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Identifying Counterfeit Product Using Deep Learning

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Abstract: The Identifying counterfeit products project aims is to develop a system that can identify fake products and distinguish them from the original product. The project will use machine learning and deep learning techniques to build a counterfeit product detector website and assess how much they resemble the original products. The project's goal is to help consumers verify whether a product is original and to help brands piracy. Counterfeit products can harm a brand's reputation and sales, and consumers can be cheated out of their money. The Counterfeit products detection system will help brands protect their brand identity and prevent fraud by detecting and eliminating e-commerce listings containing fake logos.
A logo is a distinctive sign or indictor of some kind which is used by an individual, business or other legal entity to uniquely identify the source of its products and services to consumers to the most of the time brand name or logo if similar that time consumer not understand brand or products difference. This problem overcomes to our application. The problem of counterfeit product detection using machine learning involves developing algorithms and models that can accurately identify counterfeit or manipulated logos and the products. This problem arises due to the online scams, and brands infringement, which can deceive consumers and harm brands reputation. The goal is to create a system that can automatically analyze visual characteristics and patterns in product images, enabling the classification based on logos and its features as either genuine or fake. By addressing this problem, businesses and consumers can better protect themselves against fraudulent practices, maintain brand trust, and make informed purchasing decision. The project is beneficial for both consumers and brands.

Keywords: PYTHON, SVM, CNN

INTRODUCTION

In an era marked by rapid technological advancements and globalized commerce, the proliferation of counterfeit products has emerged as a formidable threat across industries worldwide. The confluence of sophisticated technologies and increased interconnectedness has facilitated the production and distribution of fraudulent goods, posing significant risks to both companies and consumers.

As reported, counterfeit incidents witnessed a staggering 24% increase in the country in 2021 compared to the previous year, creating a colossal over Rs 1-lakh-crore hole in the economy. Globally, the World Economic Forum estimates that the illicit market drains a staggering $2.2 trillion from the global economy, accounting for over 3% of the global GDP.

The complexity of distinguishing between genuine and counterfeit items has reached unprecedented levels, necessitating innovative and effective solutions. The research project aims to harness the power of deep learning techniques to develop a robust system capable of identifying counterfeit products with heightened precision and efficiency.

The urgency of such technological interventions is underscored by the prevalence of counterfeiting across various sectors, with almost 25-30% of all products sold in the country being spurious. Notably, the apparel and fast-moving consumer goods (FMCG) sectors bear the brunt of this issue, with 31% and 28% of counterfeit products, respectively. Automotive and consumer durables follow closely, making up 25%, while pharmaceuticals account for 20% of the counterfeit market.

To illustrate the real-world impact of counterfeiting, we delve into the case of the iconic Mysore Sandal Soap, a century-old legacy confronted with a substantial challenge from counterfeit manufacturers. The Karnataka Soaps and Detergents Limited (KSDL), the state-owned entity behind the Mysore Sandal Soap, faced an estimated loss of ₹500 to ₹600 crore over the past decade due to the illegal production of counterfeit soaps during 2024. The recent raid on a fake manufacturing unit in Hyderabad brought to light the magnitude of this issue and highlighted the critical need for advanced technological solutions.

PROBLEM STATEMENT

The contemporary landscape of e-commerce and online marketplaces has witnessed a surge in the importance of visual content, specifically product images, as a primary driver influencing consumer purchasing decisions. However, the reliance on visual information introduces a critical challenge—ensuring the correctness, authenticity, and quality of product images.

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The lack of standardized mechanisms for evaluating and verifying the accuracy of these images poses a substantial risk, potentially leading to issues such as misleading representations, altered visuals, and mismatched product details.

Simultaneously, the proliferation of counterfeit or knockoff brands has become an escalating threat, undermining the integrity of well-established trademarks across diverse industries. These unauthorized logos, meticulously designed to mimic legitimate brands, serve as conduits for the distribution of fake or substandard products, thereby posing significant risks to consumers and eroding the reputations of authentic brands.

The magnitude of this challenge is exacerbated by the global trade in counterfeit goods, estimated to reach alarming figures annually, thereby demanding immediate and strategic attention. Despite advancements in technology, legal frameworks, and awareness initiatives, persistent challenges include the dynamic evolution of counterfeit practices, economic ramifications for genuine brands, and the expansive scale of illicit trade.

