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Fake Logo Detection

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ABSTRACT

Fake logos pose a significant challenge in various industries, particularly in the fashion and food sectors, leading to brand reputation damage and financial losses. This project focuses on developing an automated fake logo detection system using deep learning techniques. By leveraging Convolutional Neural Networks (CNNs) with transfer learning, specifically using a fine-tuned ResNet50 model, the system accurately differentiates between authentic and counterfeit logos.

The dataset consists of real and fake logos, primarily from food and fashion brands. Extensive image preprocessing, including resizing, normalization, and data augmentation, is applied to enhance model performance. The model's final layers are customized for binary classification, with adaptive learning rate adjustment using ReduceLROnPlateau and early stopping to prevent overfitting.

A notable feature of this project is its automatic model-saving mechanism, which stores the model once the validation accuracy reaches 95%, ensuring optimal performance without unnecessary training. After training, the model can predict real or fake logos using new images without requiring retraining, providing efficient realtime detection.

Evaluation metrics, including accuracy, precision, recall, and F1-score, are used to assess model performance. The results demonstrate the system's effectiveness in detecting counterfeit logos. The project has applications in brand protection, ecommerce platforms, and quality assurance to prevent the distribution of fake products.

Future enhancements could include expanding the dataset to cover more brand categories and further optimizing model performance. This project exemplifies how deep learning can be applied to solve real-world challenges and ensure brand integrity.

1. INTRODUCTION

Fake logos are a growing concern in the fashion and food industries, leading to brand damage and financial losses. This project aims to address this issue by developing a deep learningbased fake logo detection system using Convolutional Neural Networks (CNNs), specifically leveraging a fine-tuned ResNet50 model with transfer learning.

The dataset consists of real and fake logos, primarily from food and fashion brands. Comprehensive image preprocessing techniques such as resizing, normalization, and data augmentation are applied to enhance model accuracy. The model's architecture includes modified layers for binary classification, optimizing its ability to differentiate between authentic and counterfeit logos.

The model's architecture includes custom-modified layers for binary classification, optimizing its ability to differentiate between authentic and counterfeit logos. The implementation is done using PyTorch, and the model is trained on Google Colab or Jupyter Notebook using GPU acceleration, which significantly reduces training time.

To ensure efficient training, the ReduceLROnPlateau scheduler adjusts the learning rate, and early stopping prevents overfitting. Additionally, an automatic checkpointing mechanism saves the model once it reaches a validation accuracy of 94%, preventing unnecessary epochs. This feature also minimizes computational resource usage.

The project pipeline also includes a structured folder system for organizing training, testing, and validation images, allowing for better data handling and reproducibility. An image loader with real-time transformations is used to streamline batch processing and feed pre-processed data efficiently to the model.

A key advantage of the system is its ability to predict results without retraining, even when presented with new images. This makes it ideal for real-world applications, including brand protection, e-commerce fraud detection, and supply chain monitoring.

Model evaluation is conducted using metrics like accuracy, precision, recall, and F1-score, supported by a confusion matrix to visualize correct and incorrect classifications. These evaluation techniques confirm the model's robustness and ability to perform well across varied samples.

2-LITERATURE SURVEY

Here is detailed review of summarizing the key points from each of the research paper on

