CURRENT RESEARCH IN
COMPUTER SCIENCE
ISSN 2788-7707
MAY. 2021 VOL. 1, NO. 1

A Case Study on Neural Networks as Classifiers to Design Banknote Recognition Systems

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ABSTRACT

We proposed a banknote recognition method based on the adoption of CNN for feature extraction and FFANN as a classification. Banknote images are normalized to have the same size and fed into trained CNN models corresponding to the pre-classified size classes. When passing through the neural network, banknote features are extracted by the convolutional layers and feed into the FFANN classifier to identify its respective denomination as well as to verify its originality. Our experimental results using two-fold cross-validation on the Ethiopian currency dataset show that the proposed CNN-based banknote recognition method yields better accuracies than the method in the previous study. Although CNN-based classification has been used in various fields due to its high performance, it has the disadvantage of requiring intensive training with a lot of training data. However, it is often the case to have difficulty in collecting a lot of training data in actual experimental environments. Therefore, we have applied a data augmentation to increase the size of the datasets. Further studies are required to conduct on the CNN model by with better architecture like Google Net and ResNet with a very large dataset to classify and recognize Ethiopia banknote.

KEYWORDS

Convolutional Neural Network; Ethiopian Banknote Classification System; Ethiopian Paper Currency Recognition System.

1. Introduction

Banknote denomination classification and counterfeit identification system 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 [1, 2]. 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 will require manually extracted feature. And this manually extracted feature, are subject to human biases. This is because the discriminating power of the extracted features are more subjected to the techniques we used for obtaining the feature vector. Convolutional Neural Network algorithm is a multi-layer perceptron that is specially designed for the identification of two-dimensional data such as image [5]. 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 [3-5]. Moreover, CNN can easily identify displacement, zoom, and other forms of distortion invariance of two-dimensional image data [6, 14, 16, 14]. This feature of the CNN makes it suitable to extract more discriminating power feature the banknote image which has a number of paper qualities [13]. 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.

2. 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 [7] 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 [7]. 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 [9]. 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 [8]. 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.

3. Proposed Methods

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 [14, 16]. Therefore, this study employed the CNN model to extract the Ethiopia banknote.

In order 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) Overview of the Proposed Method

The overall flowchart of the proposed method is shown in Figure 1. The input banknote image is captured and pre-processed. In this pre-processing step, the banknote region in the captured image are resized, because the size of the input image to the CNN should be the same. Following image resizing, the brightness normalization and noise filtering tasks were performed. Moreover, the grayscale conversion tasks were done. The preprocessed image of the banknote is fed into the proposed CNN, and the performance of model is determined at the output of the network.

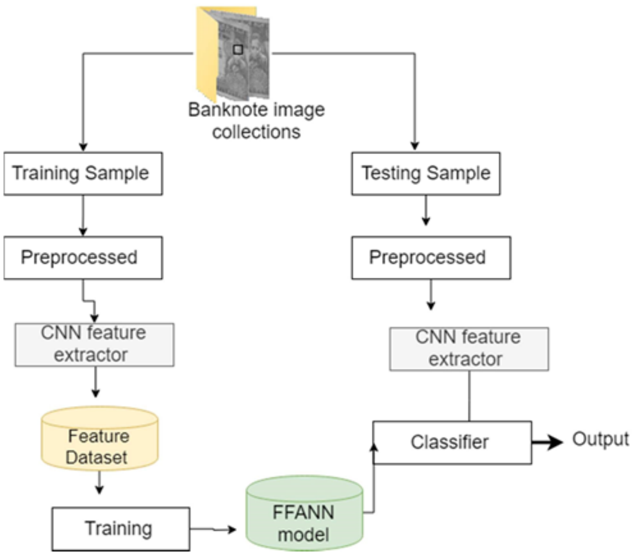

Figure 1. Overall flowchart of the proposed method.