This research endeavors to address the dual challenge of ensuring image correctness on e-commerce platforms and combating the proliferation of counterfeit brands. By adopting a comprehensive and integrated approach that combines technological innovations, robust legal frameworks, and heightened consumer awareness, the research aims to contribute to the establishment of a secure, transparent, and trustworthy environment for both businesses and consumers in the dynamic realm of online commerce.

EXSISTING SYSTEM

In the current landscape of product authentication technologies, both QR codes and low-cost RFID tags have been widely employed to enhance transparency and combat counterfeiting. However, each method faces distinctive challenges that compromise their effectiveness in ensuring the integrity of product information. QR codes on products to prove the validity of the product. But the QR code can be copied and used to label counterfeit products. In the RFID based system that low-Cost RFID tags can be used for auto identification of products, but due to cloning of RFID tags, this method is not suitable. Implementing and maintaining a blockchain network for image-related data could be costly and complex. Compliance with regulatory standards, especially concerning data protection is also difficult based on regions.

PROPOSED SYSTEM

The proposed method for detecting Counterfeit products combines NLP techniques, feature engineering, and classification algorithms. The method consists of the following steps:

- Data Pre-processing: The initial step involves pre-processing raw data to eliminate noise and irrelevant information, involving the removal of stop words, stemming, and lemmatization.
- Feature Engineering: It involves feature extraction from the pre-processed data, incorporating aspects such as sentiment polarity, word frequency, and review length.
- Classification: In the supervised learning algorithm employed for the classification of reviews as either fake or genuine, various classifiers were experimented with, including Support Vector Machines (SVM) and Convolutional Neural Networks (CNN).
- Evaluation: The performance of the proposed method is evaluated using a dataset of products. Metrics such as precision, recall, and F1-score are employed to assess the method's effectiveness.

LITERATURE REVIEW

One project described in [1] The research on logo detection using deep learning encounters notable challenges. The small size of logos proves difficult for accurate detection within complex backgrounds, as early-layer feature maps in deep learning architectures struggle to capture the necessary high-level semantic information. Diverse backgrounds associated with logos, exemplified by brands like "Nike," add complexity, making it challenging to design a robust logo detector that considers image statistics from the entire scene. The introduction of sub-brands further complicates the task, resembling fine-grained classification challenges. K-nearest neighbours (KNN) is applied for classification, it introduces drawbacks related to sensitivity to irrelevant features and computational inefficiencies, potentially impacting the overall performance of the logo detection system.

[2] The effectiveness of the Blockchain-Based Product Ownership Management System, designed to counter counterfeit products, hinges on accurate manufacturer verification. Any shortcomings or compromises in this verification process may allow counterfeit products to infiltrate the blockchain. Furthermore, the reliance on retailers to promptly activate QR codes introduces a potential vulnerability, potentially undermining the system's real-time authentication capabilities. Widespread user adoption, involving manufacturers, retailers, and customers, is imperative for success, posing a significant challenge in convincing all stakeholders to actively embrace the technology.

[3] The fake review detection that uses Random Forest classification exhibits high accuracy, its complexity may result in longer training times and increased computational demands. The model's interpretability may be a challenge, making it less suitable for applications where transparency is critical. Random Forests can be prone to overfitting, especially

when dealing with noisy or imbalanced datasets, impacting the generalization of the model. Furthermore, the sheer number of trees in the ensemble may hinder the interpretability of individual decision trees, posing a potential disadvantage in certain contexts.

[4] While the proposed fake note detector machine offers an affordable solution, potential drawbacks must be considered. Accuracy may vary based on the complexity of image processing techniques, posing challenges in detecting sophisticated counterfeit notes. The system's adaptability to evolving counterfeit techniques and dependency on image quality could impact its reliability. Moreover, limited features and a user skill requirement may present hurdles, emphasizing the need for continuous refinement to ensure effectiveness in tackling counterfeit currency challenges.

[5] focuses on Blockchain technology, it has been used extensively to ensure high data trust ability and security, from the operation of Bitcoin to BaaS (Blockchain as a Service), a cutting-edge blockchain model that functions as a form of pall-based community for organisations that expand blockchain-based apps. Significant apps outperformed the use of the blockchain, which is increasing popularity.

