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Artificial Intelligence and Machine Learning Approaches for Identifying Fake Currency: A Review

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Abstract: Financial institutions, governments, and businesses around the world face serious challenges because of the growing sophistication of counterfeit currency. Visual inspection and UV light verification are two traditional detection techniques that often miss sophisticated forgeries and require extensive human intervention. Machine learning (ML) and artificial intelligence (AI) techniques have become popular in recent years as viable means of automated, precise, and scalable counterfeit detection. This review paper offers a thorough examination of AI- and ML-based methods for detecting counterfeit currency, including hybrid approaches, image processing, feature extraction, and classification algorithms. Researchers assess how well convolutional neural networks, deep learning architectures, and supervised and unsupervised learning techniques detect counterfeit currency. The study examines the drawbacks of existing technologies, including reliance on datasets, variability in currency design, and difficulties with real-time implementation. This review outlines the advantages, disadvantages, and prospects for future integration of intelligent systems in the fight against currency counterfeiting by contrasting conventional, digital, and AI-driven approaches. According to the results, AI- and ML-based detection systems perform notably better in terms of accuracy and efficiency than traditional techniques, laying the groundwork for safer financial operations. To improve detection capabilities in dynamic financial environments, this review also highlights the need for cross-currency applications, large-scale datasets, and adaptive models.

Keywords: Counterfeit Currency Detection; Image Processing; Machine Learning (ML); Convolutional Neural Networks (CNNs); Financial Security; Feature Extraction; Classification Algorithms; Supervised Learning.

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1. Introduction

Counterfeit money is still a major problem worldwide. It hurts the economy, erodes public trust in government and businesses, and costs governments, businesses, and people a lot of money. Counterfeit banknotes facilitate organized crime, fraud, and money laundering, and distort economic indicators such as inflation and currency value. Governments and financial institutions are said to lose billions of dollars each year due to counterfeit currency in circulation [3]. This is due to both direct replacement costs and indirect economic effects, such as lower credibility, increased scrutiny of transactions, and reduced consumer trust. As global trade and digital technology grow, so do the networks that produce fake goods, making the detection of fakes a top concern in global financial regulation [5]. The design of money has changed over time, adding increasingly advanced security features that make it harder to counterfeit. Modern banknotes feature multiple levels of protection, including holographic stripes, microprinting, intaglio printing, latent images, optically variable inks, embedded security threads, tactile features, ultraviolet patterns, and complex watermarks. High-resolution printing technologies and advanced materials science are used to make these measures difficult to copy and too expensive for counterfeiters to produce. However, in the last few decades, counterfeiters have quickly adapted to new technologies that make it easy to produce phony notes that look very real. This technological arms race between security designers and counterfeiters shows why traditional detection methods are becoming less effective in today's financial world [12].

In the past, professional bank cashiers, merchants, or law enforcement agents had to examine banknotes by hand to determine whether they were fake. When doing a visual assessment, you can verify the feel of the notes, look for watermarks under transmitted light, check for colour consistency, and compare notes that you think are fake with real ones. Later, machines and electronics were added to help people make decisions. These included ultraviolet light detectors for fluorescent pattern detection, magnetic ink character recognition (MICR) devices, optical sensors, and machine-readable security thread detectors. Even though many people still use these technologies, they have significant built-in problems. Human inspection is subjective, relies heavily on experience and focus, and becomes progressively unreliable as transaction volumes increase or when exhaustion sets in [2]. Mechanical detection devices are helpful, but they need to be calibrated regularly, can be too expensive for small enterprises, and might not be able to distinguish between high-quality fake notes that mimic machine-detection features. Additionally, conventional detection methods frequently rely on predetermined attributes of genuine banknotes, rendering them susceptible when counterfeiters develop novel printing or bleaching techniques that circumvent detection limits. As counterfeiting improves, tools based on fixed traits are likely to become useless. Because of this, people have realised that detection tactics need to change from static, rule-based systems to adaptive, intelligent solutions that can learn and respond to new patterns of counterfeiting. Because of this, the need for automated, scalable, and highly precise methods to detect counterfeit money has grown in both established and emerging nations.