b) Acquisition and Pre-Processing of Banknote Image

For banknote image acquisition in this study, we used a Hp scan Jet 2710 scanner sensor that has a resolution of 741x350 pixels. Following image resizing, the pre-processed tasks are presented as follows.

i. Image size normalization

In regard to the size of the banknote, different researchers considered different size to construct the banknote recognition system. By conducting empirical analysis, the study found a 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.

ii. Image quality enhancement

Since the banknote are used for the 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 a thorn, lose its color due to some dirty appearing on the interface and this brings a degradation on the image quality. So, the applied an adaptive median filter to reduce the effect of noise appearing on the image. Afterimage noise is removed, the study also applied histogram equalization techniques are considered to adjust the contrast of the image data. iii. RGB to grayscale conversion

To simplify the computational requirement of the model, the study considered a grayscale image. This is because the grayscale images only contain the intensity information which is easy to process instead of processing RGB image. The three-technique which is used by the different researcher; averaging, weighted, and lightness method [17]. By experimental analysis, the study found better result after employing a weighting method to obtain 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 is also greater than the green color channel. By empirical analysis, the weights for each channel are obtained as shown below in the equation 1 given below.

$$Gry\_img = 0.17\times R + 0.62\times green + 0.21\times blue \qquad (1)$$

c) Feature Extraction

The feature extraction component also called dimensional reduction is used to obtain the discriminating features from banknote images. The commonly applied characteristic features to identify banknotes contain the color features, size feature, the shape feature, the texture features. And, the techniques we considered to study these properties of images are categorized as traditional and automatic feature extraction techniques. According to Lee1 and Lee [3], the traditional feature extraction techniques are unable to extract feature from an image having complicated patterns like a banknote. Therefore, it is not applicable for verification of banknote originality verification system. Moreover, the automatic feature extraction techniques implicitly learn features from the training by extracting high-level features (sophisticated features) from data. And, it also identifies the presence of image variations due to displacement, zoom, and other forms of distortion [12, 15]. This quality feature of the CNN makes it suitable for application that demands high computational capabilities like paper currency classification and recognition. The CNN model which is used for classifying and recognizing Ethiopian banknotes are depicted as shown in figure.

d) The Architecture of CNN

The CNN used in our proposed method was inspired by the VGGnet architecture [16]. Our network architecture includes eight convolutional layers, denoted by Conv1 to Conv8, and two fully-connected layers, denoted by Fc1 to Fc2, as shown in Figure 1 and Table 1. Rectified linear unit (ReLU) layers are adopted in all the convolutional and fully connected layers. This network unit performs a threshold operation that sets all the negative input values of x to zero, as shown in Equation (1). The usage of the ReLU active function helps to improve the generalization, simplify the computation, and increase the training speed of the deep network. i. Convolution process

The convolutional layers learn the various local feature that constitutes the birr note image like the identification mark, security thread, the tin and wide golden strip and much more security feature which is used to constitute the banknote. 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 the convolution layer, the input of each neuron is connected to the 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.

$$x(l)\ i, j = \sigma\ (b + \quad wr, c\ x\ (i+r, j+c)(l-1)) \quad (2)$$

Since every local receptive field takes same weights , and biases b as shown in equation 2 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 the bottom right-most with a step size /strides/ equal to the number of kernels. In the second or later 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 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. However, there are no readily available empirical formulas or adopted guideline to decide the number of convolutional layers and their optimal parameter. We, therefore, experimented the different number of convolutional layer and their optimal parameter until a better result was obtained. Accordingly, better results were found at CNN architecture with 10 number of convolutional layers with the different learnable filter size of 3×3 and 5×5 used in the convolutional layer as depicted in Table 1.

i. Non-linearity Layer

After the convolutional layer, it's always required to apply nonlinearity layer. This is because the features maps are extracted thereby applying the linear operation. We, therefore, considered a non-linearity layer immediately after the feature maps were obtained in the convolutional layers [15]. So, by in this study, the ReLUs activation is used to introduce nonlinearity between the feature maps. ii. Subsampling layer
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 as shown in figure 1. 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. 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.

