University of KwaZulu-Natal
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Mini Project

Bank Note Recognition using image processing techniques

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1 Abstract

This examination will provide data about the various techniques and algorithms used to identify the properties(features) of the depicted banknotes in a reference collection of notes. The Banknote Recognition System should compute a similarity measure between takes note of that are invariant to sides, scale and rotations, because the banknotes have two appearances, and the direction of the note can either be upstanding or upside down. In this paper, we use the image processing techniques are used. The system consists of these steps: input image, image processing, and enhancement, image segmentation, feature extraction and image classification, comparison, and output image. There are many ways to acquire an image for example, with the help of a camera or scanner. The acquired image should retain the features. Acquisition of image is the process of making digital images, from a physical scene. Here the image is captured by a basic computerized camera such that all features are highlighted. The image is then put away for processing. After processing apply the image segmentation and feature extraction. Thus a Support Vector Machine is used for feature classification to correctly classify the image.

2 Introduction

Fake currency has always been an issue that has created a lot of problems in the market. The technological advancements have made a pathway for money to be copied with the end goal that it can't be formally recognized. Banknotes play a vital role in our trading culture, and while digital currency is becoming more common, physical banknotes still account for most of the local transactions. As such, systems that can identify banknotes may be used to help manipulate such currencies. Such systems are useful to visually disabled persons, as they allow them to be more independent while minimizing the aid of untrusted individuals. They can also improve the protection and efficiency of ATMs[6] by ensuring that the maintenance operations are carried out properly and that the genuine banknotes are not replaced by counterfeits.Many less important implementations apply to automated banknote sorting and counting to speed up purchases and money transfers. To be efficient and usable, such types of systems must be able to recognize banknotes in various viewpoints, size measurements and should also accommodate cluttered areas with varying lighting conditions. In addition to these essential conditions, to be used properly to support People with visual impairments must still be able to distinguish folded, wrinkled, and aged banknotes.

The input images are pre-processed to remove ambient noise and improve contrast and brightness for implementing the robust banknote recognition system. Then there are important key points and their related descriptors calculated, to be used later to find the best match for a valid banknote database. As such, methods are employed to filter the matching inliers. There are many methods to achieve such filtering, such as ratio test[5] and removal of homography outlier[1]. Although such methods will yield very good outcomes, a pre-processing analysis is implemented to insure that the findings collected are genuine banknotes. It is attributed to the assumption that matching different pieces of wrinkle banknotes will result in numerous instances of the same banknote being identified. Similarly, images similar to banknotes or banknotes from other countries can produce partial matches that are incorrect. As such, this postprocessing phase is critical to ensuring the banknote recognition is correct. It starts by using the obtained homography to compute the banknote contour, and then excludes any result that has a convex contour, or has its area, circularity and aspect ratio beyond appropriate banknote ranges.

3 Implementation

The following sections present the main processing stages of the implemented banknote recognition system. Python was used for development and to speed up development, the OpenCV library was used.

A. ***Preprocessing and Enhancement***

A preprocessing phase is implemented to boost the identification of positive features and maintain a reliable perception of the system even though the images have significant noise. Pre-processing aims at improving image data which suppresses unwanted distortions or enhances certain image features that are necessary for further processing. Most of the noise is removed during the first phase using a bilateral filter[7]. This filter has been selected because it retains the edges of image blobs, which are very useful structures in feature point detection. A CLAHE (Contrast Limited Adaptive Histogram Equalization)[3] is applied to boost the contrast after the noise is reduced. This can enhance system recognition when the images are taken in low light environments. This technique has better results over simple histogram equalization as it can be applied to images that have high and low contrast areas, and also limits the noise spread. Lastly, the light is changed to fix too dark or too light pictures. HUmoments and haralick features = 20

