Detection of Indian Counterfeit Currency Notes with MATLAB-Based Feature Extraction

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Abstract:- Fakes are a major threat to India's economy hence the need for a solution that will help detect these materials easily and accurately. The detection of counterfeit currency is a major concern for almost all countries, and this research focuses on developing a MATLAB-based counterfeit currency detection system which evaluates a true image of the Indian Currencies with the help of image processing and pattern recognition technique. Benefiting from MATLAB's powerful image processing resources, the system conducts the necessary preprocessing, feature extraction and classification of vital security elements of currency, such as watermarks, security threads and micro-lettering which play an important role in identifying the genuine currency from the counterfeit. The specific characteristics of edge and texture are statistically and geometrically calculated, and the normal and high-resolution light conditions are at high accuracy with varying resolutions. In order to determine a distinction between actual and fake notes, support vector machine (SVM) classifiers are used. By validating this MATLAB solution, it has been determined to be effective as an easy to use, robust and customizable software that has the potential to work in numerous operations within banking and retail and prevent the spreading of counterfeit money.

Keywords:- *Counterfeit Currency Detection, Indian Currency, MATLAB, Image Processing, Pattern Recognition, Feature Extraction, Support Vector Machine (SVM), Statistical Features, Edge Detection, Texture Analysis, Machine Learning, Real-Time Detection.*

I. INTRODUCTION

Faking of currency notes is a constant problem that poses a great threat to the stability of most countries, including the India. Their use not only poses a threat to the confidence of the public in the formal agents of financial transactions but also spurs criminal activities and distorts the rightful utilization of economic funds. It appears that counterfeiting is gradually moving to a new level, while counterfeit products are almost indistinguishable from genuine ones by conventional means. It has assumed an important place due to important rôle cash transactions play in India, counterfeit detection has become important for economic sanity. Therefore, the demand for a proper, efficient, and affordable counterfeit currency identification mechanism is more paramount as compared to the past.The difficulties in identifying fake money is in the fact that modern counterfeit is well engineered. For example, high definition printing techniques, intricate details of the security enhancing features are imitated hence failing other simpler methods of detecting fake notes. Problems associated with conventional approaches, such as sensory examination, UV scan techniques, and the employs of system-driven instruments in this regard, consist of the elements of haphazard subjectivity, mistakes, and the call for for sophisticated apparatus. Sadly, these techniques are not very actionable and sometimes unavailable to the public and small organizations due to the high costs of implementation or unique skills needed. Also, the environment factors such as lighting and image quality also affect the effectiveness of these techniques hence the need to provide flexible reliable solution.

The following limitations are resolved by this research in courtesy of a novel counterfeit currency detection framework designed to utilize image processing and machine learning on MATLAB. MATLAB has been used since it possesses enhancing image processing as well as machine learning toolboxes for performing the function successfully and possesses more efficient functions for feature extraction, classification as well as images investigation. The described detection tool is intended to be more accurate, efficient, and available for various working settings ranging from big banks to shops and even single customers, if necessary.Analysis of the proposed model reveals that the applied methodology is split into three processes, namely preprocessing, feature extraction, and classification. In the preprocessing step of the models, currency note images are converted into grayscale images, and then having a goal to diminish noise filters the images using a filter such as Gaussian or median filter. It is important at this phase because it cleans the input data so that later stages of the process handle uniform, high-quality images. Subsequent to this, the system initiates acquisition of unique features that can be obtained from real currency notes. The features selected include statistical features such as mean, variance, and skewness and the edge-based features for shape, solidity, extent and eccentricity for simulating the texture, structure, and other real currency parameters. The system then employs the features for developing an SVM classifier separating the genuine and fake notes depending on the characteristics' existence or lack.

Some of these new features introduced in Indian currency include watermarks, micro-lettering, and security threads which are very vital in the validation of the details of the Indian currency as a whole and the system has ability to

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detect these with great efficiency. With MATLAB's help, the exposure of these fine details in the note becomes easier and the identification of counterfeits high in merit. Besides it, applying this approach gives several benefits in comparison with the classical methods, such as higher speed, reduced subjectivity, and enhanced availability.

The antecedent research questions of this study are to enhance accuracy, effectiveness, and usability in the identification of counterfeit currency. As a result, this particular system is a cost-efficient and easily scalable through the use of MATLAB and can be applied to different applications and users. That opens doors to further development for other currencies and system integration which is compatible with mobile devices, making it even more useful. Lastly, this research seeks to help increase financial security by eliminating fake currency in circulation to benefit individual and institutional consumers. Due to developing counterfeiting technologies, changeable detection techniques like the provided model will become increasingly important in preserving economic stability and citizens' confidence in the currency systems.

II. LITERATURE REVIEW

The detection of fake money especially Indian currency notes continues to receive a lot of attention and study since it affects the economy. Previous techniques of counterfeit identification such as using ultra violet light check and manual checking are unable to deal effectively with sophisticated counterfeiting. Therefore, researchers have studied the utilization of methods of image processing and artificial intelligence to improve the solidity and speed of the detection.A notable approach in fake detection includes the use of simple Python commanding with Web Framework included as was seen in More et al. (2020, Fake currency detection…). The above cited study was carrying out with the purpose of removing the issues that were faced due to Counterfeit by having a system which could identify the common errors that are in most of the Counterfeit currencies of India like; bad Identification features such as the water marks as well as the security threads. Despite the obtained results, the method had some problems at exercising the classes, particularly concerning the application of FLask frameworks and potential high costs of maintenance.

