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A Method of Colour-Histogram Matching for Nigerian Paper Currency Notes Classification

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Abstract— In this paper a new algorithm for classification of three Nigerian paper currency notes, namely 200, 500, and 1000 Naira (N) denominations is presented. The work examines the effectiveness of using only colour histograms to differentiate between the classes or denominations of the three Nigerian paper currency notes. The bin-heights of the histograms of the HSI component images for the paper currencies are used as features while a rule-based classifier designed to take advantage of the changes or variations in the histogram patterns is used to classify the paper currencies into the right denomination class. The algorithm involves the utilization of a simple and effective comparison strategy as opposed to the existing, too-rigid metrics for histogram-comparison used by other authors for color indexing in content-based image retrieval systems. Over a testing data-set of 300 samples, the algorithm achieved an average classification accuracy of 98.66%, and classification accuracies of 100%, 99% and 97% for the N=200, N=500 and N=1000 denominations, respectively. The proposed algorithm does not require extensive preprocessing of the paper-currency images and as such is fast in implementation.

Keywords— Algorithm; Color histograms; Rule-based classifier; Paper currency; HSI color space; Naira; Nigeria.

1. INTRODUCTION

The quest towards system automation as well as the advantages of vending machines which includes among others: low-overhead cost, increased work-team productivity, convenience, time-saving, improvement of workers moral, easy and efficient monitoring of sales, improvement of workers comfort and increased throughput has made them increasingly popular [1, 2]. A vending machine is a convenient automated self-service device that allows the sales and purchasing of goods. If these machines are to be deployed in any region of the world, banknote recognition becomes a necessity. Researchers have worked on automated currency recognition of several nations like Egypt, Japan, United States of America, Saudi Arabia, Italy and India [3-8], little or none of such works has been carried out on Nigerian paper currencies – the 'Naira' (N). This therefore, makes deployment of vending machines difficult in Nigeria. In an attempt to circumvent this difficulty, this project was born. Self-service machines will mostly require design and investigation into four aspects, which include banknote recognition, counterfeit banknote detection, serial number recognition and fitness classification [9].

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Researches in the above mentioned areas will definitely enhance the effectiveness of self-service machines in Nigeria. This paper focuses on the aspect of paper currency recognition of three Nigerian paper currency denominations, namely, N=200, N=500 and N=1000, by self-service machines; using an image analysis or image processing approach. Several approaches exists in literature for bank-currency notes recognition, among which are edge detection [8, 10] for preprocessing, discrete wavelet transform [10], principal component analysis [11] for feature extraction and artificial neural networks [7, 11], hidden Markov models [12] for classification. These methods are computationally demanding, and may be time-consuming, making them not suitable for real-time operations on simple machines [5].

In the most sophisticated systems for banknote recognition, the process flow is typically as shown in Fig. 1(a).

Banknote recognition generally concerns classification of banknotes by denomination. This classification may also involve recognition of the year of printing and the input direction of the classified denomination (forward, backward, obverse or reverse). Counterfeit banknote detection is also required for distinguishing between genuine and fake bank notes, this can usually be achieved by examining anti-counterfeiting features on the bank note. A bank-note serial number is a unique alphanumeric identifier engraved on each bank note during the production process, as such it can also serve as clue in detecting counterfeit banknotes. Fitness classification is concerned with methods of classifying the notes into acceptable or unacceptable class based on the physical condition of the note in terms of wear, tear, or soiling due to secretion of sebum from users' hands or poor handling. Given the less important roles of serial number recognition and counterfeit banknote detection functions in some applications; they could be removed from the main computational flow, and processed in the offline mode [9]. However, the actual currency recognition in step one can be decomposed into four steps as shown in Fig. 1(b) [9].

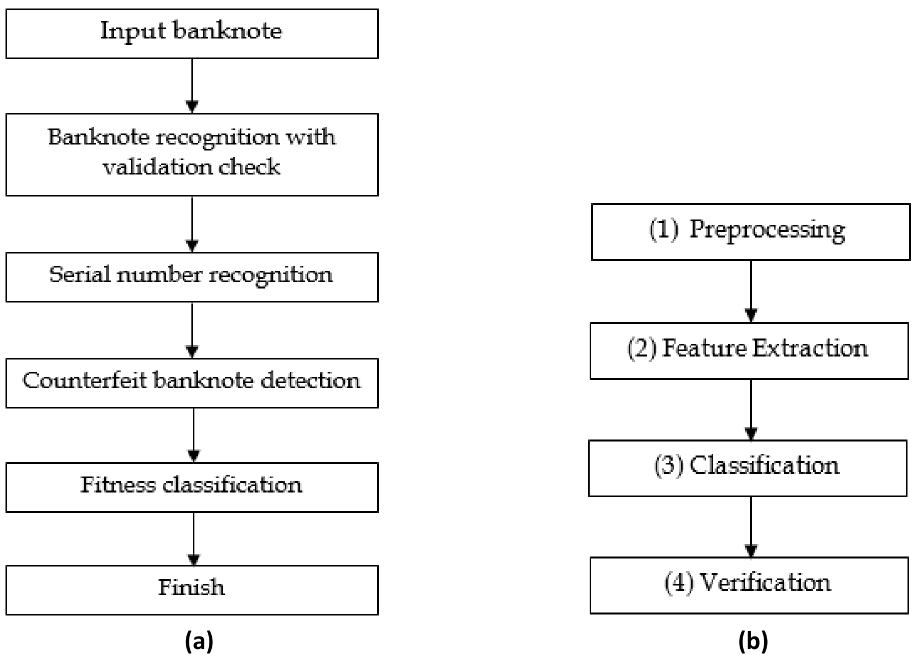

Fig. 1. a) Elaborate banknote recognition process flow in an automated device; b) Modest banknote recognition process flow.

One principal clue used by humans in recognizing the Nigerian currency in traditional trade is their colour composition. While several landmark figures and security signs are available in the currencies, these features are rarely investigated, in real-life human transactions. Therefore it is important to investigate the possibility of also taking advantage of the colour details, in machine or automatic-recognition of the currencies by self-service machines.

Colour histograms have been used in other image processing applications like glass-tile colour matching [12], content-based image retrieval (CBIR) and indexing for databases [13-19]. One translation and rotation invariant representation of colour is by colour histograms [18-20].

2. PRELIMINARIES

2.1. Conversion from RGB to HSI Colour Space

The colours that humans perceive in an object are determined by the nature of the light reflected by the object [21]. Scientifically speaking, the three primary colours of light are red, green and blue, which the International Commission on Illumination (CIE) in 1931 designated as 700 nm, 546.1 nm and 435.8 nm wavelengths, respectively. The characteristics generally used by humans to distinguish one colour from the other are: brightness (I), hue (H) and saturation (S), necessitating a change of color model in our experiments [21].

