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# Ethiopian Paper Currency Recognition System: An Optimal Feature Extraction

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Abstract—Forged banknotes are becoming serious threats hampering smooth transactions in Ethiopia. Hence, Availability of such fake notes in market needs the automation system. The banking industries in Ethiopia are unable to full fill the ATM's intensively. Nevertheless, banks have not yet utilized a reliable recognition system to identify forged banknotes. This calls for a development of a better authenticity verification system. In this study, we have examined the color momentum, SIFT, GLCM, combination of SIFT, color and GLCM, and CNN as a feature extraction technique and FFANN as a classifier to design Ethiopian banknote recognition system. Experimental result shows that the CNN feature registers 99.4% recognition accuracy in classifying Ethiopian banknote denomination. Again, for fake currency recognition, CNN feature outperformed the other feature extraction techniques with an accuracy level of 96.46 %. Therefore, it is recommended to study the CNN model by with an advanced architecture like GoogLeNet and ResNet with larger dataset.

Index Terms — CNN, FFANN, GLCM, SIFT, Color momentum



## I. Introduction

Paper currency recognition (PCR) is an important area of pattern recognition. A system for the recognition of paper currency is one kind of intelligent system which is a very important need of the current automation systems (Sarfraz and Muhammad, 2015). Automatic recognition of paper currency into their respective denomination such as paper notes 5,10,50, and 100, with the capability of fraud currency detection, are essential to automate the money transaction system, and then to intensively utilizing the self-serving devices like ATM to its fullest capacity. All the traditional machine learning algorithms required to extract the feature manually. And this manually extracted feature, are subject to human biases. Convolutional Neural Network algorithm is a multi-layer perceptron that is specially designed for the identification of two-dimensional data such as image. This model learns a high-level representation directly from the low-level representation of a given banknote image. Applying CNN algorithm offers an advantage over traditional machine learning because it avoids an explicit feature extraction; thereby implicitly learn features from the training by extracting high-level features (sophisticated features) from data (Lee1 and Lee, 2018). Moreover, CNN can easily identify displacement, zoom, and other forms of distortion invariance of two-dimensional image data (Patterson and Gibson, 2017). This quality feature of the CNN makes it suitable for application that demands high computational capabilities like paper currency classification and recognition. This also motivates the study to construct a convolution neural network (CNN) model for banknote classification and counterfeit verification system, which is mainly used in image processing fields. Moreover, the occurrence of widely spreading banknote counterfeiting practice in Ethiopia and the presence of high capability of the CNN model motivates this study.

## II. Related Work

As per the knowledge of this research there are very few researches done on Ethiopia banknotes. The research conducted by Jegnaw and Yaregal (2016) entitled "Ethiopia paper currency recognition system" considered the four characteristic features of the banknotes such as the dominant color, the distribution of the dominant color, the hue value, and speeded up robust features (SURF) were extracted as the discriminative features of banknotes. Those features in combination with local feature descriptors were involved in a four-level classification process, as a classification task executed every time one of the four features was extracted. The correlation coefficient-based template matching was implemented for classification. To check the originality of the paper notes, final verification tasks were conducted by segmenting the thin golden vertical strip which is on the paper denomination of Ethiopian birr note 50, and 100. Test results showed that the proposed design had an average recognition rate of 90.42% for genuine Ethiopian currency, with an average processing time of 1.68 seconds per banknote (Jegnaw and Yaregal, 2016). Even though the authors have used a suitable method for classification as well as fraud detection, the methods suffers accuracy problem such as classifying old genuine Ethiopian currency notes whose color become fading or changed due to rigorous circulation into wrong class because color feature only describes which colors are present in the image and in what quantity but doesn't study the spatial information. Even if we consider the illumination conditions do not vary during the image acquisition, the colors printed on the paper currency may lose their intensities because the banknotes may be worn-out or they may have dirt. Due to the RGB space is sensible to color intensity considering a color feature for recognizing paper note are sufficient. The color feature of a paper currency is not sufficient to distinguish different Ethiopia banknotes denomination because more than one Ethiopia currency denomination is the very similar dominant color. In addition, the template matching classifiers are not invariant to intensity value change (Gupta and Goswami, 2017). Since none of the above banknote recognition systems are robustly applicable to recognize and verify Ethiopian banknote with different quality status, we have designed a classification system that can accommodate the variation of banknote quality status using a combined method of CNN as a feature extraction and ANN as a classifier.

