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Intelligent Libyan Banknote Recognition System

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Abstract: This article presents two robust and efficient systems, they are based on the convolutional neural networks and the generative adversarial networks. Each one is used as a classifier to recognize the Libyan banknotes in effective way. The second system is used to generate artificial Libyan banknotes. The proposed systems were applied on three datasets using the same settings to have actual comparison. The first one was created by traditional methods involved 310 scanned images of real Libyan banknotes. While the second was generated by the second system based on the generative adversarial networks producing 540 images of Libyan banknotes. Each Dataset is divided into two divisions, one for training and the other for test. In the third dataset, some images from other banknotes were added to the test division of the second dataset. The two systems begin with extracting robust features from Libyan banknotes, and then comes the deep learning stage to create an intelligent classification. In addition to, the second system aims to have an excellent recognition of Libyan banknotes and to reach the result that the trained system cannot distinguish between the real images and the generated images. This system shows an excellent classification of the test data that are not used for the training data. The second system was designed to detect fake banknotes and applied on the dataset$_3$ to detect counterfeiting. From the experimental results, the obtained average accuracies for the two systems to classify the Libyan banknotes are 88.24% and 100% in the first two datasets respectively and 99.26% accuracy for the strange banknotes in the third dataset. The designed systems are effective and less time consuming which makes them suitable for real-time applications.

Keywords: Deep Learning, convolutional neural networks, the generative adversarial networks, Libyan banknote recognition

1. INTRODUCTION

The banknote exchange is one of the most important daily life processes. It has become increasingly difficult to identify counterfeit banknotes or determine the value of different banknotes coming from all over the world when the banknotes are unclear, damaged, or old. So, these situations need expert trained examiners, leads to time and cost consuming. A person cannot easily identify the different banknotes coming from all countries. Despite the increase and development in electronic financial transactions, traditional currencies are still in great circulation, either for fear of electronic fraud or because of public ignorance of how to use electronic transactions[1]. Thus, the importance of developing banknote recognition systems for banks and teller machines appeared. Because of its great importance in many applications such as automatic teller machines and other fields of trade, there is an urgent need for automatic banknote identification, which helps people to work quickly and efficiently. Also, since banknote is vital in the economies of countries such as vending machines, companies, banks, shopping malls, institutions, banknote exchange service, etc. [2].

Banknote recognition is the field of image processing used to distinguish between banknotes of different countries and determine their values. One of the problems that emerged with this process is counterfeiting. Most banknote recognition methods follow the following basic steps: First, banknote images are acquired. Then, preprocessing crops proper image sections and feature extraction is carried out to derive useful information from the cropped banknote images. Finally, classification using the extracted features is performed to recognize banknote direction and classify banknotes into distinct denomination categories [3-5].

According to our knowledge, there is no research focused on the recognition of Libyan banknote. So, the proposed systems can help the Libyan government to recognize the banknote in automatic way. The structure of this article is introduced as follows. Section 2 presents background containing previous works and quick illustration of Deep learning networks. Datasets preparation is mentioned in Section 3. In Section 4, the proposed systems contributions are explained in detail. The experimental results and discussion are reported in Section 5. The conclusion and future work are introduced in the last two sections.

2. Background

2.1 Related works

A technique based on neural net was introduced and enabled the selection of good masks that can effectively generate the characteristic values of the input image [6]. A Euro recognition system was suggested with three perception layers and radial basis function to the recognition process [7].

Also, Bangladeshi banknotes recognition was proposed based on neural network. The recognition system took scanned images by low cost optoelectronic sensors and then fed into a multilayer perceptron, trained by back propagation algorithm for recognition. Axis symmetric masks were used in the preprocessing stage to reduce the network size [8]. A banknote orientation recognition method was introduced to avoid dealing with large numbers of image pixels and reduce calculation; the banknote image was divided into several blocks. And then, neural network was applied to establish a universal recognition method [9]. A technique based on multiple-kernel support vector machines for counterfeit banknote recognition was developed to minimize false rates [10]. A precious paper currency recognition method was revealed to match database notes using correlating the edges of input [11]. A technique based on Euclidean distance and neural network was presented in the same field [12]. Mexican currency recognition system was suggested as the input images were suffering from different lighting change, color and texture were extracted from the banknotes, then using local binary model to characteristic the texture [13].