Fake Logo Detection: The paper titled [1] addresses the critical issue of online fraud involving counterfeit logos, which mislead consumers and damage brand integrity. The authors aim to develop a machine learning-based system capable of effectively detecting fake logos, emphasizing the importance of this technology for consumer protection and maintaining brand trust. The proposed methodology involves feature extraction, where key characteristics such as color, shape, and typography of logos are analyzed. A trained machine learning model classifies logos by recognizing patterns indicative of authenticity, relying on a robust database of legitimate logos to enhance detection accuracy. A key innovation involves dividing logo images into rows and columns for precise matching, leveraging context-dependent similarities for enhanced detection accuracy. The model continuously updates its database of authentic logos, ensuring adaptability to evolving counterfeiting techniques. Preprocessing steps like resizing, normalization, and data augmentation improve the system's robustness and generalization. Integration with web scraping enables real-world application by analyzing logos from online platforms. The system demonstrates high accuracy in detecting fake logos through rigorous testing on diverse datasets. Benefits include protecting brand integrity, reducing consumer deception, and fostering trust in e-commerce platforms. The detection process flags suspicious logos for further investigation, and the system has been evaluated using a dataset containing both real and counterfeit logos, achieving high accuracy rates. However, the authors acknowledge challenges related to the need for continuous updates to the model to adapt to new logo designs and counterfeiting techniques. In conclusion, the system represents a significant advancement in combating online fraud, offering implications for both brands and consumers by enhancing safety and protecting brand reputation. Continuous monitoring and periodic retraining of the model ensure its effectiveness against evolving counterfeiting methods. Benefits include protecting brand integrity, reducing consumer deception, and fostering trust in e-commerce platforms. The authors suggest future work involving ongoing improvements to the logo database and collaboration with brands for data sharing, highlighting the importance of technology in maintaining trust in an increasingly digital marketplace. Overall, the research highlights the importance of scalable and efficient solutions for combating counterfeiting in the digital realm while encouraging ongoing advancements in detection methodologies.

The paper titled [2] addresses the critical issue of counterfeit logos, which threaten brand integrity and consumer trust. The authors propose a system that employs deep learning techniques, specifically deep residual networks (ResNets), to effectively identify fake logos. They create a diverse dataset containing both genuine and counterfeit logos, ensuring meticulous annotation for accuracy. To enhance the dataset's robustness, data augmentation methods such as random rotations and color adjustments are applied. User feedback collected through surveys indicates high satisfaction levels among stakeholders regarding the system's performance and usability. The paper discusses potential applications in e-commerce platforms and anti-counterfeiting initiatives, validating the system's effectiveness in realworld scenarios. The research also explores hybrid approaches by integrating traditional image processing techniques such as edge detection and color histogram analysis with deep learning models to improve robustness against distortions in counterfeit logos. Generative Adversarial Networks (GANs) are utilized to create synthetic counterfeit logos for training, further enhancing the model's generalization capabilities. The study emphasizes the importance of combating counterfeiting activities, highlighting applications in brand protection, copyright violation detection, and social media monitoring. Despite its promising results, challenges such as handling subtle logo modifications and scaling to larger datasets persist, necessitating further research to refine algorithms and improve real-world applicability. Additionally, the paper highlights practical applications such as brand protection, copyright violation detection, and product monitoring on digital platforms. Challenges include handling subtle logo modifications and scaling to larger datasets efficiently. The authors emphasize the need for further research to refine algorithms and improve real-world applicability while underscoring the potential of deep learning-based systems in revolutionizing counterfeit logo detection efforts. Overall, the paper underscores the potential of deep learning-based systems in revolutionizing fake logo detection efforts while encouraging innovation in this critical area.