Given an image in RGB colour format, the H component of each RGB pixel is, given by Eq. (1):

$$H = \begin{cases} \theta & ;\ if \quad B \leq G \\ 360 - \theta & ;\ if \quad B > G \end{cases} \tag{1}$$

where,

$$\theta = cos^{-1}\left\{\frac{\frac{1}{2}(R-G)+(R-B)}{[(R-G)^2+(R-B)(G-b)]^{\frac{1}{2}}}\right\} \tag{2}$$

The saturation component is given by:

$$S = 1 - \frac{3}{(R+G+B)}\,[\min(R,G,B)] \tag{3}$$

while the intensity component is:

$$I = \frac{1}{3}\,(R+G+B) \tag{4}$$

and θ is measured with respect to the red axis of the RGB space.
Similarly colours can be converted from the HSI colour space to the RGB space.

2.2. Colour Histograms

A histogram can be constructed as follows. If a feature space $\boldsymbol{\chi}$ is divided into m regions or bins constituting a regularly spaced grid, the feature space is divided into regions

$$\chi^{(m)} \subset \chi \tag{5}$$

with

$$\cup_{m=0}^{M-1} \chi^{(m)} = \chi \tag{6}$$

and

$$\chi^{(m)} \cap \chi^{(m')} = \emptyset \quad \forall m \neq m' \tag{7}$$

For each region, the histogram corresponds to the probability of data points falling into each of the bin which is obtained by counting the number of data points within it [18]. As such, the histogram of a set $\{x^n \mid n = 0,1,\dots,N-1\}$ of feature vectors can be denoted by $h(\{x^n \mid n = 0,1,\dots,N-1\})$ or represented like vectors $h = (h_0, h_1, \dots h_{M-1})^T$. Assuming that $k^{(m)}$ of N data points fall into region $\chi^{(m)}$, then we get the estimated probability as:

$$P_m := P(x \in \chi^{(m)}) = \frac{k^{(m)}}{N} \quad (8)$$

The values P_m form the histogram and will be denoted by $h(m)$ [18].

In most imaging systems, colour is coded as a triplet of values, at each image point representing the red, blue and green components. Hence, given a discrete color space defined by some colour axes (red, green, blue), the colour histogram is obtained by discretising the image color component in each of the three axes. Counting the number of times that each discrete colour value occur in the image array, three separate histograms can be constructed for each colour component or concatenating them to make a longer one-dimensional histogram with different group of bins or buckets for the three colour axes. However, it is also possible to construct a 3-D histogram in a three dimensional space [14].

The RGB colour space is not well suited for describing colours in terms that are practical for human interpretation, as humans tend to describe colour in terms of its hue, saturation and brightness [21], as such it is often more advantageous in some applications to represent colour in the HIS colour space. In the HSI colour space, colour information is encoded by separating out an overall intensity value I from two values representing chromaticity – hue H and Saturation S [22].

2.3. Colour Histogram Matching

Several methods have been used by researchers for comparing histograms for the purpose of recognition, contest-based image retrieval and other applications. These methods often involve some colour comparison metrics, some of which are discussed below.

2.3.1. Mikowski-Form Distances

The Mikowski-form distances are calculated by Eq. (9).

$$L_p(h^{(0)}, h^{(1)}) = \left(\sum_{m=0}^{M-1} |h_m{}^{(0)} - h_m{}^{(1)}|^p\right)^{1/p} \quad (9)$$

They are simple to calculate depending on the selection of P and have a complexity that is linear in the number of histogram bins M: **O** (M) [18, 23].

2.3.2. Histogram Intersection

Swain and Ballard proposed a method of histogram intersection as a matching method between a model histogram and the database histogram for their work on colour indexing [14]. The method is described as follows. Given a pair of histograms I and M, each consisting of n bins, the intersection of the histograms is defined as:

$$Intersection\, H(I,M) = \sum_{j=1}^{n} \min(I_j, M_j) \quad (10)$$

where the intersection between image histograms is the number of pixels from the modal histogram that has corresponding pixels of the same colour in the image. To obtain a fractional value, the above value can be normalised by the number of pixels in the model or target histogram, giving:

$$Match\{H(I,M)\} = \frac{\sum_{j=1}^{n} \min(I_j, M_j)}{\sum_{j=1}^{n} M_j} \quad (11)$$

2.3.3. χ^2 Measure

The χ^2 measure is used to compare the histograms of a query image and the database images giving an indication of the difference (d) between two histograms [24]:

$$\chi^2(h_q , h_d) = d = \sum_i \frac{(h_q(i) - h_d(i))^2}{h_q(i) + h_d(i)} \quad (12)$$

where h_q and h_d are the histograms of the query image and an image in the database, respectively.

2.3.4. The IBM Query by Image Content (QBIC) Similarity Measure

The IBM Query by Image Content (QBIC) similarity measure compares the colour content of an image with the colour content of a second image or of a query specification by computing a color histogram distance given by [22, 25]:

$$d_{hist}(I, Q) = (h(I) - h(Q))^T A \, (h(I) - h(Q)) \quad (13)$$

where $h(I)$ and $h(Q)$ are the k-bin histograms of images I and Q, respectively, and **A** is a K by K similarity matrix. In the **A** matrix, colours that are very different has similarity values close or equal to zero.

2.4. Rule–Based Classification

A rule-based classifier is a technique for classifying records or objects using a collection of "if…then…" rules [26, 27]. This type of classifiers is generally used to generate a descriptive model for the classifier decision-making process. The condition used with 'if' is called the antecedent and the predicted class of each rule is called the consequent. These rules can be extracted from expert knowledge or learned from examples. A linguistic rule can be described in the form [26, 27]:

IF (a set of conditions are satisfied),

THEN (a set of consequences can be inferred)

To build a rule-based classifier, a set of rules that identifies key relationships between the attributes of a data set and the class label is extracted by direct method or indirect method. In the former, rules are extracted directly from the data by studying features' discriminative properties; where as in the indirect method, classification rules are extracted from other classification models, such as decision tree and neural networks. Direct methods partition the attribute or feature space into smaller subspaces so that all objects that belong to a subspace can be classified using a single classification rule. Both rule-based and decision tree classifiers create rectilinear partitions of the attribute space and assign a class to each partition. However, rule-based classifiers are generally used to produce descriptive models that are easier to interpret, but gives comparable performance to decision tree classifier [27].

3. THE PROPOSED METHOD

The structure of the proposed banknote classification system is shown in Fig. 2. The block diagram for the development and training of the classifier is shown in Fig. 2(a) while Fig. 2(b) shows the block diagram for the testing or validation stage. The block diagrams in Fig. 2 involves the acquisition of the paper-currency images by an appropriate two-dimensional (2-D) scanner, conversion of the acquired coloured image from RGB colour space to HSV colour space (Image Processing), development of colour feature histograms (Feature Extraction) for the paper currency under investigation, classifying the currency with a rule-based classifier using the colour histogram features (Classification) and finally outputting the determined denomination class for the paper currency.