A method to extract the amount of currency paper was proposed. The extracted region of interest and neural networks for matching. Different pixel levels were used in different quantity notes [14]. A smart system was provided to recognize the Pakistani paper currency. After finding the features, three layers using back propagation neural network for intelligent classification were used [15]. An Egyptian currency recognition system started to include image foreground segmentation, and histogram equalization to adjust the contrast based on the image histogram, modifying the brightness of the image and make the image look more clear [16].

A proposed method based on interesting features and correlation between images to recognize Saudi Arabian paper currency using radial basis function network for classification [17]. A recognition system used pattern matching and recognition, the equivalent Indian Rupee value was displayed [18]. Competitive neural networks were used in three proposed hypothetical frameworks to vision-based recognition of banknote denominations [19]. An automatic system was suggested to determine the money value [20]. A technique for Indian currency recognition was described using neural network pattern recognition tool [21]. A banknote recognition method was proposed to select the discriminative regions on the banknote image captured by a one-dimensional visible light sensor using genetic algorithm to optimize the similarity mapping result for different classes of banknotes [22]. Efficient counterfeit banknote detection algorithms were developed and tested using 20 different denominations of European Euro, Indian rupee, and US Dollars [23].

Also, an automatic and reliable currency recognition system was introduced for Myanmar currency denominations [24]. A study examined the color momentum, SIFT, GLCM, combination of SIFT, color and GLCM, and Convolutional neural network (CNN) as a feature extraction technique and FFANN as a classifier to design Ethiopian banknote recognition system [25]. A single-digit image classification using banknote serial numbers were implemented with Generative Adversarial Networks (GANs) [26]. A machine-assisted system dubbed Deep Money was proposed which had been developed to discriminate fake notes from genuine ones, GANs were employed and applied to Pakistani banknotes [27].

2.2 Deep Learning

It is a branch of machine learning, which is multi-layer neural networks, receives each neuron the output of the previous layer neurons with addition to the unit of bias. It then computes a weighted average the total input. After that, the output is computed by applying a nonlinear activation function, and is a process in which weights are learned all layers using the reverse propagation algorithm, and the processing of information is different for each layer from the other, In spite of the complexity of this network, however, implemented successfully in its use in many fields for image recognition and speech recognition. Deep learning models are trained to utilize big collections of data and that learn features directly from the data without the need for manual extraction to features. Compared to machine learning, deep learning is much better at ingesting large amounts of data, meaning the more data, the more layers of the neural network increase, the simpler the process becomes. The main focus of this topic is one of the most widely used types of deep networks: CNNs and GANs [28, 29].

2.2.1 Convolutional Neural Networks

It is one of the categories of deep multi-layered neural networks that succeeded at the outset in the competition that occurs under the name (ImageNet Challenge) and is a competition in the recognition of things, and it is one of the technologies that achieved great success in several fields, the most of used at distinguish images and classify them, as it is characterized by the existence hidden layers extract the features from photos and videos automatically [30]. Convolutional neural network (CNN) includes four basic steps:

Step 1(a): Convolution

The convolution process is used to move the filter (feature detector) on the image and calculate the total products in each site. Convolution layer processes the input data, the convolution on the input image is executed to generate feature maps of the input images, which defines the size of the filter and the number of filters and also determine the number of strides and the number of Padding [31].

Step 1(b): Batch Normalization Layer

Batch normalization is a technique for training very deep neural networks that standardizes the inputs to a layer for each mini-batch. This has the effect of stabilizing the learning process and dramatically reducing the number of training epochs required to train deep networks [31]. This process can be defined in the following steps:

1- Calculate the normalized value of the input

$$x_m^{'} = \frac{x_m - \mu_B}{\sqrt{\sigma^2{}_B + \varepsilon}} \quad (1)$$

where x_m is the inputs, and $m \in [1,2,\ldots,M]$, and μ_B is mean the values of the input, and $\sigma^2{}_B$ is the variance of input values and ε is a small positive number.

2- Calculate product y_m

$$y_m = \gamma x_m^{'} + \beta \quad (2)$$

where γ and β are two parameters that are updated during the training process.