## III. Research Methods and Procedures

In this Ethiopia banknote recognition system, considering the Golden strip ROI is not efficient while the surface of the banknote is getting old, thorn, oiled, and dilapidated. The Ethiopia banknote recognition and classification system follows image acquisition thereby with Hp scanner 2700, which is followed by employing adaptive median filter as a noise filtering techniques, and then followed by employing RGB color space to grayscale conversion by employing with weighted method thereby considering the contribution of the three primary color channels into consideration to assign weight to each color channel. After employing the preprocessing tasks, the study conducted an intensive works thereby intensively assessing the feature descriptors. From the experimental analysis, the study concludes all the manual feature descriptors are not invariant to illumination change and viewpoint change and the study observed that the CNN feature extraction model is invariant to rotation, scaled, zoomed, translation and illumination change. Therefore, this study employed the CNN model to extract the Ethiopia banknote.

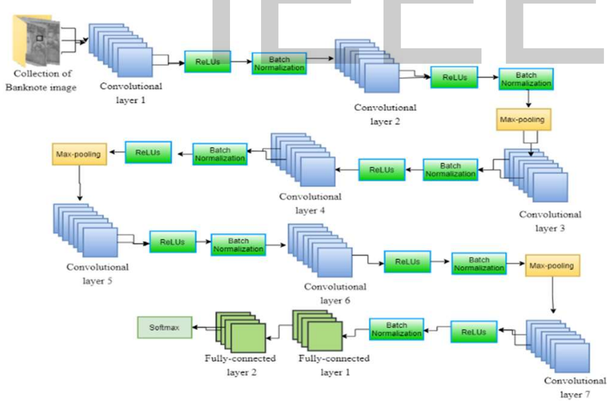


Fig. 1: The CNN model used to extract the CNN feature

To automatically classify and recognize Ethiopia banknote, the study follows the major image processing steps such as image acquisition, preprocessing, feature extraction and classification.

### A. Preprocessing

During circulation, banknotes become torn, oiled, and noise is also added with them and this cause a degradation of the image quality and it cause a challenge for the recognizer. In order to reduce the influence of the noise to the recognizer, it is essential to apply a preprocessing task. Image preprocessing is a mechanism that focuses on the manipulation of images in different ways with the intention of enhancing the image quality and it can significantly enhance the recognition rate of the recognizer thereby removing the effect of noise (Jegnaw and Yaregal, 2016). In this component of the proposed model, undesired noise appearing on the image are removed. Some of the preprocessing tasks are as follows.

#### a. Image size normalization

In regard to the size of the banknote, different researchers considered different size to construct the banknote recognition system. By conducting an empirical analysis, the study found better result at banknote size 1122×570 and 640×312 but as compared with computational complexity by far the 640×312 register better result. So, the study normalizes all the image with a size of 640×312.

#### b. Image quality enhancement

Since the banknote are used for medium of exchange, they are frequently circulated from one individual to other. Due to this frequent circulation, improper usage, and age factors, most birr notes are thorn, lose its color due to some dirty appearing on the interface and this brings a degradation on the image quality which is useful for recognition and verification tasks. By empirical analysis, the study obtained better result after employing adaptive median filter. After employing the optimal noise filtering technique, besides noise filtering, image enhancement also requires to adjust the contrast of the currency image to make it look better. In this study, histogram equalization techniques are considered to adjust the contrast of the image data.