[6] The effectiveness of the decentralized blockchain system in countering counterfeit products is hindered by several challenges. Widespread adoption is critical for success, yet limited awareness and understanding of blockchain among manufacturers and consumers pose obstacles. Additionally, the integration of blockchain and IPFS introduces technical complexities, demanding specialized expertise for seamless functionality. The high initial implementation costs associated with establishing a decentralized network may present financial challenges, particularly for smaller businesses.

In [7], The blockchain technology that underpins cryptocurrencies like Bitcoin and others has gradually gained attention in recent years due to their popularity. Following the approved launch of Facebook's cryptocurrency project Libra and the release of the Libra white paper, Libra sparked extensive discussions across the globe. The public's awareness of open finance has increased under Libra, and the traditional financial system is being significantly affected. Through a comparative analysis of Libra, Bitcoin, and Ethereum, we fully evaluate and discuss blockchain technology in this article and highlight Libra's innovations in agreement algorithm, performance, and operation script. Finally, we present the difficulties that Libra will run into in the future.

Another project, presented [8] in Current anti-counterfeiting force chains plan to fight bogus goods from a centralised location. Similar problems to single point processing, storeroom problems, and failures are caused by this armature. Blockchain technology has emerged as a potential solution for problems of this nature. In this work, we propose the block- supply-chain, a novel decentralised force chain that utilises blockchain and Near Field Communication (NFC) technologies to identify counterfeiting attempts.

[9] The paper responds to the global counterfeit goods issue, estimating $1.2 trillion in damages in 2017, projected to reach $1.82 trillion by 2020. It advocates for consumer involvement in addition to regulatory measures. The proposed solution involves machine learning for image and text recognition, creating user-friendly applications for end-users to identify and combat counterfeit products effectively.

[10] This paper introduces Discriminative CNNs (D-CNNs) to enhance remote sensing image scene classification. Utilizing a novel discriminative objective function, D-CNNs address challenges of within-class diversity and between-class similarity. The method incorporates metric learning regularization, ensuring images of the same class are closer and those of different classes are farther apart in feature spaces. Evaluation on three benchmark datasets with standard CNN models shows D-CNNs outperform existing methods, achieving state-of-the-art results.

SYSTEM ARCHITECTURE

The system architecture for Counterfeit product using deep learning can vary depending on the specific approach and techniques used. However, can provide a general overview of a possible architecture for detecting fake logos in images.

Data Collection: Gather a dataset of labeled images containing both genuine logos and fake Product Images. These images should cover a wide range of logo variations, backgrounds, and potential distortions.

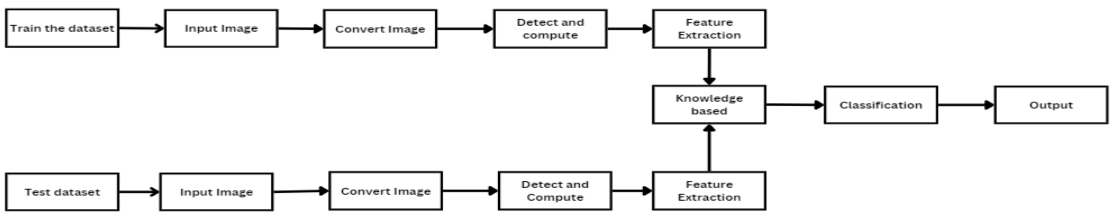

Figure 1: Implementation Design for Detecting Counterfeit Products

Data Preprocessing: Apply preprocessing techniques to the images to normalize the data and enhance important features. This may include resizing the images to a fixed size, converting them to grayscale, or applying noise reduction techniques.

Feature Extraction: Extract relevant features from the preprocessed images. One common approach is to utilize convolutional neural networks (CNNs) to automatically learn discriminative features from the images. CNNs can capture spatial patterns and local structures that are crucial for logo detection.

Model Training: Train a machine learning model using the extracted features and the corresponding labels. Popular choices for the model architecture include CNNs, such as VGG, ResNet, or Inception, which have shown excellent performance in image classification tasks.

Counterfeit Product Detection: Given a new input image, pass it through the trained model for prediction. The model will output the likelihood or probability of the input image.

Post-processing: Apply post-processing techniques to refine the detection results. This may include thresholding the predicted probabilities to classify an image as fake or genuine, performing non-maximum suppression to remove duplicate detections, or applying additional rules or heuristics to improve the accuracy of the system. It's important to note that the performance of the fake logo detection system heavily relies on the quality and diversity of the training data, the effectiveness of the feature extraction process, and the choice of the machine learning model. Further enhancements can be made by incorporating techniques such as transfer learning, data augmentation, or ensemble methods to boost the system's performance.

