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AI-Driven Detection of Forged Currency Notes by Using Image Processing Techniques

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Abstract: The detection of counterfeit currency has become an increasingly important issue in modern financial environ-ments, largely due to the growing sophistication of forgery techniques. Traditional methods of verification often rely on manual inspection, which may be time-consuming, inconsistent, and dependent on expert knowledge. This work presents a web-based application designed to identify fake currency by combining integration and analysis processing. The system analyzes multiple visual and structural features of currency notes, such as color consistency, edge sharpness, texture patterns, watermark presence, and embedded security threads Model is simulated to categorize notes using the extracted features. The system delivers detection results in real time and stores past analyses for future use. Experimental evaluation indicates that the method provides consistent accuracy while keeping computational requirements low. Additionally, the framework remains flexible, allowing future improvements through the incorporation of more sophisticated deep learning techniques.

Index Terms: Fake Currency Detection, Machine Learning, CNN, Image Processing, Computer Vision.

I. INTRODUCTION

Counterfeit currency represents a major risk to global financial systems and economic integrity. As digital printing and re-production technologies continue to evolve, forged banknotes are becoming more sophisticated and harder to differentiate from authentic ones through conventional inspection methods. Traditional manual verification depends on skilled personnel and is not practical for handling large transaction volumes, limiting its effectiveness in today's fast-paced financial envi-ronments.

Advances in machine learning and computer vision have made this possible to develop automated systems that analyze intricate visual patterns and classify them accurately. Such methods provide a reliable and scalable way to detect counterfeit currency while reducing the need for manual verification. This work proposes an online platform for counterfeit currency detection that integrates image processing method with machine learning methods. It analyzes the key characteristics of banknotes such as color variation, edge sharpness, texture patterns, watermark presence, and security features. These attributes are collectively used within a single classification framework to ensure reliable and efficient detection. The proposed system is designed with scalability and us-ability in mind, making it suitable for practical deployment in environments such as banks, retail outlets, and other financial institutions.

II. LITERATURE SURVEY

Detecting forged currency has been a significant re-search focus within image analysis and machine learning, given its importance in protecting financial stability and preventing fraud. Initial studies largely relied on conven-tional image processing methods, where manually designed features were derived from currency images and compared with established reference patterns. Methods such as edge detection were applied to evaluate the sharpness and clarity of printed details. while texture analysis examined surface details, and pattern matching evaluated structural similarities between authentic and forged notes. While these approaches established a foundation for automated detection, they were strongly influenced by environmental conditions. Factors like changes in illumination, presence of shadows, variations in image quality, and background interference often resulted in inconsistent performance, reducing their effectiveness in practical, real-world applications. With the progress of machine learning, algorithms like SVM, Decision Trees, and KNN were increasingly applied to improve detection accuracy. The advancement of machine learning led researchers to adopt classification techniques such as SVM, Decision Trees, and KNN for better detection results. These methods enabled systems to learn from labeled data and generate predictions based on features derived from currency images. However, a significant limitation persisted in the dependence on manually engineered features. The overall performance of these models were strongly shaped by the selection and quality of these features, which often required significant domain knowledge and trial-and-error experimentation. Furthermore, such methods had limited ability to adapt to unseen variations, including new counterfeit designs or changes in currency patterns, which constrained their robustness and scalability in practical applications.

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Deep learning approaches have recently revolutionized image analysis, and CNNs are now considered among the most powerful models for visual recognition. These advancements have significantly increased the accuracy and effectiveness of image classification systems, where CNNs are now widely used as a primary method for visual recognition tasks. Unlike traditional techniques, CNNs can automatically derive hierarchical directly feature from raw image inputs, removing the dependence on manual fea-ture design. This capability allows CNN models to capture detailed patterns, textures, and subtle visual variations that earlier methods often struggled to identify. Consequently, they have achieved higher accuracy in counterfeit currency detection. Despite these advantages, such models require large amounts of data, well-labeled datasets, substantial computational resources—often involving GPU support—and extended training durations. These requirements can restrict their practicality in real-time or resource-constrained environments. To overcome these challenges, The proposed system utilizes a hybrid strategy that integrates elements of traditional feature-based techniques with decision-making concepts inspired by neural networks. Rather than depending on resource-intensive training procedures, the system applies a feature-driven scor-ing mechanism in which different attributes are assigned specific weights, mimicking the behavior of a neural model. This method helps minimize computational demands while still benefiting from weighted evaluation By combining image processing approaches with a simplified learning framework, the system maintains an effective balance between performance, accuracy, and scalability, making it well-suited for practical, real-world applications.