In the feature extraction phase, three histograms are developed; one for each component of the HSI colour space. This comprise of hue histogram with bins designated as T1 to T10, saturation histogram with bins designated as P1 to P10 and intensity histogram bins designated as Q1 to Q10. The histogram bin heights (the values of T1 to T10, P1 to P10, and Q1 to Q10) are used as features for classification. The classification procedure in section 3.1 constitutes a rule-based classifier consisting of "if … then" rules built to classify the various currency denominations, based on the three sets of histograms.

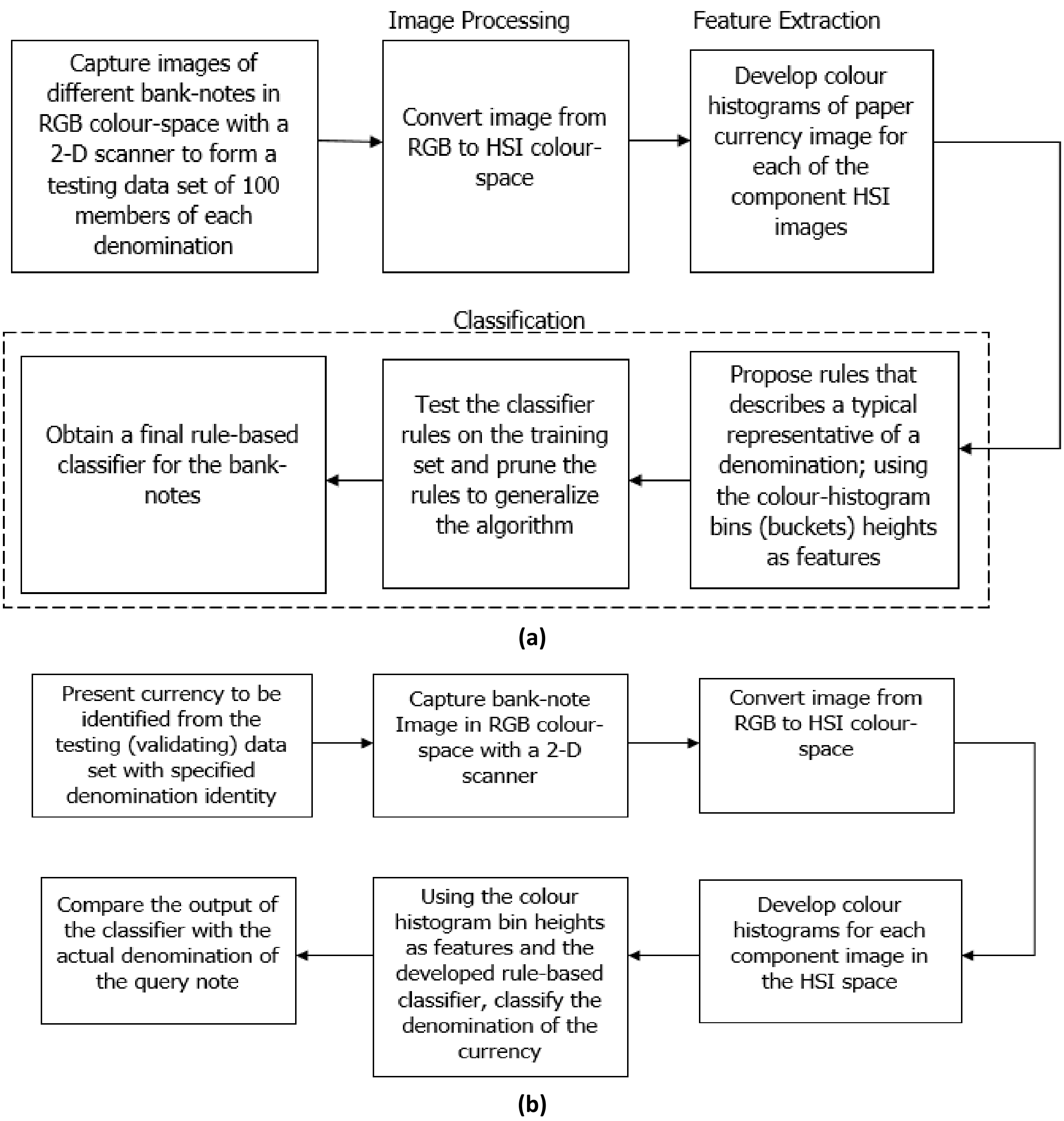

Fig. 2. a) Training; b) testing/validation stages.

The proposed algorithm extracts the rules, one class at a time. The learn-one-rule function [27] is used to first extract the best rule for the 200 Naira denomination class in which all the N=200 notes in the training record are considered to be positive examples.

Finding an optimal rule is tedious, given the size of the search space. The learn-one-rule function addresses this problem by growing the rules in a greedy fashion, i.e. it generates an initial rule r that works for one member of a class and keep refining the rule until it can accept the other members of that class. The rule is finally pruned to improve (reduce) its generalization error [27].

As the use of colour histogram in this application is relatively new and the objective slightly different, the previously listed colour matching strategies outlined in section 2 were found unsuitable for the Naira paper-currency identification job. Among the reasons for their unsuitability are:

(i) The Nigerian paper currency notes investigated has a lot of intra-class variation as the 10-bin histograms were found to vary greatly within a given class of denomination due to possible printing pigments imperfections or inconsistencies during the production process.

(ii) A good number of the paper-currency notes used in practice, especially the N=200 Naira notes are usually very dirty and soiled due to extensive use and improper handling, a situation which changed slightly, the analytic values of the colours from their actual factory values.

The above reasons necessitated the search for a more appropriate algorithm, featuring a comparison strategy that is robust enough to withstand the intra class variations in the colour histograms. It was found that only direct distance measures between corresponding histogram bins would require discrimination thresholds that were difficult to ascertain; as such in moving through adjacent bins, the more-stable trend of either increasing or decreasing bin-heights within specific group of colour-bins or colour buckets was found to be a more useful clue. The proposed algorithm utilized a lot of logical "if-then rules", augmented with a few threshold settings for some bin-value differences to describe suitable model histograms for specific paper-currencies. To separate the colour and intensity values of each pixel information, RGB colour images of the paper currency notes were obtained and converted to their H, S, and I equivalent images. The steps involved are outlined in the histogram-matching algorithm, given in section 3.1.

3.1. Histogram-Matching Algorithm

Input: (1) An RGB colour image of N=200, N=500 or N=1000 Nigerian paper-currency note.
(2) Indicate denomination of input note i.e. claim a denomination class for the note

Output: "Accept" if the estimated identity of the input currency note matches the claimed identity. If not "Reject".