#### c. RGB to grayscale conversion

To simplify the computational requirement of the model, the study Considered grayscale image. This is because, the grayscale images only contain the intensity information which is easy to process instead of processing RGB image. There technique which is used by different researcher; averaging, weighted, and lightness method (Biswas, Amitava, Ghosh, Arindrajit, Biswas, and, Banerjee, 2011). By experimental analysis, the study found better result after employing weighting method to obtained the grayscale image. So, based on their wavelength weights are assigned to each channel. So, higher wavelength means the higher contribution and the less weight to be assigned. Channel are also greater than green color channel. By empirical analysis, the weights for each channel are obtained as shown below in the equation (3.1) given bellow.

$$Gry\_img = 0.17*R + 0.62*green + 0.21*blue \ldots (3.1)$$

### B. Feature Extraction

The feature extraction component is responsible for extracting the descriptive features of the paper banknote sample constituents. The commonly applied characteristic features to identify banknotes contain the color features, size feature, the shape feature, the texture features. This

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study employed the CNN model to extract the banknote as the color features, local texture features descriptor, the size feature is most influenced by the age factor and are not illumination invariant and not effective to study the banknote complicated feature.

### a. Convolutional Neural Network (CNN)

A Convolutional Neural Network (ConvNet/CNN) is a type of ANN with multiple hidden layer which is specifically designed to classify and recognized a high dimensional data such as image. It accepts a banknote image as an input, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNet have the ability to learn these filters/characteristics. It can be used both as a feature extraction technique and a feature classifier technique. This model can be used to extract feature that are invariant to rotation, scale, illumination, and viewpoint change invariant features from the banknote.

In this study, the convolutional neural networks (CNN, ConvNet) is considered as a feature extractor. To extract the CNN feature, we have employed a supervised version of CNN model to get the description of Ethiopia banknote. As like traditional neural network, the CNN has also an input layer, hidden layer, and output layer. Unlike to ANN, the hidden layer of CNN model there are a set of layers that can be grouped by their functionality. In the hidden layer of the CNN model, both the convolutional layer and subsampling is called the feature extraction layer and the fully connected layer is also called feature selection layer. In the hidden layer of the CNN, there are a set of layers that can be grouped by their functionalities.



#### i. Convolution Layer

The convolutional layers learn the various local feature that constitutes the birr note image such as the identification mark, security thread, the tin and wide golden strip and much more security feature available. In the first convolutional layer, we have considered a number of filters to extract a number of the feature map thereby convolving the input image with a number of trainable filters to detect part of an image such as diagonal edges, vertical edges, etc. Moreover, as the image progresses through each layer, the filters are able to recognize more complex attributes. In convolution layer, the input of each neuron is connected to local receptive field of its previous layer and extract the local feature. Every neuron takes inputs from a rectangular n × n of the previous layer, the rectangular section is called local receptive field.

$$x_{,} = \sigma\,(b + \Sigma\,\Sigma\, w_{,} x^{(}{}_{,}{}^{)} \qquad (4.3)$$

Since every local receptive field takes same weights $w$, and biases b as shown in equation 4.3 above, the parameters could be viewed as a trainable filter or kernel, the convolution process could be considered as acting an image convolution and the convolutional layer is the convolution output of the previous layer. It is also called the trainable filter from the input layer to hidden layer a feature map with shared weights and bias. In this layer, the banknote image or feature maps are convolved with a number of trainable kernels starting from top leftmost to bottom right most with a step size /strides/ equal to number of kernels. In the second or latter convolutional layer, the study considered a number of filters to extract a hierarchical feature map thereby convolving a feature map with a number of filters. The output of the convolutional layer is a feature map and the dimension of this feature map is equal to the number of feature detector/kernel/ considered. The input to the first convolutional layers is a either an RGB or a grayscale image but this study used grayscale image. Each pixel in a grayscale image can be represented using a single value that indicates the intensity of the pixel. So, to extract the CNN feature, it is requiring to obtain the number of convolutional layers with its optimal high parameter. There are no readily available empirical formulas or adopted guide line to decide the number of convolutional layer and their optimal parameter. So, this study identified the number of convolutional layer and their optimal parameter based on experimental analysis. Accordingly, better results were found at CNN architecture with 12 number of convolutional layers with a trainable feature detector of size of 3x3 and 5x5 in each convolutional layer 6 with size of 3x3 and 6 with 5x5 feature detector in each convolutional layer.

