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# Smart Fake Currency Detection System using Machine Learning

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**ABSTRACT:** The rapid growth of counterfeit currency circulation has become a major concern for financial institutions, retail systems, and economic stability. Traditional currency authentication techniques, including manual inspection and hardware-based methods such as ultraviolet (UV) and infrared (IR) detection, are often expensive, time-consuming, and require trained personnel. These limitations highlight the need for an automated, cost-effective, and scalable solution for reliable counterfeit detection.

This paper presents a smart fake currency detection system using a hybrid machine learning framework integrated with advanced image processing techniques. The proposed system adopts a non-destructive, image-based approach that analyzes currency notes captured using standard cameras or mobile devices. The system processes the input image through multiple stages, including preprocessing, feature extraction, and classification, to accurately determine the authenticity of the note.

In the preprocessing stage, the input image is resized and enhanced using Gaussian filtering to reduce noise and ensure consistency. The system then extracts multiple discriminative features from both RGB and grayscale domains. RGB color variation analysis is performed to evaluate ink distribution and detect abnormalities in color consistency, which are common in counterfeit notes.

**KEYWORDS:** Fake Currency Detection, Machine Learning, Image Processing, RGB Color Analysis, Texture Analysis, Security Feature Detection, Canny Edge Detection, Laplacian Variance, Feature Extraction, Pattern Recognition, Computer Vision, Currency Authentication, Hybrid Classification, Automated Detection System

## I. INTROUDCTION

The proliferation of counterfeit currency has emerged as a significant challenge to financial systems, affecting economic stability, public trust, and secure transactions. With the advancement of printing and digital replication technologies, counterfeit notes have become increasingly sophisticated, making it difficult to distinguish them from genuine currency using conventional methods. This issue is particularly critical in developing regions where access to advanced detection systems is limited.

Traditional currency authentication techniques primarily rely on manual inspection or hardware-based methods such as ultraviolet (UV) and infrared (IR) detection. While these approaches provide a certain level of reliability, they require specialized equipment and trained personnel, which limits their scalability and practical deployment. Moreover, manual verification is subjective and prone to human error, especially when counterfeit notes closely mimic genuine security features.

In recent years, machine learning and computer vision techniques have been widely explored for automated counterfeit detection. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated high performance in image classification tasks [3], [4], [5]. However, these models often require large datasets, high

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computational resources, and operate as black-box systems, limiting their interpretability and real-time applicability [13], [17].

Feature-based machine learning approaches using algorithms such as Support Vector Machines (SVM) [8] and Random Forests [7] have also been employed for classification tasks. These methods rely on extracting meaningful features such as color distribution, texture properties, and structural patterns from images. Image processing techniques, including edge detection [12] and thresholding methods [11], have been widely used to enhance feature extraction and improve classification accuracy.
Inspired by multi-feature and interpretable machine learning frameworks [2], [13], this work proposes a smart fake currency detection system that integrates image processing and machine learning techniques. The proposed system focuses on extracting multiple discriminative features, including RGB color variation, grayscale texture analysis, and security feature verification such as the detection of the embedded security thread and Gandhi portrait.

Unlike purely deep learning-based approaches, the proposed method adopts a hybrid feature-driven model that combines statistical analysis with machine learning-based decision logic. This enhances interpretability while maintaining computational efficiency. By integrating multiple features into a unified framework, the system improves robustness against variations in lighting, noise, and counterfeit printing quality.

The remainder of this paper is organized as follows. Section II presents the related works in the domain of counterfeit currency detection. Section III describes the proposed methodology and system design. Section IV discusses implementation and experimental results. Finally, Section V concludes the paper and outlines future research directions.

## II. RELATED WORK

Counterfeit currency detection has been extensively studied using a combination of image processing, machine learning, and deep learning techniques. The evolution of these approaches reflects the increasing complexity of counterfeit generation and the need for robust, automated authentication systems.

