Detecting Counterfeit Currency with Image Processing

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Abstract

"Detecting Counterfeit currency with Image Processing" focuses on leveraging image processing techniques to identify counterfeit currency. Currency plays a crucial role in economic transactions, functioning as a means of trade, standard measure of value, and reservoir of wealth. Ensuring the integrity of currency is crucial for maintaining trust in financial systems, preventing economic disruptions, and protecting individuals and businesses from financial losses. The need for currency detection arises in the situation of counterfeit activities, which pose serious threats to the stability of economy. Counterfeit currency can lead to financial fraud, loss of confidence in monetary systems, and can negatively impact businesses and individuals. By employing efficient image processing algorithms, this paper aims to enhance the accuracy and efficiency of counterfeit currency detection, providing a robust tool for financial institutions, businesses, and law enforcement agencies to safeguard against economic threats.

Keywords: Counterfeit Currency Detection; Image Texture Analysis; Pattern Recognition Algorithms; Logical Regression Algorithm; Currency Integrity Assessment; Fraud Prevention through Image Analysis; Secure Imaging Techniques; Trust Assurance in Currency Systems; Feature Extraction for Currency Verification; Enhancing Economic Security

1. Introduction

This paper "Detecting Counterfeit currency with Image Processing " addresses a pressing concern in the financial landscape, emphasizing the significance of accurately identifying counterfeit currency. With currency playing a pivotal role as a medium of exchange in economic transactions, the integrity of banknotes is paramount for ensuring the smooth functioning of financial systems. The rise in sophisticated counterfeiting techniques necessitates the development of robust detection mechanisms to safeguard against economic threats and financial fraud.

Digital image processing emerges as a key solution in this context, offering a technologically advanced approach to currency verification. By harnessing the power of image processing techniques, the detection process is transformed into a digital realm where algorithms and computational methods can analyse intricate details of banknotes that are often challenging for the human eye to discern.

The digital detection process involves leveraging sophisticated algorithms designed to identify genuine currency features and distinguish them from counterfeit ones. This includes analysing intricate patterns, textures, watermarks, and other security elements embedded in legitimate banknotes. Image processing techniques, such as pattern recognition and machine learning, play a crucial role in enhancing the accuracy and efficiency of this detection process, enabling automated systems to rapidly and reliably identify fake currency.

The importance of currency detection plays a vital role in Economic Stability. Counterfeit currency poses a significant threat to economic stability. Large-scale circulation of fake money can lead to a loss of confidence in financial systems, disrupting the normal functioning of economies. The currency detection also has important role in financial Loss Prevention Individuals, businesses, and financial institutions may suffer substantial

Doi : https://doi.org/10.54216/JCHCI.070204
Received: November 15, 2023 Revised: February 09, 2024 Accepted: April 02, 2024

financial losses if they unknowingly accept counterfeit currency. Detection mechanisms are crucial for preventing such losses and maintaining trust in monetary transactions.

In currency detection the image processing has major roles such as pattern recognition where image processing algorithms can be trained to recognize intricate patterns and details unique to genuine banknotes, making it difficult for counterfeiters to replicate these features accurately , it also enables the analysis of subtle textures and security elements that are often embedded in authentic banknotes, providing additional layers of security for detection using advanced image processsing techniques and plays an important role in Watermark and Microprinting Detection in which Image processing can be applied to identify watermarks, microprinting, and other intricate features that are typically part of the security measures on legitimate currency.

A. Motivation and Objectives

1) Motivation: In an era marked by technological advancements and global economic interactions, the trust in financial transactions is paramount. Counterfeit currency poses a pervasive threat, challenging the integrity of monetary systems and jeopardizing the economic well-being of individuals and institutions alike. The motivation for the project lies in the critical need to develop an advanced and automated solution for detecting fake currency, leveraging the capabilities of image processing.

Traditional methods of manual inspection are becoming increasingly inadequate in the face of sophisticated counterfeiting techniques. As counterfeiters continually evolve their methods, it becomes imperative to harness cutting-edge technologies to stay one step ahead. Image processing offers a promising avenue, providing the tools to analyse intricate details of banknotes with precision, efficiency, and scalability.

The motivation stems from the desire to fortify economic systems against the detrimental effects of counterfeit currency, including financial losses, erosion of trust, and potential disruptions. By developing a robust fake currency detection system, we aim to provide financial institutions, businesses, and individuals with a powerful tool to ensure the legitimacy of transactions, fostering confidence in the monetary systems that underpin our daily lives.

Furthermore, the project's motivation extends to the broader goal of contributing to a secure and stable economic environment. A successful implementation of image processing techniques for counterfeit detection not only safeguards financial interests but also reinforces the foundations of trust and transparency in financial interactions. In a world where technology intertwines with every aspect of our lives, the motivation for this project lies in harnessing innovation to preserve the integrity of our economic systems and protect against the pervasive threat of fake currency.

