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Report: South African Bank Notes Recognition System

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ABSTRACT

Image processing and computer vision has been employed across various domains. One area that is of particular interest is the recognition of various bank note denominations. This report compares and contrasts the efficacy of various image pre-processing, segmentation, feature extraction and classification techniques for recognising South African bank notes. An empirical setup is created to fairly evaluate the various techniques with the aim of implementing a robust system which can handle most real-life recognition scenarios. Through this empirical selection of the best-performing techniques, a robust South African bank notes recognition system was built which achieves a 93% precision score during evaluation.

The full system source code, along with a setup guide, is available via this GitHub link.

1 INTRODUCTION

Machine vision has proved to be a vital asset in today's society, as evident by its integration into various everyday systems, from theft detectors to self-driving cars. Currency detection is another example of a computer vision system that has seen bounteous adoption in autonomous systems such as ATMs. Of particular interest, in this report, is the recognition of South African bank notes, hoping to capitalise off the favourable results found across other domains.

This report empirically compares and contrasts various image processing and classification techniques to determine their relative efficacy in implementing a robust South African banknote recognition system. An evaluation is made between 8 different pre-processing techniques (image scaling, grayscale conversion, histogram equalisation, median filtering, weighted average smoothing, Gaussian filtering, global binary thresholding and adaptive thresholding), 3 segmentation approaches (Sobel and Canny edge detection, and region-based segmentation), 2 feature extraction methods (Haralick GLCM and Hu's 7 Invariant moments) and 2 classifiers (SVM and KNN).

The rest of this report is structured as follows: Section 2 reviews related work in the field. Section 3 presents the employed methodology and the relevant comparisons between the various pre-processing, segmentation, feature extraction and classification techniques. These results are followed by a discussion in their appropriate subsection. Finally, Section 4 presents an overall summary of the results in the preceding section with an emphasis on examining the final classification results.

2 RELATED WORK

Image processing and computer vision has seen fruitful use across various domains such as health care [1], transportation [2], manufacturing [3], agriculture [4], construction [5] and retail [6]. An area that is of particular interest in this report is the use of image processing and computer vision for the recognition/classification of bank notes.

Most bank note recognition research is adopted in various automated systems such as money counters [7], ATMs [8], and vending machines [9]. The implementation of robust currency detection systems into these machines are essential to prevent any fraudulent activities or to eliminate human inaccuracies and inefficiencies that would otherwise result from manual counting procedures. There has also been a wealth of research centred around currency recognition systems to aid visually-impaired individuals [10]–[14].

[15] implements a banknote recognition system for the classification of Euros. In this research [15], various techniques are evaluated and employed, such as key-point detection, bilateral filtering, contouring, and bitmap comparisons, to name a few. Additionally, [15] presents various exotic

techniques such as infrared light and electromagnetic fields for banknote detection. Finally, a survey is presented which looks at various artificial neural network and point clustering approaches to classification.

Whilst prior research indicates favourable results for currency detection of foreign currencies, there is limited research concerning a South African bank notes system. To bridge this gap, this report presents an empirical evaluation of various image processing and classification techniques to determine their efficacy in recognising the highly characterised set of South African bank notes, in hopes of achieving similar favourable results seen in other bodies of work [10]-[15].

3 METHODS AND TECHNIQUES

The methodology employed throughout the development of this project, as well as the various comparisons made in each stage can be seen in Figure 1 below:

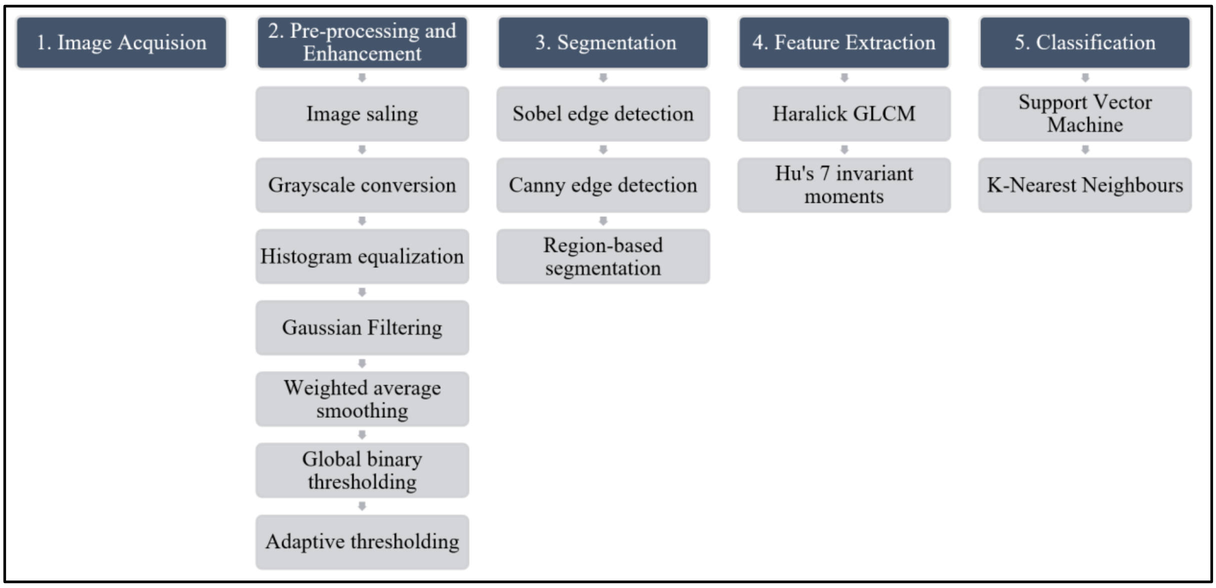


Figure 1: Visualisation of the employed methodology and evaluations at each phase

Various well-known libraries are utilized across this methodology, such as scikit-image [16], scikit-learn [17], OpenCV [18], and NumPy [19].

Throughout these phases, an empirical evaluation of various image processing techniques and approaches is conducted, comparing and contrasting their efficacy in a South African bank notes recognition system. These comparisons can be quantified by the metrics presented in Table 1.

Table 1: Comparative metrics

Metric	Description	Formula
Precision	Ratio of correctly predicted positive observations to the total predicted positive observations	$P = \frac{TP}{TP + FP}$
Recall	Ratio of correctly predicted positive observations to all observations in actual class	$R = \frac{TP}{TP + FN}$
F1-Score	Weighted average of Precision and Recall	$F1 = 2 \times \frac{P \times R}{P + R}$

Once the respective results are noted, where appropriate, a discussion is made surrounding the best technique moving forward to subsequent phases. Additionally, the findings and arguments in this section are summarised in Section 4.

3.1 BANK NOTE IMAGE PRE-PROCESSING AND ENHANCEMENT

The main aim of image pre-processing is to try and enhance/improve the quality of the image so that it is more suitable for subsequent phases. Undesirable noise and distortions are nullified, whilst enhancing those regions and features of interest.

The following image pre-processing and enhancement techniques are evaluated at this phase:

- Image scaling
- Grayscale conversion
- Histogram equalisation
- Median filtering
- Gaussian filtering
- Weighted average smoothing
- Global binary thresholding
- Adaptive thresholding

A comparison is made between three filtering techniques (median filtering, weighted smoothing, and gaussian filtering) as well as two thresholding techniques (global binary thresholding and adaptive thresholding).

For the purposes of an empirical evaluation, we shall be looking at these various pre-processing techniques on an 'R100' bank note, whose original state is provided in Figure 2.

Figure 2: Original R100 bank note image

Image scaling and grayscale conversion are mandatory pre-processing techniques required for this system and remain constant enhancement techniques when evaluating the other pre-processing methods. This allows the recognition system to be invariant to scale. The effects of these constants (rescaling and grayscale conversion) can be seen in Figure 3.

Figure 3: 400x200 Scaled and grayscale image

The results of the other individual pre-processing techniques being applied to the rescaled and grayscale converted image, in Figure 3, are presented in Table 2.

Table 2: Effects of the various image pre-processing techniques being atomically applied to Figure 3

Histogram Equalisation	Median Filtering
	
Gaussian Filtering	**3x3 Weighted Average Smoothing**
	
Binary Thresholding	**Adaptive Thresholding**
	

Image pre-processing is rarely atomic, but rather in the attempt to enhance an image, various techniques are employed sequentially [20]. Furthermore, the hyperparameters of these techniques indicate dependencies with preceding techniques [15]. Therefore, it would be infeasible to test every possible combination of the techniques presented in Table 2. Instead, through empirically testing certain configurations, the best performing sequence of techniques was selected. This “performance” is measured by the classification capabilities of the recognition system when the various combinations of pre-processing techniques are applied. A select few possible combinations of techniques along with their performance measure is presented in Table 3. To provide for a fair comparison, the results are obtained using an SVM classifier with region-based segmentation and Haralick texture features across all combinations (which are discussed in the following sections). Take note: SVM and region-segmentation are not the only respective segmentation and classification techniques looked at, but rather just play a role in providing a constant comparative baseline for the pre-processing techniques.