Artificial intelligence (AI) and machine learning (ML) have changed the way we detect fake items by providing computer-based methods that can learn from vast amounts of data and uncover patterns too small or buried for people to see. AI-based systems use advanced digital image processing techniques on high-resolution images of money to identify visual, textural, and spectral traits that distinguish genuine notes from counterfeit ones. You can use math to measure colour distributions, edge patterns, frequency spectra, texture imperfections, and microstructural inconsistencies. These measurements can then be utilised to train classification algorithms. Machine learning algorithms, such as support vector machines (SVMs), decision trees, k-nearest neighbours, artificial neural networks (ANNs), and ensemble methodologies, facilitate automated learning from labelled datasets of genuine and counterfeit banknotes to forecast authenticity for previously unexamined samples. Convolutional neural networks (CNNs) have become a very powerful tool for finding fake images among AI-driven methods. CNNs create hierarchical visual representations on their own by passing picture data through convolutional, pooling, and fully connected layers. This lets them find complex patterns, such as subtle textures or distortions, that other feature-engineering methods miss. CNN-based methods work well in the real world because they can handle noise, changes in lighting, rotations, and partial occlusions. Transfer learning approaches make models even more efficient by fine-tuning pre-trained neural networks on currency datasets.

This reduces the amount of data and computing power required while maintaining high accuracy. AI systems offer many benefits over traditional methods of finding things. First, AI approaches are more accurate when trained on large, varied datasets that include different forms of wear, printing batches, denominations, and counterfeits. Second, machine learning models improve over time as they receive more data. This means they can adapt to new ways of forging instead of being stuck with certain traits. Third, automatic detection technologies reduce the need for human judgment, reduce mistakes caused by fatigue, and make it easier to quickly verify identities at points of sale, ATMs, cash sorting facilities, and border checkpoints. Fourth, AI-based methods can be built into mobile apps or embedded systems, making them easy to use in a wide range of settings, even in distant areas where traditional detection instruments would not be available. Researchers have investigated various feature-extraction methodologies and machine learning frameworks for detecting counterfeits. Texture-based methods using grey-level co-occurrence matrices (GLCM), local binary patterns (LBP), Gabor filters, and wavelet transforms can capture the subtle textural details of banknotes. Spectral and hyperspectral imaging can detect changes in ink composition, fluorescence properties, and spectral signatures that are not visible to the naked eye. This makes it very hard for counterfeiters to copy. Other investigations have examined verifying serial numbers, authenticating watermarks, and analysing microprinting using AI classifiers and magnified images. Hybrid systems that combine feature extraction methods with ensemble learning models often perform better by leveraging the distinct capabilities of these analytical perspectives.

Even if AI and ML counterfeit-detection systems have significant potential, implementing them is not without its problems. High-performance models need big, high-quality datasets with a wide range of real and fake currency instances. It is hard to access these kinds of databases due to security concerns, central banks' need for privacy, and laws against copying currency images. In real-world situations where new types of fake products emerge, limited datasets can lead to overfitting, bias, and reduced generalizability. Also, fake methods change frequently, so models need to be retrained and the data updated regularly. Another problem is that deep learning models require significant processing power, memory, and specialised hardware such as GPUs. This makes it challenging to build the right computing infrastructure. You also need to be very mindful of moral and legal considerations. If not handled properly, digital photographs of banknotes could expose systems to forgery. To ensure that detection technologies aren't used for unlawful copying, strong encryption, limited access to data, and cybersecurity rules are all important. False positives in detection systems can also be a problem for honest currency holders, and false negatives can help fake money circulate. So, AI-based authentication systems need to find a balance between sensitivity and specificity. To make sure that AI countermeasure technologies are used responsibly, there must be clear validation processes and cooperation with monetary authorities. The use of AI-driven systems in banking and finance affects society and the economy. Automated detection systems can reduce costs, speed up transactions, and increase confidence in financial transactions. ATMs, vending machines, and automated payment kiosks equipped with AI-based recognition systems can verify banknote validity in real time without human assistance.

In underdeveloped nations where manual checks are still common, mobile-based apps that use smartphone cameras to find fake items are a cheap way to make authentication tools available to more people. This could cut fraud rates in informal markets. But for it to work, users need to be educated, regulations need to be in place, and it must align with financial inclusion initiatives to ensure everyone receives the same benefits. Future research directions encompass the development of multimodal detection systems that integrate visual imaging with tactile, auditory, chemical, or electromagnetic modalities to facilitate multi-layered verification. Blockchain technology might also be used to safely track the life cycle of money, enabling the tracing of banknote distribution and better oversight of counterfeiting. New AI research areas, such as explainable artificial intelligence (XAI), could clarify which elements are most important for classifying counterfeits. This would make the system more accountable and easier for regulatory bodies to audit. Combining AI with Internet of Things (IoT) devices could make it much easier for smart financial infrastructure, border control systems, and retail environments to have networks that can detect fake goods. Another possible path is to use ML methods to find fraud in digital currencies and cryptocurrencies. The problem of counterfeit physical currency remains very serious. However, the advent of central bank digital currencies (CBDCs) and crypto-assets introduces new problems, including digital forgeries, phishing, and transaction manipulation. Lessons learned from using AI to verify the authenticity of physical cash may help protect new digital financial systems.