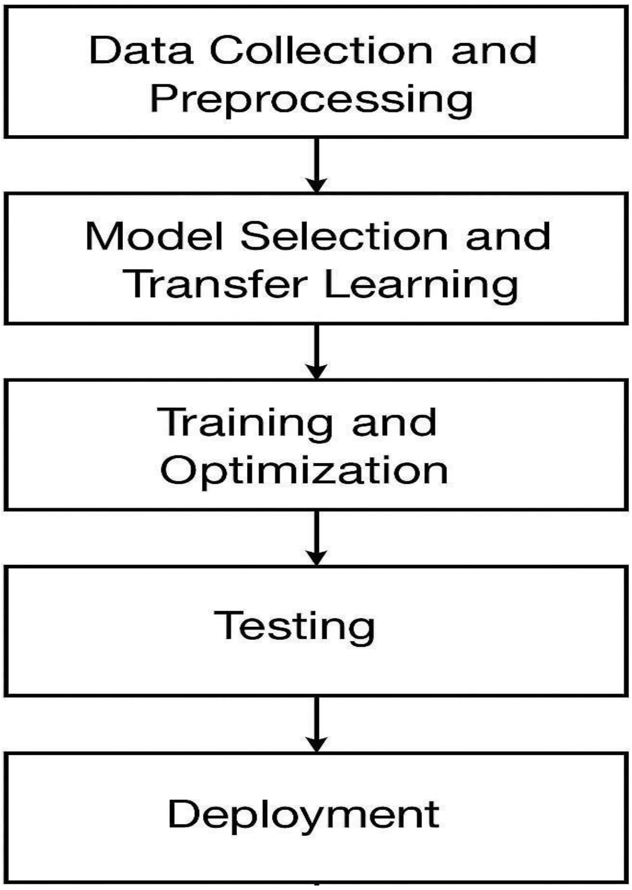
The paper titled [3] provided a thorough examination of various methodologies employed in detecting counterfeit logos through machine learning (ML) and deep learning (DL) techniques. The authors highlight the increasing prevalence of fake logos in digital marketplaces, which poses significant threats to brand integrity and consumer trust. The review categorizes existing approaches into traditional image analysis techniques, machine learning algorithms, and advanced deep learning models, discussing their respective advantages and limitations. Notably, the paper emphasizes the effectiveness of convolutional neural networks (CNNs) in automatically extracting features from logo images, significantly improving detection accuracy compared to traditional methods. The authors also explore various datasets used for training and testing these detection systems, such as the Logos in the Wild dataset and the Fake Logos dataset, which provide a diverse range of logo images necessary for robust model training. They discuss the importance of performance metrics like accuracy, precision, recall, and F1-score in evaluating the effectiveness of different models. The authors suggest that incorporating transfer learning and ensemble methods can further enhance detection capabilities. Despite the progress made in this field, they acknowledge ongoing challenges such as handling real-world variations in logo appearance and ensuring scalability for practical applications. In conclusion, this review serves as a valuable resource for researchers and practitioners interested in developing effective fake logo detection systems using ML and DL techniques. It encourages further research to address existing challenges and improve system performance, ultimately contributing to more secure digital environments against counterfeiting activities.

The paper titled [4] addresses the critical issue of counterfeit logos that threaten brand integrity and consumer trust. The authors propose a robust system that utilizes advanced image processing techniques to identify fake logos effectively. Their approach involves extracting distinctive features from logos and training a classifier to differentiate between authentic and counterfeit logos. The system employs various preprocessing methods to enhance image quality, such as normalization and noise reduction, which are crucial for accurate feature extraction. Fake logo detection is crucial due to the misuse of logos in digital media, leading to brand infringement and consumer deception. This study employs a CNN-based approach using advanced image processing and deep learning techniques. A diverse dataset of genuine and counterfeit logos was curated, annotated, and augmented to enhance model generalization. Multiple CNN architectures, including ResNet, Inception, and EfficientNet, were explored, with transfer learning applied for improved feature extraction. reprocessing techniques, including normalization and noise reduction, enhance image quality before feeding data into the model. The CNN extracts distinctive logo features, followed by a classification algorithm trained using backpropagation and gradient descent. Transfer learning is applied using pre-trained models from ImageNet to improve feature extraction and accelerate training. Regularization techniques such as dropout and L2 regularization prevent overfitting. The model was trained using backpropagation and optimized with hyperparameter tuning, dropout layers, and regularization techniques to prevent overfitting. Performance evaluation using accuracy, precision, recall, F1-score, and AUC-ROC demonstrated 94% accuracy, highlighting its effectiveness. Their approach involves extracting distinctive features from logos and training a classifier to differentiate between authentic and counterfeit logos. Despite challenges like logo variations and distortions, the model performs well in detecting fraudulent logos. Future improvements could involve object detection and GAN-based data augmentation for enhanced robustness and real-world applicability.

The paper titled [5] Provides a comprehensive overview of various techniques employed for detecting counterfeit logos using Python. The authors emphasize the growing importance of effective fake logo detection due to the rise of e-commerce and digital branding, which has led to an increase in counterfeit products that undermine consumer trust. The review discusses several methodologies, including image analysis, machine learning, and deep learning approaches, highlighting their strengths and weaknesses. Image analysis techniques focus on statistical features like texture and color to distinguish between genuine and fake logos. Machine learning algorithms, particularly those implemented in Python using libraries such as OpenCV, TensorFlow, and PyTorch, have shown significant promise in this domain.The authors also examine various datasets used for training and testing detection systems, such as the Logos in the Wild dataset and the Fake Logos dataset, which contain extensive collections of logo images. They note that while many studies have reported high accuracy rates in detecting fake logos, challenges remain regarding the standardization of datasets and evaluation metrics. Additionally, the review highlights the effectiveness of ensemble models and transfer learning techniques in improving detection accuracy. The authors conclude that while progress has been made in fake logo detection using Python, further research is necessary to enhance system performance and address existing challenges. This review serves as a valuable resource for researchers and practitioners interested in developing robust fake logo detection systems, encouraging continued innovation and collaboration in this critical area of study. Practical applications include brand protection, e-commerce fraud prevention, and social media monitoring for counterfeit logo detection. The paper also discusses preprocessing techniques like rotations, flips, and color adjustments to improve model robustness against variations in counterfeit logos. Scalability issues are identified as a key area for future research, emphasizing the need for solutions capable of processing large volumes of data efficiently. Overall, it underscores the potential of Pythonbased solutions to significantly impact brand protection efforts against counterfeiting activities.