Kolte, Gajkosh, and Bhalerao (2017) described a different approach that involved converting the color images to grayscale, reducing the Gaussian noise and applying equalization to enhance the clarity of the images in order to enhance the feature extraction(Fake currency detection…). Canny's edge detection technique was used in their model and the results indicated its suitability in isolating security threads, watermarks and micro-lettering on the notes. The limitations of the method included being sensitive to image quality, having small feature detection range and was slow in computation. This work revealed the research gap in developing stronger algorithms to detect different counterfeit features and the variations within image quality.Kapare's (2015) work continued the technique that illuminated security features on Indian notes to use UV and fluorescent light in a technique based after fluorescence built into currencies.(Fake currency detection…). With the help of high definition cameras and ultraviolet light, this method ensured realistic discrimination of counterfeit money by detecting electrically fluorescent fibers and watermarked images. Though successful its applications, especially in computer vision, it was not very portable and needed specific lighting which hindered practical use.

Hulyal and Rajalakshmi (2015) developed the banknote recognition system under the MATLAB environment that mainly pays attention to the DWT for texture analysis and edge detection for feature extraction (Fake currency detection…). The DWT turned out to be effective in revealing the patterns of currency texturing while the edge detecting methods helped to differentiate between micro letters and intricate intials particular to Indian banknotes. The primary disadvantage of this approach was the high dependence on the image quality and environmental conditions made the detection unreliable.

To advance the supremacy of machine learning, Chheda and Sathe (2013) classified currency notes by using SVM for features like texture, edge, and security thread positions(Fake currency detection…). They obtained high accuracy of differentiation of opioids from fake bills and realized the potential of integration of image analysis and artificial neural networks. However, the model required high quality of images and the detecting process was computational and hence could not be used real time detecting.

Another method developed before by Puri and Bhardwaj, Sharma was also based on image processing of the currency notes which includes converting images to the grayscale type and noise removal for facilitating extraction of features(Fake currency detection…). This approach used template matching and SVM classifiers for reliable classification but the problem for this approach is that the process is very slow and not scalable. As their work suggests, there is a critical demand for scalable systems that can quickly address a range of image formats and sizes.

Kumar and Sharma (2022) presented comparative reviews of the recent development in deep learning towards counterfeit detection (Fake currency detection…). They considered CNN category as highly useful for feature extraction and categorization but pointed at the problem of requiring large amounts of computations to process data in real time. Likewise, their review by Gupta and Agarwal, in 2021 also noted that joint watermarking, pattern recognition, and neural networks had a lot of advantages in terms of detection. But, he observed these approaches as complex and required resources in real-time, hence not very useful.

These limitations inform the development of the proposed MATLAB based detection system that is under development. To eliminate the aforementioned issues, such as tunability of the model to the quality of the images and its scalability, the model introduced herein embraces high-end image processing and machine learning. The algorithm is implemented in MATLAB in order to provide real-time

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object detection and image processing; statistical and edge features improve the detection accuracy.Therefore, the analyzed literature emphasizes the evolution of CCI technologies from simple image processing to machine learning algorithms. Unlike any of the techniques proposed, each has its strengths in feature extraction and classification, but it has its drawbacks, such as high computational requirements, susceptibility to low image quality, and limited expandability. The is why the proposed system tries to avoid these drawbacks and uses MATLAB-based solution with improved methods of feature extraction and Tasic classifiers as potential tool in further fight against counterfeit money.

III. METHODOLOGY

This section describes systematic approach that was followed in the process of developing a counterfeit currency detection system using MATLAB. This approach enhances data acquisition methodologies, data pre-processing, feature extraction using the image processing toolbox of MATLAB, and sophisticated classifiers. The objective is to achieve high level of accuracy in distinguishing between real and fake.