III. PROPOSED SYSTEM

The proposed solution is implemented as a web-based appli-cation that leverages machine learning methods with enhanced image analysis for the identification of counterfeit banknotes. It features an intuitive interface designed to simplify user inter-action that allows individuals to either upload currency images or capture them instantly using a webcam. This adaptability allows the system to be applied in various practical settings, such as banking operations, retail environments, and individual verification. After image acquisition, the input is processed through a well-defined pipeline that includes initial data preparation, feature extraction, and classification stages, ensuring a consis-tent and dependable detection workflow. In the preprocessing phase, the input image is enhanced to ensure better quality and uniformity. This stage involves applying techniques such as noise filtering, normalization, image resizing, and conversion to grayscale, all of which help reduce inconsistencies arising from lighting variations, camera differences, and background disturbances. These adjustments are necessary to achieve stable and reliable feature extraction across diverse input images. The feature extraction stage is dedicated to capturing key visual and structural attributes of the currency note. These characteristics include uniformity of color, clarity of edges, texture details, visibility of watermarks, and the identification of security threads. Such characteristics play a vital role in differentiating authentic notes from counterfeit ones, as they correspond to security elements that are challenging to reproduce with precision. After extraction, these attributes are quantified and formatted to be used in the subsequent classification process. In contrast to conventional approaches that depend en-tirely on manual verification or fully trained deep learning models, the proposed system implements a hybrid strategy that employs a feature-based scoring method influenced by the principles of Convolutional Neural Networks. Instead of performing complex training, the system assigns weights to different features based on their importance and computes a combined score that reflects the authenticity of the currency note. This approach reduces computational complexity while still maintaining a reasonable level of accuracy. The classification result is presented to the user along with a confidence score, which indicates the certainty of the prediction. This additional information enhances transparency and allows users to make informed decisions, especially in scenarios where the classification may not necessarily be highly certain. Including a confidence metric proves particularly useful in real-world applications where verification may require additional scrutiny.

IV. SYSTEM ARCHITECTURE

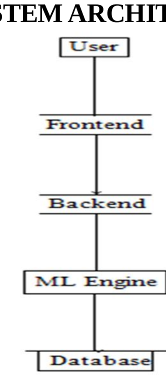

Fig. 1. System Architecture

V. MATHEMATICAL MODEL

The classification process is based on a weighted scoring mechanism:

$$S = \sum_{i=1}^{\alpha} w_i f_i \quad (1)$$

where f_i represents extracted features and w_i represents their corresponding weights.
The probability is computed using a sigmoid function:

$$P = \frac{1}{1 + e^{-S}} \quad (2)$$

VI. METHODOLOGY

The methodology of the proposed system follows a struc-tured and systematic approach that integrates image acquisition, The system follows a sequence of stages—data prepa-ration, feature identification, and classification—to effectively recognize counterfeit currency. It starts with acquiring images, where users either upload banknote photos from their device or capture them directly in real time through a webcam interface. This flexibility allows the system to operate in diverse environ-ment and ensures that it can handle inputs from the different sources, including mobile cameras and scanned images.

Once the image is acquired, it undergoes a preprocessing stage to enhance its enhance its quality and make it suitable for subsequent analysis. This phase is essential for increasing system reliability by minimizing unwanted inconsistencies in the input data. Preprocessing techniques include noise reduc-tion to eliminate random disturbances, normalization of pixel intensity values to maintain uniformity across images, and resizing to a standard resolution for consistent processing. In some cases, the image may also be converted to grayscale to simplify computations while preserving essential structural in-formation. These operations ensure that the subsequent feature extraction process is not affected by external factors such as lighting conditions, shadows, or image distortions. After preprocessing, the system proceeds to the feature extraction stage, a crucial step that focuses on identifying key attributes that differentiate authentic currency from counterfeit notes. The system analyzes multiple features, including color consistency, which helps detect variations in color distribution that may indicate forgery. Edge sharpness is evaluated to assess the clarity of printed elements, as genuine currency typically exhibits well-defined edges. Texture distribution is examined to identify irregularities in surface patterns, while watermark detection focuses on identifying embedded security marks that are difficult to replicate. Additionally, the presence of security threads is analyzed using pattern recognition techniques, since these characteristics serve as important indicators of authen-ticity. Each feature is measured and represented numerically using image processing techniques, enabling the system to convert visual information into measurable data. The derived features are then forwarded to the classification phase, where the system determines whether the currency is authentic or not. A feature-driven model is used to evaluate Image preprocessing plays a very crucial role in improving the quality, consistency, It also ensures the consistency and the input by assigning different weights to each characteristic, producing an overall score. This approach is influenced by neural network principles, where inputs contribute unequally to the final outcome based on their relevance. The aggregated score is then processed through a mathematical transformation, such as a sigmoid function, to produce a probability value indicating the likelihood that the note is genuine. Based on this probability value, the system classifies the currency note as either genuine or counterfeit by comparing it with a predefined threshold. If the probability exceeds the threshold, the note is considered genuine; otherwise, it is classified as counterfeit. The final result is presented to the user along with a confidence score, which indicates the certainty of the classification. This additional information enhances transparency and allows users to make informed decisions, especially in borderline cases.