This will help the battle against financial crime and strengthen the integrity of the global financial system. Training and building capacity are two additional important steps that must be taken for AI-based counterfeit detection systems to work. People who work in banks, police, and stores need to learn how to use AI devices correctly, understand the results, handle uncertainty, and report suspected counterfeits responsibly. To develop useful solutions that combine technology with legal frameworks and human skills, computer scientists, financial regulators, currency designers, and criminologists will need to work together across disciplines. Counterfeit money is a complex and ever-changing issue that harms economies worldwide by destabilizing them, encouraging crime, and eroding public trust in monetary systems. Traditional detection methods are becoming less useful as counterfeiting techniques become more sophisticated. Artificial intelligence and machine learning have the power to change everything by providing automatic, adaptable, and highly precise detection capabilities that go beyond what manual and mechanical methods can achieve. AI-based systems can distinguish between real and fake money using digital image processing, feature extraction, and predictive modelling. They can also learn from vast datasets and adapt to new methods of creating fake money. To make the most of AI and ML in detecting fake items, researchers need to continue researching, pay close attention to legal and ethical issues, build robust datasets, and work together as institutions. As technology improves, adding smart authentication methods to the financial system has significant promise to make currency safer, protect economies, and increase people's confidence in financial transactions.

2. Literature Review

Over the past few decades, the detection of counterfeit currency has been the subject of much research, progressing from manual techniques to sophisticated AI and machine learning methods. A thorough understanding of these techniques offers valuable perspectives on their efficacy, constraints, and potential for incorporation into contemporary financial frameworks.

2.1. Traditional Detection Methods

Human observation and mechanical verification tools are the mainstays of traditional counterfeit detection methods. Checking banknotes for variations in colour, texture, watermark, and printing quality is known as visual inspection. This method is straightforward and economical, but it is also highly subjective and prone to error, particularly when dealing with high-quality forgeries. More objective analysis is provided by mechanical devices like watermark verification tools, magnetic ink readers, and ultraviolet (UV) light detectors. Sundravadivelu et al. [6] noted that while UV and magnetic ink detectors are effective at detecting some security features, they are ineffective against advanced printing techniques. All things considered, even though conventional methods are still frequently employed, they are not flexible enough to accommodate emerging counterfeiting technologies.

2.2. Image Processing Techniques

By extracting characteristics such as texture, colour patterns, edge detection, and microprinting details, digital image processing enabled automatic analysis of banknotes. To compare real and fake notes, techniques like template matching, Fourier transforms, and histogram analysis have been used. For example, Berenguel et al. [1] detected counterfeit currency with 89% accuracy using wavelet-based texture analysis. In a similar study, Viraktamath et al. [11] showed that colour segmentation and edge detection could successfully detect counterfeit notes. Even though these methods increased automation and objectivity, they still rely heavily on carefully controlled imaging conditions and may not handle changes in note orientation, lighting, or wear.

2.3. Artificial Intelligence and Machine Learning Approaches

The limitations of conventional and image-based methods have been significantly overcome by AI- and ML-based approaches. Features extracted from currency images have been classified using Support Vector Machines (SVMs), k-Nearest Neighbours (k-NN), and Random Forests, with detection accuracies ranging from 90% to 95% [9]. Strong detection even in the face of noisy conditions and imaging environment variations is made possible by deep learning models, especially Convolutional Neural Networks (CNNs), which can automatically learn hierarchical features from raw images. Kamble et al. [4], for instance, used a CNN-based model that detected counterfeit Indian rupee notes with 97% accuracy. Hybrid methods have also been investigated to leverage both learned and handcrafted features, combining image processing with machine learning classifiers to improve performance.

2.4. Comparative Studies and Performance Metrics

Several studies have compared the effectiveness of traditional, image-based, and AI-driven methods. Generally, AI and deep learning models outperform conventional techniques in accuracy, robustness, and speed. Commonly used performance metrics include accuracy, precision, recall, F1-score, and detection time, as shown in Table 1.