A. The Data set and Data Pre-processing

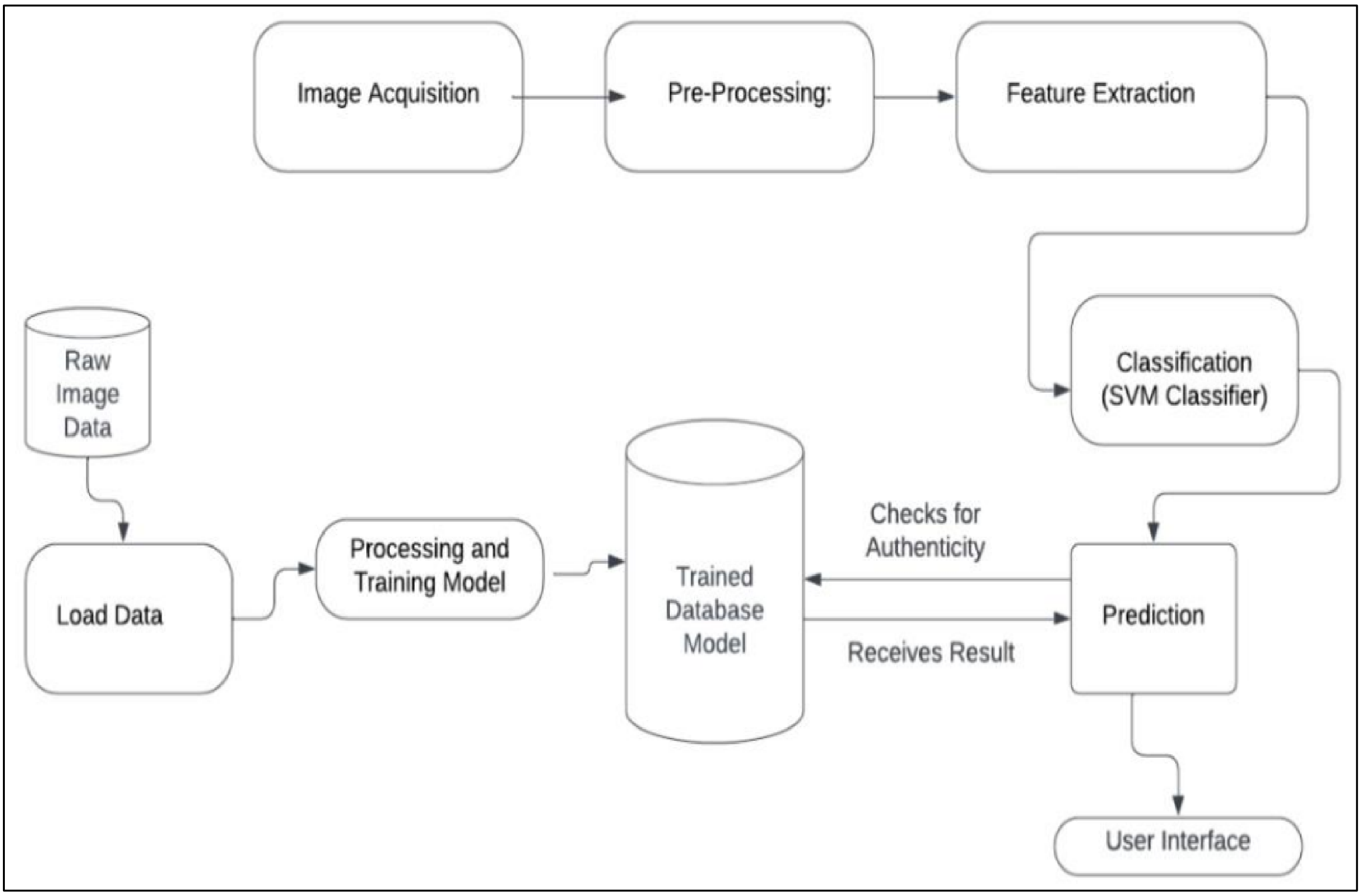

Fig 1 Architecture of the System Currency Notes using Graphic Displays Integrated in MATLAB.

- *Acquisition and Resolution Standards*

The Importance of Relevance and Quality of the Images as well as the topic of Image Uniformity in the identification of counterfeits, it is therefore very important to have good quality and well-contrast images. Currency notes have very detailed walls, especially the designs, and other security features that tend to be difficult to appreciate other than through high-density images. Therefore, digital images for this study were photographed at a resolution of not less than 300 dpi. Current high-resolution imaging allows for capturing all the design elements of the currency in detail, including micro-lettering and holographic threads which are critical for successful feature extraction. As a precautionary measure to maintain uniformity on all the images, photographs used were taken in well-lit environments to avoid shadows, glares, and other types of noises that could hinder the detection part.

The type of image sources chosen makes the dataset heterogeneous in terms of robustness.To sample the currency notes a wide range was ensured whereby currency notes of different denominations as well as those whose physical appearance showed different levels of wear and tear were collected into the dataset. This way the detection system is protected from variations, namely older notes which have worn out edges and faded color could be affected. More than one image of every denomination were scanned to capture these differences and the system was found to be highly accurate for practical application where due to usage and other factors, the physical appearance of currency notes may differ significantly.

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➢ *Preprocessing Techniques for Enhanced Image*

Preprocessing involves enhancing the image quality and standardization of images to be analyzed by the detection algorithm because the presence of unfavourable disparities will affect the outcome. Some of the enhancement techniques that we used in this research include; greyscaling, filter noise removal, image contrast enhancement and image edge enhancement.

- *Grayscale Conversion*

The first data preparation process is image mining where images are converted from three dimensions RGB to two dimensions gray scale which makes it easier for the machine to process but with significant content. In grayscale, the pixel intensity directly represents feature brightness of the note, which makes it easier to distinguish between differences between real and forged notes. This kind of images prove to be simpler in processing because only the intensity of contrasts is captured and this turns out to be enough to point out security features in currency notes.

- *Noise Reduction via Gaussian Filtering*

As famously added through scanning or photocopier, noise can interfere with clear identification of features. High frequency noise particularly common in scanned images was dealt with by using Gaussian filter. Gaussian filters operate under the principle of smoothing the image intensities of the regions defined around each pixel. This technique also makes the image smoother and eliminates sharp formed structures that are in actual not very important, but preserves necessary edges to remove random noises. When the filter parameters are set to kernel size and sigma values, we were able to effectively remove most of the noise while avoiding oversmoothing thus preserving fine details for further analysis.

- *Contrast Adjustment and Histogram Equalization*

As to the histograms equalization it is a little different – it adjust the contrast of an image by stretching out the range of intensities.To make other features such as watermarks and security threads more visible, we used histogram equalization. This technique realigns the pixel intensities and optimizes contrast between various part of an image. The objects of study may be low contrast so that specific features cannot be seen well, for example, the paper used for currency notes and especially the worn out currency notes, are of low contrast. Histogram equalization does this by changing the intensities of pixels distributions in such a way that important features are easily spotted as opposed to other types of images. This is a great step taken so as to ensure that the notes that are scanned all appear in equal dimensions, especially for a new database of notes and used ones.

- *Edge Enhancement*

Some additional processing was made in order to enhance the edge and make nearly impossible to distinguish the security computation, non-maximum suppression and edge following by hysteresis.