VII. PERFORMANCE EVALUATION

To measure performance, the system utilizes widely used classification metrics like accuracy, precision, recall, and F1-score. Together, these metrics offer a well-rounded view of how effectively the model distinguishes between genuine and counterfeit currency, with each measure highlighting a different aspect of its performance. Accuracy indicates the overall rate of correct predictions by calculating the fraction of instances that are classified correctly, whether genuine or counterfeit. Although it provides a broad indication of performance, accuracy alone may be misleading, particularly when the dataset contains an unequal distribution of classes. Precision measures the ratio of correctly recognized counterfeit notes out of all notes predicted as counterfeit. This metric is particularly important in financial applications, since a high precision rate ensures that authentic currency is rarely misidentified as counterfeit, thereby minimizing false positives and preserving confidence in the system.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

$$Recall = \frac{TP}{TP + FN} \quad (5)$$

VIII. IMAGE PREPROCESSING PIPELINE

Quality of input data prior to the feature extraction phase. Currency images obtained from various sources often in-clude imperfections such as noise, inconsistent illumination, shadows, complex backgrounds, and geometric distortions.

Subsequent analysis. A key step in this stage is noise reduc-tion,where unwanted disturbances caused by sensors or envi-ronmental conditions are minimized using filtering techniques such as Gaussian or median filters. This helps in preserving important structural details while removing irrelevant variations.

Raw Image	Grayscale	Noise Removal	Resize	Processed Image

Fig. 2. Image Preprocessing Pipeline

The preprocessing stage plays a very crucial role in preparing the input image for accurate and reliable analysis by enhancing its quality and ensuring consistency across different samples. This stage begins with the conversion of the input image from its original color space (typically RGB) into grayscale. Transforming the image to grayscale simplifies computation by eliminating eliminating unnecessary color data while preserving key structural features such as edges, shapes, and intensity variations that are very important for further analysis. Following this, denoising techniques are applied to remove unwanted artifacts introduced by factors such as camera qual-ity, surrounding conditions, or compression effects. Methods like Gaussian and median filters are often used to smooth the image while preserving important structures, especially edges. This step helps minimize the influence of random noise, which could otherwise disrupt feature extraction and negatively impact classification accuracy.

IX. RESULTS AND DISCUSSION

The results indicate that the system can successfully distinguish between genuine and counterfeit currency by analyzing both visual and structural characteristics. This feature-driven method delivers stable and dependable performance in sim-ulated environments, where factors such as color uniformity, edge clarity, and texture patterns are evaluated collectively. Among these, watermark detection and texture analysis play a particularly significant role, as these features are difficult to replicate accurately in counterfeit notes and therefore serve as strong indicators of authenticity. The combine of multiple features ensures classification process is not dependent on a single parameter, thereby improving the overall the system. Furthermore, A blend of confidence score along with the classification output, which provides an additional layer of interpretability. This score helps users understand how certain the system is about its prediction, thereby increasing user trust and making the system more transparent. Such a feature is especially useful in real-world scenarios where decision-making may require additional verification. Although the system demonstrates encouraging results, it faces some constraints arising from the use of a simulated CNN model. While the feature-based scoring approach imitates aspects of NN behavior, it cannot fully represent the complex hierarchical feature learning achieved by fully trained deep learning models. Incorporating an actual CNN trained on a large and diverse dataset would allow the system to automatically learn more detailed and abstract patterns, thereby improving classification performance. Furthermore, such a model would strengthen the system's ability to generalize across variations in lighting conditions, image quality, and differences in currency design.

X. ADVANTAGES

The proposed fake currency detection system provides multiple benefits that support its use in practical environments, including its capability for rapid authenticity verification, enabling real-time decision-making without requiring manual intervention. This is particularly useful in high-transaction environments such as banks, retail stores, and automated teller machines, where speed and accu-racy are critical.