Table 1: A comparative overview of selected studies

Method	Dataset	Accuracy	Precision	Recall	F1-Score	Reference
Visual Inspection	Indian Rupees	75%	0.72	0.70	0.71	Sundravadivelu et al. [6]
Image Processing	Indian Rupees	89%	0.88	0.87	0.87	Berenguel et al. [1]
SVM	Indian Rupees	92%	0.91	0.90	0.91	Kanawade et al. [9]
CNN	Indian Rupees	97%	0.96	0.97	0.96	Kamble et al. [4]

3. Techniques for Fake Currency Detection

Detecting counterfeit currency involves a range of methods, from conventional human inspection to modern AI-driven systems. These techniques can be broadly categorised into traditional methods, digital/image processing methods, and AI and machine learning approaches. Each category offers distinct advantages and limitations, which are discussed below.

3.1. Traditional Methods

Traditional methods rely primarily on human observation and simple mechanical tools to verify currency authenticity. Common techniques include the following Table 2.

Table 2: Common techniques for traditional methods

Visual Inspection	Observing banknotes for discrepancies in colour, texture, microprinting, watermarks, and security threads. Visual inspection is simple, cost-effective, and widely used. However, it is highly subjective and prone to human error, especially with high-quality forgeries.
Ultraviolet (UV) Light Verification	Many banknotes contain UV-sensitive inks that fluoresce under ultraviolet light. UV verification provides a quick, objective check, but cannot detect counterfeit notes that replicate or bypass UV features.

Magnetic Ink Detection	Some currencies use magnetic ink to encode security information. Magnetic detectors can sense these features, but the method may fail if the ink is imitated or altered.
Watermark Verification	Genuine banknotes feature watermarks that can be visually inspected or examined with a light. This method is simple but may be ineffective against advanced counterfeit techniques.

Traditional methods are suitable for low-volume detection but lack scalability and robustness against sophisticated forgery.

3.2. Digital and Image Processing Methods

Digital image processing techniques automate counterfeit detection by analysing visual and structural features of banknotes. These methods include Table 3.

Table 3: Digital and image processing methods

Texture and Pattern Analysis	Techniques like histogram analysis, wavelet transforms, and Gabor filters extract textural features of currency surfaces to distinguish genuine notes from forgeries.
Edge and Contour Detection	Algorithms such as the Canny or Sobel edge detectors identify edges and contours, which can reveal discrepancies in printing and microdesigns.
Colour Segmentation and Feature Matching	Colour distribution and region-based segmentation help compare the colour patterns of the test note with those of a reference. Template matching can further identify subtle differences.
Multispectral Imaging	By capturing banknotes under multiple wavelengths (infrared, UV, visible), multispectral methods enhance feature extraction for forgery detection.

These approaches improve objectivity and automation over traditional methods. However, their performance is affected by imaging conditions, banknote wear and tear, and variability in lighting and orientation.

3.3. AI and Machine Learning Approaches

Artificial intelligence and machine learning methods provide advanced solutions for counterfeit currency detection by automatically learning patterns from large datasets. Key approaches include the following Table 4.

Table 4: AI and machine learning approaches

Support Vector Machines (SVMs)	SVMs classify currency images using extracted features such as texture, colour, and shape. They are effective for binary classification (genuine vs counterfeit) and achieve high accuracy in controlled datasets.
k-Nearest Neighbours (k-NN) and Random Forests	These classifiers rely on feature similarity or ensemble learning to detect counterfeit notes. They offer simplicity and competitive performance for structured feature datasets.
Convolutional Neural Networks (CNNs)	CNNs automatically extract hierarchical features directly from images, providing robustness against variations in lighting, orientation, and noise conditions. They have achieved accuracy exceeding 95% in multiple studies.
Hybrid Models	Combining image processing techniques with machine learning classifiers enables the use of both handcrafted and learned features, further improving detection performance.

AI-based systems offer high accuracy, adaptability, and potential for real-time deployment. However, challenges include the need for large, diverse datasets, high computational resources, and cross-currency generalization (Table 5).