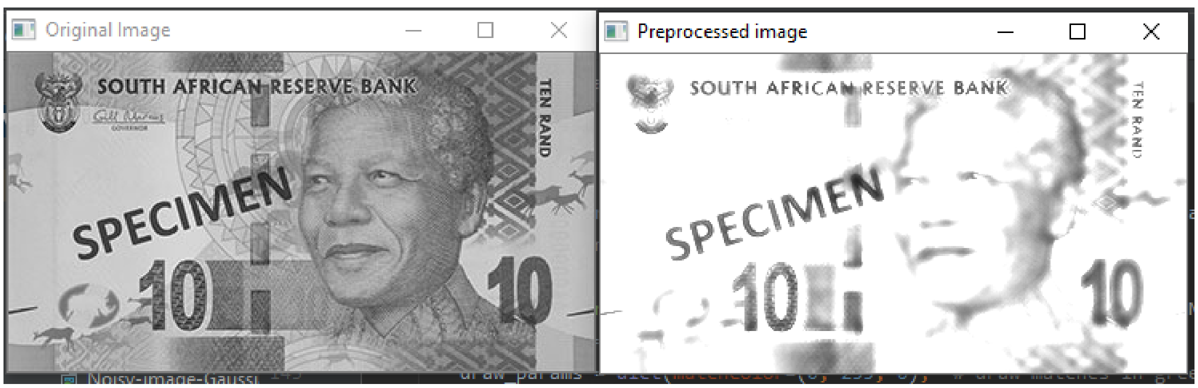

Figure 1: Impact of preprocessing stage (original image on the left, preprocessed image on the right)

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B. ***Segmentation***

Image segmentation in digital image processing and computer vision is the method of partitioning a digital image into several segments (sets of pixels, often known as image objects). The segmentation objective is to simplify and/or change the image representation into something that is more meaningful and easier to analyze. [2][4] Traditionally, image segmentation is used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process by which each pixel in an image is assigned a label, so that pixels with the same label share certain characteristics. This implementation attemps to use the Image Segmentation with Watershed Algorithm. What we do is to offer our entity, we learn, different labels. Mark the area we're sure to be the foreground or focus with one color (or intensity), mark the area we're sure to be background or non-object with another color and eventually mark it with 0 for the region we're not sure of anything. This is the marker for us. Then apply watershed algorithm. Therefore our marker will be modified to the labels we've provided, and the object boundaries will have a value of -1.

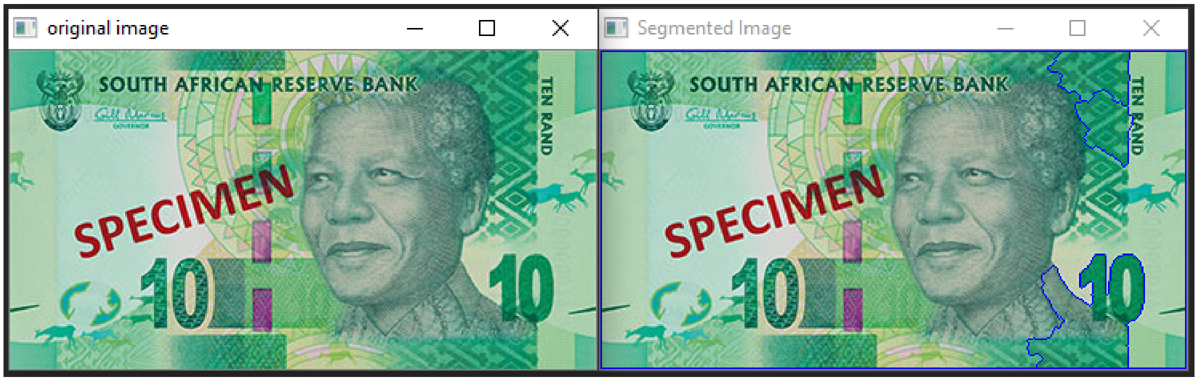

Figure 2: Impact of Segmentation stage (original image on the left, preprocessed image on the right)