Another key benefit of the system is its ability to scale effectively. Being a web-based solution, it can operate across multiple platforms without requiring specialized hardware, making it accessible to a broad range of users, including financial institutions and small enterprises. Furthermore, the adoption of lightweight machine learning techniques reduces computational requirements, contributing to both cost effi-ciency and effective operation. The system also enhances usability by providing a user-friendly interface that allows even non-technical users to operate it with ease. The inclusion of a confidence score along with the classification result improves transparency and assists users in evaluating the reliability of the predictions. Furthermore, the inclusion of historical data storage allows users to examine trends and patterns in counterfeit detection, thereby adding analytical value to the system.

In summary, the system achieves an effective balance among accuracy, affordability, and ease of use, making it a viable approach for detecting counterfeit currency.

XI. LIMITATIONS

Despite its advantages, the proposed system should be evaluated by considering certain limitations. One major constraint is its dependence on a simulated model instead of a fully trained Convolutional Neural Network (CNN). Although this approach enhances computational efficiency, it does not achieve the same level of accuracy and robustness as a CNN trained on large-scale datasets. An additional limitation stems from the reliance on prede-fined feature weights within the classification process. These weights are manually determined based on assumptions and may not generalize well to different forms of counterfeit cur-rency or variations in note design. Consequently, the system's performance may decline when encountering unfamiliar or highly sophisticated counterfeit patterns. The system is also sensitive to image quality and environ-mental conditions. Variations in lighting, resolution, and image noise can affect feature extraction and, consequently, the clas-sification outcome. Additionally, the current implementation does not incorporate real-time learning capabilities, thereby restricting its capacity to adapt to evolving patterns over time. These constraints emphasize the importance of further im-provements to enhance the system's accuracy, flexibility, and overall robustness.

XII. FUTURE WORK

Future work for the proposed system focuses on enhancing its accuracy, scalability, and real-world applicability through the integration of advanced technologies. One of the key improvements involves replacing the simulated CNN model with a fully trained deep learning model using frameworks such as TensorFlow or PyTorch. This would enable the system to automatically learns from complex patterns and significantly improve detection accuracy.

Another important area of enhancement is the broadening the dataset utilized for model training and evaluation. Incorporating a large and diverse dataset of genuine and counterfeit currency images will improve the model's generalization capability and make it more robust against variations in currency design and environmental conditions.

The development of a mobile application is also a promising direction for future work. A mobile-based solution would allow users to perform currency detection on-the-go, increasing accessibility and usability. Additionally, integrating real-time image capture and processing capabilities would further enhance the practicality of the system.

Potential future developments could involve incorporating more sophisticated image analysis methods, such as combining multiple feature representations and leveraging deep feature extraction, along with integrating cloud-based infrastructure to support scalable processing. These advancements would help evolve the system into a more adaptive, intelligent, and deployment-ready solution.

XIII. FEATURE WEIGHT DISTRIBUTION

Each feature extracted from the currency image contributes differently to the classification process. Assigning appropriate weights to these features is essential for achieving accurate results.

TABLE I
FEATURE WEIGHT DISTRIBUTION

Feature	Weight Contribution
Color Consistency	0.20
Edge Sharpness	0.15
Texture Analysis	0.20
Watermark Detection	0.25
Security Thread	0.20

The weights are determined according to the relative significance of each feature in identifying counterfeit currency. Watermark detection has the highest contribution due to its uniqueness in genuine notes.

XIV. APPLICATIONS

The developed counterfeit currency detection system can be utilized in multiple domains and practical scenarios. Within the banking industry, it can automate the process of verifying banknotes, thereby lowering staff workload and reducing the likelihood of human error. Banks and other financial organizations can incorporate this solution into their current systems to improve both security and operational efficiency.

In the retail industry, the system can assist shopkeepers and cash handlers in quickly verifying the authenticity of currency notes during transactions. This is particularly beneficial in high-volume retail environments where manual verification is impractical.

The system can also be deployed in automated teller ma-chines to enhance fraud detection and prevent the circulation of counterfeit currency. The system can also support law enforcement authorities in detecting counterfeit currency and monitoring related fraudulent activities.

Moreover, the solution can be incorporated into mobile platforms, allowing everyday users to conveniently check the authenticity of currency notes. This widespread accessibility can serve a key role in reducing the circulation of counterfeit currency and improving overall financial security.

XV. CONCLUSION

This work presents an in-depth and efficient approach to counterfeit currency detection is done using machine learn-ing and image processing techniques. The proposed system demonstrates how multiple visual and structural features of currency notes can be analyzed and combined to achieve accurate classification results. By adopting a feature-based approach inspired by convolutional neural networks, the sys-tem achieves a balance between computational efficiency and detection performance.