Early research primarily focused on **classical image processing techniques** for detecting counterfeit notes. These methods involve preprocessing steps such as grayscale conversion, histogram equalization, and noise filtering to enhance image quality and extract meaningful features. Threshold-based segmentation techniques, including Otsu's method [11], have been widely used to separate foreground and background regions in currency images. Additionally, edge detection algorithms such as the Canny operator [12] have been applied to identify structural components like borders, security threads, and printed patterns. While these approaches are computationally efficient and easy to implement, they are highly sensitive to variations in illumination, noise, and image quality, limiting their robustness in real-world scenarios.

To overcome the limitations of purely image-based techniques, researchers introduced **machine learning-based classification methods**. Algorithms such as Support Vector Machines (SVM) [8] and Random Forests [7] have been widely used for counterfeit detection tasks. These models rely on handcrafted features extracted from currency images, including color histograms, texture descriptors, and statistical measures. Feature extraction techniques play a critical role in these systems, as the classification performance heavily depends on the quality and discriminative power of the selected features. Although these methods improve classification accuracy compared to traditional approaches, they often require careful feature engineering and may struggle to generalize across different datasets.

With the rapid advancement of deep learning, **Convolutional Neural Networks (CNNs)** have gained significant attention for counterfeit currency detection. CNN-based models automatically learn hierarchical features from raw image data, eliminating the need for manual feature extraction. Architectures such as AlexNet [3], VGG [5], and ResNet [4] have demonstrated high performance in image classification tasks and have been adapted for currency authentication. More recent models, such as EfficientNet [19], provide improved accuracy with optimized computational efficiency through model scaling. Despite their superior performance, deep learning models typically require large labeled datasets and high computational resources for training. Moreover, their black-box nature reduces interpretability, which is a critical requirement in financial and security-related applications.

Recent studies have explored **hybrid approaches** that combine image processing and machine learning techniques to leverage the advantages of both paradigms. These systems integrate multiple feature extraction methods, including

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color analysis, texture analysis, and structural feature detection, to create a comprehensive representation of currency authenticity [13], [18]. Feature fusion techniques are employed to combine complementary information from different domains, improving classification robustness and accuracy. Such approaches are particularly effective in handling variations in lighting conditions and counterfeit printing quality.

In addition to general feature extraction, several works emphasize the importance of analyzing **currency-specific security features**. These include watermarks, security threads, micro-text patterns, and portrait regions, which serve as key indicators of authenticity. Edge-based detection methods are commonly used to identify security threads, while texture and contrast analysis are applied to evaluate the clarity of printed elements. Incorporating these domain-specific features enhances the reliability of counterfeit detection systems.

Furthermore, the integration of software libraries and tools such as OpenCV [10] and machine learning frameworks like Scikit-learn [9] has enabled the development of efficient and scalable detection systems. These tools facilitate real-time implementation and deployment of counterfeit detection algorithms in practical applications.

**Table.2.1 Comparison Table**

| **Author** | **Method** | **Description** | **Limitation** |
|---|---|---|---|
| Patel et al. (2021) | Image Processing + SVM | Uses color and texture features to classify notes. | Sensitive to lighting and noise. |
| Reddy et al. (2022) | ORB Feature Extraction | Detects keypoints and matches patterns in currency. | Needs proper alignment and clear images. |
| Mathe et al. (2024) | CNN (Deep Learning) | Automatically learns features for high accuracy detection. | Requires large dataset and high computation. |

## III. PROPOSED SYSTEM

The proposed system detects fake currency using image processing and machine learning techniques. The input currency image is captured using a camera and preprocessed by resizing, filtering, and converting to grayscale.

The system extracts key features such as RGB color variation, texture sharpness, and security elements like the security thread and Gandhi portrait. These features help identify differences between genuine and counterfeit notes.

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Finally, a hybrid decision model combines all features and classifies the currency as real or fake based on a confidence score. The system is suitable for real-time applications.

**A. System Overview**

The proposed smart fake currency detection system is designed to automatically identify counterfeit notes using image processing and machine learning techniques. The system follows a structured pipeline consisting of image acquisition, preprocessing, feature extraction, and classification.