Begin:

1. Scan the supplied currency note in RGB colour space.
2. Convert the acquired image from the RGB space into HSV color space.
3. (i) Generate a ten element array consisting of T(1) to T(10) by computing a 10-bin histogram of H-component-image pixels.
   (ii) Generate a ten element array designated P(1) to P(10) by computing a 10-bin histogram of S-component-image pixels.
   (iii) Generate a ten element array of Q(1) to Q(10) by computing a 10-bin histogram of I-component-image pixels.

4. Set the threshold values: Thresh1 = 1300; Thresh2 = 400; Thresh3 = 16,000; Thresh4 = 200; Thresh5 = 2000; Thresh6 = 500.
5. Procedure to classify a paper currency note (T(1) … T(10), P(1) … P(10), Q(1) … Q(10))

```
Begin
    If { T(1)< T(2)} And {T(2)>T(3)} And {T(3) > T(4)} And { T(3) > Thresh1 } And { T(10) > T(9) }
        And { P(2)  >  P(1) } And { P(8) < Thresh2 } And { P(9) < Thresh 3 }
        And {  (Q(8) > Q(7)) Or ((Q(5) > Q(6)) Or (Q(9) > Q(2)) or  (Q(8) > Q(2)) }
        Then Currency note := "200 Naira note";
    Else If {  T(5)<T(6) } And { T(8) > T(9) } And {  (T(9) > T(10))  Or  ( T(10) > T(9) ) Or ( P(1) > T(6) ) }
        Then Currency note := "500 Naira note";
    Else If { T(2) > T(3)}  And { T(3) > T(4) } And { (T(6) < T(7))  Or  (  (T(7) – T(6)) <  Thresh4  ) }
        And {   (T(7) < T(8))  Or  (  (T(8) – T(7))  <  Thresh 5  ) }
        And { T(8) < T (9) } And {  |T(10) – T(9)|  > Thresh6 }
        And { (Q(5) + Q(6))/2   <  Q(4) }  And { (Q(5) + Q (6))/2  <  Q(7) }
        Then Currency note := "1000 Naira note";
    Else If { T(1)< T(2) }  And { T(2)>T(3) } And { T(3) > T(4) } And {  (T(5) > T(4) } And { T(6) > T(7) }
        And { T(10)   > T(9) } And { P(2) > (P(1) } And { (P(3)  >  P(4) }
        Then Currency note := "200 Naira note";
    Else     Currency note := "Rejected"
End
```

6. Compare the estimated class of the currency with the claimed Class. Accept if True and Reject if false

End

Step 5 of this algorithm entails a function or procedure for the classification of the denomination of a query paper-currency note. The arguments for the procedure are the bin heights corresponding to array elements: T(1) to T(10) for the hue image, P(1) to P(10) for the saturation image and Q(1) to Q(10) for the intensity image. The rule-based classification algorithm used sequential ordering to circumvent the effect of non-total mutual exclusiveness [28] of the rules. Thus, the 200 Naira classification rules are first applied, followed by the 500 Naira rules, then the 1000 Naira rules. When the currency sample fails to satisfy all the three earlier rules, the sample is tested for classification as a dirty 200 naira note, and if the paper currency still fails the test, it is finally put in the reject class.

4. EXPERIMENTAL RESULTS

4.1. Generation of Banknote Image Datasets

For this work, we developed a training and testing dataset of 600 scanned Naira paper-currency notes, consisting of RGB-colour images of a hundred copies each, of the three Nigerian paper-currency denominations under investigation; made available in Github repository [29]. The bank notes were scanned in Tiff image format at 200 ppm as exemplified in Fig. 3. The training data set consists of 100 copies each of N=200, N=500 and N=1000 paper currency denominations, generated by scanning the sample notes with Hewlett Packard made flat-bed document-scanner, HP Scanjet 300. The training data set is comprised of Nai1c200 to Nai1c100c200, Nai1c500 to Nai100c500 and Nai1c1000 to Nai100c1000. The remaining 300 samples, consisting of Nai101c200 to Nai200c200, Nai101c500 to Nai200c500 and Nai101c1000 to Nai200c1000 were used as the testing or validating set. In fact, 300 samples (half of the total samples) were used for training while another 300 samples were used for testing the classifier. For each of the currency denomination, only the side on which human portraits are drawn was used for classification. For this work, the MATLAB tool was used as a software development environment. MATLAB is a proprietary multi-paradigm programming language and computing environment developed by "Mathworks" incorporated, USA. The codes for the feature extraction and classification were written or developed using MATLAB version R2018a and ran on a DELL microcomputer with the following specification: Intel core i3 CPU with a processor speed of 1.70 GHz, 4.00 GB memory (RAM) with a 64-bit operating system (win64). The three paper-currency denominations were typically of 1986 X 576 pixels in dimension, though with little variations in dimension from copy to copy. We converted the RGB colour images to their HSI equivalents through a MATLAB program developed for the operation using Eqs. (1) to (4).

4.2. Feature Extraction

Using codes developed in MATLAB, 10-bin histograms of the H, S and I component images of some of the samples were constructed for analyses. Specifying the number of bins desired to be 10, the total picture elements in each of the HSI image planes were distributed among 10 equidistant adjoining bins; and bin-heights of the histograms of the H, S, and I component images were then used as features for classification. Fig. 3 shows sample images of the three Nigerian paper-currency denominations under investigation. Fig. 3(d) is a sample of a dirty copy of the paper-currency note in Fig. 3(a).

Fig. 3. Sample images of three Nigerian paper-currency denominations under investigation: a) 200 Naira note:Nai1c200; b) 500 Naira note; c) 1000 Naira note; d) 200 Naira note:Nai5c200.

Figs. 4 to 6, shows typical 10-bin histograms of the three denominations in our database: entries Nai1c200, Nai2c500 and Nai5c1000 which are representative of N=200, N=500 and N=1000 notes, respectively. The histograms were studied for inter-class differences in order to develop the proposed algorithm for classifying a given note as either N=200, N=500 or N=1000 denomination. Fig. 7 shows the histograms for another 200 Naira (N=200) denomination from our database (entry Nai6c200); for intra-class comparison with the histograms for the previous 200 Naira note in Fig. 4 (Nai1c200).

4.3. Rule-Based Classification of the Nigerian Paper Currency Notes

Referring to the histograms of Figs. 4 to 6 for N=200, N=500 or N=1000 notes respectively, it is observed that the hue histograms especially, are different for the three denominations; and as such can be used to discriminate between the three currencies. Comparing the histograms of two N=200 notes from our database: Nai1c200 (Fig. 4) and Nai6c200 (Fig. 7), the two set of histograms are not exactly similar in shape, indicating some elements of intra-class variation. For instance, the height of hue-bucket 1 (bin 1) in Fig. 4(a) is 231,007 units, while the height of corresponding hue bucket 1 in Fig. 7(a) is 198,174 units. Although hue bucket 3 is higher than hue bucket 4 in the two instances, but in Fig. 4(a), hue bucket 3 is larger than hue bucket 4 by 37,922 units whereas in Fig. 7(a) hue bucket 3 is larger than hue bucket 4 by only 14,444 units. This made discrimination in terms of exact bin-height differences ineffective.