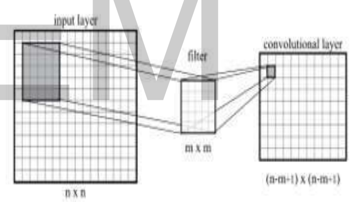


Figure 2: Convolutional process

#### ii. Pooling Layer

After each convolutional layer, there may be following a subsampling layer. This is because the features maps are extracted thereby applying the linear operations and there is a linearity in between the feature maps. So, it is requiring to apply non-linearity operations. The pooling layer takes small rectangular blocks from the feature maps obtained from the convolutional layer and subsamples it. To reduce the number of parameters and computation, we have considered max pooling layer in the first six layer and the average pooling layer in the next six layers starting from layer 7-12 to sub sample the feature map. In max pooling, one maximal value among a group of pixels that are found in the specified window is taken where as in average pooling the average value of the smaller window is taken. This pooling layer reduces the size of the feature without losing significant information thereby selecting superior invariant features. It also achieved a faster convergence rate by selecting superior invariant features that improve generalization performance. Besides lowering the computational cost, it also helps to prevent the network from overfitting. iii. Activation Layer

After the convolutional layer, it's always required to apply non linearity layer. This is because the features maps are extracted thereby applying linear operation. So, by in this study the ReLUs activation are used to introduce non linearity in between the feature map. iv. Fully-connected layer

Neurons in a fully connected layer have full connections to all activations in the previous layer, as seen in regular Neural Networks. Their activations can hence be computed with a matrix multiplication followed by a bias offset.

b. Color Momentum Feature

The second feature descriptors called color momentum which is used to extract the color feature of the banknote. To extract the color feature, it is required to obtained the optimal color space which is best suitable to study the Ethiopian banknote. As human conceptual understanding, we can identify the Ethiopian banknote using their colors. From the experimental analysis, the study observed there is a dominant color different in between the Ethiopian banknote denomination. So, we can study the banknote by using RGB color space. But, utilizing the RGB color space is not efficient to study the banknote because the RGB color space has not sufficient to differentiated colors from luminance, is affected by noise, and cannot correspond well to perceived difference in colors. The study considered HSV color space so as to support the RGB color space as the HSV color space can differentiated colors from luminance, its Hue color channel is not affected by noise, and cannot correspond well to perceived difference in colors (Jegnaw and Yargale,2016). Ones the suitable color spaces are identified and selected, the mean, standard deviation, and skewness value are calculated from both R, G, B channel of the RGB color space and H, S, V channel of the HSV color space to construct the banknote color feature.

II. SIFT (Scale Invariant Feature Transformation / feature

To obtain the scale, rotation, and illumination invariant local texture feature, the study adopted the SIFT local feature descriptor. In this local feature descriptor, orientation is assigned to each key point to achieve invariance to image rotation, key points are calculated thereby filtering the image with different scaled Gaussian filter to calculate the scaled invariant key point from the Ethiopian banknote. This makes the SIFT feature descriptor robust to deal with a different view of an object or scene such as the existence of difference due to scaling, rotation, and illumination change in an image. To extract the SIFT feature, the study follows four steps described in (Lowe, (2004). So, these four steps are scale-space extrema detection, keypoint localization, orientation assignment, and keypoint description.

Step One: Scale-space extrema detection.