2) Objectives: The primary focus of this research can be summarized as follows:

- Design and implement advanced image processing algorithms capable of accurately identifying and distinguishing genuine currency features from counterfeit ones.
- Utilize digital image processing features to enhance the analysis of intricate security elements such as patterns, textures, watermarks, and microprinting on legitimate banknotes.
- Ensure the system performs real-time processing, particularly vital for seamless integration into applications like retail and banking, where swift and accurate detection is imperative.
- Contribute to economic stability by mitigating the threats posed by counterfeit currency, protecting individuals, businesses, and financial institutions from financial losses.
- Contribute to maintaining trust in financial transactions by delivering a reliable and technologically advanced solution for detecting fake currency, thereby fostering economic stability and security.
- Ensure the developed detection system can seamlessly integrate into existing financial and retail environments, providing a practical and efficient solution for real-world scenarios.

2. Related Works

T Naveen Kumar et al. [1] They proposed approach that aims to make the system robust and accurate by integrating scores from these features to distinguish between genuine and fake currency. The mean square error is used as a parameter to measure the system's performance, indicating an approximate 1% error rate. The paper suggests that the system, based on image processing and clustering algorithms, could serve as a practical tool for individuals facing challenges in distinguishing between real and fake currency. B. Hari Chandana et al. [2] They extracted features, including security elements like watermarks and micro-printing, are then subjected to

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detection using Support Vector Machine (SVM). The proposed algorithm demonstrates improved accuracy and faster detection compared to existing methods. M. Deborah et al. [3] This paper discusses image segmentation and restoration techniques, distinguishing between enhancement and restoration. The project utilizes metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error Rate (MSE), and Structural Similarity Index (SSIM) for evaluating the performance of the proposed algorithm. Sonia Sarkar et al. [4] It emphasizes the advantages of digital IP in enabling a wide range of algorithms while mitigating issues like noise and distortion during processing. The study utilizes MATLAB software for implementing various IP techniques. Edge detection techniques, including Canny, Sobel, and Prewitt operators, are applied. Mahendra Kanojia et al. [5] The data set features focus on the distinctive characteristics of the new INR 2000 note, highlighting its magenta colour, belonging to the Mahatma Gandhi (New) series, and featuring a motif of the Mars orbiter Mangalyaan on the reverse side. The note's size is specified as 66mm x 166 mm. Dr. S. V. Viraktamath et al. [6] The study covers algorithms such as Mean intensity of RGB channels, UML and HSV Image, K-NN Technique, Super resolution method, DTCWT, Enhancement of Sift algorithm, ORB and BF matcher in OpenCV, and K-means algorithm combined with SVM algorithm. The results indicate promising accuracy rates, with some methods surpassing 95%. The limitations include the focus on specific currency denominations and the need for more extensive datasets capturing various angles to enhance accuracy in identification. Kiran et al. [7] they propose a deep learning approach, specifically a Deep CNN model, for the automatic detection of counterfeit currency using an Android platform. The approach demonstrates promising results, achieving 84.71% accuracy in detecting counterfeit notes. The study highlights the importance of leveraging deep learning models for real-time currency verification. Megh et al. [8] They use MATLAB techniques for splitting and combining image components. A threshold equivalence value is calculated, and parameters like Mean Square Error and Peak Signal to Noise Ratio are used for comparison. The paper also discusses the use of a counterfeit detection pen, relying on iodine reactions with starch, and other techniques like Ultraviolet counterfeit detection scanners for enhanced security in currency verification. Chinmay et al. [9] After image pre-processing, boundary detection and cropping focus on separating foreground and background, isolating the Region of Interest (ROI). Feature extraction involves analysing dimensions, aspect ratios, and HSV values of currency blocks, comparing them with ideal values. Euclidean distance calculations help quantify differences between target and ideal HSV features. The algorithm is equipped with a graphical user interface for result display, including a currency conversion feature based on internet-obtained rates. Agrimi et al. [10] The paper implements a process involving image acquisition, segmentation, edge detection, feature extraction, and feature matching to identify fake currency. Feature extraction employs the ORB (Oriented FAST and Rotated BRIEF) algorithm, highlighting key points with green dots. Subsequently, the Brute Force algorithm is utilized for feature matching, determining matches based on distance calculation and showcasing them with coloured lines. Vidhi et al. [11] Notably, Canny Edge detection is employed for its effectiveness in extracting structural information. Feature extraction involves the utilization of the Structure Similarity Index Method (SSIM) for comparing key aspects of a 2000 Rupees note, including Mahatma Gandhi's portrait, micro letters security thread, guarantee clause, denominational numeral, Ashoka Pillar emblem, number panel, bleed lines, year of printing, and Swachh Bharat logo. Devid et al. [12] The proposed system utilizes image processing techniques, employing ORB (Oriented FAST and Rotated BRIEF) and Brute-Force matcher in OpenCV, to detect security features of Indian currency notes. It has achieved an average success rate of 95.0% in experimental setups. Tabiya et al. [13] The proposed methodology involves obtaining image characteristics such as variance, symmetry, kurtosis, and entropy from banknote images, which are then used as input for logistic regression, a supervised machine learning algorithm. The model achieved an impressive accuracy of 98.36%. Ryutaro et al. [14] The proposed method utilizes a convolutional neural network (CNN) for the detection of portrait-containing rectangles on banknotes, a crucial step in banknote sorting. The process involves specifying candidate regions, obtaining portrait probabilities using the CNN, and applying Non-Maximum Suppression for region restriction. The CNN is fine-tuned using a dataset of portraits, and a probability map is generated to identify peak positions. Binod et al. [15] The proposed system utilizes features extracted from HSV colour space to distinguish between genuine and fake notes. The design flow of the automatic recognition system is outlined, and the experimental setup involves capturing note images with a camera and analysing them using MATLAB. The system accurately identifies genuine notes and provides visual feedback on an LCD display. Raj et al. [16] The Indian currency notes' unique property of absorbing UV light is leveraged in the system, where a UV LED source transmits rays, and a photodiode, amplifier, and comparator analyse the UV light reflected by the notes. A microcontroller processes the information and interfaces with the Arduino IDE, utilizing image processing to identify security features. Kalpana Gautam [17] The paper presents a currency recognition system designed in MATLAB with a Graphical User Interface (GUI) using a hybrid correlation technique incorporating Local Binary Pattern (LBP) and Principal Component Analysis (PCA). Four different methodologies, including PCA, LBP, Euclidean Distance, and a combination of LBP, PCA, and Euclidean Distance, are deployed. Sanjan et al. [18] The system employs feature extraction, classification using Support Vector Machines (SVM), Neural Networks (ANN), and heuristic