Initially, the currency image is captured using a camera or mobile device. The captured image is preprocessed to improve quality by resizing, noise removal, and grayscale conversion. This ensures consistent input for further analysis.

The system then extracts important features such as RGB color variation, texture sharpness, and security elements like the security thread and Gandhi portrait. These features help differentiate genuine notes from counterfeit ones.
Finally, a hybrid classification module combines all extracted features and classifies the currency as real or fake based on a confidence score. The system is efficient, cost-effective, and suitable for real-time applications in banking, retail, and mobile platforms.

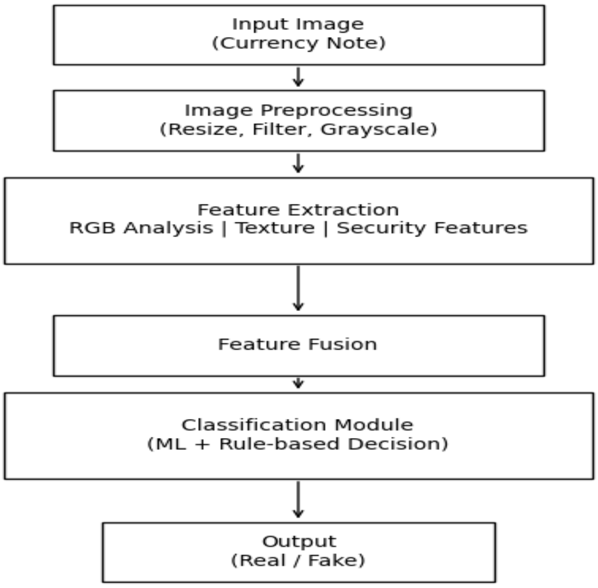


**Fig.3.1 Block Diagram of Proposed System.**

**B. Input Image Acquisition**

The proposed system begins with the acquisition of the currency note image using a digital camera, scanner, or smartphone. The quality of the input image plays a crucial role in the overall performance of the system, as it directly affects the accuracy of feature extraction. The captured image is typically in RGB format, preserving all color information required for further analysis.

To ensure reliable detection, images should be captured under proper lighting conditions and with minimal distortion. The system is designed to handle variations in image orientation and scale to some extent, making it suitable for real-world applications. This stage ensures that all important visual elements, such as color patterns, texture details, and security features, are available for processing.

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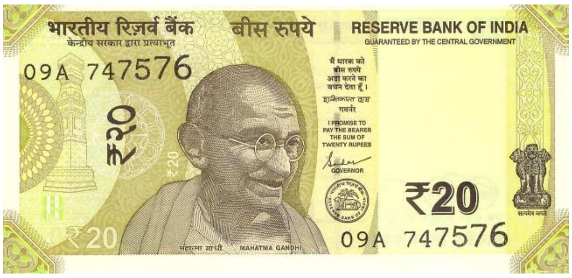


**Fig. 3.2 Real Indian Twenty Rupees Currency Image**

**C. Image Preprocessing**

Once the image is acquired, it undergoes preprocessing to enhance its quality and standardize the input. The image is first resized to a fixed resolution (e.g., 256×256 pixels) to ensure uniformity across all inputs. This step reduces computational complexity and ensures that the system processes all images consistently.

In addition, noise reduction techniques such as Gaussian filtering are applied to remove unwanted disturbances caused by lighting variations or camera noise. The image is then converted into grayscale, reducing complexity while preserving structural details. These preprocessing steps improve the reliability and efficiency of subsequent feature extraction processes.

G=e^ −(x2+y2)

**D.Feature Extraction**

Feature extraction is the most critical stage of the system, where important characteristics of the currency note are identified. The system analyzes RGB color variation to detect irregularities in ink distribution, as genuine notes exhibit consistent color patterns while counterfeit notes often show deviations. Statistical measures such as mean and standard deviation are used to quantify these variations.

