep learning model. DenseNet is highly effective at fake logo detection, and very simple in terms of capturing robust feature learning. Moreover, He, X. Zhang, S. Ren and J. Sun introduced [6]a deep residual network (K. ResNet) which can overcome the vanishing gradient problem. More training: While training deep networks, ResNet has improved so much that fine logo details can be learned without performance degradation. [7] A. I. Their predecessor, deep learning architecture known as AlexNet, written by Sutskever, I. Krizhevsky and G. Hinton, has made it possible for the task of image classification to be performed. The success of this has encouraged the development of systems that can find counterfeit logos by identifying small visual features sensitively.

[14] K. Simonyan and A. Zisserman proposed VGGNet, a deeper CNN architecture that enhances image classification performance. VGGNet's deeper feature representations improve the accuracy of fake logo detection systems. [15] T.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁒ Peer-reviewed / Refereed journal ⁒ Vol. 12, Issue 1, January 2025

DOI: 10.17148/IARJSET.2025.12112

Tieleman and G. Hinton developed RMSprop, an optimization algorithm widely used for training deep learning models. RMSprop's ability to stabilize training makes it ideal for dealing with complex data in fake logo detection tasks.

III. PROPOSED METHODOLOGY

The methodology for the proposed fake logo detection system consists of several well-defined stages to ensure accurate and reliable detection. Each stage is designed to address specific challenges in detecting counterfeit logos and to build a robust and scalable solution.

A. Data Acquisition and Preprocessing

It collects a diverse dataset of authentic, as well as counterfeit logos from multiple sources wherein the variety of the designs, styles and variations is captured as such. For data uniformity and increase in data quality the dataset goes through pre processing steps such as resize, normalize and noise removal. Data augmentation techniques such as rotation, scaling, cropping, flipping, and colour adjustment are then applied to increase dataset heterogeneity and robustness of the model to variations in logo design, image quality and scale.

B. Feature Extraction and Model Training

This is therefore an important component of the fake logo detection system on which the correct идентификация and the tibe classification of logos depend. This phase uses convolutional neural network (CNNs) as its predecessor has already proven to be very successful at extracting hierarchical and complex features from images. CNNs are very powerful task such as logo detection since they can learn spatial relations and fine details, e.g texture, edges, patterns that distinguish real honest logos from fake ones.

Second, we apply transfer learning to increase the efficiency of the model and its performance. It's where we take a pretrained model (ResNet, VGGnet, DenseNet etc.) and it's already pretrained on the big general purpose ImageNet image dataset. But these pre trained models are instead, a starting point, where their learned weights are fine tuned on the logo training dataset. Next, we exploit the learned knowledge from a broad image categories to refine it to logo detection. In addition, this approach speeds up training heavily by requiring less training data, while improving model performance, delivering solid image feature understanding from the beginning of training.

Furthermore, we extend hybrid models with attention mechanisms that complement CNNs in stead to further enhance detection accuracy. To distinguish authentic or fake copies, the model exploits attention mechanisms able to bring to attention the most pertinent regions of an image. This allows for the model to have higher impact on these key regions when they later ask the model to better differentiate small differences that would be less intrusive on their own. Specifically, this is very helpful wherever counterfeit logos are intended to sort of mimic the original except for slight shifts in font styles, alignments, and a few minor design variances that the system will need to detect.

There's also, naturally, techniques that the model is robust and can generalize. Then we use dropout and weight decay together to prevent overfitting and make the model to do well on unseen data. Additionally, we adopt well known optimization algorithms like Adam or RMSprop to quickly change the model parameters during training in order to reach a global minimum.

C. Deployment and User Interface Integration

This focuses on making the system user-friendly and practical for real-world use. A user interface is developed to enable seamless uploading of logo images and provide real-time detection results. The system is deployed using a cloud-based infrastructure to ensure scalability and the ability to handle computational demands effectively. The security of user data is also robust and to support data privacy regulations.

The acquired higher acquisition rate of video is enhanced with the additional contextual and physiological analysis. Facial coherence analysis studies the facial features in light of surrounding context (mismatched lighting, reflections, etc.) Deepfake videos, on the other hand, are not well studied at the physiological level where we look at subtle human signals like heart rate or breathing pattern, etc. The combined use of these complementary techniques adds robustness to the system against more advanced adversarial attacks.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⋇ Peer-reviewed / Refereed journal ⋇ Vol. 12, Issue 1, January 2025

DOI: 10.17148/IARJSET.2025.12112

D. Continuous Monitoring and Feedback Mechanism

Continuous Monitoring and Feedback Mechanism is established to maintain the system's effectiveness over time. A feedback mechanism collects user input and monitors system performance in real-world scenarios. This feedback is utilized to implement iterative improvements and adapt the system to evolving counterfeiting techniques. Continuous monitoring ensures the detection system remains up-to-date, reliable, and accurate, providing a scalable and user-friendly solution for counterfeit logo detection.