Comparing the hue histogram for N=200 note in Fig. 4(a), N=500 note in Fig. 5(a) and N=1000 in Fig. 6(a), we made the followed observations. For the N=200, bin 1 (bucket 1) and bin 2 (bucket 2) in Fig. 4(a) are almost equal in height, whereas bin 2 is significantly higher than bin 1 for N =500 note as in Fig. 5(a). Comparing the heights of bins 6, 7 and 8; for N=200 note, bin 6 > bin 7 > bin 8 whereas bin 7 > bin 8 > bin 6 for N=500 note. The two currency denomination can be discriminated on that basis. In contrast, in the hue histogram of the N=1000 note shown in Fig. 6(a), bin 1 has the greatest height while there is a consistent decrease in heights of adjacent bins until the lowest height is attained at bin 6, then the subsequent bins increased progressively in height until a local maximum is attained at bin 10. This systematic pattern change in the histogram bins was formulated into a rule induction algorithm [26-28] for a rule-based classifier to differentiate between the three currency denominations. The later refers to the process of extracting relevant IF-THEN rules from the histogram-bins height data. Care was taken to ensure that: the rule for classifying a currency note as N=200 note is designed to accept the histogram of Fig. 4(a) but relaxed enough to also admit the histogram of Fig. 7(a) since both are for different samples of N=200 denomination.

Sequential covering rules [27] was initially generated to admit a specific sample note in a denomination class while it is subsequently pruned or adjusted to admit other members of the class for generalization. For instance, for a hue histogram to be accepted as representative of the N=200 denomination, the following must hold: “bin 1 < bin 2” in height, “bin 2 > bin 3”, “bin 3 > Threshold1” and “bin 10 > bin 9”. This constitute the first part of line 3 of step 5 of the classification procedure in the proposed classification algorithm in section 3.1, where the value of “Threshold1” is found to be 1300 units or pixels by experimentation. For a currency image to pass the test for classification as N=200 note, bins of the saturation component image must satisfy the following: “P(2) > P(1)”, “P(8) < 400”, “P(9) < 16000”, meaning bin 2 > bin 1 in height, bin 8 < 400 and bin 9 < 16000 ; while the bins of the histogram of the intensity component image must satisfy the following rule, Q(8) > Q(7) or Q(5) > Q(6) or Q(9) > Q(2) or Q(8) > Q(2). In fact, arrays T, P and Q represent the bins of the histogram of the H, S, and I image, respectively.

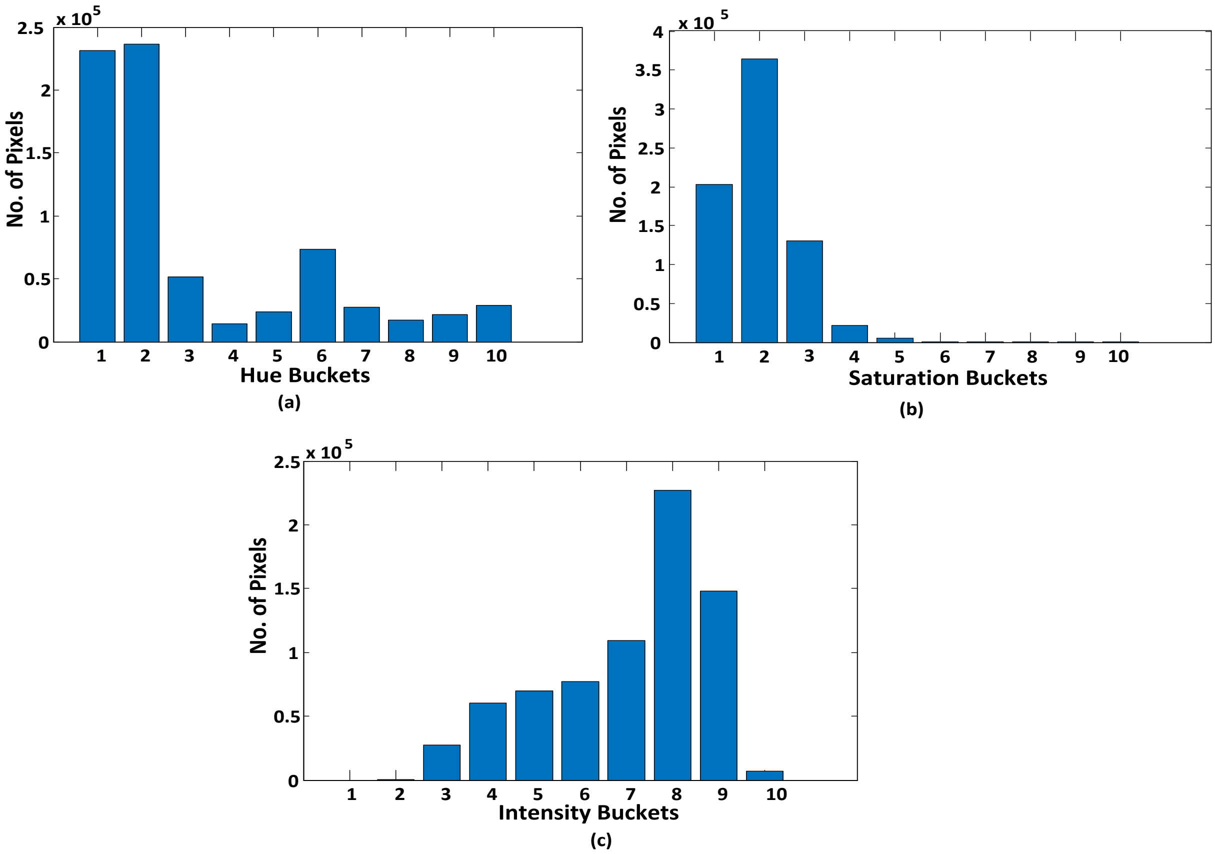

Fig. 4. a) Hue histogram; b) saturation histogram; c) intensity histogram for N=200.