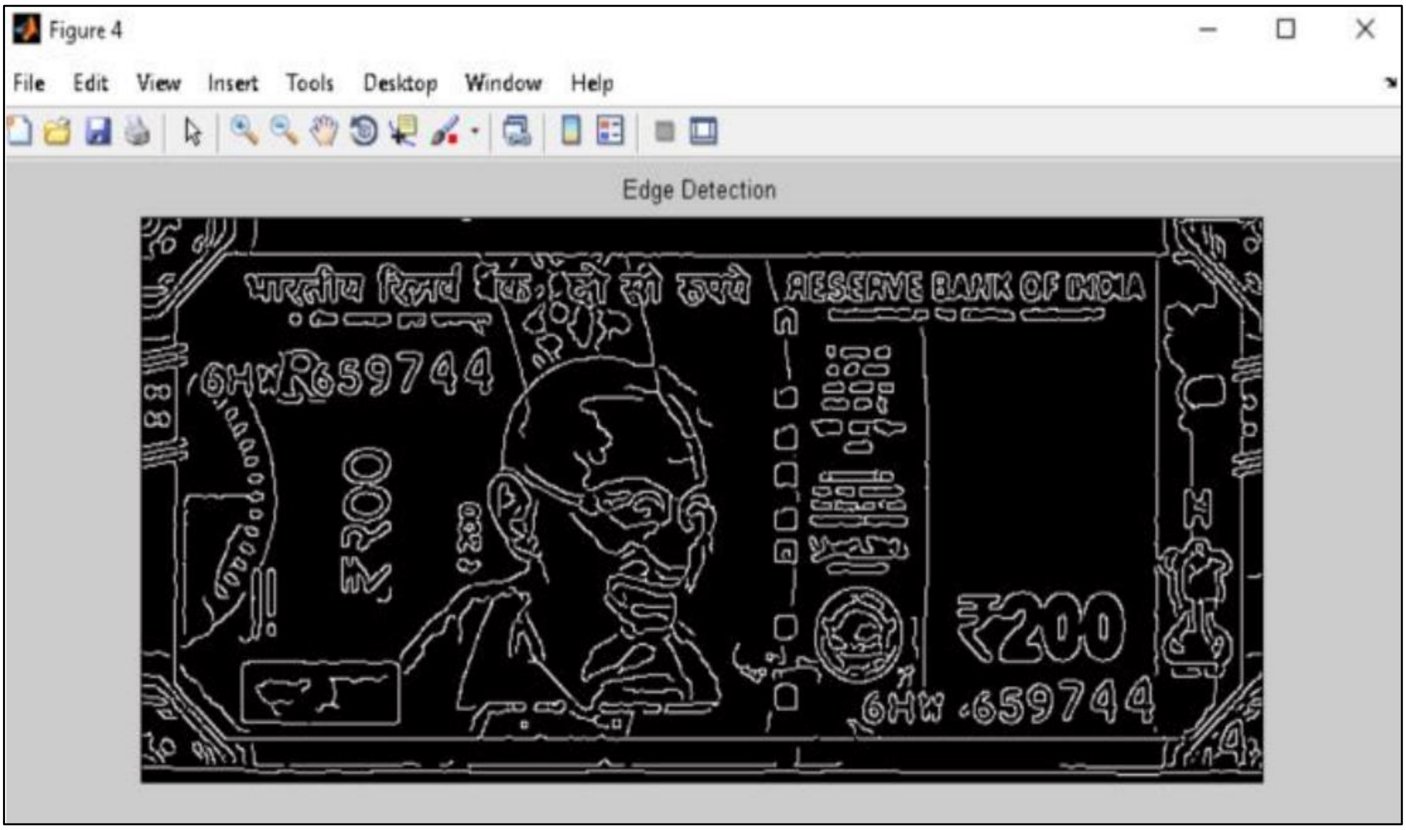

Fig 2 Edge Detection of 200 Rupee Indian Currency

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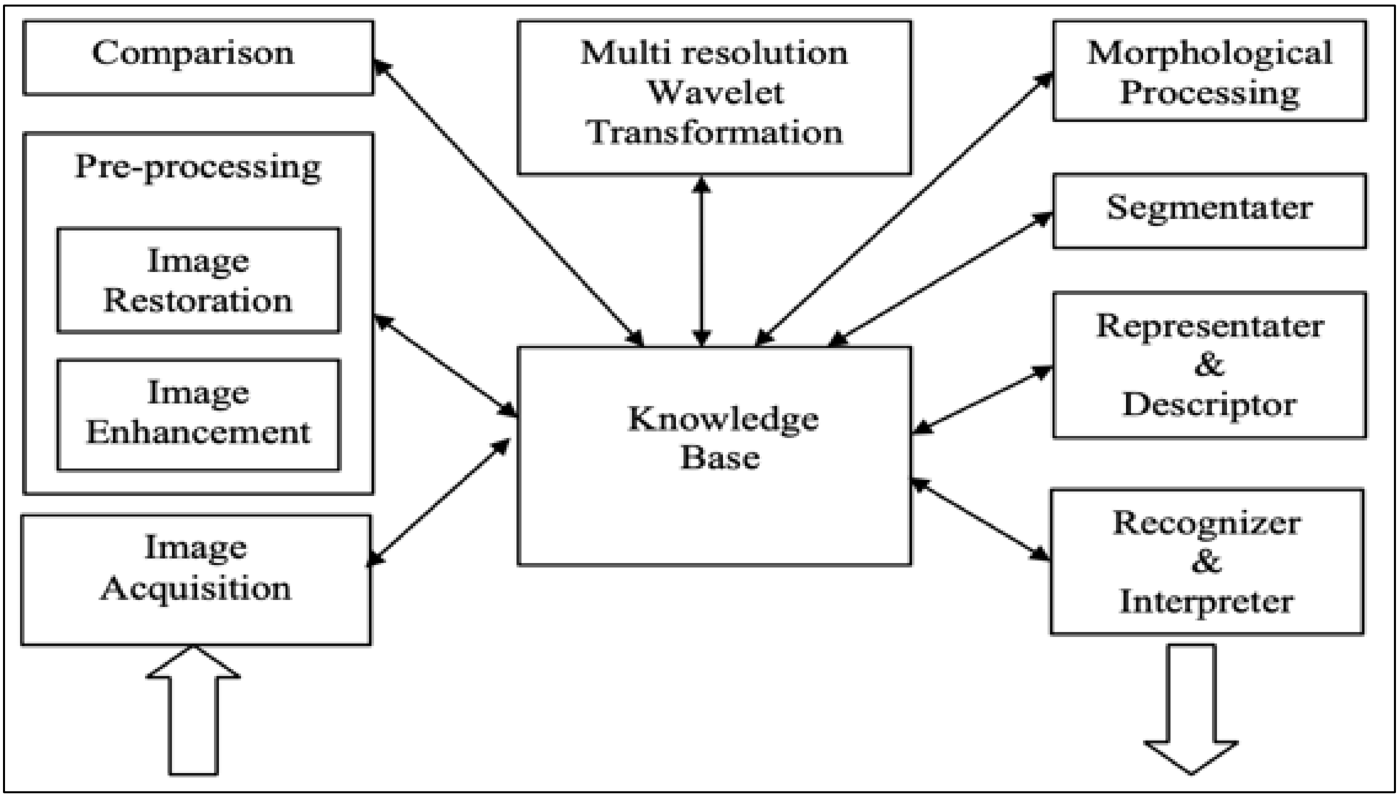