To extract and detect ROI in Ethiopian banknotes such as the vertical golden strip, identification marks written in intaglio printing, numeric indicator written in both Arabic and geez number and any other ROI. It is obvious that we cannot used the same window to filter the ROI found the banknote image. In line with filter size, it is required to examined the banknote by with different scaled gaussian filter. So, the study examined the banknote by with different sigma value in different scale and octaves until detecting the specific ROI that constitute the banknote. From the experimental analysis, the study identified the ROI at sigma value

1.26 with a scaling factor of √2 in five different scaled gaussian filter found in three different octaves. as shown in Table 4.13 bellow.

| | | | | |
|---|---|---|---|---|
| 1.26 | 1.78191 | 2.52 | 3.56382 | 5.04 |
| 2.52 | 3.56382 | 5.04 | 7.12764 | 10.08 |
| 5.04 | 7.12764 | 10.08 | 14.2553 | 20.16 |

Table 1 Sigma value in the three octaves and four different scale

The sigma value as shown in Table 4.13 are calculated as multiplying the sigma value of the first octave by with a scaling factor $k = \sqrt{2}$.

To blurred the banknote, the study used the formula given by Lowe (2014) as shown in equation 4.4 bellow.

$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$ ……………. (4.4)

The figure given bellow shows the Gaussian blurred Ethiopia 100-birr note image.



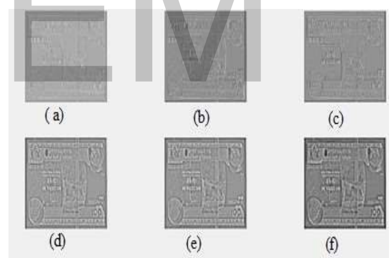


Figure 3: Gaussian blurred Ethiopia 100- notes

After blurring the banknote image as shown in figure 4.5 above, we then compute the DoG thereby subtracting the two nearby gaussian blurred banknotes image.

Figure 4: DoG image found by subtracting two blurred images found in the same scale

After computing the DoG, we then compute the local extrema value thereby taking 3x3 smaller sub block in the DoG image starting from the left most and repeatedly done until reaching to the right moist with a step size equal to 3. The local extrema are the reference point which can be later used to study the banknote. To search the key point, 3×3 pixel of the DoG image is taken. Then, the central element of the 3×3 pixel with its eight neighbors compared and the maximal are taken as an extrema point. Then this extrema point is further compared with nine pixels in its two nearby images as shown in figure 4.7

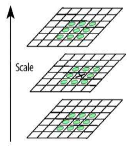


Figure 5: Local extrema value identification process

The calculation of the DoG is presented as shown in equation 4.5 bellow.

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \quad (4.5)$$
$$= L(x, y, k\sigma) - L(x, y, \sigma).$$

Where D (x, y, σ) is the image obtained after finding the difference between the two nearby gaussian blurred images, L (x, y, kσ) is the Gaussian blurred image with sigma value of 1.26, 2.52, and 5.04 in the first, second and third octave as shown in Table 4.9 above.

Step two: Select potential key points

To identified the potential key points, it is requiring to eliminate key points that are poorly localized. So, the poorly localized key points are found at the edge. Since at the edge the DoG are maximal. The other poorly localized key points are found at contrast of less than or equal to a threshold value 30. So, the study is not considered the key points calculated with a contrast of less than or equal to a threshold value 30.

**Step three**: Compute orientation assignment

Ones obtained scale invariant interest key point; the remaining task is to compute rotation invariant keypoint. In this regard, an orientation is assigned to each keypoint to achieve invariance to image rotation. A neighborhood is taken around the keypoint location depending on the scale, and the gradient magnitude and direction is calculated in that region as shown in equation 3.16 and 3.17 bellow. An orientation histogram with 36 bins covering 360 degrees is created. The highest peak in the histogram is considered an ideal orientation.