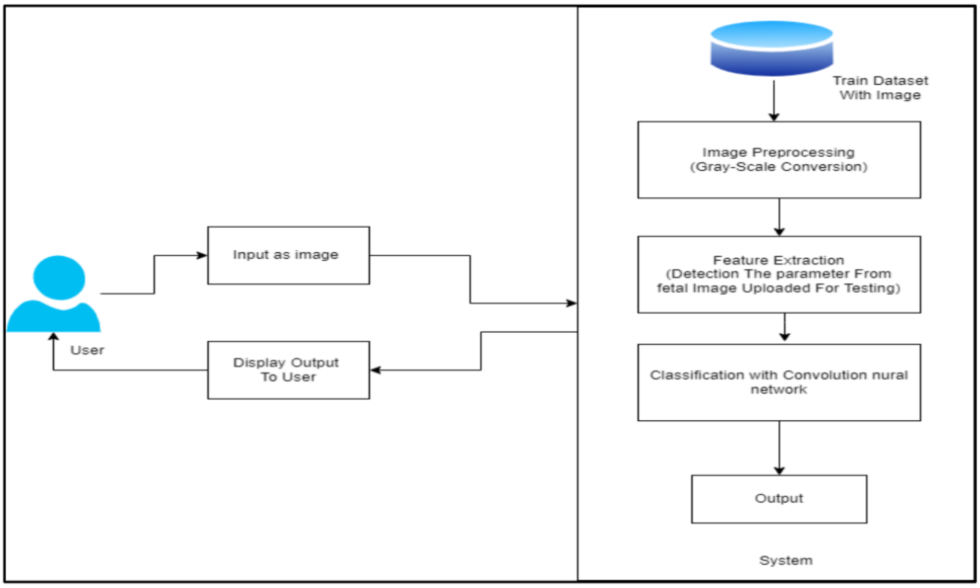

Figure 2: System Architecture Design for Detecting Counterfeit Products

MODEL DEVELOPMENT

ETL (Extract, Transform, Load)

Created 'target_dict' to map labels of the dataset ("Original" and "Fake") to integer labels (0 and 1). After that, created two empty lists for storing images and corresponding for its labels. Then created a 'for' loop to iterate over all the subdirectories in the "Brands" directory and process the images in each subdirectory based on their corresponding label. It allows the code to prepare the image data for the model by organizing the images into separate classes based on their labels. The 'current_label' variable is later used to assign integer label to each image, which is necessary for training the model to recognize the different classes of images. We have created 'for' loop and 'current_label'for the subfolder also. Put 'if img.is_file ()' for checking the file.).

Loaded all the images as grayscale images using load_img(img, color_mode = "grayscale"). After that, converted all the images into a Numpy array using 'img_to_array(img)' and using smart_resize() all the images are resized to 256x256 pixel size. The code'images.append(img_array_resized)' add the resized image array to the list of images and 'labels. Append (target_dict [current_label])' adds the corresponding label for the current image to the list of labels using ' target_dict ' dictionary to map the label to an integer label. We calculated number of images using the 'len()' function and we have used train_test_split() from scikit-learn library to split the images and labels into training and testing sets(20% of the data is used for testing and 80% for training).We also converted values to the numpy array and scale values in [0,1] interval. After that, flatten the image data to prepare it for use as features in a model.

SVM MODEL

The SVM model is used to classify data into two categories - 'fake' and 'original'. The model is trained to classify images into two classes - 'fake' and 'original'. The SVM model is trained using the 'linear' kernel, the regularization parameter 'C' is set to 1, which controls the trade-off between maximizing the margin and minimizing the classification error. The random state parameter is set to 42.

After training, it is evaluated on a validation set and a test set using the predict method to measure its performance in classifying new data. The validation set and test set both contain data with known labels of 'fake' or 'original', which are used to assess how well the SVM model can classify new data into these categories.

The accuracy score is calculated for both the validation set and the test set.

Validation accuracy: 0.8175
Test accuracy: 0.845

After that calculated precision, recall, and F1 score for the predicted labels for Validation and test datasets.