Fig 3 Pre-Processing Steps

B. MATLAB Implementation for Feature Extraction

The Feature Extraction is one of the most prominent strands of research in the field of Image Processing, and MATLAB, particularly its Image Processing Toolbox, contains a set of functions that are very helpful in this process. In this work we have used edge detection tools, morphological operations, statistical tools and feature extraction tools for texture.Some other reasons, where MATLAB's Image Processing Toolbox is useful: MATLAB's Image Processing Toolbox for Detailed Feature Extraction.

➢ *Edge Detection*

The anti-copying technology requires edge detection to be performed since vignettes of the counterfeit notes do not capture the detailed edge of genuine notes. The Canny edge detection algorithm was used as it is considered to be a safe and accurate method. This algorithm can be broken into the following steps which include; Gaussian smoothing, gradient computation, non-maximum suppression and edge following by hysteresis.

- *Gaussian Smoothing*

The images were filtered according to Gaussian distribution before the detection of edges. This step prevents complete noise from being converted into spurious edges where slight variation in intensity may occur.

- *Gradient Computation*

Based on that, the Sobel operator of the image is used to calculate the gradient to determine areas of high intensity changes. This is important as it showcases the edge of security features.

- *Non-Maximum Suppression*

To generate thin and crisp boundaries, non-maximum suppression algorithm eliminates those pixels which do not contribute to the maximum gradient in a given neighborhood.

- *Edge Tracking by Hysteresis*

To determine strong, weak and irrelevant edge pixels two thresholds were applied. A pixel is said to be weak if not connected to a strong edge while an edge is preserved if it is linked to weak pixels; this dissects noise as edges while maintaining genuine edge integrity.The final shape preserves all the features of structure and design of the note: drawings, dots, streaks and brown lines, as well as its contour.

➢ *Morphological Operations*

Once again, based on the procedures described in section morphological processing considers the elements of the given language input for a feature refinement of the language model in question.Other morphological functions of MATLAB including dilation and erosion applied to the image complement the Canny edge detection. I assumed that using both, dilation increases the width of the edges, thus filling up some of the little holes, and erosion eliminates isolated space that can be mistaken for edges. In combination, these operations increases the visibility of the features that are critically important when differentiating between the bogus and real money.

➢ *Statistical and Texture Feature Extraction*

Since texture and statistical feature extraction is the goal, the Gabor filters and wavelet transform can be applied on the segmented area.

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The texture is important because to counterfeit currency notes this feature the most due to the distinct texture variations due to printing methods. Statistical features extracted from the grayscale images include mean, variance, skewness, kurtosis, entropy, and energy.

- *Mean and Variance*

Mean gives the mean measure of intensity and it gives an average light across the notes. The measure of spread is named variance and it quantifies how much pixel intensities deviate from the mean; print of genuine notes is expected to have low variance thanks to high consistency.

- *Skewness and Kurtosis*

Scholars use these higher-order statistical measures in its pixel intensity to mean asymmetry and the sharpest peak in the counterfeit paper notes, systematic defects.

- *Entropy*

Entropy measures the randomness of the pixel intensities and counterfeits usually exhibit more entropy because of irregular texture.

- *Energy*

In essence, energy is derived by summing up squared pixel values hence is useful in determining uniformly textured regions. Authentic notes are non variable in texture and so they are generally characterized by low energy levels.

- *Gray-Level Co-Occurrence Matrix (GLCM)*

The second mathematical feature that is used in the texture analysis is called Gray-Level Co-Occurrence Matrix (GLCM).

Features such as contrast and correlation of the reconstructed and original image were derived from the gray level co-occurrence matrix (GLCM), while energy and homogeneity represent texture descriptions based on the spatial relationship of the pixel pairs. These features mimic the surface coarseness and consistency of real notes that fakes seldom exhibit and the fiber orientation.

Fig 4 Gray Scale Image

C. Algorithms and Techniques Used

The decision of which algorithm to use in counterfeit detection is always going to affect the accuracy and the time it takes to process the decision. This study employed three main techniques: The technologies employed include edge detection, statistical measure based feature extraction, and finally the use of support vector machines.