Table 3: Comparison of a few pre-processing technique combinations

	Weighted Average Metric		
	Precision	Recall	F1-Score
Histogram equalization, binary thresholding, median filtering	0.90	0.80	0.80
Histogram equalization, adaptive thresholding, median filtering	0.88	0.70	0.71
Binary thresholding, histogram equalization, median filtering	0.88	0.70	0.71
Weighted average smoothing, histogram equalisation, adaptive thresholding, median filtering	0.87	0.60	0.63
Histogram equalization, binary thresholding, gaussian filtering	0.70	0.60	0.61

Thus, through evaluation of various configurations of pre-processing techniques, with their appropriate hypermeters, it was concluded that *Rescaling → Grayscale conversion → Histogram equalisation → Global binary thresholding → Median filtering* was the best combination of techniques for the classification constants described above. As shown in Table 3, this combination outperformed the second-best combination by 10% in flat accuracy. The output of these pre-processing techniques can be visualised in Figure 4.

Figure 4: Final pre-processed image

The reason why this pre-processing combination was most optimal can be best explained by the SVM's use of region-segmentation in this particular experimental setup. As a precursor to Sections 3.2 – 3.4, the enhancement of the note’s textual value is particularly important, hence why this configuration has proved best as it eliminates the surrounding noise and enhances the clarity of the value. [20] indicates how image enhancement is mostly a subjective domain and how its final form is dependent on the classification philosophy adopted by the system.

Hence, median filtering was preferred over weighted average smoothing and Gaussian filtering because median filters are non-linear and can preserve edge details while removing noise from the image. Furthermore, it was shown that global binary filtering is preferred over adaptive thresholding in this case due to its sequencing – coming before median filtering. This combination proves best in enhancing the number on the face of the note.

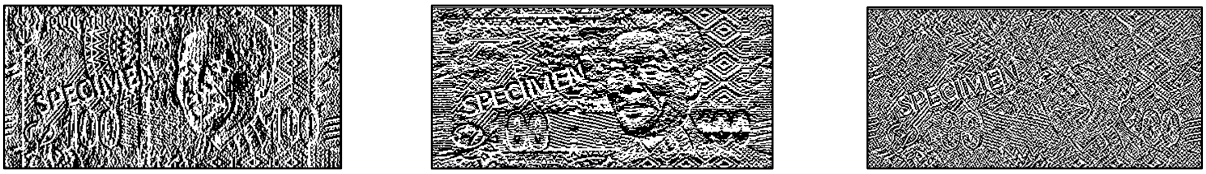
3.2 BANK NOTE SEGMENTATION

Once the images have gone through their pre-processing stage, we can continue to the next phase of our methodology – image segmentation. Image segmentation is concerned with the division of an image into various discernible segments to allow for more meaningful insights for feature extraction.

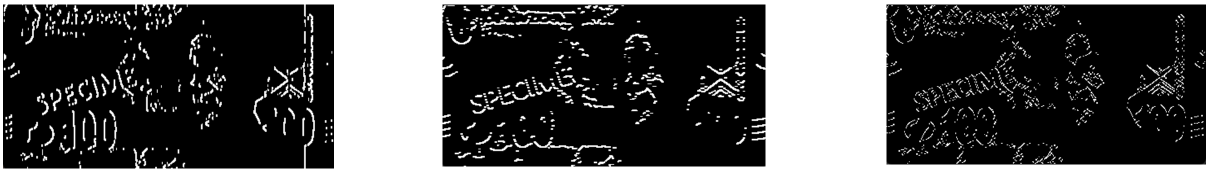
The following segmentation techniques are compared and contrasted:

- Sobel edge detection
- Canny edge detection
- Region-based segmentation

In a similar experimental setup to that described in Section 3.1, the following segmentation techniques are applied to the pre-processed images shown in Figure 3 and Figure 4. Firstly, the Sobel edge detection segmentation technique is presented in Figures 5a-f.