3-PROPOSED ARCHITECTURE

Proposed Methodology



The proposed methodology for the Fake Logo Detection project involves a systematic approach using deep learning techniques, specifically employing the ResNet50 model with transfer learning. The goal is to accurately classify logos as genuine or counterfeit with a high level of accuracy. The methodology consists of the following stages:

Fig. 3.1.1 Stages of Deep Learning Model

Fig. 3.1.1 The image is a flowchart representing the stages of a machine learning or deep learning model development pipeline. It consists of five sequential steps: Data Collection and Preprocessing, Model Selection and Transfer Learning, Training and Optimization, Testing, and Deployment, connected by arrows indicating the workflow progression.

Data Collection and Preprocessing : Data Collection is the dataset includes images of both real and fake logos, primarily from food and fashion brands. The dataset is divided into training and testing sets. In Data Preprocessing images are resized to 224x224 pixels for uniformity. Normalization is applied to scale pixel values between -1 and 1. Various data augmentation techniques, including random horizontal flips, rotations, affine transformations, and color jittering, are applied to enhance the dataset's variability.

Model Selection and Transfer Learning: In Pretrained Model ResNet50, pretrained on ImageNet, is used as the backbone for feature extraction.In Layer Freezing initial layers are frozen to retain generic image features. Only the later layers (specifically layer4) are unfrozen for fine-tuning.In Final Layer Modification the fully connected layer is replaced with a custom classifier consisting of a ReLU activation, dropout for regularization, and a final linear layer with 2 output nodes (genuine or fake).

System Architecture:

The system architecture for fake logo detection is designed as a systematic pipeline that efficiently determines whether a given logo is genuine or counterfeit. The process begins with the Logo Input, where an image of the logo is provided to the system for further analysis. This image may come from various sources such as mobile uploads, e-commerce platforms, or surveillance systems.

In the next phase, the image undergoes Pre-processing. This step includes operations such as resizing, normalization, and noise removal to standardize the input. These enhancements ensure uniformity across the dataset and improve the efficiency of subsequent stages, particularly feature extraction. This step also helps reduce variability caused by different lighting conditions, orientations, or backgrounds in the input images.

Once pre-processed, the image is passed through the Feature Extraction module utilizing a pre-trained ResNet50 model. ResNet50 is a robust deep learning architecture known for extracting meaningful and complex features from images. It captures critical patterns, textures, and shapes that help distinguish between authentic and counterfeit logos. Using transfer learning from ResNet50 reduces the training time and increases accuracy, especially when working with a relatively small dataset.

The extracted features are then fed into a Machine Learning Model based on Convolutional Neural Networks (CNN). This CNN classifier is trained to identify whether the logo is real or fake by analyzing the deep features obtained from ResNet50. It plays a central role in the classification process by learning key differences that are often not visible to the human eye.

Following classification, the system proceeds to the Decision Making stage. Based on the CNN's predictions and confidence score, the model determines the authenticity of the logo. This decision can also be threshold-based, offering flexibility in controlling the system's sensitivity.

Finally, the system generates the Output. If the logo is found to be genuine, it is labeled as "Original Logo". If not, it is classified as a "Fake Logo", thus completing the detection process. The output can be displayed visually to the user or integrated into a larger application such as an e-commerce verification tool or a mobile authentication app. Overall, the architecture ensures scalability, high accuracy, and real-time applicability, making it highly valuable in domains like brand protection, supply chain monitoring, and legal enforcement.