Validation precision: 0.8045191900806326
Validation recall: 0.8175
Validation F1 score: 0.8100635927302098

The validation precision of 0.8045191900806326 and recall of 0.8175. means that the precision and recall are around 0.80-0.82%, which indicates that the model is able to identify positive cases (i.e., fake images) with a high degree of accuracy. The F1 score is around 0.81, which suggests that the model is able to balance precision and recall reasonably well.

Test precision: 0.8380048076923078
Test recall: 0.845
Test F1 score: 0.8411936036550542

The model achieved a test precision of 0.84, which means that 84% of the predictions made by the model for the positive class were correct. The test recall is 0.85, which means that 85% of the actual positive examples in the test set were correctly identified by the model. F1 score is 0.84, which indicates that the model has a good balance of precision and recall and is performing well overall.

The confusion matrix of the model's predictions on the test set.

array ([[937, 83], [103, 77]])

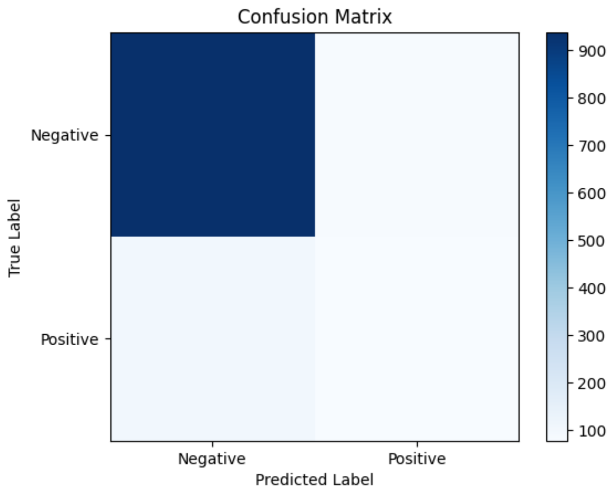

Figure 3: Confusion matrix of the model's predictions on the test set.

In this case, there were 937 true negative predictions, 83 false positive predictions, 103 false negative predictions and 77 true positive predictions.

Precision recall curve

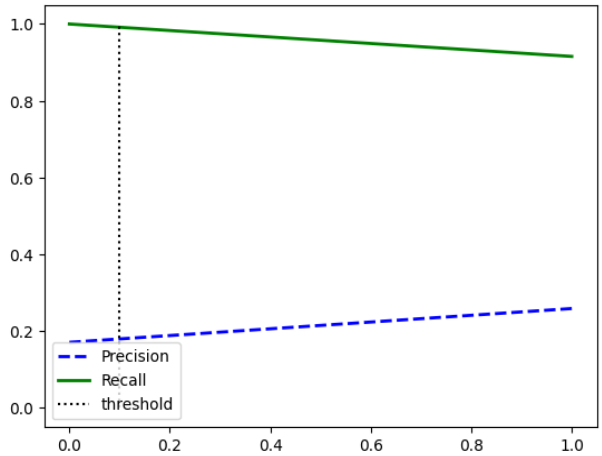

Figure 4: Precision recall Curve for the Trained Datasets

The above plot Figure 4 shows that when threshold is set to 0.1, the precision slightly increases and recall slightly decreases.

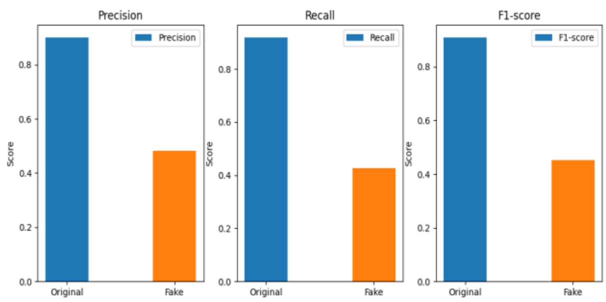

Figure 5: Precision recall Graph for Original and Fake Products

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The precision, recall and F1 score for original class is higher as compared to Fake class.

CNN MODEL

Developed a CNN model using the Keras API in TensorFlow to classify images of brand logos as original or fake. The model architecture consisted of 6 convolutional ,2 max-pooling layers, 1 flatten layer, 2 dense layers along with 2 dropout and 2 batch normalization layers to prevent overfitting. The dataset was preprocessed to ensure that the images are of consistent size. The training dataset consisted of images of both authentic and fake brand logos, while the validation and test datasets were used to evaluate the model's performance. The model is initialized using the “HeUniform initializer”, with the input shape (256, 256, 1). The activation function used for all the convolutional layers is ReLU. The padding used is "same", which means the input and output dimensions are the same. The first two convolutional layers have 128 filters of size (3, 3). Then a max-pooling layer is applied to down sample the feature maps by a factor of 2. A dropout layer is added to avoid overfitting, and batch normalization is performed to normalize the activations between layers.

