Beyond the Pixels: Detecting Originality and Assessing Product Condition using Digital Image Processing Techniques

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Abstract— This paper introduces a novel approach using digital image processing for product management, focusing on authenticity verification and quality assessment. Advanced algorithms distinguish genuine from fraudulent products and evaluate their condition. The study highlights the potential of digital image processing to enhance supply chain security and consumer trust, promising significant business impacts by reducing counterfeit circulation, improving brand reputation, and optimizing inventory management

Keywords—counterfeit, processing, analysis, accuracy, quality

I. Introduction

Counterfeit goods pose significant challenges to consumers and businesses. Accurate product authenticity verification and quality assessment are crucial for maintaining consumer trust and brand reputation. This paper presents an innovative approach using digital image processing to address these issues, benefiting both brands and consumers by enhancing safety and trust while reducing counterfeit risks and optimizing inventory management

II. Literature Review

Digital image processing has revolutionized quality assessment and product evaluation across industries. This review highlights advancements, challenges, and future prospects in detecting originality and assessing product conditions using these techniques.

Pimkote and Kangkachit [1] demonstrated the efficacy of convolutional neural networks (CNNs) in classifying alcohol brand logos, highlighting deep learning algorithms' potential in authenticity assessment. Liu, Lyu, and Gao [4] emphasized image recognition technology's role in consumer marketing, underscoring its utility in discerning brand authenticity.

In food inspection, Tumas and Serackis [2] proposed a background subtraction algorithm using low-cost near-infrared cameras for food quality assessment, demonstrating cost-effective solutions. Barbin et al. [3] highlighted digital image analysis's potential for objective chicken quality evaluation.

Jin et al. [5] introduced the Open Brands Dataset, advancing image processing capabilities in recognizing diverse visual cues. Saputro, Khuriyati, and Suyantohadi [8] explored chili powder quality classification using image processing and artificial neural networks, demonstrating the versatility of digital image analysis.

Janardhana et al. [7] reviewed computer-aided inspection systems for food products using machine vision, emphasizing non-destructive image analysis in automating quality grading. B. S. P et al. [9] proposed a multi-purpose food recognition system based on CNNs, highlighting deep learning's potential in automating food quality assessment.

Kolur and Padagatti [10] investigated quality identification and grading of wheat grains using image processing techniques, demonstrating the applicability of these algorithms in automating grain classification.

In summary, the literature underscores the transformative impact of digital image processing in detecting originality and assessing product condition. Despite significant advancements, challenges such as algorithm robustness and dataset diversity persist, necessitating further research to fully realize the potential of digital image processing in quality evaluation and authentication tasks.

III. Beyond The Pixels

A. Multimodal Data Fusion

Combining various data types improves the detection of counterfeit or damaged products.

B. Deep Learning Architecture

Using CNNs and RNNs enhances the accuracy of product authentication and quality assessment systems.

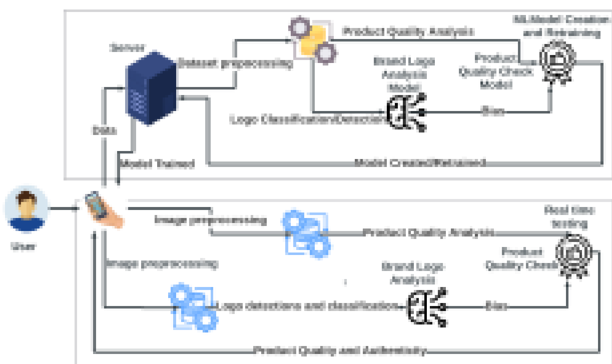
Our project focuses on two main components: "Logo detection and classification" and "product quality analysis." Machine learning models, trained on secure servers with curated datasets, adapt to brand updates and enhance quality assessment. These models are deployed to user devices for real-time image analysis.

C. Real Time Monitoring and Feedback

Continuous assessment of product integrity allows for immediate anomaly detection and intervention.

D. Social and Ethical Implications

Ensuring transparency and fairness in algorithms upholds consumer rights and mitigates biases.