4. Experimental Results

In order to train and test the proposed model, we have used Ethiopian banknote which is collected from the commercial bank of Ethiopia. The collected banknote dataset is composed of banknotes in four denominations, 5, 10, 50, and 100-birr. 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.

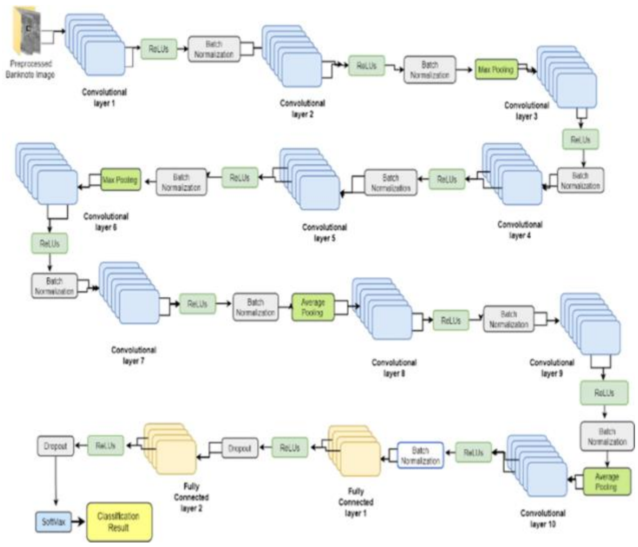

Figure 2. The customized CNN models.

Figure 3. Examples of banknote images used for experiments.

Banknote Classification and verification result and analysis

In this study, we have considered the banknote classification system to evaluate the performance of the feed-forward ANN, SVM, and KNN classifiers. Accordingly, the following result is Therefore, we used feed-forward ANN as a classifier to study the banknote denomination classification system.

Table 1. Classifier performance comparisions.

Feature constructed from	Classifier used		
	ANN	SVM	KNN
CNN model	99.04%	99.00%	75.20%

Even though the CNN model has backpropagation artificial neural network in its fully connected layer, the study registered better result while considering only the CNN model as a feature extractor and the feed-forward ANN as a classifier. This is because the training time required to design the CNN model both for feature extraction and classification would require higher training time as compared with that of considering only for feature extraction. For studying the performance of the ANN classifier on fake detection system, we also used the CNN feature for both classification and counterfeit identification system, to detect counterfeiting.

Table 2. FFANN classifier performance on various paper quality status.

Banknote	Categories	Total test set	Correctly recognize	Incorrectly recognize	Accuracy in %
Genuine birr note	Clean average	240	235	5	97.9
		240	232	8	96.7
	Very noisy	240	229	11	95.4

Fake birr note	Clean average	240	236	4 13	98.33
		240	227		94.6
	Very noisy	240	230	10	95.8
	A total average accuracy of				96.46%

Feature constructed from	Classifier used		
	ANN SVM		KNN
CNN model	99.04%	99.00%	75.20%

Feature constructed from	Classifier used		
	ANN SVM		KNN
CNN model	99.04%	99.00%	75.20%

Feature constructed from	Classifier used		
	ANN SVM		KNN
CNN model	99.04%	99.00%	75.20%

As shown in the comparison Table 2 above, the FFAN FFANN as a classifier and CNN as a feature extractor as performs an average accuracy of 99.4% to classify the depicted in Table 2. The following figures as shown in the Ethiopian banknote denomination. For banknote verification, figures 4 and 5 show the training performance of the designed an average accuracy of 96% was registered while considering CNN model depicted in figure 4.