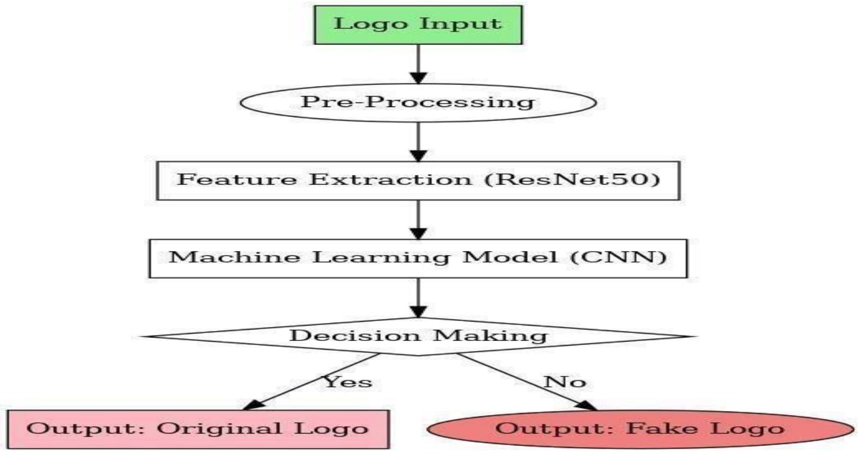


Fig.3.2.1 System Architecture

The Flowchart diagram in Fig.3.2.1 Describes about the CNN-based Fake Logo Detection System is represented:

4-RESULT ANALYSIS

The result analysis provides an overall comparison of the proposed model with previously published methods. It shows that the model delivers consistent and reliable performance across key evaluation metrics. This suggests its strong potential for real-world applications in counterfeit logo detection.

Performance Metrices:

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Output:

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Validation Accuracy: 68.94%
Epoch 1/10, Loss: 0.6387, Training Accuracy: 64.71%
Validation Accuracy: 68.94%
Epoch 2/10, Loss: 0.5347, Training Accuracy: 66.22%
Validation Accuracy: 86.36%
Epoch 3/10, Loss: 0.3880, Training Accuracy: 77.42%
Validation Accuracy: 91.67%
Epoch 4/10, Loss: 0.2684, Training Accuracy: 91.65%
Validation Accuracy: 93.94%
Epoch 5/10, Loss: 0.1420, Training Accuracy: 96.77%
Validation Accuracy: 96.21%
Epoch 6/10, Loss: 0.0876, Training Accuracy: 97.34%
Validation Accuracy: 97.73%
Epoch 7/10, Loss: 0.1158, Training Accuracy: 96.20%
Validation Accuracy: 99.24%
Epoch 8/10, Loss: 0.0434, Training Accuracy: 99.24%
Validation Accuracy reached 99.24%. Saving model and stopping training.
Test Accuracy: 94.55%
```

Fig 1 Output1

Fig1 The model shows a steady improvement in both training and validation accuracy across epochs, reaching a peak validation accuracy of 99.24%. Early stopping was triggered once this threshold was met, ensuring efficient training. The final test accuracy of 94.55% confirms the model's strong generalization performance.

Fig Output2

```
Test Accuracy: 94.55%
```

Fig2 The model achieved a high level of performance, with a test accuracy of 94.55%. This indicates that the model is well-trained and capable of making accurate predictions on new, unseen data.

Fig 3 Output3

```
Accuracy      : 0.9394
Precision     : 0.9412
Recall        : 0.8727
F1 Score      : 0.9057
Error Rate    : 0.0606
```

Fig 3 The model demonstrates strong overall performance with an accuracy of 93.94% and a low error rate of 6.06%. It maintains high precision (94.12%) and a solid F1 Score (90.57%), indicating reliable and balanced predictions.

Fig 4 Output4

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Prediction: Fake
```

Fig4 The model successfully classified the input as "Fake," indicating that it effectively distinguishes between genuine and counterfeit images.