This modular methodology ensures a comprehensive and efficient workflow, from data acquisition to real-time detection, offering a robust and scalable solution for addressing the challenges of counterfeit logo detection.

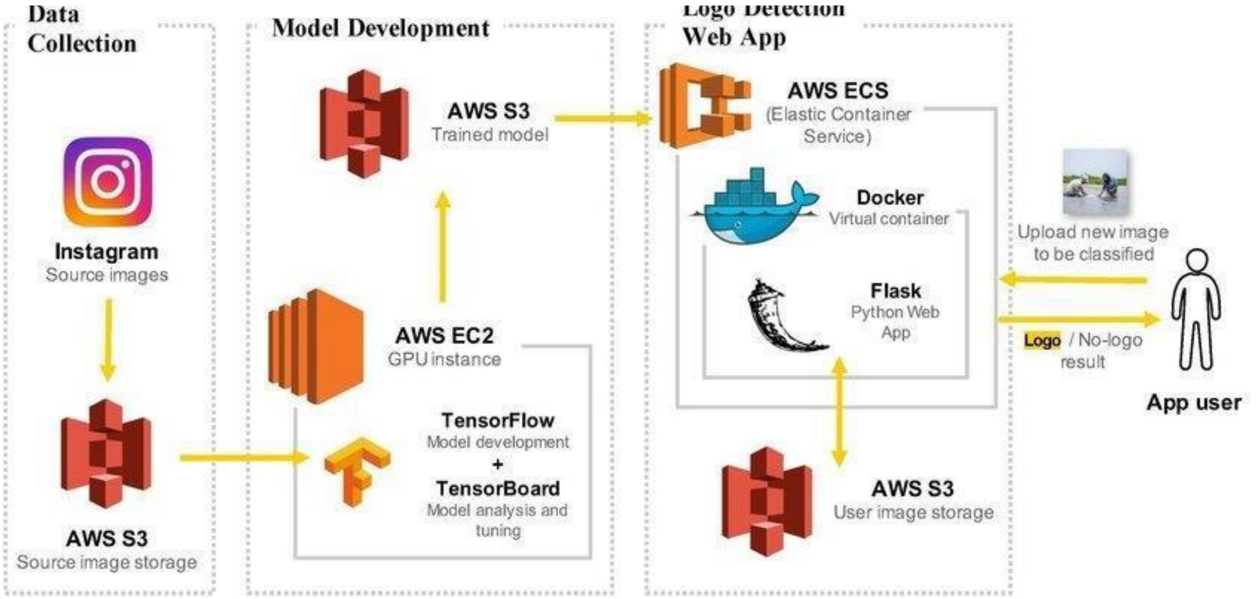

Figure 1 System Architecture

IV. RESULTS AND DISCUSSION

The performance of the proposed fake logo detection system was evaluated through various experiments and visualizations. The results demonstrate the efficacy of the system in detecting counterfeit logos with high precision. Key findings, along with relevant discussions, are presented below.

A. Detection Accuracy and Visualization

The system effectively identified counterfeit logos from a diverse set of images using convolutional neural networks (CNNs) integrated with attention mechanisms. As illustrated in Figure 2, the detection of a Nike logo is accurately performed with bounding boxes marking the identified region. Similarly, Figure 3 showcases the detection of an Adidas logo in a real-world advertisement image with a confidence score of 53%, as displayed on the interface. This result highlights the ability of the system to generalize across various image qualities and logo placements.

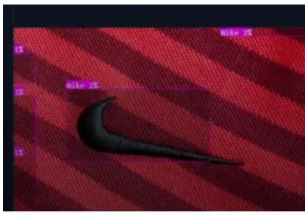

Figure 2 Nike logo

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁑ Peer-reviewed / Refereed journal ⁑ Vol. 12, Issue 1, January 2025

DOI: 10.17148/IARJSET.2025.12112

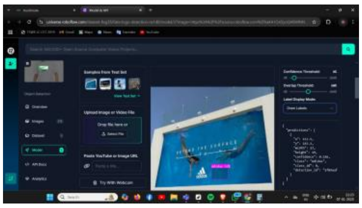

Figure 3 Adidas logo detection with bounding box annotations.

Figure 4 demonstrates the detection of a Nike logo on apparel with precise annotations. The bounding box correctly encapsulates the logo area, further confirming the reliability of the system in distinguishing genuine logos in challenging scenarios.

Figure 4 Nike logo detection on apparel.