Furthermore, texture analysis is performed using techniques such as Laplacian variance to evaluate the sharpness and clarity of the printed patterns. The system also detects key security features, including the security thread using edge detection and the Gandhi portrait using contrast and sharpness analysis. These combined features provide a strong basis for distinguishing between genuine and fake currency.

- **Mean:** $\mu = \frac{1}{N}\sum x_i$
- **Standard Deviation:** $\sigma = \sqrt{\frac{1}{N}\sum (x_i - \mu)^2}$
- **Laplacian Variance:** $\mathrm{Var} = \frac{1}{N}\sum (L - \bar{L})^2$
- **Gradient (Edge Detection):** $G = \sqrt{G_x^2 + G_y^2}$
- **Contrast:** $C = I_{max} - I_{min}$

**E. Feature Fusion**

After extracting individual features, the system integrates them into a unified feature vector through a process known as feature fusion. This step ensures that information from different domains, such as color, texture, and structural features, is combined to provide a comprehensive representation of the currency note.

Feature fusion improves the robustness and accuracy of the system by reducing dependence on any single feature. For example, if color analysis is affected by lighting conditions, texture or security feature analysis can compensate for it. This multi-feature approach enhances the system's ability to make reliable decisions under varying conditions.

**1. Concept of Feature Fusion**

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Feature fusion is the process of combining multiple extracted features such as color, texture, and security elements into a single unified representation. Instead of relying on one feature, the system integrates all features to improve decision accuracy.

This approach enhances the robustness of the system, as different features compensate for each other. For example, if color information is affected by lighting, texture or structural features can still provide reliable information.

**2. Types of Features Combined**

The proposed system combines three main types of features:

- **Color Features:** RGB mean and standard deviation
- **Texture Features:** Sharpness using Laplacian variance
- **Structural Features:** Security thread and portrait clarity

These features represent different aspects of the currency note, providing a comprehensive analysis.

**3. Feature Vector Formation**

All extracted features are combined into a single feature vector:

**F = [Color, Texture, Security Features]**

This vector acts as the input to the classification model. Each component contributes to the final decision-making process.

**4. Feature Normalization**

Before fusion, features are normalized to ensure they are on the same scale. This prevents one feature from dominating others during classification.

Example:

- Color values → 0–255
- Texture values → larger range
- Normalization balances them

**5. Feature Weighting**

Different features are assigned weights based on their importance. For example:

- Security features → high importance
- Texture → medium
- Color → lower

**F. Hybrid Classification Model**

The classification module processes the fused features to determine whether the currency note is genuine or counterfeit. A hybrid approach is used, combining rule-based thresholds with machine learning techniques. This allows the system to balance interpretability and accuracy while avoiding the complexity of purely deep learning-based models.

The classifier generates a confidence score based on the extracted features. If the score exceeds a predefined threshold, the note is classified as genuine; otherwise, it is identified as counterfeit. In cases where the confidence score falls within an uncertain range, the system flags the note for manual verification, ensuring reliability in borderline cases.

**1. Concept of Hybrid Classification**

Hybrid classification combines rule-based logic and machine learning techniques to improve decision accuracy. Instead of depending only on one method, the system uses predefined thresholds along with learned patterns.

This approach ensures both interpretability (rules) and adaptability (ML), making it more reliable for real-time applications.

**2. Rule-Based Decision System**

The system first applies threshold-based rules on extracted features.

Example:

- Color variation $<$ threshold → Fake
- Sharpness $<$ threshold → Fake

These rules provide quick initial filtering and reduce computational load.

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**3. Machine Learning-Based Classification**

After rule evaluation, the feature vector is passed to a machine learning model such as:

- Support Vector Machine (SVM)
- Random Forest

The ML model learns patterns from data and improves classification accuracy over time.

**4. Confidence Score Calculation**

The system generates a confidence score based on combined features:

Example: $\text{Score} = w_1F_1 + w_2F_2 + w_3F_3$

- $F_1, F_2, F_3 \rightarrow$ features
- $w_1, w_2, w_3 \rightarrow$ weights

**5. Decision Thresholding**

Final classification is based on score:

- Score > 0.7 → Real
- Score < 0.5 → Fake
- 0.5–0.7 → Uncertain

This improves reliability by avoiding incorrect decisions.