Step 1(c): The Rectified Linear Unit (ReLU)

The Rectified Linear Unit is a syndrome step of the convolution process, which works to replace all negative values with zero in the feature map. The purpose is to insert nonlinearity into a feature map. It is calculated using the following two equations [31].

$$ReLU(x) = \max(0, x) \quad (3)$$

$$ReLU(x) = \begin{cases} x & if\ x > 0 \\ 0 & otherwise \end{cases} \quad (4)$$

Step 2: Pooling

Pooling or sampling is a process that reduces the size of the producing rectified feature maps from the ReLU step. The best values are extracted from the rectified feature map through the application of spatial pooling, there are several types of pooling, for example, Max pooling, Mean pooling, Sum pooling…etc. [32].

Step 3: Flattening

It is one of the easiest layers, where the two-dimensional matrix is converted into a one-dimensional matrix. This process is necessary before the classification process so that it can be easily inserted into the artificial neural network in order can make classification decisions [33].

Step 4(a): Full Connection Layer

The goal of the fully connected layer is to take the results and all learned features through the previous steps to classify the image. All the neurons of the fully connected layer are connected to all the neurons in the previous layer, the CNNs and the artificial neural network are integrated. This layer defines the number of the output which equal to the number of target classes and the more complex journey begins. Where, the artificial neural network works to classify the entered images into several categories based on the features extracted from the previous layers that entered through training the neural network using back propagation [34].

Step 4(b): Softmax Function

The softmax layer is an activation function is used to transform the inputs to a probability distribution over classes, the output consists of positive numbers that sum to one, these probabilities are used for a classification process. This softmax function f(x) is defined as follows:

$$\text{softmax}: \{x \in R^C\} \rightarrow \{p \in R^C | p_i > 0, \textstyle\sum_{i=1}^{C} p_i = 1\} \quad (5)$$

$$p_j = \frac{\exp(x_j)}{\sum_{c=1}^{C} exp(x_c)} \qquad \text{for } j = 1, \dots, C$$

where x_i is one element of the input neuron to the softmax layer and x is the input vector. p_i represents the relative output of x_i and p is the output vector and C is the total number of classes [31].

Step 4(c): Classification (Loss Function)

During the training of network, the cross-entropy function is working for side, to side, with the softmax function and is considered the better option after listing the softmax function. This function is mostly used to measure the difference between a probability distribution the output of softmax function f(x) and desired distribution d(x). The cross-entropy is expressed as follows:

$$L_i = -\textstyle\sum_{c=1}^{C} \left[d(x^{(i)})\right]_c log\left[f(x^{(i)})\right]_c \quad (6)$$

where C is the total number of classes [35].

2.2.2 Generative Adversarial Networks

GAN is a deep learning network type. GAN is used to generate new data images similar to training images in its characteristics (generative modeling). During the generation process, CNN is used. GAN is composed of two networks: Generator and Discriminator. The generator gives random values of the input vector and during the training phase, the generator learns to generate data similar to the inputted training data in the characteristics. The discriminator is trying to classify the entered data as real (training data) or bogus [36], as shown in Figure 1.

- **GAN Training (Training the Discriminator and the Generator)**

The GAN is trained by training the two models, training the discriminator's then training the generator and the two processes are repeated alternately. During the discriminator's network training and after the classification process, the discriminant loss is calculated, the highlighter updates its weights via back propagation of the discriminator loss. During the generator network training, the generator loss is calculated from discriminator classification, gives a signal to the generator network to update its weights via backpropagation of the generator loss. This process continues between the discriminator's network and the generator network until the classification process becomes the discriminator's network does not differentiate between the real data and the created data [27].