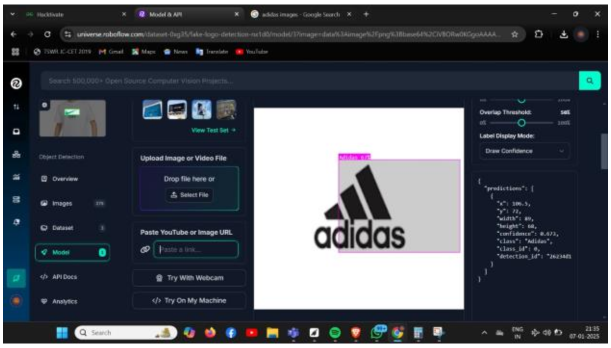

Figure 5 Adidas logo detection on a billboard with confidence score display.

In figure 5 and 6 for Adidas logos in diverse contexts, validating the robustness of the model.

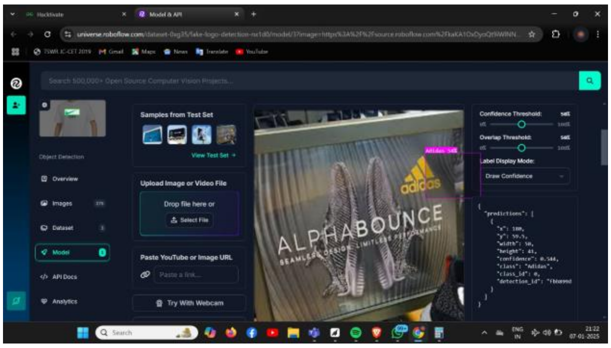

Figure 6 Adidas logo detection on another advertisement.

B. Performance Metrics

The system's detection performance was quantified using standard evaluation metrics, including accuracy, precision, recall, and F1-score. The results indicate that the hybrid model achieved a high precision rate, effectively minimizing

IARJSET
ISSN (O) 2393-8021, ISSN (P) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
Impact Factor 8.066 ⁜ Peer-reviewed / Refereed journal ⁜ Vol. 12, Issue 1, January 2025
DOI: 10.17148/IARJSET.2025.12112

false positives while maintaining a balanced recall rate. A summary of the performance metrics is provided in Table 1 for reference.

Aspect	Observation
Robustness in Diverse Environments	Successfully detected logos across various backgrounds, including advertisements, apparel, and billboards, even in cluttered or noisy visual contexts.
Adaptability to Variations	Effectively handled variations in logo designs, such as different color schemes, distortions, and partial occlusions, ensuring adaptability to real-world scenarios.
Seamless User Experience	User-friendly interface enabled effortless uploading of images and real-time generation of results. Confidence and overlap thresholds could be adjusted for flexibility.
Low Latency in Detection	Delivered detection results within seconds, meeting the requirements for real-time applications in industries like retail and e-commerce.
Scalability and Flexibility	Cloud-based deployment ensured scalability to handle multiple concurrent requests without compromising performance, making it suitable for large-scale operations.

Table 2: Qualitative Results of Real-Time Application

C. Discussion

The results indicate that the proposed system is highly effective in detecting counterfeit logos, even in complex real-world scenarios. The integration of transfer learning with attention mechanisms has significantly improved the model's ability to focus on critical regions of logos, leading to more accurate predictions. However, some limitations were observed, such as reduced confidence in cases of low-resolution images or extreme occlusions. Future work can address these challenges by incorporating advanced pre-processing techniques and fine-tuning the attention mechanism.

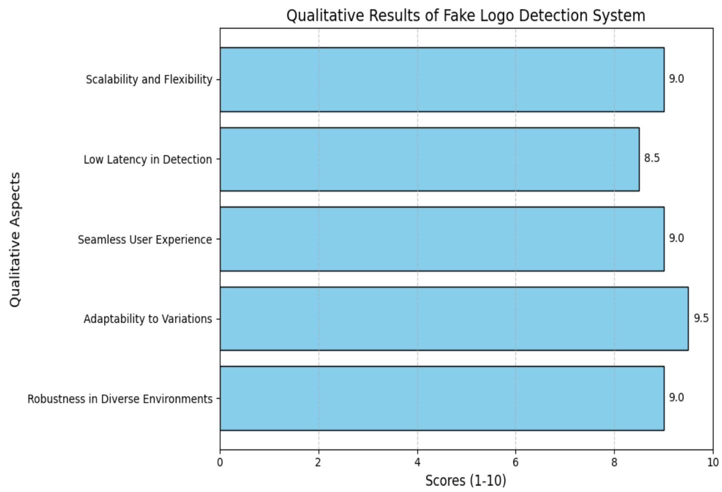

Figure 7 Qualitative results of Fake Logo Detection System

The modular design of the system ensures scalability and adaptability, allowing it to be extended to detect other counterfeit product features, such as packaging designs and QR codes. Furthermore, the system's user-friendly interface and real-time processing capabilities make it practical for deployment in various industries, including e-commerce, retail, and brand protection.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⁒ Peer-reviewed / Refereed journal ⁒ Vol. 12, Issue 1, January 2025