(a) – Sobel x-axis on Fig 3 (b) – Sobel y-axis on Fig 3 (c) – Sobel x and y on Fig 3



(d) – Sobel x-axis on Fig 4 (e) – Sobel y-axis on Fig 4 (f) – Sobel x and y on Fig 4

Figure 5: Sobel Edge detection

As a second form of edge detection approach to segmentation, we evaluate Canny edge detection. The result of this segmentation is presented in Figure 6.

(a) – Canny on Fig 3 (b) – Canny on Fig 4

Figure 6: Canny edge detection

The last explored approach to segmentation is region-based segmentation. Here, particular regions of the image are extracted and considered as regions of interest. Based on two categories (age – old or new, and orientation – front or back), various image region subsets were identified for each bank note. The results of this region-based segmentation, performed on Figure 3, is presented in Figure 7.

Figure 7 – Screenshot of image segments for front side of a new note

Evaluating the two edge detectors (Sobel – Figure 5, and Canny – Figure 6) it can be noted that Canny does a better job at capturing the edge detail in the image. Whilst Sobel is fast, it suffers from additive noise in the image due to its gradient approximation [18]. Consequently, Sobel cannot detect edges in these noisy scenarios. With its current configuration, Canny performs better as it can filter through this noise and enhance the signal-to-noise ratio.

However, as alluded to in Section 3.1, region-based segmentation is the preferred segmentation technique for this particular task. This is because we have a finer degree of control with regards to which regions we wish to evaluate. This form of segmentation is particularly powerful when the task at hand is identifying if the user has inputted foreign or artificial currencies [8]. For example, the national Coat of Arms would not appear in foreign currencies. Whilst the regions of interest in Figure 7 are indeed worth segmenting for discerning a South African note from other currencies, not all segments are descriptive in discerning between the RSA currency denominations themselves. Hence, for a South African bank note recognition system, the most discriminative region of interest is the money denomination text. This most discernible region of interest for the pre-processed image, Figure 4, is shown in Figure 8.

Figure 8: The most discernible region of interest (text value)

This chosen region of interest is the most discernible because, unlike the other segments, it is a common feature amongst old, new, front, and back of all South African bank notes.

Given that the pre-processing techniques have been optimised with region segmentation in mind, it would not be a fair evaluation to give the classification results for the edge detectors, as naturally, the region-based segmentation would excel.

3.3 BANK NOTE FEATURE EXTRACTION

The next step in the methodology, feature extraction, concerns itself with extracting various features from our identified region(s) of interest to be used later in the overall classification of an image sample.

In this section, two main feature extraction techniques are examined:

- Haralick Gray-Level Co-Occurrence Matrix (GLCM) feature extraction
- Hu's 7 Invariant Moments

The first examined technique is the Haralick GLCM matrix features [21]. Roughly speaking, this is a statistical texture analysis approach which is focused on identifying the spatial relationships of pixels. This is achieved through the GLCM, which embodies the texture of an image. There are various ways to generate the GLCM, however in these findings the GLCM is created with an angle of '0' degrees and a distance of '1', which was adequate to determine its efficacy in this system. Furthermore, Haralick provides 13 texture descriptors, however the five: Contrast, energy, homogeneity, dissimilarity, and correlation were once again enough to provide an adequate description of a region. This is empirically shown via a comparison between utilising all 13 features and the mentioned 5, which is presented in Table 6. These chosen five Haralick GLCM formulae, are presented in Table 4:

Table 4 – Haralick GLCM texture features employed in this research

Texture Parameter	Formula
Contrast	$\sum_{i,j=0}^{L-1} P_{i,j}(i-j)^2$
Dissimilarity	$\sum_{i,j=0}^{L-1} P_{i,j}\lvert i-j\rvert$
Homogeneity	$\sum_{i,j=0}^{L-1} \frac{P_{i,j}}{1+(i-j)^2}$
Energy	$\sqrt{\sum_{i,j=0}^{L-1} {P_{i,j}}^2}$
Correlation	$\sum_{i,j=0}^{L-1} P_{i,j}\left[\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right]$

The second feature extraction technique is Hu's 7 invariant moments [22], which are based on the normalised central moments [20], and are said to be relatively invariant to sides, scale, and rotation. Table 5 shows their formal specification.