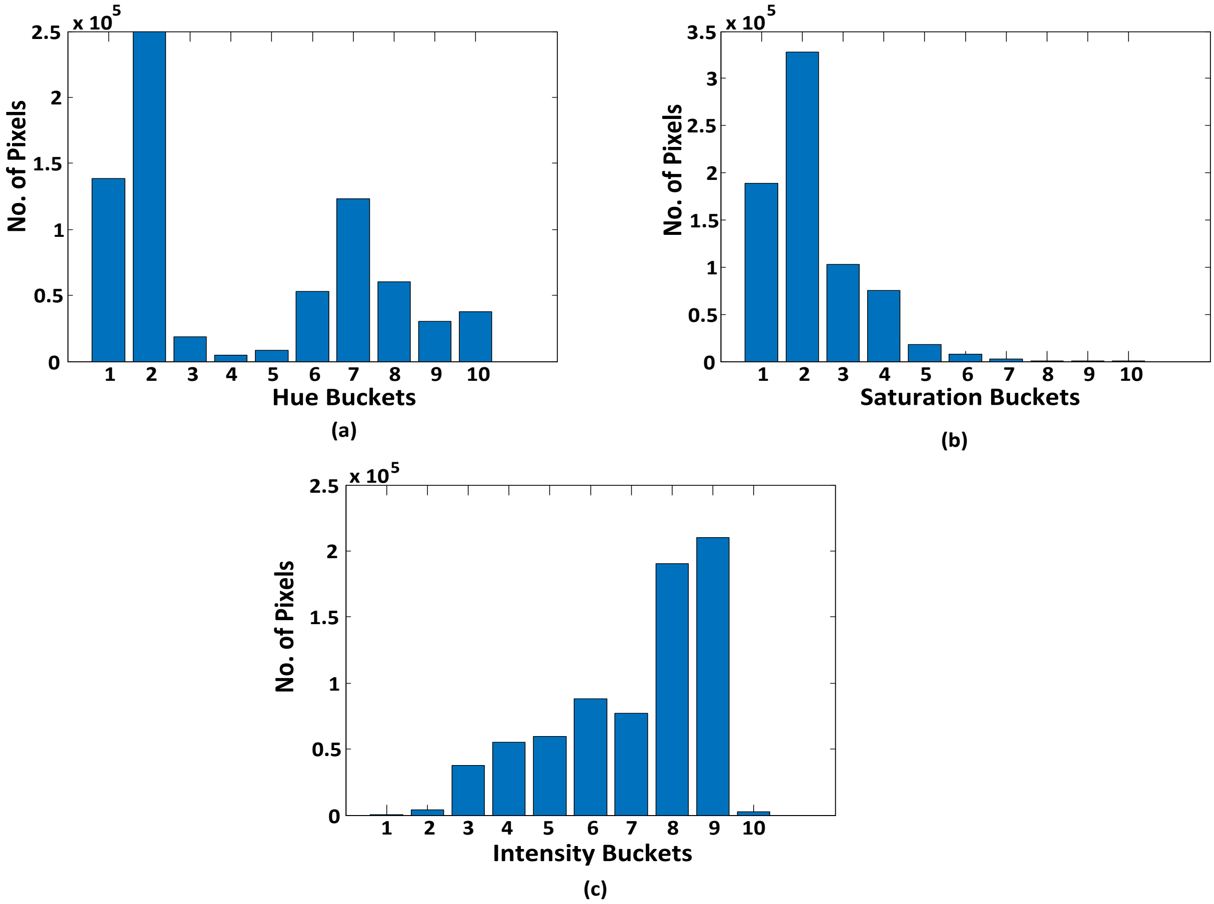

Fig. 5. a) Hue histogram; b) saturation histogram; c) intensity histogram for N=500.

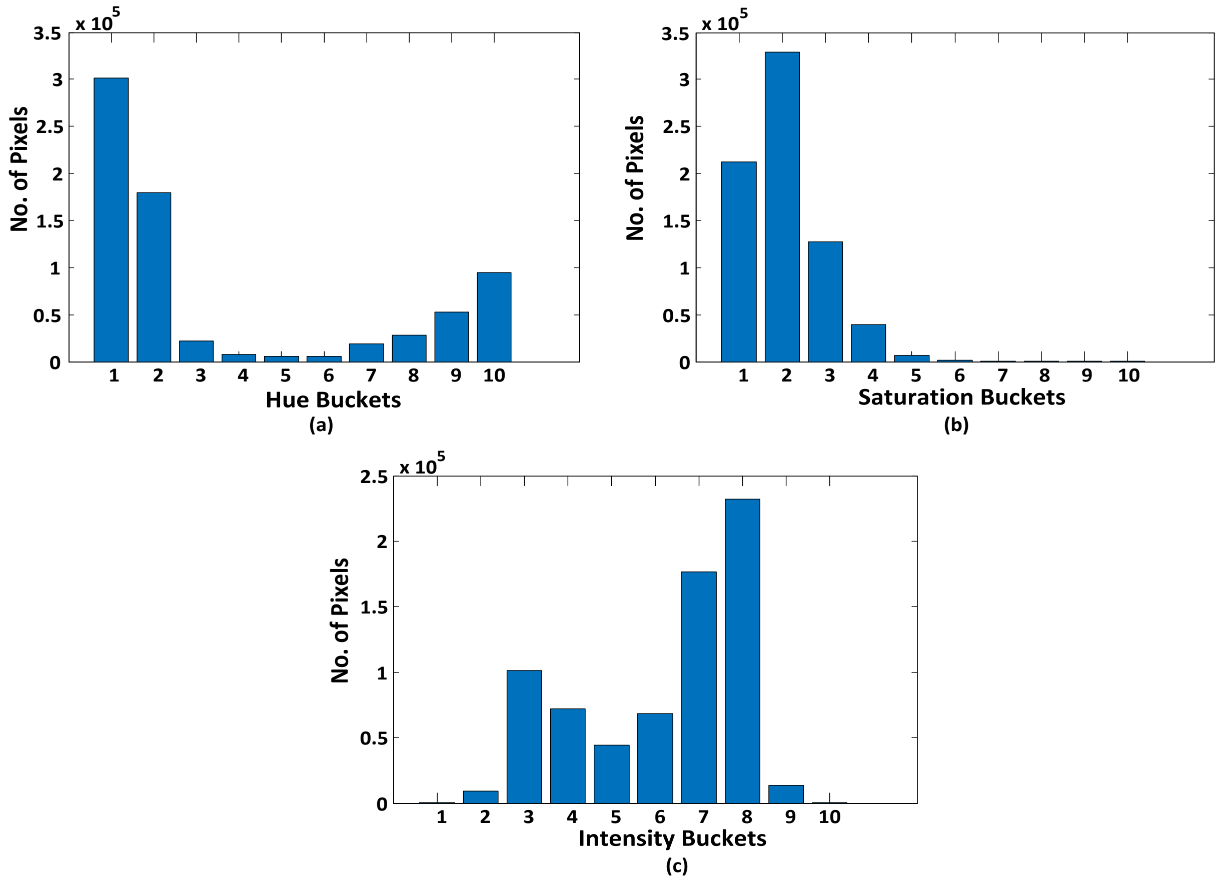

Fig. 6. a) Hue histogram; b) saturation histogram; c) intensity histogram for N=1000.