The next two convolutional layers have 128 filters of size (3, 3), followed by another max-pooling layer and a dropout layer with a rate of 0.2. Then batch normalization is performed again. The output is then flattened and fed into a fully connected dense layer with 128 units and a ReLU activation function. Batch normalization is performed before the final dense layer, which has two units and a SoftMax activation function. The model is trained for 20 epochs with a batch size of 25, using the RMSprop optimizer with categorical cross-entropy loss function. The model's accuracy is used as the primary metric to evaluate its performance on the validation and test datasets. The results showed that the model was able to accurately classify images of brand logos into their respective categories.

Test accuracy: 0.8675000071525574
Validation accuracy: 0.8583333492279053

Created two plots to visualize the performance of the model during training. The first plot shows the training and validation accuracy per epoch. The second plot shows the training and validation loss per epoch.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 256, 256, 128)     1280

 conv2d_1 (Conv2D)           (None, 256, 256, 128)     147584

 max_pooling2d (MaxPooling2D  (None, 128, 128, 128)    0
 )

 dropout (Dropout)           (None, 128, 128, 128)     0

 batch_normalization (BatchN  (None, 128, 128, 128)    512
 ormalization)

 conv2d_2 (Conv2D)           (None, 128, 128, 128)     147584

 conv2d_3 (Conv2D)           (None, 128, 128, 128)     147584

 max_pooling2d_1 (MaxPooling  (None, 64, 64, 128)      0
 2D)

 dropout_1 (Dropout)         (None, 64, 64, 128)       0

 batch_normalization_1 (Batc  (None, 64, 64, 128)      512
 hNormalization)

 flatten (Flatten)           (None, 524288)            0

 dense (Dense)               (None, 128)               67108992

 batch_normalization_2 (Batc  (None, 128)              512
 hNormalization)

 dense_1 (Dense)             (None, 2)                 258

=================================================================
Total params: 67,554,818
Trainable params: 67,554,050
Non-trainable params: 768
```

