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Fake Currency Detection

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Abstract- The proliferation of counterfeit currency poses a significant threat to global economies and financial stability. Traditional manual inspection methods are prone to human error, time-consuming, and require specialized knowledge. This paper proposes an automated, real-time counterfeit currency detection system utilizing image processing techniques combined with a supervised machine learning classifier. The proposed methodology leverages key security features, including watermarks, security threads, and intaglio printing patterns, by analyzing high-resolution digital images captured under visible and ultraviolet light. Feature extraction focuses on texture analysis (using Local Binary Patterns), dimensional accuracy, and color spectrum profiling. A Support Vector Machine (SVM) is trained on a robust dataset of genuine and counterfeit banknotes to classify the currency as authentic or fake with high accuracy. The experimental results demonstrate the system's effectiveness and its potential for deployment in automated teller machines (ATMs) and point-of-sale (POS) systems, providing a rapid and reliable solution to combat currency fraud.

Index Terms- Counterfeit Detection, Currency Recognition, Image Processing, Machine Learning, Security Features, Support Vector Machine.

I. INTRODUCTION

The issue of fake currency remains a persistent global challenge. Counterfeit notes often circulate undetected, devaluing currency and eroding public trust in financial institutions. Automated detection systems are essential to mitigate this risk. Existing solutions often rely on proprietary hardware sensors (e.g., magnetic ink and infrared scanners), which can be costly and difficult to update as new security features are introduced.

This research aims to develop a software-based solution that uses readily available hardware (a high-resolution scanner or camera) to analyze visible and tactile security features, offering a flexible and cost-effective alternative. The system focuses on replicating the key steps of human inspection—texture, size, and color verification—but with objective, quantifiable metrics derived through computer vision.

II. PROCEDURE FOR PAPER SUBMISSION

The proposed system comprises four primary stages: Image Acquisition, Preprocessing, Feature Extraction, and Classification.

A. Image Acquisition

Digital images of the banknotes are captured under two conditions: standard visible light (to inspect color, print quality, and alignment) and ultraviolet (UV) light (to detect fluorescent security threads and features). High-resolution images (≥ 600 DPI) are necessary to capture fine details like micro-printing and intaglio lines.

B. Preprocessing

Preprocessing standardizes the input image for reliable feature extraction. This stage is critical as it compensates for variations in image capture (e.g., lighting changes or slight rotations) and isolates the most informative regions of the banknote.

1. Perspective Correction and Alignment: Before any other operation, the image must be geometrically corrected. Since banknotes may be slightly tilted or viewed under mild perspective, a homography transformation is calculated using four identified corner points or reference markers on the note. This step rectifies the image to a standardized, frontal view, ensuring that dimensional measurements and ROI cropping are accurate regardless of the initial capture angle.
2. Grayscale Conversion: The original RGB image is converted to grayscale using a weighted average method ($G = 0.299R + 0.587G + 0.114B$) to simplify texture analysis, preserving essential contrast information while reducing the computational load by two-thirds.
3. Noise Reduction: A Gaussian blur filter with a small kernel size ($\sigma=0.5$) is applied to

smooth out minor imaging noise and subtle print imperfections (like specks of dust) that are irrelevant to the core security features. This helps to make the subsequent texture descriptors more robust against noise while preserving the sharp edges of intaglio printing.

4. Region of Interest (ROI) Selection: Specific areas containing invariant security features, such as the watermark area, the security thread, and a defined region of the central intaglio printing, are automatically located and cropped. This is achieved using template matching (specifically, the Normalized Cross-Correlation method) against a genuine banknote template. By focusing the analysis on these critical ROIs, the feature vector's discriminative power is maximized, and processing time is minimized.

C. Feature Extraction

Three critical features are extracted to form the input vector for the machine learning model:

1. Texture Analysis (Local Binary Patterns - LBP): LBP is a potent operator for describing local texture. The image is divided into $N \times N$ blocks, and the LBP histogram of each block is computed. The concatenated histograms provide a robust texture descriptor. Fake notes often exhibit smoother, less defined texture due to inferior printing techniques, resulting in distinct LBP patterns.
2. Dimensional Verification: The height and width of the note are measured in pixels and converted to a standard ratio. A tolerance threshold is applied to detect notes that deviate significantly from the mandated size, a common flaw in counterfeits.
3. Color Spectrum Profiling (UV Light): The UV image ROI is analyzed to quantify the presence and intensity of fluorescence. Genuine notes display specific, calibrated fluorescent threads and speckles, which are measured as the average pixel intensity and variance in the UV channel.

D. Classification (Support Vector Machine - SVM)

A kernel-based Support Vector Machine (SVM) is employed for the final classification. The extracted feature vector $F = [F_{\text{LBP}}, F_{\text{Dimension}}, F_{\text{UV}}]$ is used as the input. The SVM is trained to separate the data into two classes:

$$\text{Classification} = \begin{cases} \text{Genuine} & \text{if } f(\mathbf{x}) \ge 0 \\ \text{Counterfeit} & \text{if } f(\mathbf{x}) < 0 \end{cases}$$

where $f(\mathbf{x})$ is the decision function learned by the SVM. The SVM is chosen for its effectiveness in high-dimensional feature spaces and its ability to construct a clear decision boundary.

III. EXPERIMENTAL RESULTS

The system was tested on a dataset comprising 500 genuine and 500 counterfeit banknotes of varying denominations and conditions. A 5-fold cross-validation technique was used to evaluate performance metrics.

Metric	Texture Only (LBP)	LBP + Dimension	Full System
Accuracy	92.1%	95.8%	99.2%
Precision	93.5%	96.1%	99.0%
Recall	90.1%	95.5%	99.4%

The integration of all three feature sets resulted in the highest accuracy (99.2%), significantly outperforming methods that rely solely on texture. The UV feature proved crucial for catching high-quality counterfeits that mimic visible security elements effectively.

IV. FUTURE WORK

To further enhance the system's robustness and applicability, several areas of future research are identified:

1. Deep Learning Implementation: Explore the transition from handcrafted features (LBP) to automated feature extraction using Deep Learning models, specifically Convolutional Neural Networks (CNNs). This shift could potentially capture more subtle, non-linear print variations that are missed by traditional methods.
2. Multi-Currency Adaptability: Generalize the system to efficiently handle multiple global currencies (e.g., Euro, Yen, Pound) without requiring complete retraining, focusing on feature normalization techniques.
3. Real-World Degradation Modeling: Incorporate images of genuine banknotes in various states of

wear, tear, and soiling into the training dataset to ensure the system maintains high accuracy even with degraded notes.

4. Hardware Optimization: Investigate the use of embedded systems (e.g., FPGAs or specialized microprocessors) to implement the real-time processing and classification pipeline, optimizing the system's speed for high-throughput applications like banknote sorters.

V. CONCLUSION

The automated system for counterfeit currency detection presented in this paper successfully validates a computer vision approach based on measurable physical security features. By combining Local Binary Patterns for texture, standard dimensional checks, and UV-spectrum fluorescence analysis, the system achieves a highly reliable classification accuracy of 99.2% using a Support Vector Machine. This performance demonstrates that readily available, non-proprietary hardware can be leveraged to create a powerful, scalable, and cost-effective defense against currency fraud in contexts such as ATMs and POS systems. The methodology provides a robust and adaptable framework for verifying banknote authenticity.

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