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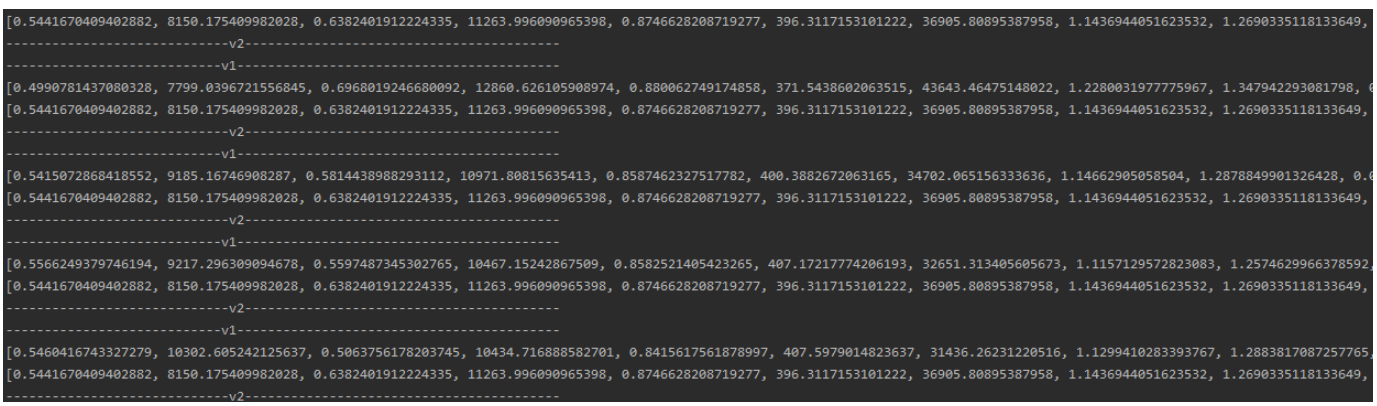
C. ***Features Extraction***

Feature extraction defines the relevant shape details found in a pattern, such that a systematic process allows the task of classifying the pattern straightforward. Throughout pattern detection and image processing, the extraction of features is a special form of reducing dimensionality. The key objective of the extraction of the features is to collect the most important information from the original data and to represent the information in a space of lower dimensionality. This project calculates moment variants for each image in the dataset to obtain 7 invariant moments of each image. Then after the haralick 13 features were calculated for each image in the dataset. Thus each image in the dataset is represented by a feature vector that contains 20 features which are the combination moment variants and haralick features.Figure 3 below represents the feature vectors, V1 represents 20 extracted features of the extracted image in the dataset and V2 represents 20 extracted features of the extracted of our input image. In order to properly classify the image the 20 features of the input image must be exacly the same as the 20 features of the image in the dataset. In that way we are sure that we have properly classified the image.



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---------------------------v2----------------------------------------
---------------------------v1----------------------------------------
[0.4990781437080328, 7799.0396721556845, 0.6968019246680092, 12860.626105908974, 0.880062749174858, 371.5438602063515, 43643.46475148022, 1.2280031977775967, 1.347942293081798, 0
[0.5441670409402882, 8150.175409982028, 0.6382401912224335, 11263.996090965398, 0.8746628208719277, 396.3117153101222, 36905.80895387958, 1.1436944051623532, 1.2690335118133649,
---------------------------v2----------------------------------------
---------------------------v1----------------------------------------
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---------------------------v2----------------------------------------
---------------------------v1----------------------------------------
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---------------------------v1----------------------------------------
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---------------------------v2----------------------------------------
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Figure 3: Feature vectors that contain the extracted features

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D. ***Classification***

Image classification is a two-step process. Initially feature extraction techniques are used to obtain visual features from image data and second step is to use machine intelligence algorithms that use these features and classify images into defined groups or classes. Image classification is the process of categorizing and labeling groups of pixels or vectors within an image based on specific rules.With regards to this project we used a supervised machine learning algorithm called support vector machine(SVM) that uses classification algorithms for two-group classification problems. After model of labeled training data for each category, they're able to categorize new text.