Table 5: Hu's 7 Invariant Moments

Moment	Formula
1	$\Phi_1 = \eta_{20} + \eta_{02}$
2	$\Phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$
3	$\Phi_3 = (\eta_{30} - \eta_{12})^2 + (3\eta_{21} - \mu_{03})^2$
4	$\Phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \mu_{03})^2$
5	$\Phi_5 = (\eta_{30} - 3\eta_{12})^1(\eta_{30} + \eta_{12})^1[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + 3(\eta_{21} - \eta_{03})^1(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$
6	$\Phi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$
7	$\Phi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$

To compare these two techniques, an experimental setup was created, similar to that described in Section 3.1 – an SVM and region-based segmentation are employed as the constants, therefore any changes in the accuracies is owing to the feature extraction technique itself. A summary of these comparative results is provided in Table 6.

Table 6: Comparison between different feature extraction techniques

	Weighted Average Metric		
	Precision	Recall	F1-Score
5 Haralick GLCM Features	0.90	0.80	0.80
13 Haralick GLCM Features	0.87	0.60	0.63
Hu's 7 Invariant Moments	0.80	0.70	0.70

Thus, this empirical evaluation found that the Haralick GLCM features provided a better flat accuracy score than Hu's 7 invariant moments in this particular recognition system. Furthermore, it can be shown that using only '5' of these features was sufficient in providing a descriptive measure of the region(s) of interest.

3.4 BANK NOTE CLASSIFICATION

The methodology's final stage involves classifying these features into one of the South African Rand denominations.

For this system, two classification techniques are evaluated:

- Support Vector Machine (SVM)
- K-Nearest Neighbours (KNN)

However, before evaluating these classifiers, it is only appropriate to provide a description of the samples (bank notes) they were trained and evaluated on. A dataset containing 50 bank notes was provided. All rand denominations were present (R10, R20, R50, R100, and R200) with a mixture of different ages (old, new) as well as orientation (inverse, obverse). The training set was constituted of at least one inverse and obverse bank note for each denomination. For the testing set, the bank notes were selected such that they would be representative of a real-life recognition system scenario. That is, a mixture of orientation and age was chosen. Furthermore, to simulate a real-life test, the testing set was extended with additional bank notes that were captured with a smartphone camera. These newly captured notes were characterised by crunches, wrinkles, and various lighting conditions, as seen in Figure 9, which would be a challenging task for the classifiers.

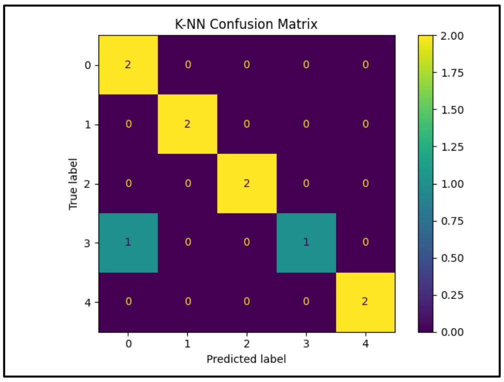
Figure 9: Example of crinkled R20 bank note as part of the testing set (captured via a smartphone camera)

Both models were trained and evaluated with the same training and testing set, respectively, to provide for a fair comparison. Using the best performing image enhancements (empirically evaluated in Section 3.1), along with region-based segmentation (Section 3.2) and the five Haralick features (Section 3.3), the results of the comparative classification can be summarised in Table 7.

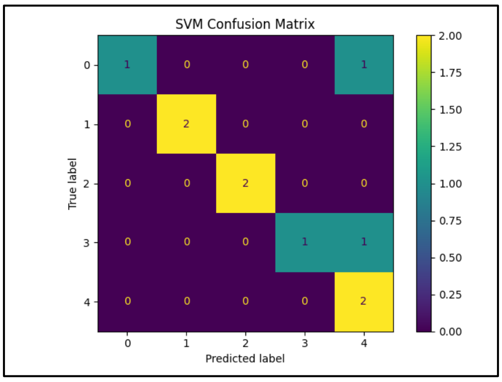
Table 7: Summary of classification report for each classifier

	Weighted Average Metric			
	Precision	Recall	F1-Score	Flat Accuracy
K-Nearest Neighbour (KNN)	0.93	0.90	0.89	0.90
Support Vector Machine (SVM)	0.90	0.80	0.80	0.80

These comparisons can be accompanied by their respective confusion matrices in Figures 10a and 10b.



(a) – KNN Confusion Matrix



(b) – SVM Confusion Matrix

Figure 10: Classification Confusion Matrices

Furthermore, the training (data fitting) and prediction times for each classifier is noted in Table 8.