## IV. DATASET

The dataset used for this project was obtained from the Kaggle platform, which provides a wide collection of publicly available datasets for machine learning applications. The selected dataset consists of images of both genuine and counterfeit currency notes, enabling the system to learn distinguishing features effectively.

The dataset typically includes high-resolution images of currency notes captured under different lighting conditions and orientations. It contains two main classes: **real (genuine)** and **fake (counterfeit)** notes. These images are used to train and test the proposed system by extracting features such as color distribution, texture patterns, and security elements. The diversity in the dataset improves the robustness of the model and helps it generalize better to real-world scenarios.

**Table 4.1 Dataset Distribution**

| Dataset Split | Real | Fake | Total |
|---|---|---|---|
| Training | 4000 | 4000 | 8000 |
| Validation | 400 | 400 | 800 |
| Testing | 400 | 400 | 800 |


**Fig.4.1 Real 500 Rupees image from Dataset**

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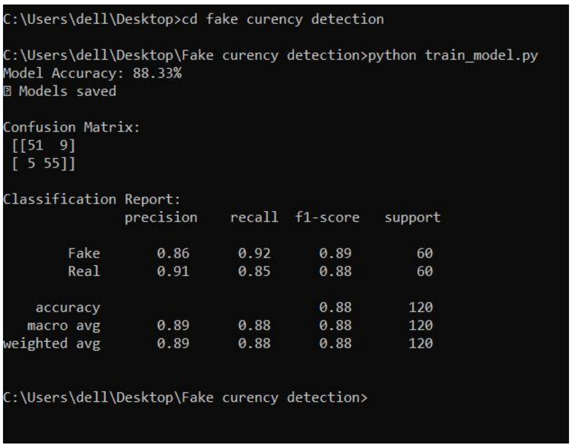
**Fig.4.2 Fake 500 Rupees image from Dataset**

## V. RESULT AND DISCUSSION

### B. Model Performance

The performance of the proposed system is evaluated using accuracy, precision, recall, and F1-score. The results show that the model effectively classifies real and fake currency notes with high accuracy. The use of multiple features such as color, texture, and security elements improves detection performance and reduces errors, making the system reliable for real-time applications.



```
C:\Users\dell\Desktop>cd fake curency detection

C:\Users\dell\Desktop\Fake curency detection>python train_model.py
Model Accuracy: 88.33%
□ Models saved

Confusion Matrix:
 [[51  9]
 [ 5 55]]

Classification Report:
               precision    recall  f1-score   support

        Fake       0.86      0.92      0.89        60
        Real       0.91      0.85      0.88        60

    accuracy                           0.88       120
   macro avg       0.89      0.88      0.88       120
weighted avg       0.89      0.88      0.88       120


C:\Users\dell\Desktop\Fake curency detection>
```

**Fig. 5.1 Training Output for model accuracy**

### C. Confusion Matrix

The confusion matrix of the hybrid model is shown in Fig. 5.2. It provides detailed information about correct and incorrect predictions. The model shows balanced performance in both Real and Fake classes, with most samples correctly classified.

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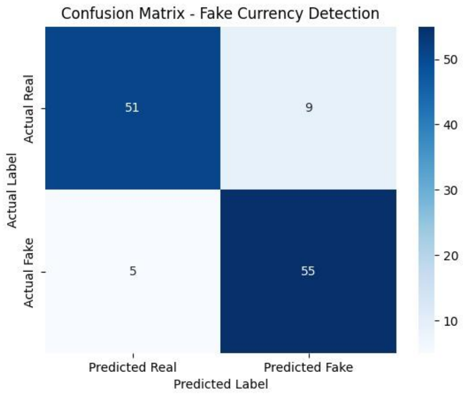


**Fig. 5.2 Confusion Matrix for Hybrid Model**

### E. Web Application Implementation and Ouput

The proposed fake currency detection system is implemented as a web application to provide a user-friendly and accessible interface. The system includes a secure login page where users can authenticate themselves before accessing the application. After successful login, the user is directed to the main dashboard, where they can upload or scan a currency image for analysis.