```
Epoch 1/20
144/144 [==============================] - 122s 703ms/step - loss: 0.5683 - accuracy: 0.7536 - val_loss: 1.0916 - val_accuracy: 0.5533
Epoch 2/20
144/144 [==============================] - 101s 700ms/step - loss: 0.3833 - accuracy: 0.8472 - val_loss: 0.6764 - val_accuracy: 0.7050
Epoch 3/20
144/144 [==============================] - 104s 725ms/step - loss: 0.2938 - accuracy: 0.8839 - val_loss: 0.4625 - val_accuracy: 0.8300
Epoch 4/20
144/144 [==============================] - 104s 722ms/step - loss: 0.1901 - accuracy: 0.9311 - val_loss: 0.5317 - val_accuracy: 0.8392
Epoch 5/20
144/144 [==============================] - 104s 721ms/step - loss: 0.0991 - accuracy: 0.9636 - val_loss: 0.5858 - val_accuracy: 0.8325
Epoch 6/20
144/144 [==============================] - 104s 720ms/step - loss: 0.0582 - accuracy: 0.9806 - val_loss: 0.6527 - val_accuracy: 0.8725
Epoch 7/20
144/144 [==============================] - 100s 692ms/step - loss: 0.0539 - accuracy: 0.9828 - val_loss: 0.5565 - val_accuracy: 0.8492
Epoch 8/20
144/144 [==============================] - 99s 691ms/step - loss: 0.0385 - accuracy: 0.9900 - val_loss: 0.6477 - val_accuracy: 0.8400
Epoch 9/20
144/144 [==============================] - 103s 719ms/step - loss: 0.0257 - accuracy: 0.9931 - val_loss: 0.6808 - val_accuracy: 0.8642
Epoch 10/20
144/144 [==============================] - 99s 689ms/step - loss: 0.0237 - accuracy: 0.9931 - val_loss: 0.6770 - val_accuracy: 0.8683
Epoch 11/20
144/144 [==============================] - 103s 717ms/step - loss: 0.0261 - accuracy: 0.9933 - val_loss: 0.8921 - val_accuracy: 0.8617
Epoch 12/20
144/144 [==============================] - 99s 687ms/step - loss: 0.0169 - accuracy: 0.9942 - val_loss: 0.7383 - val_accuracy: 0.8700
Epoch 13/20
144/144 [==============================] - 103s 714ms/step - loss: 0.0101 - accuracy: 0.9975 - val_loss: 0.9672 - val_accuracy: 0.8450
Epoch 14/20
144/144 [==============================] - 99s 686ms/step - loss: 0.0070 - accuracy: 0.9975 - val_loss: 0.8967 - val_accuracy: 0.8583
Epoch 15/20
144/144 [==============================] - 99s 687ms/step - loss: 0.0165 - accuracy: 0.9947 - val_loss: 0.7728 - val_accuracy: 0.8658
Epoch 16/20
144/144 [==============================] - 99s 688ms/step - loss: 0.0062 - accuracy: 0.9981 - val_loss: 1.0471 - val_accuracy: 0.8633
Epoch 17/20
144/144 [==============================] - 103s 716ms/step - loss: 0.0077 - accuracy: 0.9975 - val_loss: 0.8989 - val_accuracy: 0.8500
Epoch 18/20
144/144 [==============================] - 99s 687ms/step - loss: 0.0049 - accuracy: 0.9992 - val_loss: 0.8773 - val_accuracy: 0.8683
Epoch 19/20
144/144 [==============================] - 99s 687ms/step - loss: 0.0065 - accuracy: 0.9978 - val_loss: 1.1916 - val_accuracy: 0.8675
Epoch 20/20
144/144 [==============================] - 99s 685ms/step - loss: 0.0154 - accuracy: 0.9944 - val_loss: 1.0363 - val_accuracy: 0.8583
38/38 [==============================] - 11s 198ms/step - loss: 0.9140 - accuracy: 0.8675