We used SVM in the wake of the following advantages:

- SVM works relatively well when there is clear margin of separation between classes.
- SVM is more effective in high dimensional spaces.
- SVM is effective in cases where number of dimensions is greater than the number of samples.
- SVM is relatively memory efficient.

Figure 4: Impact of feature classification using SVM

4 Results and Discussion

As explained above once the training data is model the paper currency recognition system, can classify correctly whether input banknote is depicted banknote or not. In training and testing datasets, all images of banknotes are genuine and current working South African banknotes. The system of classification identification and verification validity of South African banknote is evaluated as below. The classification prototype classifies the denomination of each South African banknote as R10, R20, R50, R100, and R200 on the test set image accordingly based on the trained sample images. The system was tested with images that contained south african banknotes both old and new, and the bank note has two faces, and the orientation of the note can either be upright or up-side-down. Once datasets are trained and system is modeled for recognition, we can take any banknote and predict whether south african banknote or other banknote. With the proper calculation of the 7 invariant moments and the haralick 13 features (depending on the image contents), the system successfully recognized all the banknotes in the test images. Once the security features are extracted into the feature set vector, each vector is treated as an individual feature in order to train the machine learning model. We target to optimize accuracy and interpretability of the classifiers, and we compare the performance of the proposed Support vector classifier with various Machine Learning classifying algorithms.

The objective of Support Vector Machine classifier is to find the optimal hyperplane which linearly separates the data points in two components by maximizing the margin. Also, SVM is used to find the separating hyperplane optimally so that the classification error is minimized for the given test samples. An SVM attain the optimal hyperplane which linearly classifies (separates) the larger portion of the training data points while maximizing the distance from the hyperplane. Twice of this distance is called the margin. The figures below represents the correct classifications of the South African banknotes.

Figure 5:

Figure 6:

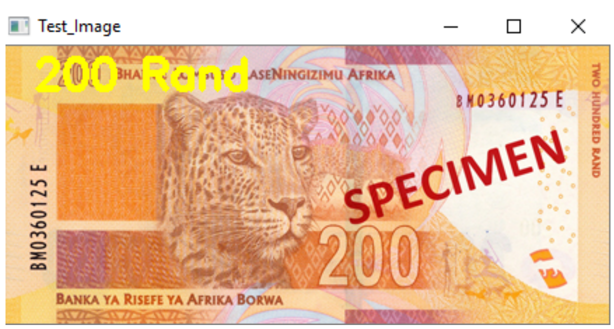

Figure 7:

Figure 8:

Figure 9:

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Analyzing Figures 4 it can be seen that the proposed recognition system managed to correctly detect the South African banknotes. However our feature classification is kind of misbehaving at some point, this may be due to issues an error of maximum iterations. When the number of iterations is reached, it's return whatever prediction it's holds at that particular time but this is not always the case.

5 Conclusion

The proposed approach follows an image processing technique followed by the machine learning technique. With use of Support Vector Machine, the identification of depicted banknote of specific denomination is done. It was also robust enough to handle folded and wrinkled banknotes with different kinds of illumination. This was achieved by carefully identifying the regions of the banknotes that had unique features in order to avoid the usage of structures that were similar between banknotes. This technique is crucial to improve the correct calculation of the 7 invariant moments and the haralick 13 features and ensure the correct recognition of the banknotes. The system was configured to recognize South African banknotes, but can easily be reconfigured to detect other currencies. The achieved results make it a viable option to be used by visually impaired people or to improve automatic banknote counting machines and even increase the security of Automated Teller Machines (ATMs) by detecting counterfeit banknotes. However our feature classification is kind of misbehaving at some point, this may be due to issues an error of maximum iterations. When the number of iterations is reached, it's return whatever prediction it's holds at that particular time but this is not always the case.

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