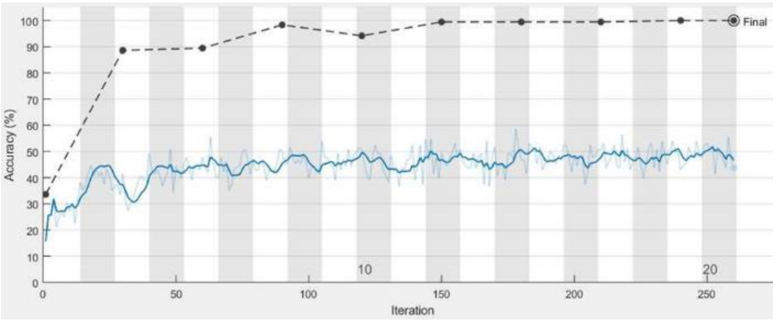

Figure 4. The validation performance of the CNN model.

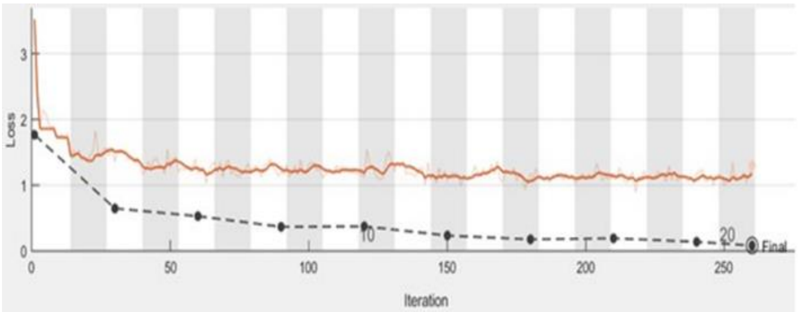

Figure 5. The validation loss of the designed CNN model.

5. Discussion

A prototype for banknote denomination classification and counterfeit verification system have been formulated based on the recognition of the birr notes using their intrinsic color, texture, and hierarchical features. In line with this, the CNN model is used to extract features from the banknotes. Experiments have been conducted to assess the performance of the CNN features extraction techniques by using FFANN, SVM, and KNN as a classifier.

We have investigated the banknote denomination classification system through automatic feature extraction techniques named CNN model. Through the experimental phase, the possible factors affecting the performance of the CNN model were compared. The shortlisted factors are identified through initial pilot tests, and these include the number of convolutional layers, number of pooling layers, and number of fully connected layer, activation, and hypermeter using each layer in designing the model. Though a number of CNN model, like LeNet, AlexNet, ZFNet, Google Net/Inception, VGGnet, and ResNet model, were developed on deep learning model on various problems, they are computationally intensive [16]. However, it is possible to improve the performance of the CNN model with regard to computational time by limiting the learnable parameters.

Accordingly, this study investigates the CNN model by restructuring the different parameters to identify the optimal architecture that gives less computational cost with better accuracy. The cost of computation is more related to the number of parameters to be trained by the model. a number of interrelated tasks were done to model the CNN feature extraction model and these were outlined as follows.

Firstly, we have examined the number of the hidden layers, better result was registered while considering eleven hidden layers to construct the CNN model as shown in figure 2. The study also examined the designed model without using a batch normalization layer, and an overfitting problem was observed. Therefore, the significant performance improvement was observed while batch normalization layers were used in each convolutional layer immediately next to the nonlinearity layers and drop out layer after each fully connected layer next to nonlinearity layers.

Secondly, the study also examined the effect of the different hypermeter like trainable kernels, the number of kernels, and the size of the strides. In the experimental phase, an accuracy of 99.38% was observed when using a trainable kernel size of 5×5, 98.96% for 3×3, 97.30% for 7×7, 97.92% for 11×11, and 58.96% for 13×13. And, the experimental result shows the filter size is more related to the nature of the data being studied.

Finally, we have explored the relationship between number and dimension of the feature detector thereby taking a filter size of 5×5 with 12 number of learnable kernels in each convolutional layer, and different number of kernels, and different pooling strategies to classify Ethiopian banknotes. The Final test shows that the classification accuracy has been able to be increased from 98.96% to 99.0%, and then, 99.4%. The first improvement was observed during the experimental phase, whereby a different learnable kernel was used in the different layers. It was found that considering different kernel while designing the CNN model can enhance the model performance for Ethiopian banknotes classification system. Performance improvement was also observed during an experimental phase when we used different learnable kernels of 3×3 and 5×5 with max and average pooling strategies, inserting batch normalization and dropout layers to design the model.