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approaches, integrating computer vision through a CCD camera. Nunna et al. [19] The paper highlights the importance of image processing, particularly utilizing Convolutional Neural Networks (CNN) for enhanced accuracy in future work. Performance analysis includes measures like accuracy, precision, and F-score, with KNN consistently outperforming other algorithms. Arvind et al. [20] The study introduces a cost-effective and portable Hyperspectral Imaging (HSI) system using a Raspberry Pi camera and a simple module with low-cost components. The Visible Snapshot-Based RGB to HSI Conversion Algorithm is developed to convert RGB images into hyperspectral images, eliminating the need for expensive equipment. The classification method involves measuring Mean Gray Value (MGV) at specific wavelengths and utilizing confidence intervals. Naga Lakshmi et al. [21] The proposed system involves data preprocessing, feature extraction, and result analysis, with the application of decision tree classifiers, gradient boosting, K-Nearest Neighbours, logistic regression, Naïve Bayes, Random Forest, and Support Vector Machines.

3. Problem Statement

The escalation of counterfeit currency threatens the integrity of financial transactions, giving rise to economic instability, financial fraud, and substantial losses. Existing detection methods are often manual, prone to human error, and inadequate against sophisticated counterfeiting techniques. This project addresses the urgent need for an advanced solution by employing image processing algorithms to enhance the accuracy and efficiency of fake currency detection, mitigating the risks faced by individuals, businesses, and financial institutions in the modern economic landscape.

4. System Model

Counterfeit currency detection aims to develop a robust system for accurately distinguishing between genuine and counterfeit banknotes. Leveraging machine learning techniques, particularly logistic regression, the system processes features extracted from banknote images to make informed classification decisions. Logistic regression, a well-established algorithm for binary classification tasks, serves as the core component in this project. By training on a dataset containing labelled examples of both real and fake banknotes, the logistic regression model learns to predict the authenticity of banknotes based on extracted features, offering a reliable solution for combating counterfeit currency.

In the context of fake currency detection, logistic regression serves as a powerful tool for binary classification, distinguishing between genuine and counterfeit banknotes based on extracted features. The steps involved are:

1.Data preprocessing:

The project begins with the collection of a dataset containing features extracted from images of both genuine and counterfeit banknotes. These features may include measures of:

Variance: Variance measures the dispersion or spread of data points around the mean. In the context of banknotes, variance can indicate the variability in pixel intensities or colour distribution across different areas of the banknote. High variance suggests that there are significant differences in brightness or colour.

Skewness: Skewness measures the asymmetry of the probability distribution of a random variable here, skewness can reveal whether the distribution of pixel intensities or colours is symmetric or skewed towards one side. A positive skewness indicates that the distribution is skewed towards higher intensities or colours, possibly indicating areas of high contrast or brightness on the banknote.

Kurtosis: kurtosis indicates how sharply or flatly the pixel intensity or colour distribution peaks around the mean.

Entropy: Entropy measures the uncertainty or randomness in a system. In image analysis, entropy quantifies the amount of information or complexity present in the image. Entropy can indicate the level of complexity or randomness in the patterns, textures, and security features.