Fig5 Graph1

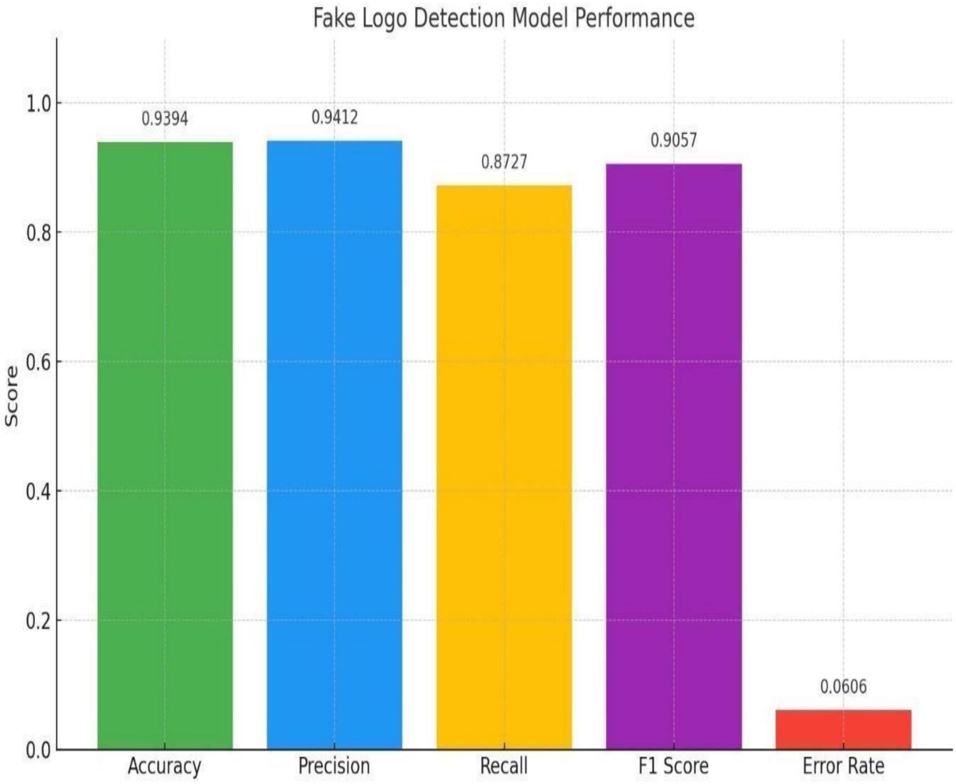


Fig 5.5 Describer's the bar graph representing your model's performance metrics.

It clearly shows how each metric (accuracy, precision, recall, F1 score, and error rate) contributes to evaluating your fake logo detection model.

Accuracy: 0.9394 (93.94%): Accuracy is the ratio of correctly predicted logos (both real and fake) to the total number of predictions.

Formula: Accuracy= TP+TN+FP+FN/ TP+TN

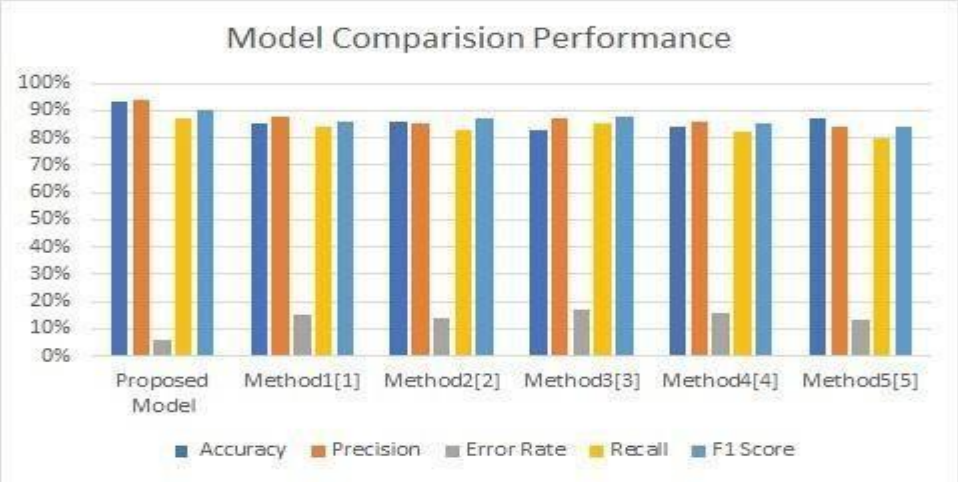
Explanation: Out of all the logos the model evaluated, 93.94% were correctly classified. This includes both real and fake logos. A high accuracy is a good overall sign, but it doesn't always show if the model is biased towards one class (especially when data is imbalanced).