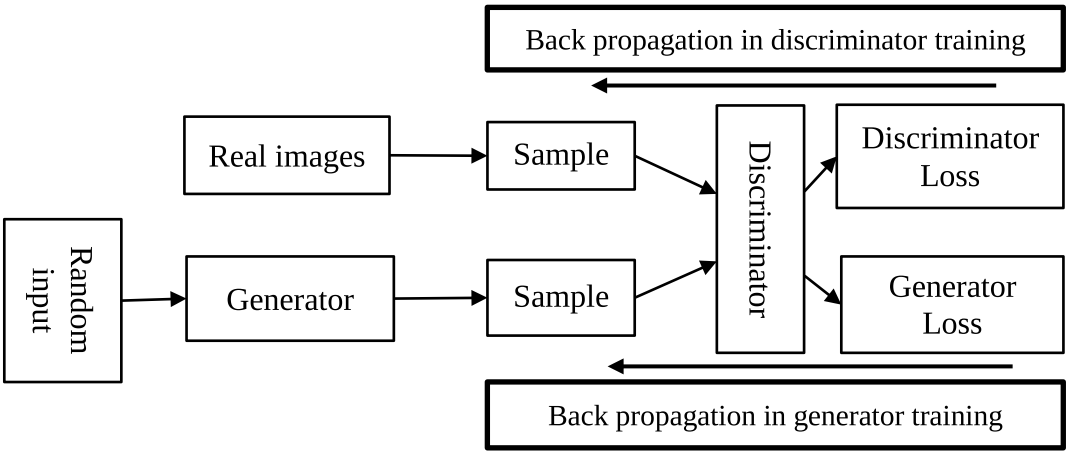


Figure 1. GAN networks

- **GAN Loss Functions (Discriminator Loss and Generator Loss)**

The main goal of GAN Loss Functions is to reduce the difference between the distribution of the images that have been created and the real distribution of images. The loss function of generative model (G) is calculated as follows:

$$= \frac{1}{m}\sum_{1}^{m}\left[log\left(1-\left(D\left(G(b)\right)\right)\right)\right] \qquad (7)$$

and the loss function of the Discriminator (D) is computed as follows:

$$= \frac{1}{m}\sum_{1}^{m}\left[logD(a)+log\left(1-\left(D\left(G(b)\right)\right)\right)\right] \qquad (8)$$

where a is the real images that trained in the discriminator model D, b is the images that generated from the generative model GAN [27, 37].

3. Datasets preparation

The implementation of electronic recognition systems is generally depended on datasets. The main problem for banknotes recognition systems is there no dataset available to train and evaluate these systems. So, a first dataset of Libyan banknote images was initially created using traditional methods using five categories of Libyan banknotes. These categories are 1, 5, 10, 20 and 50 Libyan Dinars (LYD) as shown in Figure 2. This dataset is called Dataset$_1$. The five Libyan banknotes are scanned on their faces and the backs, yields ten color images. The characteristics of the scanned images are: resolutions are 200 dpi; the depth of images is 24-bit using HP scanner. The dataset$_1$ was finally created by adding noises to all scanned images. It contains 310 images, 62 images of faces and backs for each category. While, the second dataset was generated using the GAN system. This dataset is called Dataset$_2$. It contains 540 images, 108 images of faces and backs for each category; see Section 5. Finally, the third dataset was created by adding strange banknotes to the test set in Dataset$_2$. The following number of images (7, 6, 5, 4, 3) are added to the five categories respectively. Each dataset is divided into two divisions, one for training and the other for test. The number of images of the training sets for the three datasets are 225, 405 and 405; the test sets are 85, 135 and 135 respectively.

Figure 2. RGB Libyan banknote images

4. Proposed Systems

This article presents two systems: one based on the original banknote images only and apply the CNN for classification. This network architecture includes several convolutional layers, denoted by Convolution_1 to Convolution_n and fully-connected layer, as shown in Figure 3.c. 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. In the first convolutional layer, some filters are used to extract a number of features convolving the input image with a number of trainable filters. The input to this layer is a grayscale image. In the second or later convolutional layer, some filters are considered to extract a hierarchical feature map that convolving a feature map with a number of filters. The output of the convolutional layer is a feature map, its dimension is equal to the number of considered features. The ReLU layers are adopted in all convolutional layers, denoted by ReLU_1 to ReLU_n. Where, all neurons in the fully connected layer have full connections to all activations in the previous layer. The ReLU active function may improve the generalization, simplify the computation and decrease the training time of the deep network. The ReLUs activation are used to introduce nonlinearity between the feature maps. Where, the proposed learnable filter sizes are 11x11, 11x11, 5x5 and 3x3.The other system is designed based on GAN for generating more images. The features extraction and classification processes are automatically applied using the CNN. The two systems steps are illustrated in details in the following subsections respectively and are illustrated in Figure 3 (a, b, c).