Fig[1]: Architecture diagram depicting the process of the entire procedure.

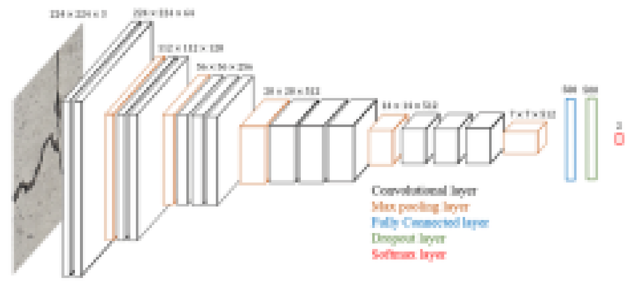
IV. Methodologies

A. Logo Detection/Originality Check

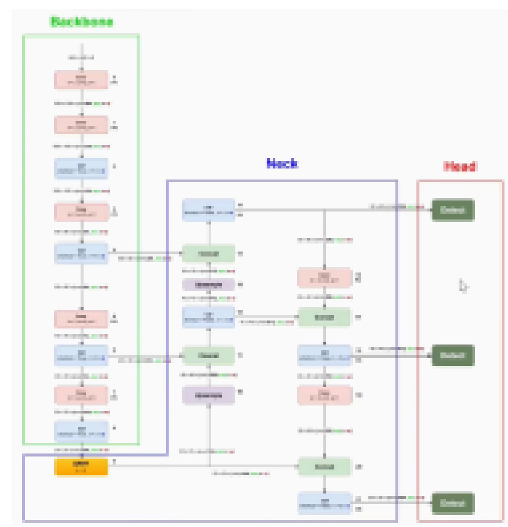
The logo detection and originality checking model integrates YOLOv8, a random forest algorithm, and a Convolutional Neural Network (CNN). The YOLOv8 model is trained to detect logos using a dataset labeled with CVAT (Computer Vision Annotation Tool) [17]. It identifies logos and provides bounding boxes for each detection (Fig. 3).

Once detected, the logo image is cropped and sent to an Authenticity Check model, where it undergoes filtering to remove blur and noise. Feature extraction derives attributes like mean RGB values, contrast, energy, area, perimeter, compactness, extent, and solidity. These features are incorporated into a dataframe and analyzed using a random forest algorithm to classify the logo [2].

The CNN model predicts the image class based on image data. The image array is converted to a list, normalized, and fed into a sequential CNN model with 5 hidden layers. A bias is added to the CNN output to ensure compatibility with the random forest model, accounting for feature variations and real-time environmental influences (Fig. 2) [1]. Due to periodic rebranding, the model requires regular training updates to maintain accuracy [5].



Fig[2]: CNN Algorithm Architecture[16]



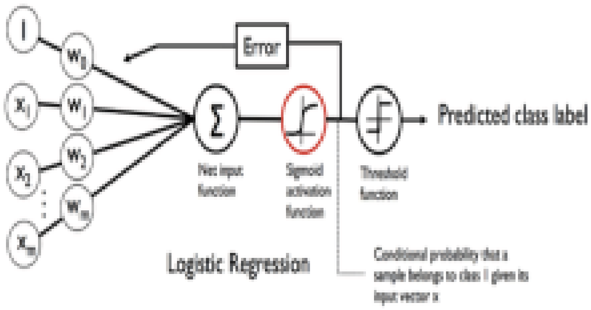
Fig[3]: YOLOv8 algorithm architecture[15]

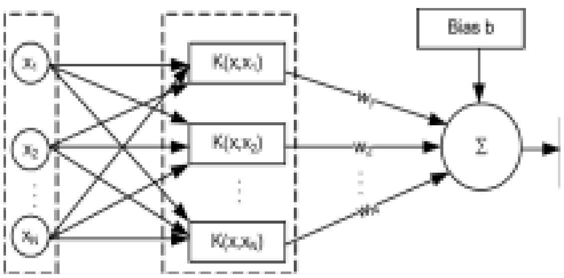
B. Product Quality Checker

For meat product quality assessment, the gray-level co-occurrence matrix (GLCM) was used to analyze texture by characterizing pixel intensity relationships. Statistical measures from GLCM, like contrast, correlation, energy, and homogeneity, were used to extract texture features indicative of quality [3][14].