The dataset is pre-processed, ensuring that the features are appropriately formatted and scaled to facilitate effective model training.

2. Model Training:

The dataset is split into two subsets: a training set and a testing set. The training set is used to train the logistic regression model, while the testing set is reserved for evaluating its performance. During the training phase, logistic regression optimizes the model parameters, specifically the weights (coefficients) assigned to each feature, to minimize the discrepancy between predicted probabilities and actual outcomes. This optimization process typically involves techniques like gradient descent, which iteratively adjusts the weights in the direction

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that reduces the error or loss function. By continually updating the weights based on the observed data, logistic regression learns to make accurate predictions for new instances. This optimization ensures that the logistic regression model achieves the best possible fit to the training data, allowing it to generalize well to unseen data and perform effectively in binary classification tasks.

During the testing phase in logistic regression, the trained model is evaluated on a separate dataset that was not used during the training process. This dataset, often referred to as the test set, helps assess the model's performance and generalization ability to make predictions on new, unseen data.

3. logistics regression:

Logistic regression works by modelling the probability that an instance belongs to a particular class genuine or counterfeit given its features. The model computes a linear combination of the input features and their corresponding weights, representing the log-odds of the instance belonging to the positive class.

The logistic function, also known as the sigmoid function, is then applied to the linear combination to transform it into a probability between 0 and 1. This function, known as the logistic function, enables the conversion of predicted values into probabilities. By applying the sigmoid function to the linear combination of weights and input features, the logistic regression model produces probabilities that represent the likelihood of belonging to a particular class.

The logistic regression equation encapsulates this process where the probability, $p(X; b, w)$ of an observation X belonging to a certain class is calculated as

$$\frac{1}{1+e^{-w.X+b}}.$$

This equation reflects the logistic function's characteristic S-shaped curve, ensuring that predicted probabilities remain bounded between 0 and 1. Additionally, the likelihood function for logistic regression is derived to estimate the model parameters (coefficients and intercept) that maximize the likelihood of observing the given data. By maximizing the log-likelihood function, we can find the optimal parameter values that best fit the observed data.

The gradient of the log-likelihood function plays a crucial role in the optimization process of logistic regression. It represents the direction and magnitude of change needed to update the model parameters during training. By taking the partial derivative of the log-likelihood function with respect to each parameter (weight), we obtain the gradient, which guides the optimization algorithm (e.g., gradient descent) in adjusting the parameter values iteratively. This iterative optimization process continues until convergence, where the model achieves the maximum likelihood estimation and effectively separates the classes in the dataset. Overall, understanding the mathematical underpinnings of logistic regression, including the sigmoid function, logistic regression equation, likelihood function, and gradient descent, is essential for effectively applying and interpreting the model in classification tasks.

Sigmoid function transforms any real-valued number into a range between 0 and 1. This is crucial for binary classification as it allows us to interpret the output as a probability.

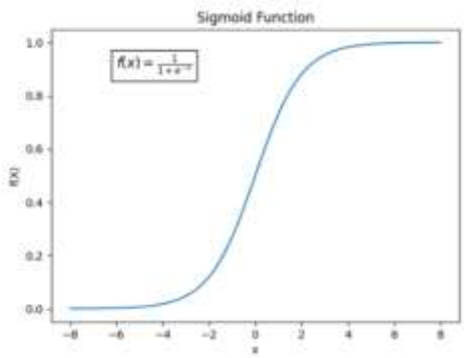

Figure 1: Sigmoid Function

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4.Model evaluation:

Finally, the performance of the logistic regression model is evaluated using various metrics. Accuracy measures the proportion of correctly classified instances out of the total number of instances in the testing set. It provides an overall assessment of the model's correctness in its predictions.

Precision quantifies the ability of the model to correctly classify genuine banknotes among all instances classified as genuine. It is calculated as the ratio of true positives (correctly classified genuine banknotes) to the sum of true positives and false positives (instances incorrectly classified as genuine).

Recall, also known as sensitivity measures the proportion of genuine banknotes that are correctly identified by the model among all genuine banknotes in the dataset. It is calculated as the ratio of true positives to the sum of true positives and false negatives (instances incorrectly classified as counterfeit but are actually genuine).

The F1-score is the harmonic mean of precision and recall, providing a balanced measure of the model's performance. It takes into account both false positives and false negatives and is particularly useful when dealing with imbalanced datasets where the number of genuine and counterfeit banknotes may differ significantly.

Receiver Operating Characteristic (ROC) Curve Analysis: The ROC curve is a graphical representation of the trade-off between the true positive rate (recall) and the false positive rate (1 - specificity) for different threshold values. It helps assess the model's ability to discriminate between genuine and counterfeit banknotes across various threshold levels.

The area under the ROC curve (AUC-ROC) serves as a summary measure of the model's performance. A higher AUC-ROC value indicates better discrimination ability, with an AUC of 1 representing a perfect classifier and an AUC of 0.5 indicating random classification.