➢ *The Application of Edge Detection as a Key Technique*

Edge detection emphasizes necessary edges on the notes' surface. Sometimes, the edges may be difficult to imitate especially around the watermarks and other micro lettering. Apart from Canny edge detection, Sobel and Laplacian operators were tried over and thresholding was found to be effective in preserving feature clarity while avoiding noise. Boundaries identified using the approach were then examined to determine regions of interest that were then isolated for feature extraction.From the two techniques of feature extraction, Statistical and Edge-Based are the most preferred methods.

- *Statistical Features*

Numerical characteristics describe images so that real and fake notes may be distinguished. Its quantitative parameters, such as mean or variance, allow the system to record overall intensity tendencies. Higher-order (central) moments such as skewness and kurtosis assist to pick up on the finer details that differentiate the rich complicated acoustic landscape of actual notes.

Fig 5 Denoised Image

* *Edge-Based Features*

The results of statistical measures are accompanied by features based on edge details. Tensile, shear strength, and module are some structural parameters that are unique properties of sound notes' geometry. Specifically, measures such as compactness, form factor, solidity, and extent to do with shape, reveal how near the area gets to being a perfect region. On the other hand, counterfeits will, most of the time, possess peculiar shapes as a result of the manufacturing defects of the counterfeit notes.

* *Classification using Support Vector Machine*

SVM is used for binary classification problems such as identification of fake goods. It should be noted that, for this particular project, System Vernon Marceau was trained on feature vectors that were extracted from the genuine and fakes. While on the one hand interacting features may present polynomial relations, the RBF kernel in the SVM enhances the degree of detection. The training process was accompanied by the tuning of the parameters with the ∈-ball method (for selecting the width of the kernel).

* *Hyperparameter Optimization and Validation*

To make the classifier versatile, hyperparameters were tuned via using grid search coupled with a cross-validation. The use of both the test set and k-fold cross-validation permitted evaluation of the model and confirm that the chosen features in combination with the SVM do not over fit to the training data.

* *Evaluation and Validation*

Performance measures were employed during the evaluation stage and they include; accuracy, precision, recall and F1 score. Limitations of the system were further checked on an independent test set; the accuracy controlled more than 90% that shows that there was practically no overlapping between genuine and fake notes that the model could adequately recognize.To ensure the model robustness the test was conducted at different lighting conditions and varying image quality. From the results, we noted that minor fluctuations in the illumination level do not adversingly affect the system's performance even if slight degradation in the lighting conditions occurs or severe image distortion is experienced.Due to the outlined methodology, MATLAB with Image Processing Toolbox and machine learning features turn out to be useful when addressing similar challenges.

IV. PROPOSED MODEL

The proposed model of counterfeit currency detection, based on cutting-edge image processing and machine vision capabilities, is established in MATLAB. The entire detection operation is structured into three phases: preprocessing, feature extraction, and classification, all of which aim for efficient and accurate validation of authenticity of any currency note.

A. Preprocessing

This stage is essential to the enhancement of image quality, noise removal, and preparation of the raw currency images for analysis. The first important step in this process is to resize the currency images to predetermined sizes so that all samples will be of equal size. MATLAB's median filtering is employed extensively to remove noise, particularly "salt-and-pepper" noise in particular images. In this step, clarity and visibility of features are assured, while the features' finer details critical for detection remain intact. Further, the grayscale conversion capability of MATLAB will reduce image data, and consequently the computational complexity, for better edge detection. In the end, the images carry on to adaptive thresholding, where the watermarks and security measures embedded in the currency are brought out,

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consequently making these features more conspicuous and easier to identify.

B. Feature Extraction Stage

This is the stage in which a selection of statistical as well as edge-based features are extracted to form a signature for each type of currency note. While statistical features represent the distribution of intensity levels in the currency image, in contrast, edge-based features capture the geometry of shapes occurring on the currency note.