4.1 The first system (SYS1)

This system is illustrated in the following steps:

1- Scan and store the banknote images.
   - Scan the banknote papers.
   - Classify the images into five categories, each category in a specific folder.
2- Load the dataset images of Libyan banknotes and label them.
3- Convert the images from RGB to gray scale.
4- Enhance the gray scale images by using histogram equalization.
5- Divide the dataset images into two groups, one for training and the other for test.
6- Store the training images in a cell array.
7- Design and apply the deep learning neural networks on the training group using various filters.
8- Apply the test (prediction) process, after the training process is correctly completed.
9- Compute the accuracy.
10- Stop.

4.2 The second system (SYS2

This system is described in the following steps:

1- Load all images of Dataset1 and label them according to their folder names.
2- Assign the number of images for each category.
3- Apply random horizontal reflection of all images.
4- Design a GAN to generate images having similar characteristics to the input real images of size 128x128.

5- Divide the second dataset (real and generated images) into two groups, one for training and the other for test.
6- Store the training images in a cell array.
7- Design and apply the deep learning neural networks on the training part using various filters.
8- After the training process is finished in corrected way, apply the test (prediction) process.
9- Compute the accuracy.
10- Stop.

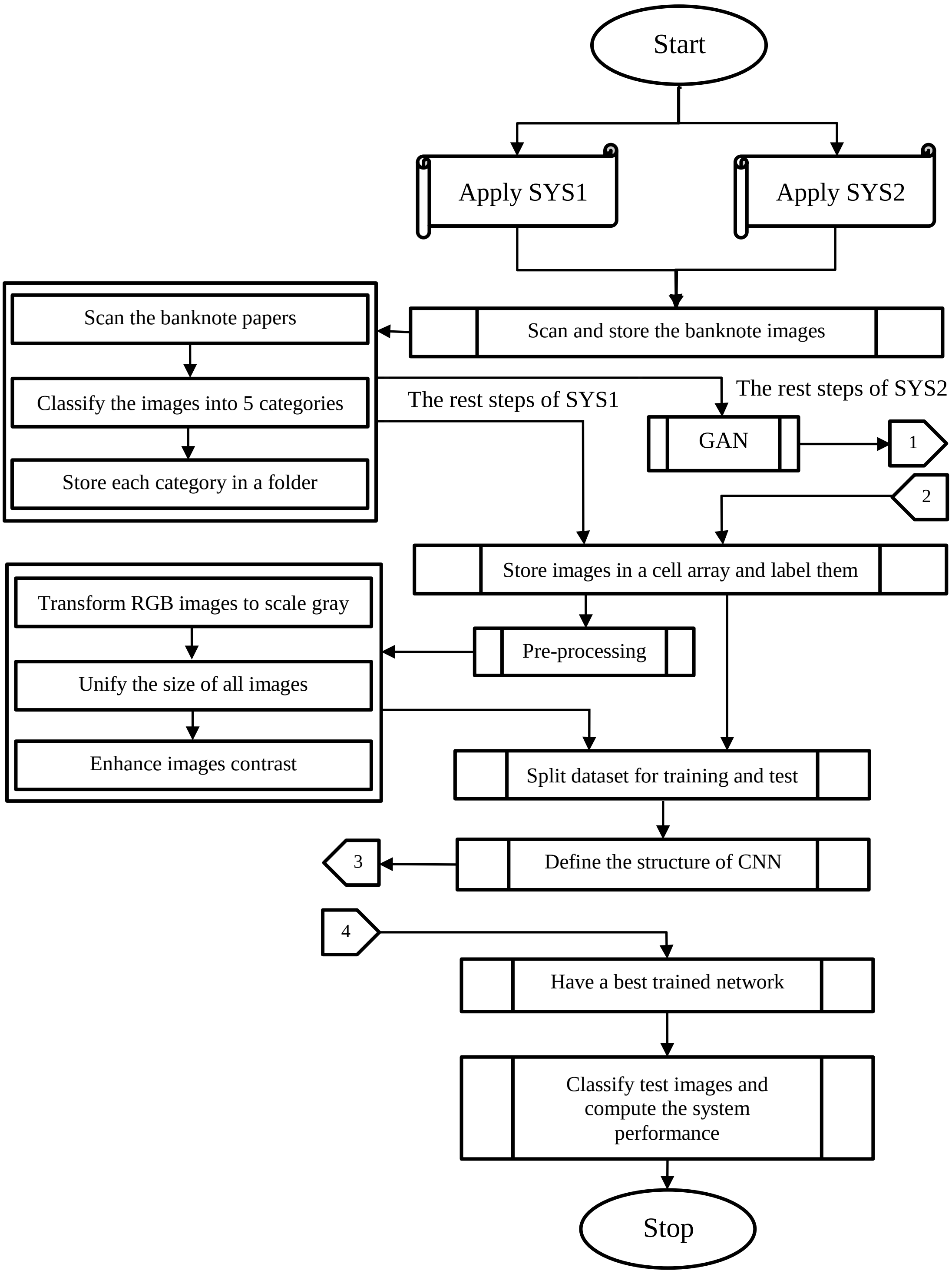


Figure 3(a). The detailed processes of the two systems.

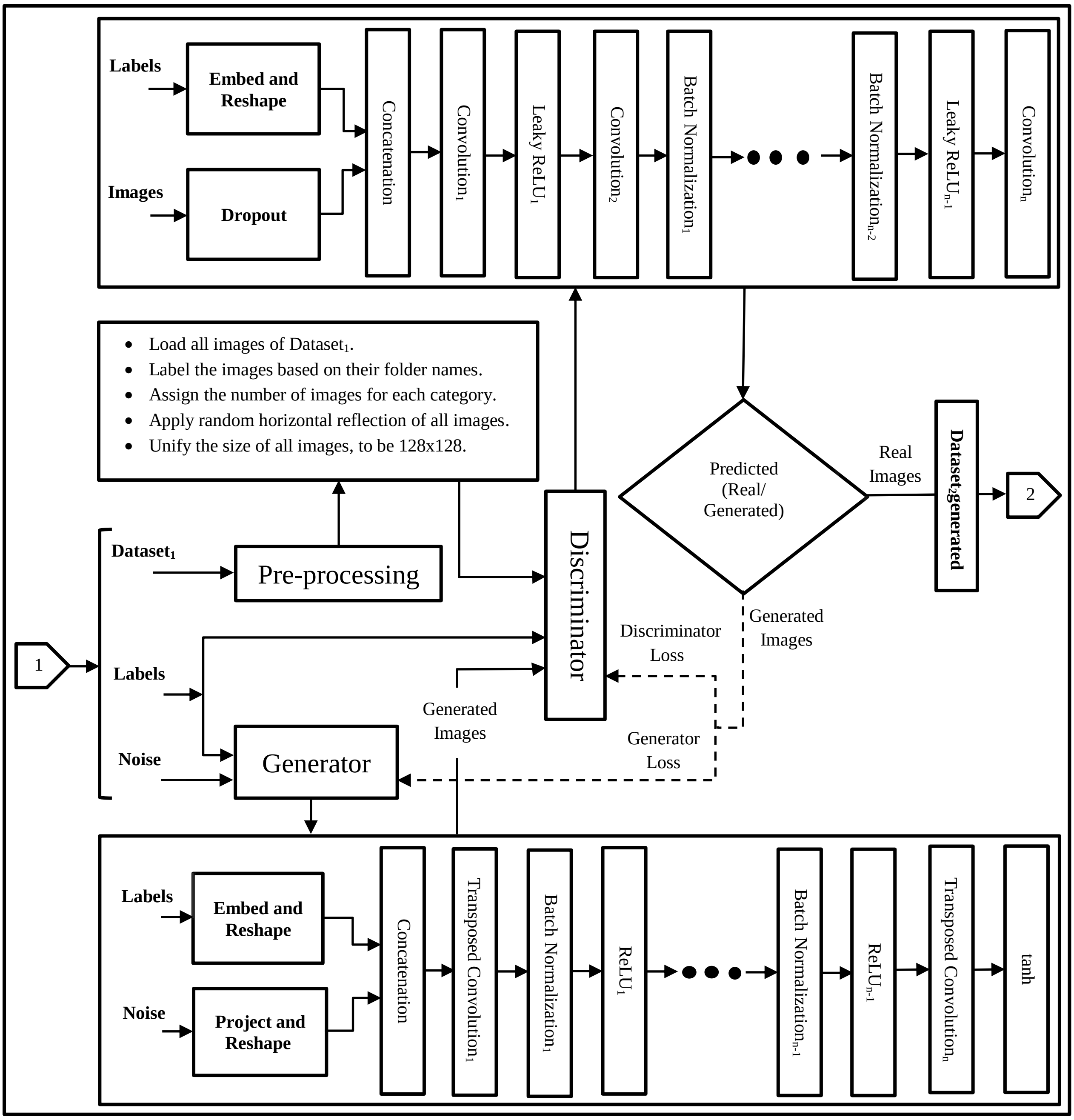


Figure 3(b). The structure of GAN.