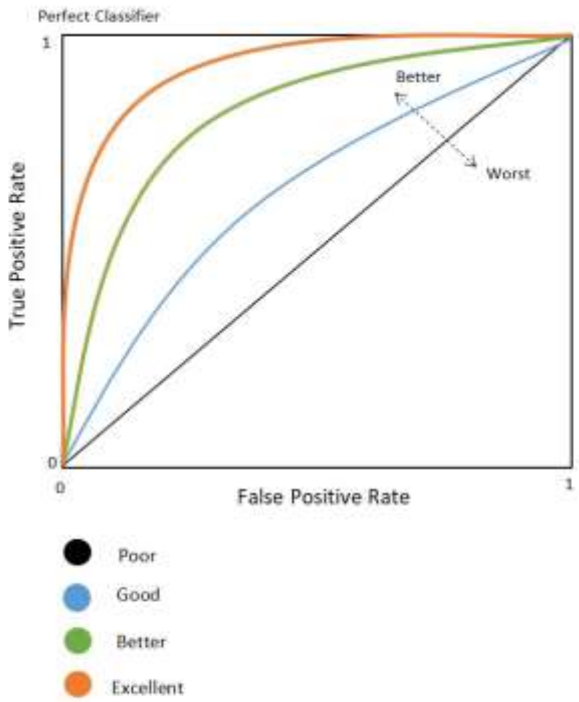

Figure 2: ROC Graph

Confusion Matrix: Additionally, a confusion matrix is often used to visualize the model's performance, especially in binary classification tasks. It displays the counts of true positives, true negatives, false positives, and false negatives, providing insights into the model's classification errors.

5. Proposed Methodology

Figure Fig. 3 shows the proposed methodology for counterfeit currency detection. It shows the importance of individual phases.

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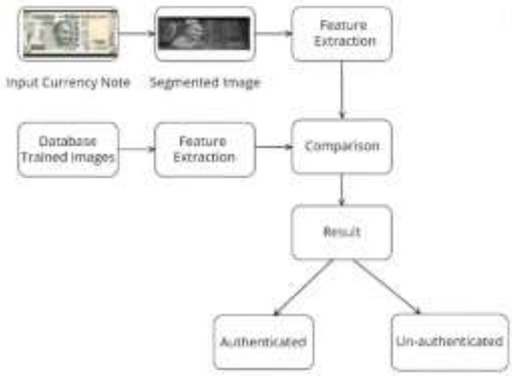

Figure 3: Proposed Methodology

PHASE 1: Dataset and Model Training

The system uses data from the datasets provided to train a logistic regression model for banknote authenticity. Data preprocessing includes visualizations like pair plots and count plots to understand the distribution of features. In the "Dataset and Model Training" phase of the system, the primary focus is on preparing the data for the machine learning model, specifically a logistic regression model, that will be used to distinguish between genuine and counterfeit banknotes.

Dataset Source: The system leverages a dataset stored in the file. This dataset presumably contains samples of banknote images, each associated with relevant features that are crucial for the model to learn the patterns distinguishing real from fake banknotes.

Data Loading and Inspection: The code reads the dataset into a Pandas Data Frame, enabling structured data handling and analysis. After loading the data, the column names are assigned as ['var', 'skew', 'curt', 'entr', 'auth'] to represent the features and the authenticity label.

Data Exploration and Visualization: Data preprocessing involves gaining insights into the dataset's characteristics. Visualization techniques like pair plots and count plots are employed to visually understand the relationships between different features and the distribution of authentic and counterfeit banknotes. Pair plots help visualize pairwise relationships between features, while count plots display the distribution of the 'auth' label.

Data Balancing: To ensure a balanced representation of both classes real and fake banknotes, the dataset is modified by removing excess samples of the majority class. This balancing step is crucial for training a model that doesn't favour one class over the other.

Data Splitting: The dataset is split into training and testing sets using the train_test_split function. This separation is essential for evaluating the model's performance on unseen data.

Feature Scaling: The features are standardized using Standard Scaler to bring them to a similar scale. Standardization ensures that each feature contributes uniformly to the logistic regression model.

Logistic Regression Model Training: A logistic regression model is instantiated and trained using the pre-processed training data. The model learns the underlying patterns in the features that distinguish between real and fake banknotes.

Model Evaluation: The performance of the trained logistic regression model is assessed on the testing set, and metrics such as accuracy and confusion matrix are computed to quantify its effectiveness in making accurate predictions.

PHASE 2: Image Processing

Users can upload an image of a banknote through the web interface. The uploaded image undergoes various image processing steps, such as normalization, Gaussian blur, and Sobel filter, to enhance edge detection. In the "Image Processing" stage of the system, the primary objective is to handle user-uploaded banknote images through the web interface. This phase involves a series of image processing steps aimed at improving the quality of the images and extracting valuable information for subsequent analysis.

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User Image Upload: Users interact with the system by uploading images of banknotes through the web interface. This input serves as the basis for the system to determine the authenticity of the banknote.