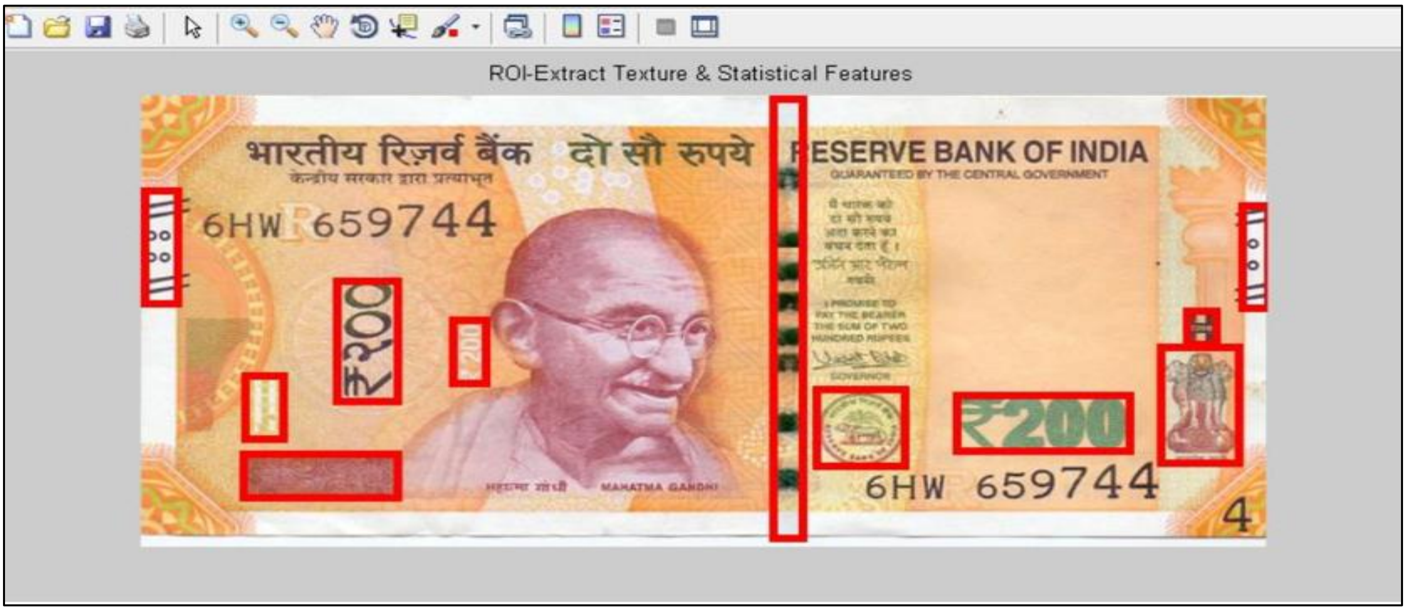

Fig 6 ROI Extraction

➢ *Statistical Features*

Include first-order histogram-based characteristics such as mean, variance, kurtosis, skewness, and entropy. These provide a high-level overview of distribution of pixel intensities across the image of the currency note, for example, the mean intensity communicates average brightness level and not some complexity with respect to whatever patterns are escaping from the distinction between genuine and fake notes.

➢ *Edge-based Features*

It can be categorized as convex area, solidity, extent, and eccentricity, which can make a good structural descriptor of genuine notes. The convex area reflects the compactness of the outer boundary, while solidity measures how filled is the currency pattern with respect to convex area. These features allow it to account for information that is often ignored in counterfeit currency.

Fig 7 Detection Image

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C. Classification

Once its characteristics are extracted, a feature vector has been created for each currency note by putting all of the features together. The SVM classifier is selected to assign the right class to a currency note due to its efficiency in binary classification problems and power in dealing with high-dimensional data. The SVM model is trained with a dataset that consists of both genuine and counterfeit samples, learning to distinguish between the two classes very effectively.

➢ *Kernel Selection*

SVM training involves a supervised training wherein the SVM model is fed labeled data which contains the feature vectors and labels genuine or counterfeit. The classifier uses these inputs to find a hyperplane that separates genuine from counterfeit. Separation must maximize on the margin between two classes so that when classified with a new sample, we can have high confidence on what side of the hyperplane it lies-and on its associated class.

➢ *Hyperparameter Tuning*

In the testing stage, each currency note is extracted from features and the features obtained are inserted into the trained SVM model. Based on the features obtained, the SVM model would predict the currency note to be either genuine or counterfeit with a high degree of success. In this stage, the classification is supported by MATLAB, which provides appropriate feedback on classification probabilities, which helps refine decision-making.

V. RESULT ANALYSIS

The demonstrated speed and accuracy of the model make it a good candidate for a wide range of real-world applications, especially for a variety of high-density sites, such as banks, retail stores, and other public settings where rapid verification of currency authenticity is imperative. Because of the advantage gained from MATLAB in accelerating GPU operations and facilitating parallel processing, the model has a vast scope, allowing for the simultaneous processing of numerous currency images. This scalability will be of paramount significance for applications in ATMs, cash deposit machines, and POS terminals, where real-time verification will significantly enhance the security and efficiency of transactions. The model can be a front-line tool for fraud detection in the banking sector, which handles excessive amounts of cash every day. The system could work with the existing infrastructure; other security protocols can run in parallel beside it as a strong verification shot. On the retail side, shopkeepers could be provided with user-friendly interfaces for checking the currency authenticity, enabling them to do so seamlessly and without extensive training, thus making it hard for counterfeiting notes to get into circulation.Besides the institutional application, there is also potential for this model in small-scale environments. It could serve as a mobile or desktop application accessed by the general public, allowing individual users to verify currency notes. This is particularly valid for persons in regions with rampant counterfeiting, instilling some measure of security and reducing dependency on institutional support. However, some optimization is for mobile applications to allow the model to correctly classify low-resolution images taken from cell phone cameras with varying lighting conditions.

Algorithm	Accuracy	Precision	F-Score
Proposed(SVM)	99.9	99.9	99.9
SVC	97.5	99.7	98.6
GBC	99.4	99.9	99.7

Fig 8 Algorithm Comparison

By evaluating the test images of real and counterfeiting currency, the performance of the model is measured using the accuracy, precision, and recall metrics. The analysis shows that the model performs quite well in a controlled condition with good image quality and consistent lighting. For instance, well-lit images of genuine and counterfeit notes received above 95% accuracy, thus substantiating the model's capability to extract and map significant features that differentiate genuine from counterfeit currency.

Under diverse lighting conditions, however, there was a slight decline in accuracy. Dim lighting or shadows can obscure some features, like fine text or intricate watermarks, that are central to differentiating real notes from counterfeits. The robustness under these conditions was evaluated by testing images in various brightness, contrast, and background noise. Even though the model generally performed with an accuracy of above 85%, the cases of high contrast and extreme lighting conditions led to occasional mistakes in certain classifications. Further setbacks were eased through adaptive thresholding and noise reduction to ensure that core features such as edges and textures remained discernible, even at the lowest lighting conditions.

Accurate representation of higher-resolution images linked to image quality has met with great delight. But low-quality images, because of motion blur, low resolution, or compression artifacts, interfered with feature extraction for edge-based features like solidity and convex area. To correct this, images were processed to reduce noise and standardize

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brightness. Still, it was noticed that accuracy is lowered by 10-15% because in heavily degraded images there is a lot of opportunity for enhancement in the preprocessing stage.