Table 5: Representative methods for counterfeit currency detection

Method Category	Specific Method	Principle	Advantages	Limitations	Representative References
Traditional	Visual Inspection	Observing banknotes for irregularities in colour, texture, watermark, and printing	Simple, low cost, widely used	Subjective, error-prone, limited scalability	Sundravadivelu et al. [6]

Traditional	UV / Magnetic Ink Detection	Detecting UV-sensitive inks or magnetic features	Fast, objective, and detects certain security features	Fails against high-quality forgeries	Sundravadivelu et al. [6]
Image Processing	Texture and Pattern Analysis	Feature extraction using wavelet transforms, histograms, and Gabor filters	Automated, objective	Sensitive to lighting, note wear	Berenguel et al. [1]
Image Processing	Edge / Colour Segmentation	Detects edges, contours, and colour patterns for comparison	Effective for visual discrepancies	Depends on imaging conditions	Viraktamath et al. [11]
AI / ML	SVM, k-NN, Random Forest	Classifies extracted features of currency images	High accuracy, adaptable	Requires labelled datasets, medium computational cost	Kanawade et al. [9]
AI / ML	Convolutional Neural Networks (CNN)	Deep learning model automatically learns hierarchical features	Robust to variations, high accuracy	High computational resources, dataset dependent	Kamble et al. [4]
Hybrid	Image Processing + ML	Combines handcrafted features with ML classification	Improved detection combines the strengths of both methods	Complex implementation, dataset dependent	Dhapare et al. [8]; Tarawneh [7]
Multispectral / Advanced Sensors	Spectral Imaging	Analyses multiple wavelengths for forgery detection	Detects subtle security features	High-cost equipment, limited availability	Baek et al. [10]

4. Challenges in Fake Currency Detection

Despite significant advances in counterfeit detection, several challenges hinder the effectiveness and widespread adoption of detection systems. These challenges span technological, operational, and practical aspects.

4.1. Dataset Limitations

AI and ML-based detection systems rely heavily on large, high-quality datasets for training. However, acquiring comprehensive datasets of both genuine and counterfeit banknotes is challenging due to security restrictions and limited access. Additionally, the lack of standardisation across different currencies makes it difficult to compare methods or general models for international applications. Small or imbalanced datasets may result in overfitting and reduced detection accuracy.

4.2. High-Quality Forgeries

These days, counterfeiters create fake banknotes that closely resemble real ones by using high-resolution scanners, 3D printing, and sophisticated printing technologies. Even with advanced AI models, these high-quality forgeries are challenging to identify because they often mimic security features such as holograms, watermarks, and colour-shifting inks. It is still very difficult to identify minute irregularities in texture, microprinting, or spectral properties.

4.3. Variability of Currency Designs

New security features, denominations, or seasonal redesigns often result in changes to currency designs. New variations may go unnoticed by models trained on older designs. Furthermore, environmental conditions, stains, folding, and wear and tear can alter the appearance of authentic notes, increasing the risk of false-positive or false-negative results. It is crucial to ensure that detection systems can adapt to changing designs without requiring extensive retraining.

4.4. Real-Time Implementation and Scalability

Scalability and real-time processing are essential when implementing AI-based detection systems in real-world settings such as banks, shops, or ATMs. Latency problems can arise from the computationally demanding processes of high-resolution image acquisition, feature extraction, and classification. Practical adoption may be limited by the inability of low-power edge devices to run complex deep learning models effectively.

4.5. Security and Privacy Concerns

High-resolution photos of banknotes and other sensitive information may be collected and stored by counterfeit-detection systems. Particularly in centralised financial systems, it is crucial to ensure secure data handling, prevent leaks, and protect privacy. To overcome these obstacles, standardised datasets, cross-currency applicability, optimised deployment techniques, and adaptive, effective, and robust detection models must be developed.

5. Comparative Analysis of Methods

A comprehensive comparison of counterfeit currency detection techniques provides insight into their relative strengths, limitations, and suitability for different applications. Methods can be broadly categorised into traditional, digital/image processing, and AI/ML-based approaches.

5.1. Performance Comparison

Table 6 shows a side-by-side comparison of classical, digital image processing, AI/ML, and hybrid detection methods, focusing on their accuracy, cost, scalability, and reliability. It shows a clear improvement in performance from cheap standard methods to deep learning and hybrid methods that are very accurate but use a lot of resources.

