Department of Electrical and Information Engineering

University of Ruhuna

Mini Project Proposal

Artificial Intelligence

EC6301

Counterfeit Sri Lankan Currency Identification Using Smartphone Images and Convolutional Neural Networks

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Contents

1. Problem Statement

The problem of counterfeit currency is a major issue of concern for the overall well-being ofthe economy. Traditionally, techniques for detecting counterfeit Sri Lankan currency notes involved cumbersome and subjective methods, which are beyond the reach of the general public (R01). With the widespread use of smartphones, it is possible to capture high-quality images of currency notes, thereby creating a viable opportunity for developing an automated technique for counterfeit currency detection (R02). It is, however, difficult to differentiate between genuine and counterfeit currency using image processing techniques, as there are a wide variety of possible lighting conditions, wear and tear of currency, print quality, and similarities between genuine and counterfeit currency. The current techniques are based on handcrafted features, which are limited, thereby restraining the overall accuracy of the techniques (R03). The proposed work aims at addressing all the issues by using smartphone images and Convolutional Neural Network (CNN) techniques for developing an efficient, accurate, and automated technique for counterfeit currency detection

Back to Table of Contents

2. Objectives

The main goals of this mini project are:

1. Collect and analyze images of Sri Lankan currency notes using smartphones, with actual and counterfeit samples.
2. Preprocess the captured images of currency notes using various operations such as resizing, noise reduction, contrast enhancement, and normalization.
3. Derive meaningful visual features that are relevant to Sri Lankan currency security features such as watermarks, security threads, micro text, and texture.
4. Develop an AI model based on Convolutional Neural Networks (CNNs) that classifies genuine and counterfeit currency notes based on images.
5. Evaluate the performance of the proposed model using various parameters such as accuracy, precision, recall, and F1 score.
6. Present a method of identifying counterfeit currency using a smartphone that could be used by various entities such as financial institutions, industries, and common users.

Back to Table of Contents

3. Literature Review

The issue of counterfeit currencies is increasingly affecting economies around the world. It is affecting economic stability, trust, and security. Detection of counterfeit currencies is critical and essential for various economic entities and individuals. Conventional detection of counterfeit currencies mostly relies on manual inspection or devices like ultraviolet scanners. These devices may not be feasible or easily accessible. Advances in computer vision and artificial intelligence have made counterfeit currency detection using images a vital domain of academic study. In recent times, several studies have been carried out on detecting counterfeit currencies using images and artificial intelligence. This literature survey discusses a few notable studies on detecting counterfeit currencies using images, their methodologies, advantages, disadvantages, and gaps filled by the current study.

Study 1: Patil and Sherekar (2017) – Currency Recognition and Counterfeit Detection Using Image Processing [1]

A framework for image processing in the detection of counterfeit currency has been proposed by Patil and Sherekar. In this framework, the visual features of the currency, such as the color patterns, edges, and texture, are analyzed. Pre-processing techniques such as grayscale conversion, noise removal, and edge detection are used in this framework. Feature extraction is performed using handcrafted methods, and traditional machine learning classifiers are used for classification.

Strengths:

- The feasibility of image-based counterfeit detection is demonstrated.
- Focus is placed on the security features of the currency notes, which can be easily visualized.

Limitations:

- The dependence on handcrafted features is such that the approach is affected by lighting and variations in the quality of images.
- The approach is not flexible enough to accommodate changes in the state of the currency notes and counterfeit techniques.

Relevance to Current Project:

- The importance of preprocessing and feature extraction is highlighted.
- The approach is not very robust due to its dependence on handcrafted features.
- The proposed project replaces the feature extraction process with CNN-based deep learning, which can automatically learn discriminative features from images captured using a smartphone.

Study 2: Hassanpour et al. (2019) – Banknote Authentication Using Convolutional Neural Networks [2]

Another study conducted by Hassanpour et al. focused on a method based on CNN for banknote authentication by using high-resolution images. The method allows the model to automatically learn the features from the images; as a result, there is no need for any human involvement in the feature engineering process, as occurs with traditional machine learning approaches.

Strengths:

- Successful implementation of CNN for automatic feature learning.
- Better robustness is achieved for variations in texture and print quality.

Limitations:

- The evaluation of the proposed approach is based on controlled conditions for image acquisition.
- The proposed approach does not address image acquisition using mobile or smartphone devices.

Relevance to Current Project: The proposed approach in this study is based on using convolutional neural networks for counterfeit detection. The current project is an extension of this approach, using smartphone images for classification of Sri Lankan currency notes.

Study 3: Kumar et al. (2018) – Fake Currency Detection Using Image Processing Techniques [3]

Kumar et al. propose a counterfeit currency detection system that uses image processing techniques to analyze security features like watermarks, security threads, and micro-text.

Strengths:

- Emphasis on security features of currency.
- Direct correlation between visual signs and currency authenticity.

Limitations:

- Rule-based systems are not scalable.
- Accuracy decreases if currency is worn or partially damaged.

Relevance to Current Project: This study confirms the significance of security features for counterfeit currency detection. In the proposed project, security features are incorporated indirectly through the learning process of convolutional neural networks.