38/38 [==============================] - 6s 147ms/step - loss: 1.0363 - accuracy: 0.8583
Test accuracy: 0.8675000071525574
Validation accuracy: 0.8583333492279053
```

Figure 6: Training Models with Different kinds of Datasets

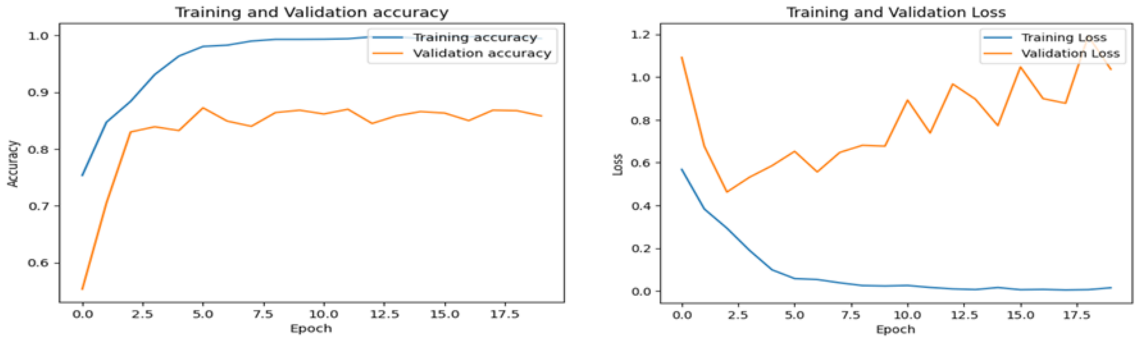

Figure 7: Training and Validation accuracy per epoch & loss per epoch

Precision, Recall and F1 score for Fake and Original

	Precision	Recall	F1-Score	Support
0	0.91	0.94	0.92	1020
1	0.57	0.47	0.52	180
accuracy			0.87	1200
macro avg	0.74	0.70	0.72	1200
weighted avg	0.86	0.87	0.86	1200

The "precision" for class 0 is 0.91, which means that out of all the samples predicted as class 0 by the model, 91% of them were class 0. The "recall" for class 0 is 0.94, which means that out of all the actual class 0 samples, the model correctly identified 94% of them. The "f1-score" for class 0 is 0.92, which is the harmonic mean of the precision and recall. The "precision" for class 1 is 0.57, which means that out of all the samples predicted as class 1 by the model, 57% of them were actually class 1. The "recall" for class 1 is 0.47, which means that out of all the actual class 1 samples, the model correctly identified 47% of them. The "f1-score" for class 1 is 0.52The "accuracy" of the model on this dataset is 0.87, which means that the model correctly classified 87% of the samples. The "macro avg" and "weighted avg" are the average precision, recall, and f1-score across all classes, weighted by the number of samples in each class. The "macro avg" gives equal weight to each class, while the "weighted avg" gives higher weight to the class with more samples. In this case, the "macro avg" and "weighted avg" f1-scores are 0.72 and 0.86, respectively.

Confusion matrix
[[956 64], [95 85]]

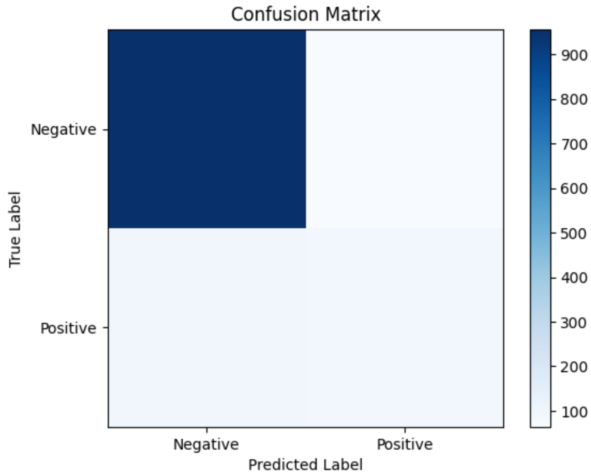

Figure 8: Negative and Positive Predicted Graph for Datasets

In this case, there were 956 true negative predictions, 64 false positive predictions, 95 false negative predictions and 85 true positive predictions.

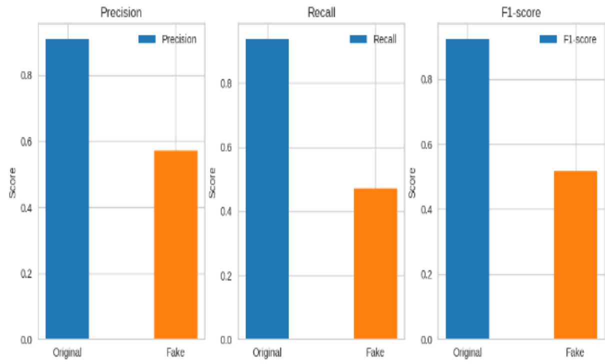

Figure 9: Precision recall Graph for Original and Fake Products

The precision, recall and F1 score for original class is higher as compared to Fake class.

FINAL RESULTS

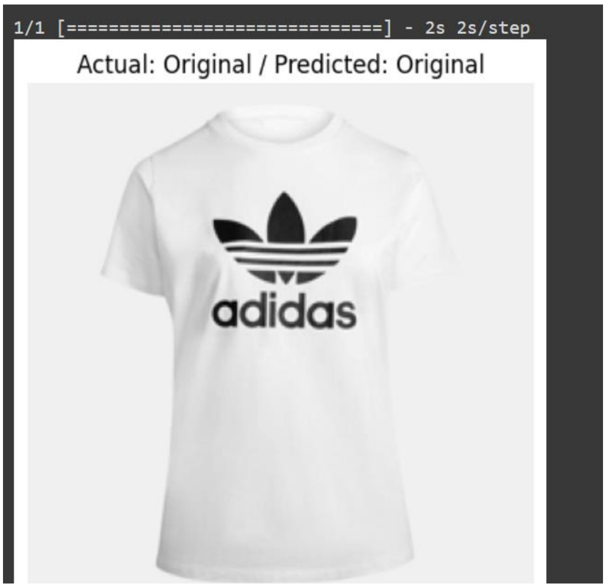

Figure 10: Final Result for the Uploaded Product

CONCLUSION

This system utilizes advanced image processing and deep learning techniques to effectively detect counterfeit products like ADIDAS shoes and others.

This showcased the potential of these methodologies in combating counterfeiting, offering a user-friendly solution for consumers to verify product authenticity.

By bolstering brand protection and consumer trust, this project significantly contributes to the ongoing fight against counterfeit goods, highlighting the practical impact of image processing in real-world applications.

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