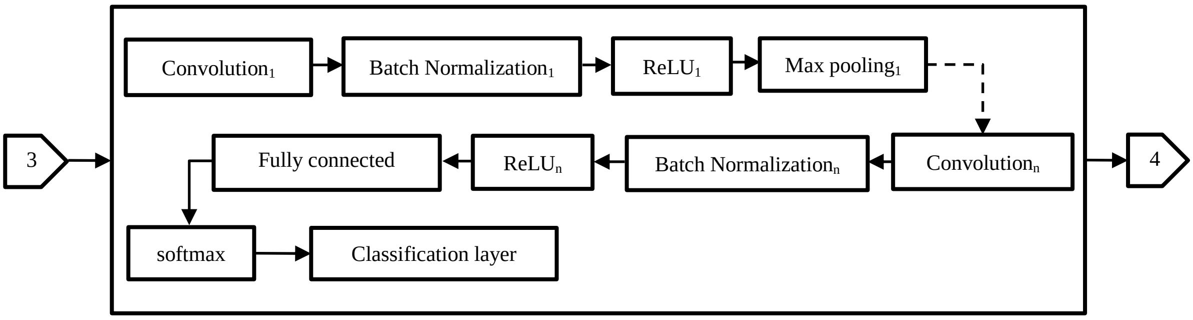


Figure 3(c). The structure of CNN

5. Results and discussion

The two proposed systems are applied on the three created datasets. These systems are performed using two Matlab programs. The $dataset_1$ was created containing 310 Libyan banknotes images of five categories. The first system has been applied and tested on this dataset. The obtained performance is ranged as average from 62.35% to 88.24%, see the confusion matrix in Figure 4. The training monitor progress is shown in Figure 5. While, the second dataset was generated during the implementation of the second system producing 540 Libyan banknotes images of five categories similar to the real images that are created in the $dataset_1$. The second system has been applied and tested on the $dataset_2$. Sample of the generated banknote images is shown in Figure 6. The obtained performance of the second system is ranged as average from 91.11% to 100%, see the confusion matrix in Figure 7. For studying the performance of the second system for detecting fake banknotes. This system is applied on the $dataset_3$ to detect counterfeiting. The obtained performance of the second system is as average from 99.26%, see details in the Table 1. It was found that the two systems obtained their performances using four numbers of convolutional layers; the structure of the trained convolution neural network is shown in Figure 8. In addition to, the used learned filter sizes were 11x11 in the first two convolutional layers, 5x5 in the third convolutional layer and 3x3 in the fourth convolutional layer.