**Step four**: Compute the description to the keypoint

Once the study computes the scale invariant and rotation invariant useful keypoint, the final task is to find a description to these key points. To compute the description, the local image gradients are measured at the selected scale in the region around each keypoint. So, 16 sub blocks of each 4x4 neighbor for each key point are used to compute the description to each key point. Then the local image gradients are measured at the selected scale in the region around each key point are calculated as shown in equation 3.16 bellow.

$$M(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2} \ . \ (3.16)$$

$$\theta = \tan((L((x,y+1) - \frac{L(x,y-1)}{L(x+1,y)} - L(x-1,y))\text{-----}\ (3.17)$$

c. GLCM texture Feature

GLCM studies the spatial dependency between gray levels. It is used to refer the overall average of degree of correlation between pair of pixels in different aspects such as in terms of correlation, contrast, energy, and homogeneity. Whereas the correlation studies the linear dependency between gray levels. Contrast studies the local variations in the gray levels. Homogeneity referees the tightness of the distribution of the elements in the gray levels. To calculate the GLCM feature of the grayscale banknote image as a whole without lowering the scale are computationally expensive. So, the study first quantizes the image into a lower scale. So, it is required to obtained the optimal gray level that lower the computational time as well as computational capability. By empirical analysis, the study found better result at gray level 12. To further investigate the GLCM feature, we examined the GLCM feature thereby with different neighboring distance and orientation. By empirical analysis, the study found better result at neighboring distance 4 and an orientation of 0, 45, 90, and 135-degree to study the spatial dependency of gray levels. Then the contrast, Correlation, Energy, and Homogeneity of each glcm matrix are calculated.

## III. Experiments and Results

In order to design Ethiopian banknote recognition system, we have selected the best feature extraction techniques used to study the banknotes in terms of its colour, texture and hierarchically by taking pixel wise through literature review. Accordingly, CNN, SIFT, GLCM, and color momentum technique are identified. And, also ANN model as a classifier. Because of high computing devices requirement and computational complexity, the study is not considered the CNN model as a classifier. A total of 2400 banknote image obtained through scanner are used to rain and test the model. And, also 70% of the banknote are used for training and 15 % for validating and 15% for testing the proposed model.

Table 2: Performance of the feature extraction techniques

| No | Feature extraction technique used | Result achieved in hidden layer | | | |
|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 |
| 1 | CNN feature | 98.5% | 99.4% | 99.4% | 99.4% |
| 2 | Color momentum | 84.13 | 97.1 | 97.1 | 97.1 |
| 3 | GLCM | 94.5% | 96.3 % | 96.3 % | 96.3 % |
| 4 | SIFT feature | 88.5 | 99.2% | 99.2% | 99.2% |
| 5 | Color &GLCM composite feature | 89.75% | 98.4% | 98.42% | 98.4% |
| 6 | Color & SIFT composite feature | 99.4% | 99.4% | 99.4% | 99.4% |
| 7 | SIFT & GLCM composite feature | 99% | 99.2% | 99.2% | 99.2% |
| 8 | SIFT, color, & GLCM composite features | 99% | 99.2% | 99.2% | 99.2% |

As shown in in the comparison Table 2 above, both the CNN feature and the combined feature of SIFT and color momentum features comes first with an average accuracy of 99.4% to classify the Ethiopian banknote denomination. For banknote verification, the study considered the SIFT with color momentum feature and the CNN feature to identify the originality and better results are registered at CNN feature extraction technique with an average accuracy of 96% were achieved.