Study 4: Arora and Saini (2020) – Deep Learning-Based Currency Authentication [4]

In another study, Arora and Saini explored the possibility of using deep learning techniques for currency authentication using convolutional neural network (CNN)-based architectures and banknote image data sets. The results of the study reveal that deep learning techniques can outperform traditional image processing techniques, especially in handling complex patterns.

Strengths:

- It shows the efficiency of deep learning techniques.
- It minimizes manual preprocessing and feature design.

Limitations:

- The data set is small, which may limit the generalization of the results.
- It does not consider the possibility of using the technique in real-time or mobile device scenarios.

Relevance to Current Project: The study is relevant because it shows that CNN can be applied for counterfeit detection. However, the proposed project aims to improve generalization using different smartphone images, as well as its applicability in system design..

Study 5: Sharma et al. (2021) – Smartphone-Based Fake Currency Detection Using CNNs [5]

Sharma et al. presented a counterfeit currency detection algorithm based on convolutional neural networks, which was designed to be implemented on a smartphone device. The authors used images collected through mobile phone cameras to test the effectiveness of their model.

Strengths:

- Emphasizes image capture directly from a smartphone.
- Shows its potential for use in practical applications in real-world life.

Limitations:

- Only tested on a small number of currency denominations.
- Not tailored to specific security features of a country.

Relevance to Current Project: This work is similar in direction to our project. Our current project is an extension with emphasis on Sri Lankan banknotes and with a more thorough evaluation.

3.1. 6.1 Gap Analysis and Proposed Improvements

Even though image-based counterfeit bills detection appears useful, there are existing gaps:

- Real-world robustness gaps: Many works have used controlled capturing methods. This has a disadvantage in strongly variable lighting conditions and backgrounds.
- Dependence on handcrafted features: Conventional image processing techniques have difficulty adapting to changing counterfeit methodologies.
- Limited focus on usability on smart phones: Some deep learning research lacks explicit considerations about usability on smart phones.
- Country-specific blind spots: A lot of existing research mainly studies generic or foreign currencies, without focusing on the security features in each country.

Proposed Project Improvements:

- Smartphone-based image capturing: Make use of actual images obtained using smartphones.
- CNN-based Deep Learning: Use the models to automatically learn complex visual cues and security markers.
- Sri Lankan currency emphasis: Add denomination-specific security features and country-specific security features.
- Real-time Viability: Ensure design for quick and efficient inferences for mobile apps.

By addressing these issues, the project seeks to develop an effective, accurate, and accessible AI system in detecting counterfeit Sri Lankan currency through images taken with a smartphone.

Back to Table of Contents

4. Methodology

The project aims to generate an AI-based technique for identifying fake currency notes from Sri Lanka using pictures taken with a smartphone and analyzed with the help of Convolutional Neural Networks (CNNs), where specific attributes of the image, such as texture, color pattern, microtext, watermark, and security threads, help in distinguishing real or fake notes. In simple words, we aim to improve the quality of currency images, recognize specific features, and classify real or fake notes with the help of deep learning techniques.

4.1. Overall System Approach

The proposed framework for counterfeit currency identification follows a well-defined pipeline consisting of the following key steps:

- Acquisition of currency images using smartphone cameras
- Preprocessing and enhancement of images
- Segmentation or region of interest identification
- Feature extraction using Convolutional Neural Networks
- Currency classification using artificial intelligence-based techniques
- Evaluation and analysis of results

This approach allows for a well-defined sequence of operations to transform the currency images into a more meaningful representation for effective counterfeit currency identification.

4.2. Data Source and Utilization

This approach is based on using a data set of images of Sri Lankan monetary notes taken with smartphone cameras; the set contains real and fake Sri Lankan currency. These images have been taken from various lighting conditions and backgrounds to replicate real-world testing conditions. The data set involves various denominations of money in order to provide maximum variations. This set of images has been categorized as real or fake and is for research purposes only. This data set is the primary source of data for the proposed approach and meets the criteria for the training of the CNN model under supervised learning.

4.3. Data Preprocessing

Also, images of currency notes received through a smartphone may have additional noise, different lighting conditions, messy backgrounds, and perspective distortions. Due to these differences, preprocessing plays a significant role to enhance image quality for further processing.

The following data preprocessing techniques are used in this methodology:

- Image resizing: The collected images are resized to a suitable size that can be used as an input image for the CNN model.
- Noise reduction: Noise reduction techniques are applied to the images to remove unwanted noise and artifacts that may have appeared during the image acquisition process.
- Color normalization: Changes in lighting conditions are minimized by using normalization techniques.
- Contrast enhancement: Contrast enhancement techniques are used to highlight the features of the currency notes, especially the micro-text and texture features.
- Handling background noise: The background noise in the images is removed by using techniques that mask the background and highlight the currency note region in the image.

This will ensure that extracted features are intrinsic to the currency note rather than being affected by environmental noises.

4.4. Image Segmentation

The visual security features of the currency notes have a spatial distribution of characteristics in various areas. Hence, the images can be segmented into regions of interest or can be divided into fixed-size patches.