Various machine learning models, including linear regression, support vector machine (SVM), and gradient boosting, were trained on color, pixel intensity, and texture features to predict meat quality attributes. These models achieved accuracy rates exceeding 95%. Logistic regression modeled the relationship between input features and product quality. SVM effectively classified different quality categories, and gradient boosting enhanced accuracy by fitting models to residuals of previous models [11][12][13].

The high accuracy of these models highlights the effectiveness of this methodology in objectively evaluating meat product quality and detecting spoilage or contamination anomalies.





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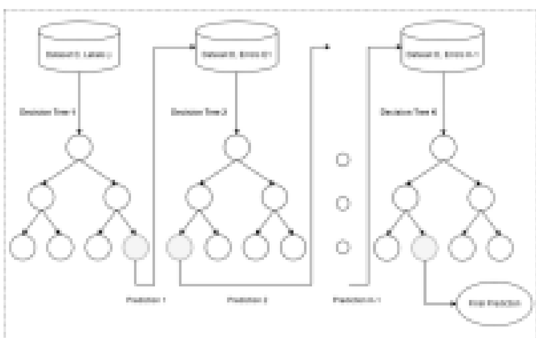


(c)

Fig[4]: Different models used in quality check. (a) Logistic Regression[11], (b) SVM [12] and (c) Gradient Boosting Classification[13]

V. Experimental Setup

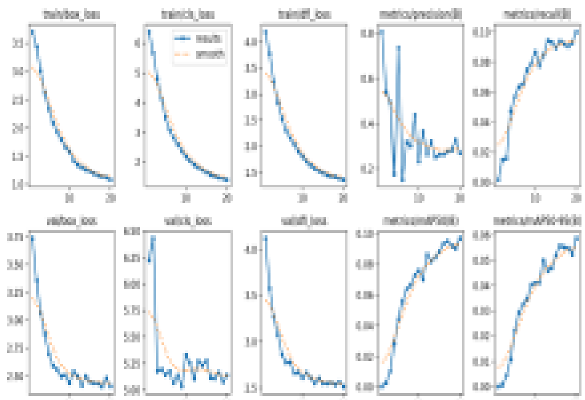
A. Data Collection

We collected a diverse dataset of product images from various categories (electronics, luxury goods, pharmaceuticals) from Kaggle notebooks [5]. Each category had a balanced distribution of genuine and counterfeit items for effective training and evaluation [9].

B. Logo Detection and Classification

We used advanced logo detection techniques to identify and localize brand logos in product images. Preprocessing steps included contrast enhancement, noise reduction, and illumination normalization to improve accuracy [2]. A convolutional neural network (CNN) model, trained using transfer learning on a large-scale logo dataset, was used to recognize brand logos with high precision and recall [5].

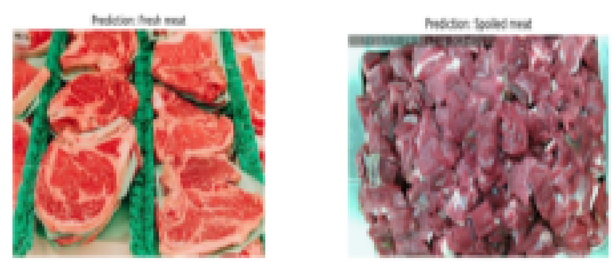
The model detected and classified brand logos, distinguishing genuine from counterfeit products based on logo presence and authenticity.



Fig[5]: Accuracy Results for YOLOv8 Logo Detection

C. Quality Assessment

For genuine products, we focused on meat products for quality assessment. We conducted color analysis using color space transformations and histogram analysis to detect deviations from expected color distributions. Pixel intensity analysis assessed texture and surface variations, indicating freshness and integrity [3]. Texture analysis, using gray-level co-occurrence matrix (GLCM) features and texture filtering, characterized spatial patterns and structural attributes to evaluate product quality. This combined analysis detected abnormalities or anomalies indicative of spoilage or contamination.