## IV. Discussion

A banknote denomination identification and fake detection system have been defined, a recognition and verification system has been formulated based on the recognition of the birr notes using intrinsic color, texture, and pixel by pixel features. Therefore, the color momentum feature extraction techniques, the SIFT local texture features descriptor, the GLCM statistical texture features descriptor, and a hierarchical feature descriptor called CNN model were considered as a candidate feature extraction technique. Experiments have been conducted to assess the performance of the candidate features techniques by using FFANN classifier. In these regards, eight experimental scenarios were prepared to investigate the performance of the feature's extraction techniques; GLCM, SIFT, color momentum, color momentum with GLCM combined feature, SIFT with color momentum, SIFT with GLCM, SIFT with color momentum and GLCM, and the CNN features to classify the Ethiopian banknote were designed. These Ethiopian banknotes features are tested by using the feedforward artificial neural network classifier.

The classification process entails eight experimental scenarios with distinctive features. The first scenario is focused on classifying the banknote by using the color momentum feature meanwhile scenario two do the same steps using GLCM feature. On the other hand, scenario three using SIFT feature and scenario four will combine the features of color and GLCM (scenario 1 and 2). For remaining scenarios from five to eight, GLCM with SIFT feature, SIFT with color momentum, SIFT with color and GLCM, and CNN features respectively. On the other hand, the study contained one experimental scenario with the CNN model to recognize the banknote.

The experimental result shows we can study the Ethiopian banknote using its dominant color. Since the dominant color of banknote denomination, 10 and 50-birr are red, 100-birr and 5-birr are green, and old 5-birr are sometimes blue which is as similar to Jegnaw and Yaregal (2016). From the literature reviewed, the study concluded that the color space used to study the color properties of the banknotes can have an impact on the recognition performance. Therefore, this study identified the two possible candidate color spaces to examine the Ethiopian banknote recognition system. From the experimental studies, the classification accuracy of 89.5%, 90.3%, 95.1%, and 97.1% are registered while considering RGB, HSV, HSV with RGB composite feature, and RGB with HSV color space composite feature respectively. The study also observed a slight performance improvement while considering RGB color space first and then HSV color space to construct the color momentum feature over while considering HSV color space first and then RGB color space next to construct the color momentum composite feature.

The study also examined the banknote texture feature thereby with SIFT feature and GLCM feature descriptor. To extract the texture feature, the study considered the grayscale image. From the literature reviewed, the study concluded that the performance of the GLCM feature was mainly affected by the RGB to grayscale image conversion techniques, the number of gray-level, the number of neighboring distances, and the orientation considered while studying the spatial relationship of the gray levels. To convert the image from RGB to Grayscale there are technique; averaging and weighting or luminance techniques. The experimental result showed better recognition rate while considering weighting technique to transforms the RGB image to grayscale over averaging techniques. In order to construct the GLCM feature, we take a gray level value from 4, 8, 12, and 20 to examine the performance of the GLCM feature and a recognition rate of 65%, 72%, 90%, 87%, 87% was achieved. Even though the experimental result showed better recognition rate at gray level 12 and 20, the study observed better result at gray level 12 by far in terms of computational.

Once the optimal gray level is identified, we have also examined the optimal neighboring orientation by taking four different candidate orientation; 0 degrees, 45 degrees, degree, and 135 degrees to study the spatial information of the gray levels. The experimental result showed a performance improvement from 87% to 90.8% was registered while considering an orientation of 0. 90, 135 degree to study the spatial information. Lastly, we also studied the GLCM feature by considering four different neighboring distance and performance improvement from 90.8% to 96.3% were registered while studied the spatial information of the gray levels.

In the other banknote texture feature, we have considered the SIFT feature extraction techniques. In order to extract the SIFT feature, we have considered the Lowes (2014) algorithm to construct the SIFT feature. The first steps in the SIFT feature extraction technique are to identify the key points with in different size and orientation. So, it is required to identify the key points in different orientation and size and viewpoint changes. Therefore, we examined the different sigma value starting from 0 to 1, with a default scaling factors of $\sqrt{2}$, by in five different scales, and three different octaves to identify the potential key points. The experimental result shows a better result at a sigma value of 0.707107. Once, the potential key points are identified, it's required to eliminate the poorly localized key points by reducing the key points found at low contrast and the keypoint locating at the edge Therefore, it is required to identify the threshold value in order to decide the contrast level. By empirical analysis, the study registered better result at a threshold value of less or equal to 0.3 are low contrast values and any key points found less than the threshold is considered as poorly localized key points and not be considered.