According to Simonyan and Zisserman [4], utilizing the VGG model for designing a classification system suffered a high computational burden due to 140 million trainable parameters. It is not a good fit for real-time processing demands as the correctness of the real-time system depends not only on the logical result but also the processing time it was delivered. Accordingly, in the newly designed CNN model for Ethiopian birr notes which is described in figure 2, an achievement is obtained by reducing the number of trainable parameters to 421,342 as compared with the existing CNN model like VGGnet. It implies that it will be required to train 421,342 learnable parameters for classifying one Ethiopian banknote image. Therefore, the current designed model is converged faster as compared with the VGGnet model. This is because the number of parameters to be learned was very less as compared with the VGG net model.

The following confusion matrix shows the Performance of the FFAN performance.

ANALYSIS RESULT

	Name	Type	Activations	Learnables
1	imageinput 210x312x1 images with 'zerocenter' normalization	Image Input	210×312×1	-
2	conv_1 8 3x3x1 convolutions with stride [1 1] and padding 'same'	Convolution	210×312×8	Weights 3×3×1×8 Bias 1×1×8
3	relu_1 ReLU	ReLU	210×312×8	-
4	batchnorm_1 Batch normalization with 8 channels	Batch Normalization	210×312×8	Offset 1×1×8 Scale 1×1×8
5	conv_2 16 3x3x8 convolutions with stride [1 1] and padding 'same'	Convolution	210×312×16	Weights 3×3×8×16 Bias 1×1×16
6	relu_2 ReLU	ReLU	210×312×16	-
7	batchnorm_2 Batch normalization with 16 channels	Batch Normalization	210×312×16	Offset 1×1×16 Scale 1×1×16
8	maxpool_1 2x2 max pooling with stride [2 2] and padding [0 0 0 0]	Max Pooling	105×156×16	-
9	conv_3 16 5x5x16 convolutions with stride [1 1] and padding 'same'	Convolution	105×156×16	Weights 5×5×16×16 Bias 1×1×16
10	relu_3 ReLU	ReLU	105×156×16	-
11	batchnorm_3 Batch normalization with 16 channels	Batch Normalization	105×156×16	Offset 1×1×16 Scale 1×1×16
12	conv_4 32 5x5x16 convolutions with stride [1 1] and padding 'same'	Convolution	105×156×32	Weights 5×5×16×32 Bias 1×1×32
13	relu_4 ReLU	ReLU	105×156×32	-
14	conv_5 32 5x5x32 convolutions with stride [1 1] and padding 'same'	Convolution	105×156×32	Weights 5×5×32×32 Bias 1×1×32
15	relu_5 ReLU	ReLU	105×156×32	-
16	batchnorm_4 Batch normalization with 32 channels	Batch Normalization	105×156×32	Offset 1×1×32 Scale 1×1×32
17	maxpool_2 2x2 max pooling with stride [2 2] and padding [0 0 0 0]	Max Pooling	52×78×32	-
18	conv_6 32 5x5x32 convolutions with stride [1 1] and padding 'same'	Convolution	52×78×32	Weights 5×5×32×32 Bias 1×1×32
19	relu_6 ReLU	ReLU	52×78×32	-
20	batchnorm_5 Batch normalization with 32 channels	Batch Normalization	52×78×32	Offset 1×1×32 Scale 1×1×32
21	conv_7 32 5x5x32 convolutions with stride [1 1] and padding 'same'	Convolution	52×78×32	Weights 5×5×32×32 Bias 1×1×32
22	relu_7 ReLU	ReLU	52×78×32	-
23	batchnorm_6 Batch normalization with 32 channels	Batch Normalization	52×78×32	Offset 1×1×32 Scale 1×1×32
24	avgpool2d_1 3x3 average pooling with stride [2 2] and padding [0 0 0 0]	Average Pooling	25×38×32	-
25	conv_8 32 5x5x32 convolutions with stride [1 1] and padding 'same'	Convolution	25×38×32	Weights 5×5×32×32 Bias 1×1×32
26	relu_8 ReLU	ReLU	25×38×32	-
27	conv_9 32 5x5x32 convolutions with stride [1 1] and padding 'same'	Convolution	25×38×32	Weights 5×5×32×32 Bias 1×1×32
28	relu_9 ReLU	ReLU	25×38×32	-
29	batchnorm_7 Batch normalization with 32 channels	Batch Normalization	25×38×32	Offset 1×1×32 Scale 1×1×32
30	avgpool2d_2 3x3 average pooling with stride [2 2] and padding [0 0 0 0]	Average Pooling	12×18×32	-
31	conv_10 32 5x5x32 convolutions with stride [1 1] and padding 'same'	Convolution	12×18×32	Weights 5×5×32×32 Bias 1×1×32
32	relu_10 ReLU	ReLU	12×18×32	-
33	batchnorm_8 Batch normalization with 32 channels	Batch Normalization	12×18×32	Offset 1×1×32 Scale 1×1×32
34	fc_1 40 fully connected layer	Fully Connected	1×1×40	Weights 40×6912 Bias 40×1
35	relu_11 ReLU	ReLU	1×1×40	-
36	dropout_1 50% dropout	Dropout	1×1×40	-
37	fc_2 6 fully connected layer	Fully Connected	1×1×6	Weights 6×40 Bias 6×1
38	relu_12 ReLU	ReLU	1×1×6	-
39	dropout_2 50% dropout	Dropout	1×1×6	-
40	softmax softmax	Softmax	1×1×6	-
41	classoutput crossentropyex with '1' and 5 other classes	Classification Output	-	-