Table 6: Summarises the key characteristics and performance metrics of selected detection techniques

Method Category	Technique	Accuracy	Cost	Scalability	Robustness	Advantages	Limitations
Traditional	Visual Inspection	70–80%	Low	Low	Low	Simple, low-cost	Subjective, error-prone
Traditional	UV/Magnetic Detection	75–85%	Low-Medium	Medium	Medium	Objective, fast	Limited against high-quality forgeries
Digital/Image Processing	Edge/Texture Analysis	85–90%	Medium	Medium	Medium	Automated, objective	Sensitive to lighting, wear, and orientation
AI/ML	SVM, k-NN, Random Forest	90–95%	Medium-High	High	Medium-High	High accuracy, adaptable	Requires labelled datasets and computational cost
AI/ML	CNN / Deep Learning	95–98%	High	High	High	Robust to variations, automated	High computational resources, dataset dependent
Hybrid	Image Processing + ML	92–97%	Medium-High	High	High	Combines the strengths of both approaches	Complex implementation, dataset dependent

6. Future Directions

As counterfeit currency techniques continue to evolve, future research in detection and prevention must focus on developing adaptive, efficient, and intelligent systems. Several key directions have emerged from recent studies and technological trends:

6.1. Development of Large-Scale, Standardised Datasets

The lack of comprehensive, standardised datasets remains a significant barrier to AI- and ML-based systems. Future efforts should focus on creating large, publicly accessible datasets that include multiple currencies, denominations, and forgery types. Such datasets will enable robust training, benchmarking, and cross-currency generalisation of detection models.

6.2. Advanced Deep Learning Architectures

Emerging deep learning architectures, such as transformers, attention-based networks, and generative models, have the potential to further improve counterfeit detection. These models can learn complex spatial and spectral patterns in banknotes, enabling higher accuracy even under challenging conditions such as variable lighting, note wear, and high-quality forgeries.

6.3. Multimodal and Hybrid Approaches

Integrating multiple sources of information, such as image data, spectral analysis, and sensor-based features, can enhance detection accuracy. Hybrid systems that combine traditional, image-processing, and AI-based methods can leverage the strengths of each approach while mitigating their weaknesses.

6.4. Real-Time and Edge Deployment

Real-world applications, including ATMs, banks, and retail environments, require real-time processing on devices with limited computational resources. Future research should focus on lightweight models optimised for edge deployment that achieve rapid detection without compromising accuracy.

6.5. Adaptive and Continual Learning

Counterfeiters continuously innovate, producing new forgery methods that may bypass existing detection systems. Adaptive models capable of continual learning—updating themselves with new data without full retraining—will be essential to maintain long-term effectiveness.

6.6. Cross-Currency and Global Applications

Most current research focuses on specific currencies or regions. Future detection systems should aim for cross-currency generalisation, enabling financial institutions to deploy a unified solution across multiple countries, denominations, and note designs.

6.7. Integration with Blockchain and Financial Security Systems

Blockchain-based tracking and other emerging technologies present chances to supplement physical counterfeit detection. Financial transactions can be made more secure and transparent by combining AI-based detection with digital verification techniques. In conclusion, future studies should concentrate on integrating sophisticated AI models, reliable datasets, and practical deployment techniques to develop robust, effective, and flexible counterfeit currency detection systems. To combat the growing complexity of forgery techniques, these innovations will be essential.

7. Conclusion

Globally, counterfeit currency continues to present serious economic and security issues, making the creation of trustworthy and effective detection systems imperative. This review covers the principles, benefits, and drawbacks of conventional, digital, and AI-driven methods for counterfeit detection. Conventional techniques, like mechanical verification and visual inspection, are straightforward and economical, but they are not robust or scalable against high-quality forgeries. Techniques for digital image processing increase automation and objectivity while maintaining sensitivity to environmental changes and conditions. Artificial intelligence and machine learning techniques, especially deep learning models such as convolutional neural networks, perform exceptionally well, offering high accuracy, flexibility, and the potential for real-time deployment. By combining the strengths of multiple methods, hybrid models that integrate AI and image processing further improve detection reliability. Notwithstanding these developments, there are still issues such as limited data sets, changing currency designs, and limitations on real-time implementation.

The creation of extensive, standardised datasets, sophisticated deep learning architectures, multimodal strategies, edge deployment, adaptive learning, and cross-currency applicability are the main focus areas for future directions. One promising approach to improving efficiency and trust in international financial systems is integrating AI-based detection with more comprehensive financial security frameworks, such as blockchain verification. To sum up, AI- and ML-powered detection systems are a revolutionary development in the fight against counterfeit money, offering highly accurate, scalable, and adaptable solutions. Adopting advanced, data-driven detection frameworks will be crucial as counterfeiting techniques continue to advance, helping preserve economic stability, public confidence in monetary systems, and financial integrity.

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