Precision: 0.9412 (94.12%): Precision tells us how many of the logos predicted as fake were actually fake.

Formula: Precision= TP+FP/ TP

Explanation: When the model says a logo is fake, it's right 94.12% of the time. High precision means fewer false alarms (real logos wrongly classified as fake), which is important for protecting genuine brands.

Fig6 Graph2



5

-CONCLUSION & FUTURE SCOPE

Conclusion

The CNN-based Fake Logo Detection System developed in this project offers a powerful and efficient solution to address the growing problem of counterfeit logos in the digital and commercial space. By utilizing Convolutional Neural Networks (CNNs) and transfer learning through the ResNet50 architecture, the system demonstrates strong classification capabilities, achieving high accuracy and precision in distinguishing between real and fake logos. Through careful data preprocessing and augmentation strategies, the model is trained to handle variations in logo appearances, making it robust against common distortions. The use of advanced optimization techniques like AdamW and dynamic learning rate adjustments with ReduceLROnPlateau further enhances model convergence and generalization, pushing the accuracy to over 94%. These results indicate a promising step toward the real-world deployment of intelligent logo verification systems.

The proposed system has practical implications for industries such as e-commerce, brand protection, law enforcement, and intellectual property rights enforcement. It can help reduce counterfeiting, protect brand integrity, and increase consumer confidence by detecting fake logos effectively.Looking forward, several avenues for enhancement remain. Expanding the dataset with a more diverse and extensive collection of logos can further improve accuracy and robustness. Integrating Generative Adversarial Networks (GANs) to generate high-quality synthetic counterfeit logos can make the model more resilient to sophisticated forgeries. Additionally, deploying the system on mobile platforms using lightweight models will enable real-time, on-the-go detection. Advanced features like blockchain-based verification can ensure a secure and tamper-proof history of logo authenticity checks. Incorporating adversarial training can further strengthen the system’s resistance to intentionally manipulated logos designed to fool detection algorithms.

In conclusion, the Fake Logo Detection System is a step toward smarter, AI-powered brand protection. With future enhancements, it can evolve into a comprehensive tool to tackle counterfeiting across industries, contributing to a safer and more transparent digital marketplace.

Future Scope

This project serves as a valuable contribution to brand protection efforts, supporting companies, e-commerce platforms, and regulatory authorities in combating counterfeit products and maintaining brand authenticity. The future of fake logo detection holds immense potential across various technological and commercial domains. One significant direction is the integration of real-time detection capabilities into applications such as mobile apps, surveillance systems, and e-commerce platforms. This would allow users to instantly verify the authenticity of logos, enhancing brand protection and consumer trust. Another promising scope lies in leveraging multimodal learning, where visual features are combined with textual, contextual, or metadata-based cues to improve detection accuracy. As counterfeiters evolve and generate more realistic fake logos, the use of Generative Adversarial Networks (GANs) becomes increasingly relevant—not only for creating challenging adversarial examples to test and strengthen detection models but also for generating synthetic training data to augment datasets and improve model robustness.

Furthermore, there's a growing need for cross-domain generalization, enabling models to perform accurately across diverse industries, logo styles, and image conditions. Transfer learning and domain adaptation techniques will be key in making models adaptable and scalable. Enhancing the robustness of detection systems against adversarial attacks is another critical area, ensuring models can withstand subtle manipulations crafted to bypass detection. Additionally, the push toward on-device and edge computing will open up avenues for deploying lightweight models that work efficiently on smartphones, IoT devices, or embedded systems, offering faster responses and greater privacy.

The availability of large-scale, diverse, and labeled datasets will continue to be a cornerstone for advancing fake logo detection. Future systems may also benefit from the integration of blockchain technology, offering a secure and immutable method to verify logo authenticity across supply chains. Finally, designing systems that can handle multilingual and culturally adaptive logos will broaden the global applicability of these solutions, making them more inclusive and reliable in a variety of regional and linguistic contexts.

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