Figure 6. Learnable parameters, in the proposed CNN model (Obtained directly from Experiments in MATHLAB).

Table 3. CNN features performance on fake detection.

5-Birr	112 23.3%	0 0.0%	7 1.5%	0 0.0%	94.1 5.9%
10-Birr	0 1.0%	120 25.0%	0 0.0%	4 0.8%	96.8% 3.2%
50-Birr	8 1.7%	0 0.0%	113 23.5%	0 0.0%	93.4% 6.6%
100-Birr	0 0.0%	0 0.0%	0 0.0%	116 24.2%	100% 0.0%
	5-Birr	10-Birr	50-Birr	100-Birr	96.0% 4.0%

As indicates in Table 3, the summary result of ANN classifier using the CNN feature of the banknotes to verify fake currency showed that from the total 480 test images, 381 (96%) were correctly classified and 19 (4%) were incorrectly classified. The result of feed-forward ANN classification using CNN feature showed that the classification accuracy of 50-birr note, 10-birr note, 50-birr note, and 100-birr note were 93.3%, 100%, 94.2%, and 96.7% respectively with an overall recognition accuracy of 96.0%.

6. Conclusion

In this research, we proposed a banknote recognition method based on the adoption of CNN for feature extraction and FFANN as a classification. Banknote images are normalized to have the same size and fed into trained CNN models corresponding to the pre-classified size classes. When passing through the neural network, banknote features are extracted by the convolutional layers and feed into the FFANN classifier to identify its respective denomination as well as to verify its originality. Our experimental results using two-fold cross-validation on the Ethiopian currency dataset show that the proposed CNN-based banknote recognition method yields better accuracies than the method in the previous study. Although CNN-based classification has been used in various fields due to its high performance, it has the disadvantage of requiring intensive training with a lot of training data. However, it is often the case to have difficulty in collecting a lot of training data in actual experimental environments. Therefore, we have applied a data augmentation to increase the size of the datasets. Further studies are required to conduct on the CNN model by with better architecture like Google Net and ResNet with a very large dataset to classify and recognize Ethiopia banknote.

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