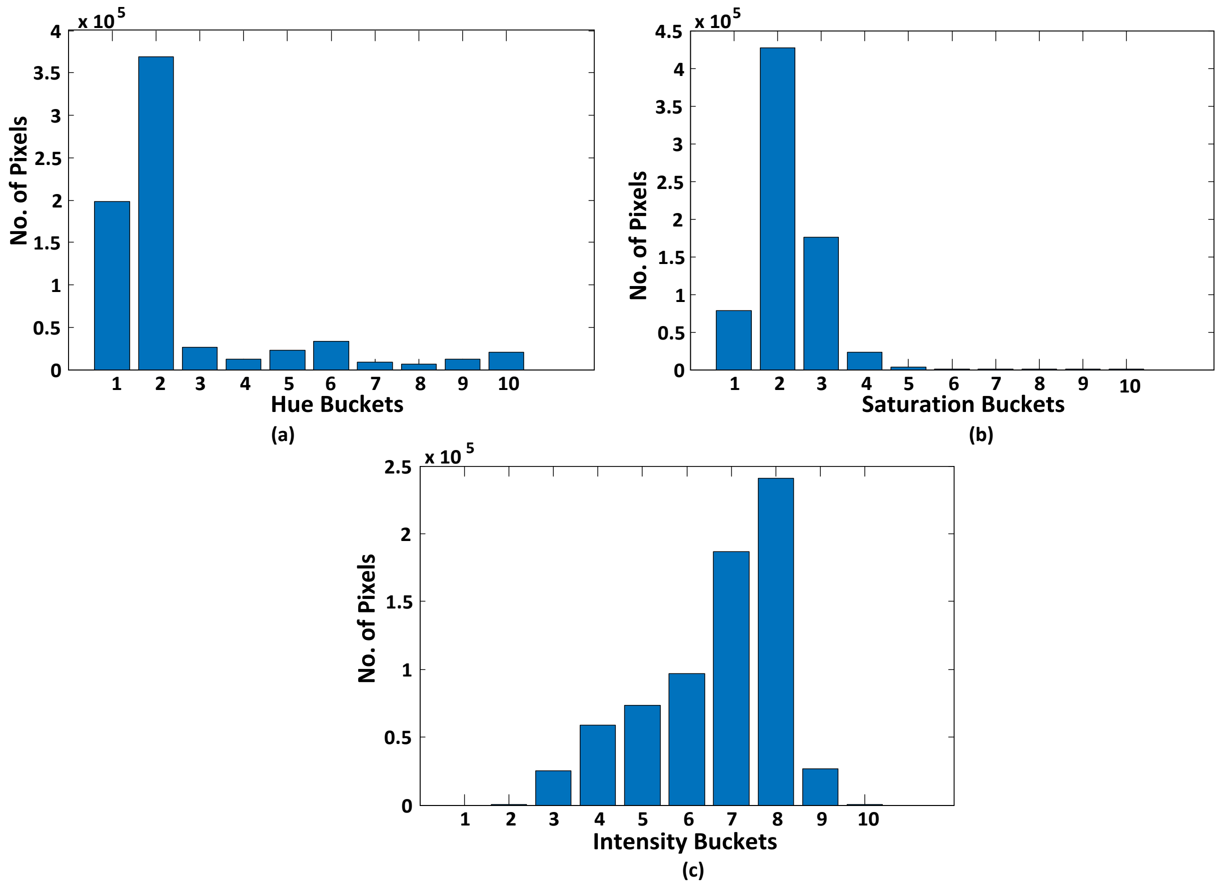

Fig. 7. a) Hue histogram; b) saturation histogram; c) intensity histogram for N=200.

4.4. Performance of the Banknote Classification Algorithm

To evaluate the effectiveness of the developed Algorithm in section 3.1 for classifying a given Nigerian paper-currency note into its appropriate denomination class, the developed algorithm was coded in MATLAB and tested on a validation dataset made up of another 100 copies of N=200, N=500 and N=1000 denominations of the Nigerian paper-currency notes (Nai101c200 to Nai200c200, Nai101c500 to Nai200c500, Nai101c100 to Nai200c100), different from the testing set (Nai1c200 to Nai100c200, Nai1c500 to Nai100c500, Nai1c1000 to Nai100c1000). Discriminating between the three denominations on the basis of their colour histograms is quite straight forward if all the notes are of high quality, but in practice many of the N=200 notes are usually very dirty and soiled and become similar in colour to the N=1000 notes and gets misclassified into the N=1000 class, which is unacceptable in the envisioned application. Therefore, our proposed algorithm was finally modified or tuned in favour of the N=200 notes, so that it has greater accuracy in classifying the N=200 Naira notes, but reject a little percentage of N=1000 notes that would have been misclassified as N=200 notes. An example of an overused copy of N=200 note is shown in Fig. 2(d). The confusion matrix of Fig. 8 shows the obtained result after using the algorithm of section 3.1 to classify all the 100 members of our validating data set. According to Fig. 8, among the 100 copies of N=1000 notes in the validating or testing data set, 97 were classified correctly while 3 are rejected.

Output class

True object class		N=200	N=500	N=1000	Reject
	N=200	100	0	0	0
	N=500	0	99	0	1
	N=1000	0	0	97	3

Fig. 8. Confusion matrix for the classification of three Nigerian paper currency notes.

From the obtained confusion matrix (Fig. 8) which is derived from classification experiment on the testing data set, the accuracy of the classification experiment or procedure is estimated using Eq. (14) [30, 31] as follows:

$$a_{cc} = \frac{cc}{cc + uc} X \ 100\,\% \ , \tag{14}$$

where cc and uc represents the number of correctly classified samples of a particular currency denomination, and the number of incorrectly classified samples of the same denomination in the testing dataset, respectively. This implies that the total number of a particular denomination is given by the sum of cc and uc. For example, there were a total of 100 samples of N=1000 notes in the testing dataset and 97 samples were classified correctly giving an accuracy of 97%.

It was observed that the proposed algorithm was finally able to classify correctly all the one hundred copies of the N=200 notes (Nai101c200 to Nai200c200) in our validation dataset [29]. However, one out of N=500 notes was rejected while three of the N=1000 notes in the validation data set were rejected, none was actually misclassified. In effect, a classification accuracy of 100% was obtained for the N=200 class, while classification accuracies of 99% and 97% were obtained for the N=500 and N=1000 notes denomination, respectively. A lower value of effectiveness was obtained for the N=200 notes class because a good number of the notes in circulation is usually deteriorated, as it has a higher frequency of use and suffers poor or careless handling due to its lower economic value. This drawback shall be made up for by including a quality assessment or fitness module in our future work, in order to eliminate such notes at initio. In general, 10-bin colour-histograms for the H, S and I images were found good enough for comparing the three different currency notes. We also observed that, while a good number of the ten bins of the hue-image were required for the effective classification, only few of the bins from the saturation and intensity image histograms were utilized in the algorithm. For comparing the query histogram with the target histograms, histogram-intersection and χ^2 distance measures were found not suitable. Hence, a less-rigid and simpler histogram-comparison strategy was utilized in the developed algorithm given in section 3.1.