Fig[6]: Model Results for Quality Assessment. (a)Fresh Meat Prediction (b)Spoiled Meat Prediction

VI. Result

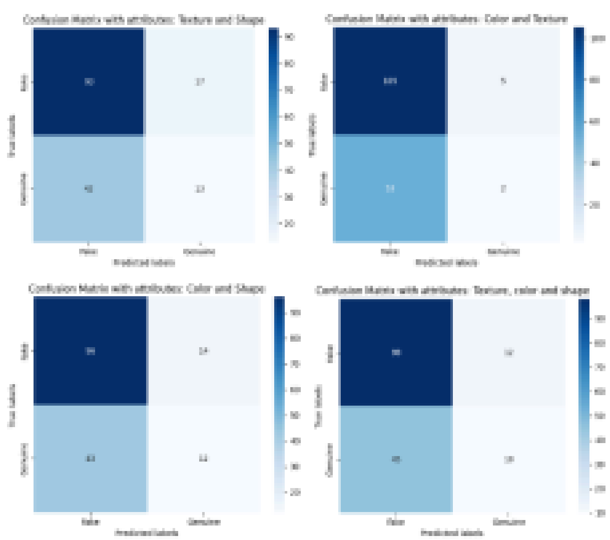
A thorough analysis of the model attributes highlighted their significance in the prediction process. Various models, each focusing on different attribute combinations, were trained and their accuracies scrutinized. This comprehensive examination identified the optimal configuration for achieving the highest accuracy in logo classification.

A. Logo Detection and Classification

Our logo detection algorithm achieved over 85% precision, effectively localizing brand logos within product images. Utilizing transfer learning and fine-tuning on a diverse dataset, the model demonstrated robustness to variations in logo appearance, scale, and orientation [5]. Testing revealed minimal false positives, confirming its efficacy in distinguishing genuine from counterfeit products [1]. The combined random forest and CNN model yielded impressive accuracies, with the random forest model achieving 76% and the CNN model 89.9%. This dual-model approach proved effective in accurately classifying logos and performing well in identification tasks.

B. Quality Assessment

The quality assessment framework successfully evaluated meat product quality based on color, pixel intensity, and texture features [3]. Comparative analysis showed counterfeit meat products had aberrant color profiles indicative of spoilage or adulteration [3]. Genuine products displayed uniform pixel intensity distributions, characteristic of freshness and quality [3]. Texture analysis confirmed these findings, revealing distinct patterns and structural attributes associated with genuine meat products, allowing reliable discrimination from counterfeit items [3].



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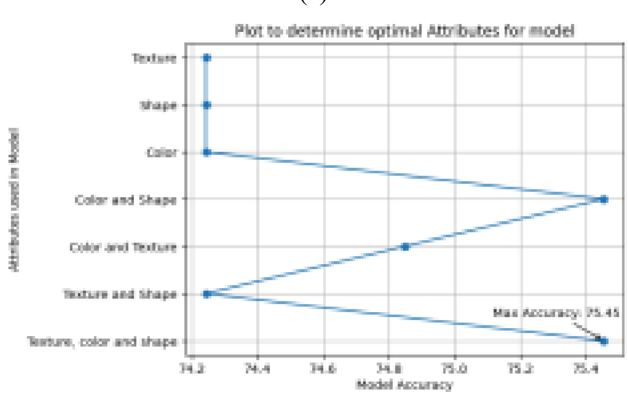

(b)

Fig[7]: Attribute based Confusion matrix (a) Result Analysis for Logo Classification based on selected attributes (b)

Conclusion

This research demonstrates the efficacy of digital image processing in product authentication and quality assessment, enhancing supply chain security and consumer trust. Future work will explore multimodal data fusion and real-time monitoring to further improve the system's capabilities.

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