Segmenting the images provides the following benefits:

- Focused analysis of the regions of interest
- Reduced effects of background noise
- Improved learning of local texture and feature patterns
- Increased number of training samples using patches

Each segmented image has the same label as the authentic image.

Segmenting the images is helpful in improving the classification accuracy.

4.5. Feature Extraction

In the proposed system, the Feature extraction module transforms the enhanced images into a format that can identify the key features. Contrast to the traditional approach, which required pulling out the key features manually, Convolutional Neural Networks are used to learn the key features directly.

Texture and Pattern Features

- Fine-grained texture patterns of the paper and ink
- Printing patterns and consistencies
- Irregularities in the surface of the paper due to counterfeit printing

Color and Intensity Features

- Color patterns and consistencies in the images
- Patterns of ink density
- Fading patterns of colors

Security Feature Representation

- Implicit learning of watermarks and security threads
- Micro-text representation of the images
- Edge and contour representation of the images

The CNN model processes the features and provides a feature representation of the images.

4.6. Currency Classification

After feature extraction, artificial intelligence techniques are used for the classification of currency notes as genuine or counterfeit. Due to the ability of CNNs to learn spatial hierarchy from images, the classification model is able to learn the overall and local patterns from the images.

The steps of the classification process include the following:

- Input of the preprocessed images of the currency
- Learning of the visual features of the images
- Prediction of the authenticity of the images

This process of classification is the main part of the proposed model, which can be used for the detection of counterfeit currency using smartphones. CNNs have been used in this process due to their effectiveness in image recognition.

4.7. Model Training Strategy

To avoid any biases in the model during the testing process, the data set is divided into training and testing data sets.

Key considerations during the training process include the following:

- Avoiding overfitting using regularization
- Choosing the learning rate and batch size
- Using an equal number of genuine and counterfeit currency images

Data augmentation can be used during the training process. CNNs use the backpropagation algorithm during the training process.

4.8. Performance Evaluation

The performance of the developed counterfeit currency identification system using the proposed methodology is evaluated using classification performance metrics.

The evaluation metrics used for evaluating the system include:

- Accuracy: The correctness of the classification of the currency.
- Precision: The ratio of correctly classified counterfeit notes.
- Recall: The measure of the system's capacity for identifying actual counterfeit currency.
- F1-score: A measure of both precision and recall.

The evaluation of the system using these metrics provides an overall evaluation of the system's effectiveness and reliability.

4.9. Tools and Software Frameworks

The developed system for implementing the proposed methodology utilizes software tools and frameworks, which are widely accepted and suitable for implementing an AI-based system for image analysis.

The tools and software used include:

- Python: The main programming language used for implementing the system.
- OpenCV: A tool used for image enhancement and processing.
- TensorFlow/Keras: A tool used for implementing and training CNN-based systems.
- Matplotlib/Seaborn: A tool used for visualization of images and results.

These tools and software frameworks provide the scalability, flexibility, and support required for implementing a computer vision-based system.

4.10. System Workflow

The overall workflow of the proposed system can be outlined as follows:

- Currency images acquired through a smartphone
- Image preprocessing and enhancement
- Image segmentation or selection of regions of interest
- Extraction of visual features using a convolutional neural network
- AI model training
- Evaluation and analysis of results

This workflow outline Promotes clarity and ease of implementation.

4.11. Significance of the Proposed Methodology

The proposed methodology shows the viability of using images acquired through a smartphone and deep learning concepts in identifying counterfeit currency. The methodology avoids the need to physically examine the currency with specialized equipment.

The methodology also shows that it can be used as a base in developing applications such as a mobile app that can be used by the public and in developing a real-time transaction verification system in the field of banking and finance.

Back to Table of Contents

5. Dataset / Data Collection

The paper utilizes a set of banknote photographs which have been judiciously collected featuring various denominations, as well as real and fake banknotes. This encompasses photographs which have been captured through different lighting, backgrounds, as well as different states of wear, tagged as real or fake, hence enabling classification in a supervised learning instance by the AI model.

The use of this dataset is limited to purely academic purposes. They are stored in conventional data formats. The varying conditions in which these images were made help create a robust AI program for the detection of counterfeits.

Back to Table of Contents

6. Expected Outcomes

The idea is to effectively create a viable AI-assisted tool that can recognize phony Sri Lankan currency merely by scanning an image with a smartphone. This will be accomplished by designing a properly trained CNN and producing corresponding code to process images and execute classification on currency. The project will also include a set of visual outputs, like predictions, feature maps, and graphs of training.

To determine how efficient this system is, we will use different parameters such as accuracy, precision, recall, and F1-score to measure efficiency. The project shows that deep learning can successfully identify counterfeit currency in a highly efficient manner and make it accessible to anyone.

Back to Table of Contents

7. Percentage of AI Involvement

The project also comprises over 85 cases for developing and testing AI models by employing tools like Python, TensorFlow, and Keras. The pervasiveness and use of deep learning for decision-making and feature learning highlight the role of artificial intelligence within the system..

Back to Table of Contents

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