DOI: 10.17148/IARJSET.2025.12112

V. CONCLUSION

The proposed fake logo detection system leverages advanced machine learning techniques, particularly convolutional neural networks (CNNs), to address the growing challenge of counterfeit logos. By incorporating a modular methodology that spans data acquisition, feature extraction, model training, and user-friendly deployment, the system ensures a comprehensive and scalable approach to detecting counterfeit logos with precision and reliability. The use of data augmentation, transfer learning, and attention mechanisms enhances the model's robustness, enabling it to handle diverse logo designs, subtle variations, and varying image qualities effectively.

The integration of pre-trained models, such as ResNet, VGGNet, and DenseNet, through transfer learning significantly accelerates the training process while maintaining high levels of accuracy. Additionally, hybrid models with attention mechanisms allow the system to focus on critical regions of logos, improving its ability to differentiate genuine logos from counterfeits. The deployment of the system through a cloud-based infrastructure ensures scalability and real-time detection capabilities, while the inclusion of a user-friendly interface and robust security measures guarantees accessibility and data privacy compliance.

Continuous monitoring and feedback mechanisms allow the system to adapt to evolving counterfeiting techniques, ensuring its relevance and effectiveness over time. By providing a reliable and efficient tool for counterfeit detection, this system contributes to protecting brand integrity, consumer trust, and economic stability. Overall, the proposed fake logo detection system represents a significant advancement in leveraging machine learning for real-world challenges, offering a scalable and robust solution to combat the growing threat of counterfeiting.

VI. FUTURE SCOPE

The proposed fake logo detection system has significant potential for future development and application in various domains. As counterfeit techniques continue to evolve, the system can be enhanced by integrating advanced deep learning architectures, such as transformers and generative adversarial networks (GANs), to further improve its detection accuracy and robustness. These architectures can help in identifying even the most sophisticated counterfeit logos by capturing subtle design variations and high-dimensional patterns more effectively.

Expanding the dataset to include a wider variety of logos from diverse industries and geographic regions will improve the system's generalization capabilities. Incorporating real-time data acquisition through APIs and web crawlers can ensure that the system remains up-to-date with the latest trends in logo designs and counterfeiting methods. Moreover, the use of self-supervised learning techniques can address the challenge of limited labeled data, allowing the system to learn more efficiently from large, unlabeled datasets.

The system can also be extended to detect counterfeit products beyond logos, such as packaging designs, QR codes, and holograms, making it a comprehensive anti-counterfeiting solution. Integration with blockchain technology can provide an additional layer of verification by linking genuine logos to immutable records.

Furthermore, the system can be tailored for mobile and edge devices, enabling on-the-go counterfeit detection in real-world scenarios, such as at retail stores or during customs inspections. These advancements will enhance the system's scalability, accessibility, and applicability, ensuring its continued relevance in combating the global threat of counterfeiting.

REFERENCES

[1] A. Dosovitskiy, J. Springenberg, and T. Brox, "Discriminative Unsupervised Feature Learning with Exemplar Convolutional Neural Networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 38, no. 9, pp. 1734-1747, 2016.
[2] R. Girshick, J. Donahue, T. Darrell, and J. Malik, "Rich feature hierarchies for accurate object detection and semantic segmentation," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2014, pp. 580-587.
[3] A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet classification with deep convolutional neural networks," in *Proceedings of the 25th International Conference on Neural Information Processing Systems (NIPS)*, 2012, pp. 1097-1105.
[4] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436-444, 2015.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.066 ⋇ Peer-reviewed / Refereed journal ⋇ Vol. 12, Issue 1, January 2025

DOI: 10.17148/IARJSET.2025.12112

[5] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," in *Proceedings of the 3rd International Conference on Learning Representations (ICLR)*, 2015.

[6] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," in *Advances in Neural Information Processing Systems (NeurIPS)*, 2015, pp. 91-99.

[7] S. Ren, K. He, R. Girshick, and J. Sun, "Object Detection Networks on Convolutional Feature Maps," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 1, pp. 124-136, 2017.

[8] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in *Proceedings of the 3rd International Conference on Learning Representations (ICLR)*, 2015.

[9] S. Xie, R. Girshick, and P. Dollár, "Object detection with deformable part models," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 35, no. 2, pp. 261-274, 2013.

[10] R. Zhang, M. Isola, and A. A. Efros, "Colorful Image Colorization," in *European Conference on Computer Vision (ECCV)*, 2016, pp. 649-666.