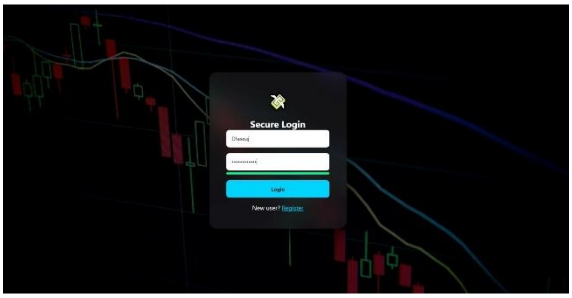


**Fig. 5.4 Website Login**

The web interface is designed with simple navigation options such as scanning currency, viewing features, and logging out. Once the user uploads an image, the system processes it using the proposed pipeline, including preprocessing, feature extraction, and classification. The backend performs computations and sends the results to the frontend for display.

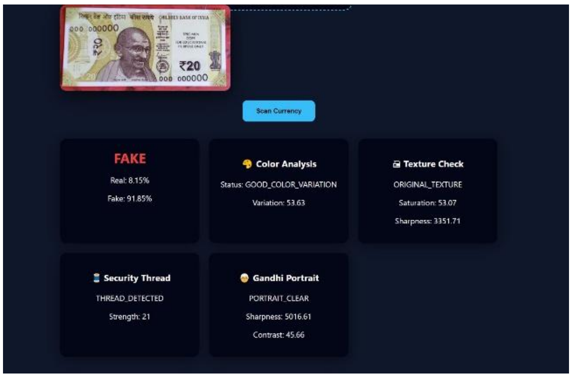


**Fig. 5.5 Output of Glaucoma Detection in Website**

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The output screen presents the classification result clearly as **real or fake**, along with a confidence percentage. In addition to the final result, the system provides detailed feature analysis, including color variation, texture properties, security thread detection, and Gandhi portrait verification. These intermediate outputs help improve transparency and allow users to understand how the decision is made. The application also displays numerical values such as sharpness, contrast, and variation metrics, which are used during classification. This makes the system more interpretable compared to black-box models. The overall implementation demonstrates that the system can efficiently perform real-time fake currency detection in a practical environment.

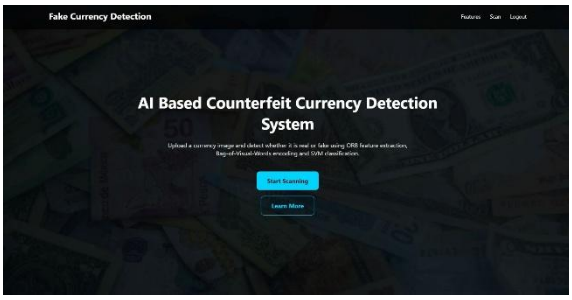


**Fig.5.6 Generated Medical Report**

## VI. CONCLUSION

This paper presented a smart fake currency detection system using machine learning and image processing techniques. The system effectively analyzes multiple features such as RGB color variation, texture sharpness, and security elements to distinguish between genuine and counterfeit currency notes. By integrating these features using a hybrid classification approach, the system achieves reliable and accurate detection.

The proposed method is cost-effective, non-destructive, and suitable for real-time applications. It reduces dependency on specialized hardware and provides an interpretable decision-making process. The implementation as a web application further demonstrates its practical usability in banking, retail, and mobile-based systems. Overall, the system offers a scalable and efficient solution for counterfeit currency detection.

## VII. FUTURE WORK

The proposed fake currency detection system demonstrates reliable performance using a hybrid machine learning and image processing approach. However, several enhancements can be made to further improve its accuracy, scalability, and real-world applicability.