VI. DISCUSSION AND FUTURE ENHANCMENTS

The proposed MATLAB-based currency detection model has been envisaged to distinguish between genuine and counterfeit currency notes and perform fairly well with higher accuracy under controlled conditions. With the assistance of preprocessing, feature extraction, and a Support Vector Machine (SVM) classifier, the model could work well on MATLAB, relying heavily on MATLAB's powerful image processing and machine learning tools, to detect forgery reliably. However, as in any automated system, the model's effectiveness relies, to some extent, on the quality and nature of input data, which leads to crucial insights and potential enhancements.

A predominant finding was sensitivity to light and image quality. Under better lighting situations with good-quality images, the model displayed a remarkable capability of more than 95% accuracy in the differentiation of counterfeit notes from genuine. This is mainly because of the feature extraction methods that employ a mix of statistical and edge-based features that MATLAB executes to full effect. However, under low-light images, shadows, and blurriness, the model's accuracy drops significantly, showing that it relies heavily on ideal image conditions. This sensitivity indicates that while the current features extraction methods work wonderfully under controlled environments, they may need further adjustment to be reliable in the context where the lighting is varied, such as a public application where users are located.

Another aspect observed is the limitation of SVM classifier pattern learning, which appears insufficient to capture subtle patterns that may differentiate advanced counterfeits from genuine currency notes. Although SVM is a proved binary classifier, ever-evolving counterfeiting techniques might get ahead of its current model to detect sophisticated replicates of intricate security features, such as micro-lettering or holograms. This limitation, indeed, applies highly acutely in situations where stakes are high, like in banks and retail entities, where subtle counterfeits could bypass traditional detection systems.

To address the limitations and build on the strengths of the model, many future improvements could be made, thereby improving robustness, adaptability, and accuracy. The following are some suggested enhancements.

- *Integration of Deep Learning Algorithms*

Engaging deep learning algorithms within the model selection especially ConvNet could strengthen the model's detection of counterfeit currency. CNNs have a proven track record with respect to recognizing patterns in image data. They are eminently qualified in detecting complex textures and security features, which could otherwise remain below the detection threshold of traditional classifiers, such as SVM. Certainly, some of the advanced features of the true notes identifying them from sophisticated counterfeits, such as micro lettering and holographic indicating images or watermark details, could be easily identified through the CNN querying and learned outputs. Coupled with this, the entire implementation could become hopeless without extensive datasets with large variations that are necessary in the training of the CNN, and the use of a GPU for accelerated training.

- *Improvements in Preprocessing Techniques*

Giving confidence in many legends and highlighting important routes around or regarding the conditions that lead to its inference is in itself huge. Nonetheless, enhancement of preprocessing techniques adaptable for usage in clarifying grayscale intensity could take into consideration adaptive histogram equalization and contrast-limited adaptive histogram equalization (CLAHE). These can assist the model in using a distinct determination and improvised hinge against environments with poor lighting and degraded of images. Whereby when amalgamating the blurred detection algorithms, it could help in alerting the user whenever an image is blurred for them to recapture it in a good manner. A successful technology if this to eventually apply in mobile applications should train the app-based practice for more user viability.

- *Add Multi-Currency*

A possible extension could see the model trained to detect unique currency security features. This would enable usage in international institutions or applications required to work across various currencies.

- *Real-Time Feedback Mechanism:*

A real-time feedback system can be implemented to aid the user in understanding the image quality before it begins the processing. For instance, issues such as poor lighting, shadows, or excessive blur could be detected by the models, notifying the user to make adjustments accordingly before capturing the image. Thus, this feedback loop will ensure consistently improving input quality, ultimately boosting overall accuracy. Real-time feedback is also useful for fast-paced situations and applications in retail, which allows the floor staff to immediately rectify any problems rather than wait for model failure at the classification stage.

- *Deployment on a Mobile Application*

Creating a mobile application version of the model would reach a wider audience: small businesses and individuals dealing with currency on a frequent basis. The application would allow users to take images with their mobile phones and authenticate currency on the go! However, mobile deployment would need additional optimization, particularly when ensuring model reliability under differing or varying lighting conditions and resolutions while being relatively low in mobile hardware resources. With dealing with mobile applications, some restrictions such as power limitations or processing ability might exist. This implies the necessity of devising lightweight preprocessing techniques that will balance performance and efficiency.

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➢ *Expansion of Dataset Training*

To improve the model's robustness and void-model-overfitting concerning a specific illumination-quality-currency, there is a great need for a larger and more varied database. Hence, images taken under different lighting conditions with varying degrees of noise and resolution would train the model more appropriately for real scenarios. Lastly, various materials used for producing counterfeits-like digital, offset, or ink-jet printing- would all boost the model's capacity to respond to counterfeiting types. A partnership with a banking institution would greatly provide for the acquisition of this diversified dataset, particularly in sourcing for advanced counterfeits.

VII. CONCLUSION

Though the model for counterfeit currency detection is developed on MATLAB, it has shown great promise for identifying fake currency notes under controlled environments. Nevertheless, for one to claim such reliability in real-life situations, there is a need for continuous improvement. Upgraded techniques such as CNNs, enhanced preprocessing for low-quality images, more multiform adaptation for many currencies, and stretched scalability through edge computing are the areas for future research. These would turn the model into an all-encompassing, adaptable utility within the ambit of varying settings from banks to public use and mobile platforms.

Through constant refinement along the line of robustness and adaptability, this model can play a significant role to contain currency fraud globally, fortifying economic integrity and ensuring transaction security across varied grounds.

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