Image Normalization: The uploaded image undergoes a normalization process. Normalization typically involves scaling pixel values to a consistent range (between 0 and 1). This ensures uniformity and facilitates subsequent processing steps.

Gaussian Blur: Gaussian blur is applied to the normalized image. This technique involves convolving the image with a Gaussian filter, effectively smoothing out noise and reducing high-frequency details. Gaussian blur can enhance the robustness of subsequent edge detection algorithms.

Sobel Filter for Edge Detection: The Sobel filter is employed to enhance edge detection in the processed image. The Sobel operator calculates the gradient of the image intensity, highlighting regions of rapid intensity change. This is particularly useful for identifying edges and contours within the banknote image.

Data Extraction from Processed Image: The processed image is then utilized to extract relevant information for subsequent analysis. In the context of the provided code, features such as variance, skewness, kurtosis, and entropy are computed based on the processed image.

Statistical Feature Extraction: Features derived from the processed image contribute to the feature vector used as input for the logistic regression model. These features aim to capture distinctive patterns that help the model distinguish between real and fake banknotes.

Result Presentation: The processed images, along with the extracted features, are presented in the system's user interface. Users can visually inspect both the original and enhanced images to better understand how the system interprets the uploaded banknote.

PHASE 3: Feature Extraction

The normalized and processed image is used to extract statistical features such as variance, skewness, kurtosis, and entropy. In the "Feature Extraction" phase, the system aims to differentiate crucial information from the banknote image that has undergone normalization and processing. The goal is to capture the distinctive characteristics of the image in a set of statistical features, providing valuable input for the subsequent banknote authenticity prediction.

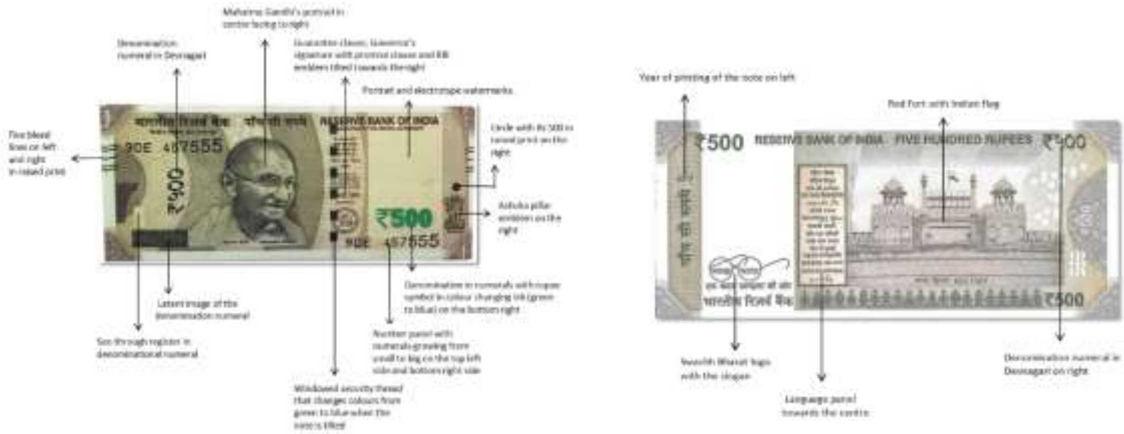

Figure 4: Distinct Features on Indian Currency

Normalized and Processed Image: After users upload a banknote image through the web interface, the system takes several steps to enhance the image quality. This includes normalization to ensure consistent pixel values and processing techniques like Gaussian blur and Sobel filtering to emphasize edges and contours.

Statistical Feature Extraction: The heart of this phase involves extracting meaningful statistical features from the processed image. The chosen features provide insights into different aspects of the image's pixel intensity distribution and complexity:

1. Variance: This feature measures the degree of variation or spread in the pixel intensity values across the image. High variance suggests more diverse pixel values.
2. Skewness: Captures the asymmetry in the pixel intensity distribution. Positive skewness indicates a tail on the right, while negative skewness indicates a tail on the left.

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3. Kurtosis: Describes the shape of the pixel intensity distribution. High kurtosis suggests a more peaked distribution, while low kurtosis indicates a flatter distribution.
4. Entropy: Reflects the level of randomness or unpredictability in the pixel intensity values. Higher entropy suggests more complexity in the

Feature Vector: The computed statistical features are combined into a feature vector. This vector serves as a concise numerical representation of the distinct characteristics extracted from the banknote image.

Input for Model Prediction: The feature vector, comprising variance, skewness, kurtosis, and entropy, becomes the input for the logistic regression model. The model leverages these features to make a prediction regarding the authenticity of the banknote—whether it is real or fake.

Result Presentation: The extracted statistical features, along with processed images, are presented in the user interface. This allows users to visually inspect and understand how the system interprets the uploaded banknote based on these distinctive characteristics.