One of the primary areas for future work is the integration of advanced deep learning techniques such as Convolutional Neural Networks (CNNs) and transfer learning models. These approaches can automatically learn complex patterns and improve detection accuracy, especially for highly sophisticated counterfeit notes. Additionally, expanding the dataset with more diverse and high-quality images, including different denominations and conditions, can enhance the model's generalization capability.

Another important extension is the development of a mobile application for real-time currency detection. By deploying the system on smartphones, users can easily verify currency notes in everyday transactions. Furthermore, integrating the system with IoT-based devices or embedded systems can enable automated currency verification in ATMs, vending machines, and banking systems.

Future work can also focus on improving robustness under challenging conditions such as poor lighting, image blur, and occlusions. Advanced preprocessing techniques and adaptive algorithms can be incorporated to handle these variations effectively. Additionally, incorporating more security features such as watermark detection, serial number recognition, and micro-text analysis can further strengthen the system's reliability.

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## REFERENCES

1. Gonzalez, R. C. and Woods, R. E., "Digital Image Processing," Pearson Education, 2018.
2. Goodfellow, I., Bengio, Y. and Courville, A., "Deep Learning," MIT Press, 2016.
3. Krizhevsky, A., Sutskever, I. and Hinton, G., "ImageNet Classification with Deep Convolutional Neural Networks," NeurIPS, 2012.
4. He, K., Zhang, X., Ren, S. and Sun, J., "Deep Residual Learning for Image Recognition," IEEE CVPR, 2016.
5. Simonyan, K. and Zisserman, A., "Very Deep Convolutional Networks for Large-Scale Image Recognition," 2014.
6. Szegedy, C., et al., "Going Deeper with Convolutions," IEEE CVPR, 2015.
7. Breiman, L., "Random Forests," Machine Learning Journal, 2001.
8. Cortes, C. and Vapnik, V., "Support Vector Machines," Machine Learning, 1995.
9. Pedregosa, F., et al., "Scikit-learn: Machine Learning in Python," Journal of Machine Learning Research, 2011.
10. Bradski, G., "The OpenCV Library," Dr. Dobb's Journal of Software Tools, 2000.
11. Otsu, N., "A Threshold Selection Method from Gray-Level Histograms," IEEE Transactions on Systems, Man, and Cybernetics, 1979.
12. Canny, J., "A Computational Approach to Edge Detection," IEEE Transactions on Pattern Analysis and Machine Intelligence, 1986.
13. Patel, K., Shah, M. and Desai, R., "Fake Currency Detection Using Image Processing and Machine Learning," International Journal of Engineering Research, 2021.
14. Sharma, A. and Singh, R., "Fake Indian Currency Detection Using Machine Learning Techniques," International Journal of Computer Applications, 2020.
15. Kumar, S. and Singh, P., "Currency Recognition and Fake Note Detection Using Image Processing," International Conference on Signal Processing, 2019.
16. Reddy, V., et al., "Automated Banknote Authentication Using ORB Features," IEEE Conference on Computer Vision, 2022.
17. Chen, X., et al., "Banknote Classification Based on Bag of Visual Words and SVM," Pattern Recognition Letters, 2021.
18. Rao, P. S., et al., "Counterfeit Currency Detection Using Machine Learning," i-Manager's Journal on Software Engineering, 2023.
19. Tan, M. and Le, Q., "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," ICML, 2019.
20. Redmon, J., et al., "You Only Look Once: Unified, Real-Time Object Detection," IEEE CVPR, 2016
21. C.Nagarajan and M.Madheswaran - 'Stability Analysis of Series Parallel Resonant Converter with Fuzzy Logic Controller Using State Space Techniques'- Taylor &Francis, Electric Power Components and Systems, Vol.39 (8), pp.780-793, May 2011. DOI: 10.1080/15325008.2010.541746
22. C.Nagarajan and M.Madheswaran - 'Experimental verification and stability state space analysis of CLL-T Series Parallel Resonant Converter' - Journal of Electrical Engineering, Vol.63 (6), pp.365-372, Dec.2012. DOI: 10.2478/v10187-012-0054-2
23. C.Nagarajan and M.Madheswaran - 'Performance Analysis of LCL-T Resonant Converter with Fuzzy/PID Using State Space Analysis'- Springer, Electrical Engineering, Vol.93 (3), pp.167-178, September 2011. DOI 10.1007/s00202-011-0203-9
24. S.Tamilselvi, R.Prakash, C.Nagarajan,"Solar System Integrated Smart Grid Utilizing Hybrid Coot-Genetic Algorithm Optimized ANN Controller" Iranian Journal Of Science And Technology-Transactions Of Electrical Engineering, DOI10.1007/s40998-025-00917-z,2025
25. S.Tamilselvi, R.Prakash, C.Nagarajan," Adaptive sliding mode control of multilevel grid-connected inverters using reinforcement learning for enhanced LVRT performance" Electric Power Systems Research 253 (2026) 112428, doi.org/10.1016/j.epsr.2025.112428
26. S.Thirunavukkarasu, C. Nagarajan, 2024, "Performance Investigation on OCF and SCF study in BLDC machine using FTANN Controller," Journal of Electrical Engineering And Technology, Volume 20, pages 2675–2688, (2025), doi.org/10.1007/s42835-024-02126-w
27. C. Nagarajan, M.Madheswaran and D.Ramasubramanian- 'Development of DSP based Robust Control Method for General Resonant Converter Topologies using Transfer Function Model'- Acta Electrotechnica et Informatica Journal , Vol.13 (2), pp.18-31,April-June.2013, DOI: 10.2478/aeei-2013-0025.
28. C.Nagarajan and M.Madheswaran - 'DSP Based Fuzzy Controller for Series Parallel Resonant converter'- Springer, Frontiers of Electrical and Electronic Engineering, Vol. 7(4), pp. 438-446, Dec.12. DOI 10.1007/s11460-012-0212-0.