In the last feature, we have examined the banknote by using the CNN model. From the literature review, we have concluded that the CNN model is more affected by the number of layers, the number, and size of the trainable kernel (feature detector), step size, number of convolutional layer, number of pooling layer and their pooling strategies, and number of fully connected layer, and the activation function considered in designing the classification layer of the CNN and its arrangement.

In order to achieve better recognition result, the study modified the VGGnet CNN model architecture until obtaining better recognition result. Firstly, we have examined the number of the hidden layers, the better result was registered while considering 9 hidden layers to construct the CNN model as shown in figure 1. From the experimental studies, the CNN model is more affected by vanishing gradient and overfitting problem. In order to reduce the effect of vanishing gradient, the study considered batch normalization after each convolutional layer next to nonlinearity layers and drop out layer after each fully connected layer next to nonlinearity layers. In addition to vanishing gradients, the study also considered the pooling layer to reduce the effects of overfitting

Once, obtaining the optimal hidden layer, the study examined the effect of the size of kernel by taking a filter of size 3 x 3 and 5 x 5 performance improvement was observed from 98.96 to 99.38% recognition accuracy were registered while considering a kernel size of 5 x 5 over that of kernel size of 3 x 3. In the current CNN model also called modified VGG net (19) model, we have designed the current CNN model by reducing the number of hidden layers from sixteen to nine, the filter size from 3 x 3 to 5 x 5, and by inserting the batch normalization and drop out layer in the convolutional layer and the filly connected layer respectively.

The proposed model reduced the number of training parameter thereby reducing the number of hidden layers and the dimension the filter considered in the convolutional layer where the number of learned parameters is dropped from 432 to 225 which is reduced by 47.9% and this also reduce the computational time. According to Simonian and Zisserman (2014), the fewer parameters to be learned, it is better for faster convergence, and reduced overfitting problem. Therefore, the current designed model is converged faster because it reduced the number of parameters to be learned by 47.9% as compared with the VGG net model. From the experimental analysis, we have observed better computational cost while considering the current designed modified VGG net (19) model that the VGG net (19) CNN model. Accordingly, the study registered 96% recognition rate while considering the VGG net (19) model and 96% recognition rate while considering the customized VGG net (19) model. In regard to computational time, by far the proposed CNN model achieved better recognition time as compared with VGG net model.

## V. Conclusion and Recommendation

We described the performance of both the handcrafted and automatic feature descriptor to automatically recognized the Ethiopian banknote into its respective denomination as well as verifying its originality. The efficiency of the SIFT, GLCM, color momentum, and CNN feature extraction technique were also evaluated on various banknotes image quality. The recognition accuracy of the CNN feature, SIFT, color momentum, GLCM, combined feature of SIFT and GLCM, combined feature of SIFT with color momentum, combined feature of color momentum with GLCM, and the combined feature of color momentum, SIFT, and GLCM feature were 99.4%, 99.2%, 97.1%, 96.3%, 99.2%, 99.4%, 98.8%,99.2% respectively. According to recognition accuracy, both the CNN and combined feature of color and SIFT feature gives similar recognition rate. Though, both the CNN and composite feature of SIFT and color achieved similar accuracy of classification, in regards to the cost of computational time and computational power requirement, the composite feature of the color and SIFT feature outperforms the CNN feature. As concerning the overall objective of the model, the CNN is the optimal feature extraction technique. Therefore, to classify the banknote, the CNN model is the ideal solution. Thus, feature work is directed towards improving the performance of the system thereby considering the CNN model by with better architecture like GoogLeNet and ResNet with very large dataset to classify and recognize Ethiopia banknote.

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