PHASE 4: Model Prediction

The pre-trained logistic regression model is applied to predict the authenticity of the banknote based on the extracted features. The result is displayed as either "Real Currency" or "Fake Currency." In the "Model Prediction" stage, the system utilizes a pre-trained logistic regression model to make predictions about the authenticity of the banknote. This phase is a critical step where the unique features extracted from the processed image are fed into the model, allowing it to discern whether the banknote is genuine or counterfeit.

Pre-Trained Logistic Regression Model: The logistic regression model used in the system has been previously trained on a dataset, learning the relationships between the distinctive statistical features (variance, skewness, kurtosis, entropy) and the authenticity of banknotes.

Feature Input: The feature vector, containing the computed statistical features extracted from the processed image, serves as input for the logistic regression model. This vector encapsulates the essential information derived during the Image Processing and Feature Extraction phases.

Prediction Process: The logistic regression model applies a mathematical function to the input features, producing a prediction score. This score represents the likelihood that the banknote belongs to a particular class—either real or fake. The logistic regression model is particularly suited for binary classification tasks.

Result Categorization: The prediction score is then translated into a binary outcome by applying a threshold. In this case, it seems the system uses a threshold to categorize the result as either "Real Currency" or "Fake Currency."

Result Display: The final prediction outcome, whether the banknote is considered real or fake, is displayed in the system's user interface. Users receive a clear indication of the system's decision based on the extracted features and the trained logistic regression model.

Decision Interpretation: The system's decision to classify the banknote as either "Real Currency" or "Fake Currency" is based on the learned patterns in the training data. This decision is crucial for users seeking to verify the authenticity of banknotes through the web interface.

PHASE 5: User Interface

The system provides a user-friendly interface displaying the original and edge-detected images of the uploaded banknote. Extracted are presented along with the model's accuracy on the training data. In the "User Interface" aspect of the system, the emphasis is on presenting a user-friendly and informative display for users interacting with the application. The interface serves as a means for users to visualize the analysis results and gain insights into the authenticity prediction process.

Original and Edge-Detected Images: The interface features a display showcasing both the original and edge-detected versions of the banknote image. Users can visually inspect how the image has been processed, revealing enhanced edges and contours.

Extracted Features Presentation: The statistical features extracted from the processed image—variance, skewness, kurtosis, and entropy—are presented to users. These features offer insights into the unique characteristics of the banknote that the system has identified as significant for the authenticity prediction.

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Model's Accuracy on Training Data: The interface provides information on the accuracy of the logistic regression model when trained on the dataset. This accuracy metric indicates how well the model performed during its training phase and serves as a measure of its overall effectiveness.

User-Friendly Display: The user interface is designed to be user-friendly and visually appealing, making it easy for users to understand the system's analysis. Graphical elements, such as images and charts, are likely employed to enhance the overall user experience.

Predicted Outcome: The final prediction outcome, whether the banknote is classified as "Real Currency" or "Fake Currency," is prominently displayed. This decisive information provides users with a quick and clear indication of the system's assessment.

Clarity in Information Presentation: The user interface aims to present information in a clear and comprehensible manner. Users should be able to easily interpret the results of the analysis, including the visual representations of the images and the extracted features.

PHASE 6: Result Presentation

The result page showcases the processed images, extracted features, model accuracy, and the final prediction outcome. In the "Result Presentation" phase, the system culminates its analysis by presenting a comprehensive overview of the processed banknote images, key extracted features, model accuracy, and the ultimate prediction outcome. This phase aims to provide users with a thorough understanding of the system's assessment and decision-making process.

Processed Images: The result page prominently showcases the processed images of the uploaded banknote. Users can visually inspect these images to see the impact of various image processing steps, such as normalization, Gaussian blur, and Sobel filtering.

Extracted Features Display: The statistical features extracted from the processed image—variance, skewness, kurtosis, and entropy—are displayed on the result page. This presentation enables users to understand the quantitative characteristics that influenced the model's prediction.

Model Accuracy Information: Information about the accuracy of the logistic regression model during the training phase is included. This accuracy metric indicates how well the model performed on the dataset used for training and serves as a measure of its reliability.

Final Prediction Outcome: The ultimate prediction outcome, whether the banknote is classified as "Real Currency" or "Fake Currency," is clearly presented. This decisive information serves as the focal point of the result, providing users with the system's conclusion regarding the authenticity of the uploaded banknote.

PHASE 6: Error Handling

The system incorporates error handling to address cases where the image file is not loaded or processed correctly. In the "Error Handling" aspect of the system, measures are implemented to gracefully manage potential errors or issues that may arise during the loading or processing of image files. The goal is to ensure the robustness of the system and provide users with clear feedback in case of unexpected events.