Table 8: Time taken by classifiers for training and predictions

Classifier	Data Fitting Time (s)	Prediction Time (s)
Support Vector Machine (SVM)	9.9×10^{-4}	8.7×10^{-7}
K-Nearest Neighbour (KNN)	3.9×10^{-3}	6.3×10^{-6}

Thus, it can be empirically shown that, with regard to accuracy, the KNN classifier performs better than the SVM for this particular image recognition system, whilst it can be noted that the SVM is faster than the KNN. These results are explored in greater detail in Section 4.

4 RESULTS AND DISCUSSION

In wake of the results and discussions already made in Sections 3.1 – 3.3, a summary of their findings is presented in this section, along with a more detailed analysis of the classification results presented in Section 3.4.

All results were obtained through empirical evaluation with an experimental setup that allowed for a fair comparison, via experimental constants. From this setup, various comparisons were made, and the best technique for the relevant stage was selected moving forward in subsequent processes.

From Section 3.1, an evaluation of various pre-processing techniques was made. More specifically, an empirical investigation was made into the efficacy of three filtering techniques (median filtering, weighted smoothing, and Gaussian filtering) and two thresholding techniques (global binary and adaptive). It was shown that the combination of binary thresholding with median filtering was best for our discriminative region segmentation. This resulted in *Rescaling → Grayscale conversion → Histogram equalisation → Global binary thresholding → Median filtering* being the best-tested enhancement combination, achieving a 10% higher accuracy than its closest competitor (refer to Table 3).

In Section 3.2, two edge detection segmentation techniques (Sobel and Canny) were compared with visual empirical results concluding that Canny is the better edge detector (see Figures 5 and 6). However, when compared to region-based segmentation, it was shown that the ability to segment discriminative subsets from the image was more powerful for a robust recognition system. Hence, region-based segmentation was chosen as the segmentation technique for the presented system.

Section 3.3 evaluated two feature extraction techniques: Haralick GLCM, and Hu's 7 Invariant Moments. Furthermore, a comparison was made between a chosen five and all thirteen Haralick features. It was empirically shown that using five Haralick features provided an average precision increase of 3% over utilising the full thirteen descriptions (refer to Table 6). Additionally, it was shown that the five Haralick features provided an average precision increase of 10% over Hu's 7 invariant moments.

Lastly, with the pre-processing, segmentation, and feature extraction techniques being selected, two classification methods were evaluated: K-Nearest Neighbour (KNN) and Support Vector Machine (SVM). From Table 7, it can be empirically noted that both classifiers achieve a flat accuracy of 80% or above. This is encouraging given the unique nature some of the testing samples consisting of crinkled notes (refer to Figure 9). However, in comparing the KNN and SVM we find that the KNN enjoys an increase of 3% in precision, 10% in recall, 9% in F1-Score and 10% in flat accuracy when compared against the SVM (refer to Table 7 and Figure 10). In fact, the only comparative advantage of using the SVM can be seen in Table 8 when examining the training (data fitting) and prediction times. However, as we are dealing with milliseconds of a difference, this criterion is negligible.

These differences in accuracy and time performance can be explained by their different approach to separability. The SVM assumes that there is some hyperplane separating the different classification classes, which can be viewed as quite restrictive. In contrast, the KNN attempts to approximate this underlying distribution in a non-parametric manner [20]. This makes the SVM less computationally taxing and provides an easier interpretation, but it can only identify on a limited set of patterns. Therefore, it can be empirically shown that the KNN is the preferred classifier for this system when taking into consideration the previous pre-processing, segmentation, and feature extraction steps.

5 CONCLUSION

This report has compared and contrasted various image pre-processing, segmentation, feature extraction, and classification techniques through an experimental setup. For the particular classification philosophy of identifying the most discriminative image region(s), it was empirically shown that *Rescaling → Grayscale conversion → Histogram equalisation → Global binary thresholding → Median filtering*, region-based segmentation, Haralick GLCM, and KNN were the best performers in their respective category. The culmination of these findings resulted in the implementation of a robust South African bank notes recognition system, which achieved a 93% precision score when tested against a diverse range of notes, some of which were crinkled and captured in various lighting conditions.

The full system source code, along with a setup guide, is available via this [GitHub link](https://github.com/MagneticPanda/South-African-Bank-Notes-Recognition-System) (https://github.com/MagneticPanda/South-African-Bank-Notes-Recognition-System)

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