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29. C.Nagarajan and M.Madheswaran - 'Experimental Study and steady state stability analysis of CLL-T Series Parallel Resonant Converter with Fuzzy controller using State Space Analysis'- Iranian Journal of Electrical & Electronic Engineering, Vol.8 (3), pp.259-267, September 2012.
30. C.Nagarajan and M.Madheswaran, "Analysis and Simulation of LCL Series Resonant Full Bridge Converter Using PWM Technique with Load Independent Operation" has been presented in ICTES'08, a IEEE / IET International Conference organized by M.G.R.University, Chennai.Vol.no.1, pp.190-195, Dec.2007
31. Suganthi Mullainathan, Ramesh Natarajan, "An SPSS and CNN modelling based quality assessment using ceramic materials and membrane filtration techniques", Revista Materia (Rio J.) Vol. 30, 2025, DOI: https://doi.org/10.1590/1517-7076-RMAT-2024-0721
32. M Suganthi, N Ramesh, "Treatment of water using natural zeolite as membrane filter", Journal of Environmental Protection and Ecology, Volume 23, Issue 2, pp: 520-530,2022
33. Inbavalli, M., & Arasu, T. (2015). Efficient Analysis of Frequent Item Set Association Rule Mining Methods. International Journal of Scientific & Engineering Research, 6(4).
34. Mathew, A. (2023). Cybercrime-as-a-service & AI-enabled threats. International Journal of Computer Science and Mobile Computing, 12(1), 28-31.
35. Anand, L. (2024). AI-Powered Cloud Cybersecurity Architecture for Risk Prediction and Threat Mitigation in Healthcare and Finance. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 7(Special Issue 1), 5-12.
36. Mathew, A. Trust Is Not a Default Control: AI-Powered Social Engineering and the Need to Have New Governance.
37. Anbazhagan, K., Kumar, R., Thilagavathy, R., & Anuradha, D. (2024, March). Shortest Job First with Gateway-based Resource Management Strategy for Fog Enabled Cloud Computing. In 2024 4th International Conference on Data Engineering and Communication Systems (ICDECS) (pp. 1-6). IEEE.