The web-based design enhances accessibility, scalability, and ease of use, making the system suitable for deployment in a wide range of real-world settings. Although the current version relies on a simulated CNN model, the results suggest that it can deliver dependable detection performance under controlled conditions.

The research highlights the potential of integrating artificial intelligence into financial security systems and underscores the importance of automated solutions in combating counterfeit currency. With further enhancements, including deep learn-ing integration and large-scale dataset training, the proposed system can evolve into a highly robust and production-ready solution for counterfeit detection.

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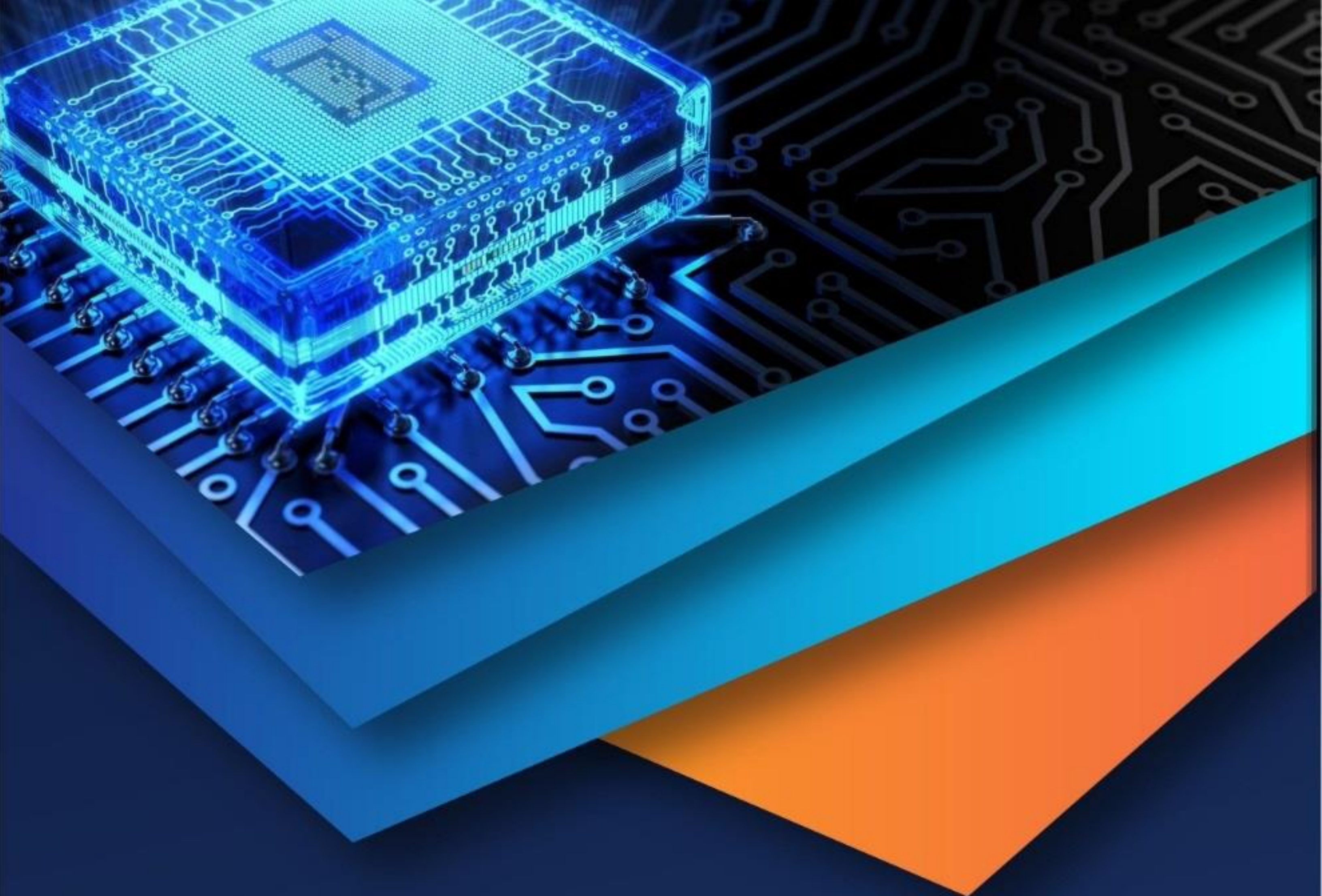

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