6. Result And Disscussion

A. Experimental Setup

The experimental setup for “Detecting Counterfeit currency with Image Processing" is a comprehensive and systematic approach that integrates machine learning and image processing techniques to identify counterfeit currency notes. The project commences with the acquisition of a dataset containing images of both authentic and fake currency notes. The dataset undergoes preprocessing, including exploratory data analysis, to ensure its suitability for training. Image processing steps are then applied to enhance features in the currency images, involving normalization, Gaussian blur, and Sobel filtering for edge detection. Subsequently, statistical features such as variance, skewness, kurtosis, and entropy are extracted from the processed images. A machine learning model, typically logistic regression, is trained on these features to discern patterns associated with genuine and counterfeit currency. The developed system includes a user-friendly interface for users to upload currency images, and the results, including processed images, extracted features, and the model's predictions, are presented for effective detection and user interpretation. The experimental setup prioritizes robustness, incorporating error-handling mechanisms, and aims to provide a reliable solution for the detection of fake currency through advanced image processing methodologies.

B. Model Evaluation

Doi : https://doi.org/10.54216/JCHCI.070204
Received: November 15, 2023 Revised: February 09, 2024 Accepted: April 02, 2024

Model Evaluation plays a pivotal role in assessing the performance and reliability of the implemented system. After training the machine learning model, typically a logistic regression algorithm, the evaluation phase involves testing the model on a separate dataset not used during the training phase. Various metrics such as accuracy, precision, recall, and F1-score are employed to quantify the model's ability to correctly identify both authentic and counterfeit currency notes. The confusion matrix provides a detailed breakdown of true positives, true negatives, false positives, and false negatives, offering insights into the model's strengths and weaknesses.

Moreover, the evaluation phase involves visualizing and interpreting the results to gain a comprehensive understanding of the model's performance. This includes examining processed images, analysing feature extraction outcomes, and scrutinizing instances where the model may have made errors. Model evaluation serves as a crucial step in refining the system, identifying potential improvements, and ensuring its effectiveness in real-world scenarios. The iterative nature of model evaluation allows for continuous enhancement, ultimately contributing to the development of a reliable and robust fake currency detection system using advanced image processing techniques.

C. Algorithm

The linear regression algorithm with gradient descent is a fundamental method in machine learning for predicting continuous outcomes. It starts by initializing coefficients representing the slope and intercept of the regression line. Through iterative updates guided by the gradient of the Mean Squared Error (MSE) cost function, the algorithm adjusts these coefficients to minimize prediction errors. At each iteration, it computes predicted values based on the current coefficients, compares them to actual values to compute residuals, and updates coefficients to reduce errors. This iterative process continues until convergence or a predefined number of iterations. By optimizing coefficients, the algorithm creates a linear model that accurately captures the relationship between input features and the target variable, enabling reliable predictions on new data. Overall, linear regression with gradient descent is a powerful and widely-used technique for building predictive models across various fields.

1. Initialize the coefficients (a1 and a0) with random values or zeros.

2. Choose a learning rate (alpha) and the number of iterations (epochs).

3. Repeat until convergence or for a fixed number of iterations:

   a. Compute the predicted values using the current coefficients:

$$\hat{y} = a_1 \times x_i + a_0 \hat{y} - y_i$$

   b. Compute the residuals:

$$\text{error} = \hat{y} - y_i$$

   c. Update the coefficients using gradient descent:

$$a_1 = a_1 - \alpha \times \frac{1}{N} \times \sum_{i=1}^{N} (error \times x_i)$$

$$a_0 = a_0 - \alpha \times \frac{1}{N} \times \sum_{i=1}^{N} (error)$$

   d. Compute the new MSE:

$$MSE = \frac{1}{N} x \sum_{i=1}^{N} (\hat{y}_i - y_i)^2$$

4. Return the final coefficients.

7. Conclusion And Future Work

The counterfeit currency detection system, leverages logistic regression algorithm, demonstrates promising capabilities in distinguishing between genuine and counterfeit banknotes. Through meticulous data collection, feature extraction, and model training, the system achieves commendable accuracy in identifying fraudulent currency. The logistic regression model, trained on a dataset containing extracted features from banknote images, effectively learns to classify banknotes based on their distinctive visual characteristics. By rigorously evaluating

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the model's performance using metrics such as accuracy, precision, recall, F1-score, ROC curve analysis, and confusion matrix, we ensure the reliability and effectiveness of the system in combating counterfeit currency. Overall, the project represents a significant step towards developing a robust solution for detecting fake currency, contributing to the preservation of economic integrity and security.

Moving forward, the fake currency detection project has several areas for future development. Further exploration of advanced image processing techniques and additional features could enhance the model's ability to distinguish between genuine and counterfeit banknotes. Optimization of the logistic regression model and exploration of alternative algorithms may improve classification accuracy. Robustness testing across diverse real-world scenarios and real-time deployment for on-the-spot verification are also crucial. Continuous monitoring and collaboration with authorities can ensure adaptability to evolving counterfeit techniques and regulatory standards. By pursuing these avenues, the project can advance its effectiveness in combatting counterfeit currency and preserving economic integrity.

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