To the best of our knowledge there are no published works on automatic currency recognition of the Nigerian paper currency notes, so this work is more of a pioneering work, so for comparison we can only compare our approach with that of other researchers who worked on other Nation's currencies. These researchers used different approaches for their currency denomination recognition which involves extraction of different features based on colour and texture information. For classification, some used minimum distance classifiers, learning vector quantization, and artificial neural networks etc.

In Chambers' study [32] on New Zealand notes, part of the composite feature set was based on the intensity histogram derived from RGB colored images whereas in our research, we used the histogram of the actual colour components of the paper currency notes directly, but in the HIS colour space, which is truly representative of the colour information of the banknotes. However, he then used histogram shape descriptors like mean, skew, variance, standard deviation and kutorsis obtained from the intensity histogram as features as opposed to our approach of using the bin heights of the colour component histograms directly as colour features. Chambers also combined the above mentioned features with gray-level co-occurrence matrix based statistical measures like homogeneity, contrast, correlation and energy, forming a combined features set of colour and texture features. He obtained accuracy of 81.69%, when the colour features comes first in the concatenation of the two subsets; but with only colour features used for the discrimination, he obtained a maximum accuracy of 60.56% on the testing or validating set. In our approach of using only component-colour histogram bin-heights as features and a rule-based classifier as opposed to his feed-forward Neural Network Classifier, we obtained a better accuracy of 97%. His technique was tested with 71 samples of each denomination while we tested with 100 samples of each denomination. Like in our approach, his work does not include a counterfeit note checker.

Garcia-Lamont et al. [33] in their work on Mexican paper-currency notes extracted their colour-features based on RGB colour space while in our research we used the HSI colour space because it matches the human vision system [34]. Garcia-Lamont et al. employed traditional local binary pattern (LBP) operator for extracting the texture feature part of their composite feature set. They treated the colour of each picture element as a three dimensional vector in the RGB space and took the vector sum of those vectors throughout the image to derive a dominant colour for each paper currency note under consideration. As side the requirement for vector addition, the LBP procedure processes the 8-pixel circularneighbourhood of each pixel of the image requiring 2^p computations where p denotes the number of circular neighbouring pixels with respect to the center pixel [35] making the operations computationally demanding than our approach that involves only addition and subtraction operations. They used learning vector quantization (LVQ) classifier and obtained a maximum accuracy of 83.28% as opposed to our rule-based classifier which gave an accuracy of 97%. Like our work, Garcia-Lamont et al. does not include a counterfeit note detection module.

Comparing our work with that of Zeggeye and Assebie [36] on Ethiopian paper currencies, four feature sets were used for their classification. The feature sets are dominant colour of the currency note acquired in the RGB format, the distribution of the dominant colour through the image evaluated by correlation, the hue value of the image evaluated in the HSV space and Speeded-Up Robust Feature (SURF) features. They also used a rule- based classifier whose classification rules are based on comparison with set threshold values of computed feature values as well as SURF matching results. Unlike ours, their work includes a verification phase to eliminate counterfeit notes through the detection of a thin or wide security golden strip. The authors reported an average classification rate of 90.42%. Our approach yielded an average classification rate of 98.7% overall, with a worst classification rate of 97% for the 200 Naira notes.

Finally in comparison with another work by Garcia-Lamont et al. [34] on classification on Mexican currency denomination purely by colour features only, the approach reported in this paper still yielded higher accuracy value. In their work, Garcia-Lamont and his team [34] considered the colour of a pixel as a linear combination of the basis vectors red, green and blue, written as: $\emptyset_p = r_p\hat{\imath} + g_p\hat{\jmath} + b_p\hat{k}$ where the scalars r, g, and b are the red, green and blue components of the colour vector, respectively. By vector addition, the resultant vector is computed and normalized after eliminating colours with high variance (preprocessing) given a feature subset denoted RGB. This dominant colour selection process is also done in the HSV space with the same pre-processing, giving a feature subset denoted HSV, while another feature subset is obtained in the RGB space without the above mentioned low-contrast-colour data elimination, denoted W. Different combinations of this feature subsets are used as feature sets to test their discriminative abilities while using an LVQ classifier. The authors reported the highest average classification rate of 97.73% obtained with W-HSV concatenated or combined feature set which is slightly lower than our result (98.7% classification rate), though our algorithm is designed to discriminate between only three Nigerian paper currency denominations while their work is on the discrimination of six denominations of Mexican paper-currency notes.

One limitation of our algorithm is that, the currency can only be classified correctly when placed on the scanner with the side that has the human portraits facing the scanner, as the algorithm was developed based on colour characteristics of that surface only. This limitation will be considered in subsequent studies. Our study was limited to only three Nigerian paper currency denominations, namely N=200, N=500 and N=1000. This pioneering study would be extended to other denominations in subsequent studies. However, from this study, it has been established that using only colour information without additional texture characteristics, an effective classification of the N=200, N=500 and N=1000 is possible. Avoiding the use and computation of time-consuming image texture parameters makes the computational demand feasible and attainable on low-end computing facilities, making room for its deployment in cheaper and more affordable products.

5. CONCLUSIONS

A fast and effective algorithm for classification/recognition of three Nigerian paper currencies (Naira) solely by colour details was developed through a new approach of colour-histogram comparison of the component images in the HSI colour space. From the component images, 10-bin histograms were constructed and the bin heights used as features for classification. Similarity/dissimilarity studies were done on the histogram patterns to develop a rule-based classifier for discriminating between the three different Naira denominations. The algorithm was developed using a training set comprising of 100 samples for each of the three Naira denomination and tested over a validating set of another three hundred samples (one hundred samples for each denomination). Classification accuracies of 100%, 99% and 97% were obtained for the N=200, N=500 and N=1000 denominations respectively, giving an average classification accuracy of 98.6% for three denominations. Since the intra-class variations in the 200 Naira class was found to be higher than in the other classes our algorithm was tuned to favour the 200 Naira class while giving poorer performance for the other classes. To avoid the serious consequences of misclassification in this application domain, the algorithm was designed to put in a reject class; any paper-currency note that cannot be rightly identified as belonging to any of denomination categories.

The low recall rate implies a high level of accuracy or effectiveness of the algorithm. It was observed that previously existing histogram comparison metrics were ill-fitted for effectiveness in this application domain, rather a new and simple paradigm of loosely observing the increasing or decreasing trends of size of adjacent histogram-bins was proposed in the algorithm; and augmented by specific bin size limits or thresholds which were obtained by experimentation. On the whole, colour-histogram was found to be effective in discriminating between three Nigerian paper currency notes investigated, although a full standalone system may require an inclusion of a module for specifically examining anti-counterfeiting features in the notes. Moreover, our algorithm does not require extensive pre-processing operations like segmentation, or edge-map construction etc., it is, therefore, simple and fast in implementation. The success of the developed colour-based classification algorithm shows high promise as a suitable component of a full Nigerian paper-currency-recognition engine.

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