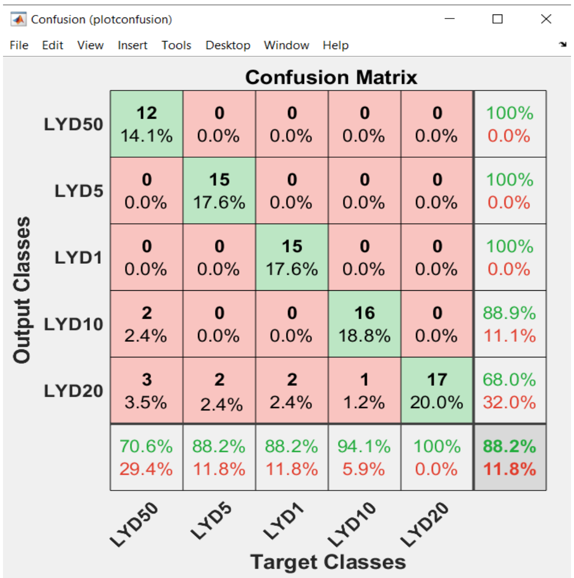


Figure 4. Confusion matrix of $Dataset_1$

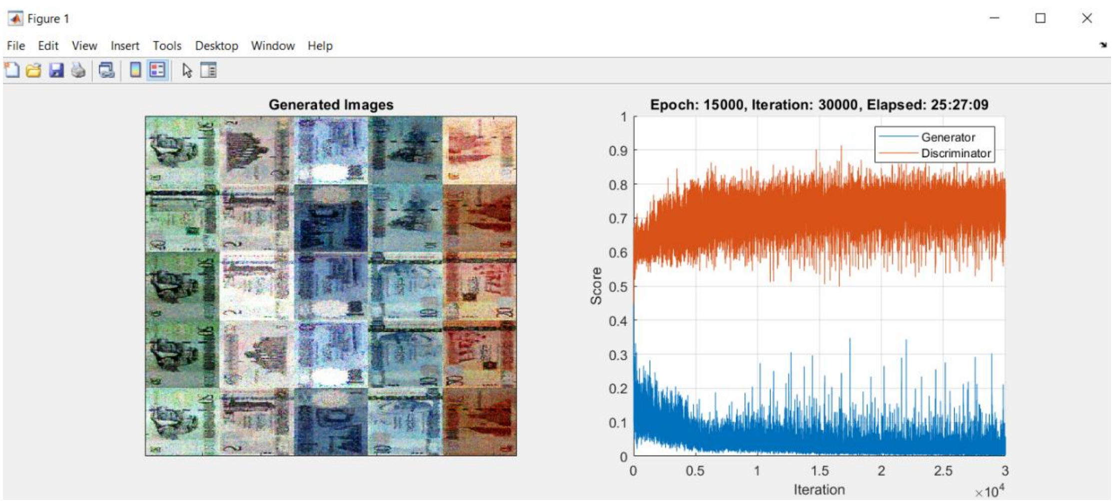


Figure 5. Training monitor progress

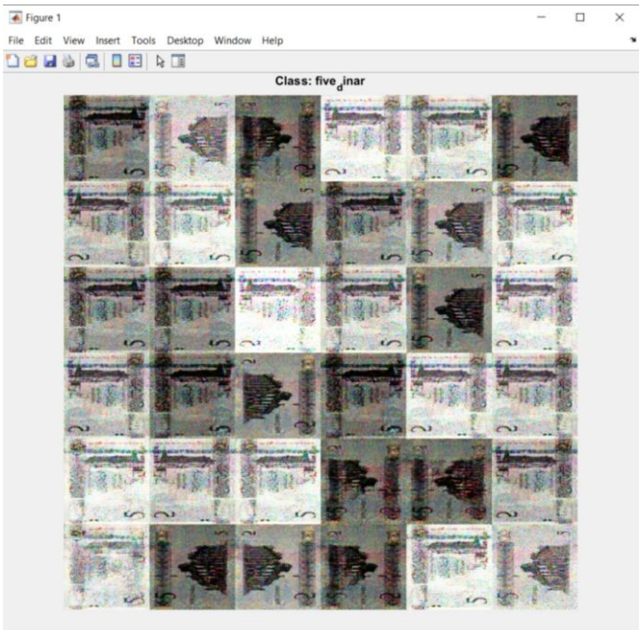


Figure 6. Generated banknote images by GAN

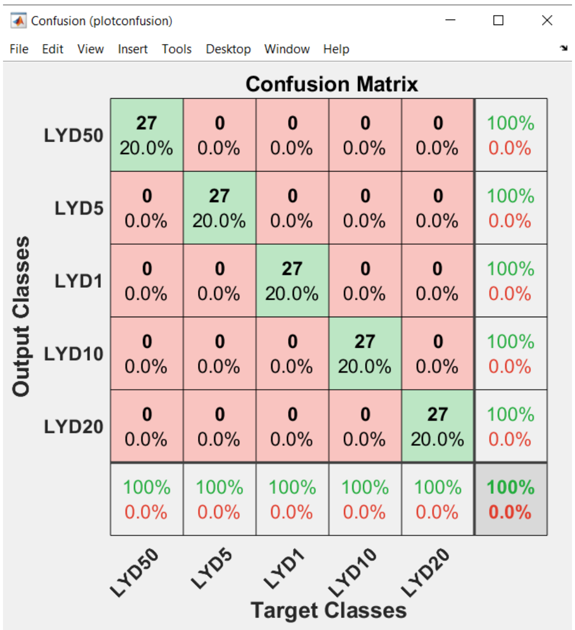
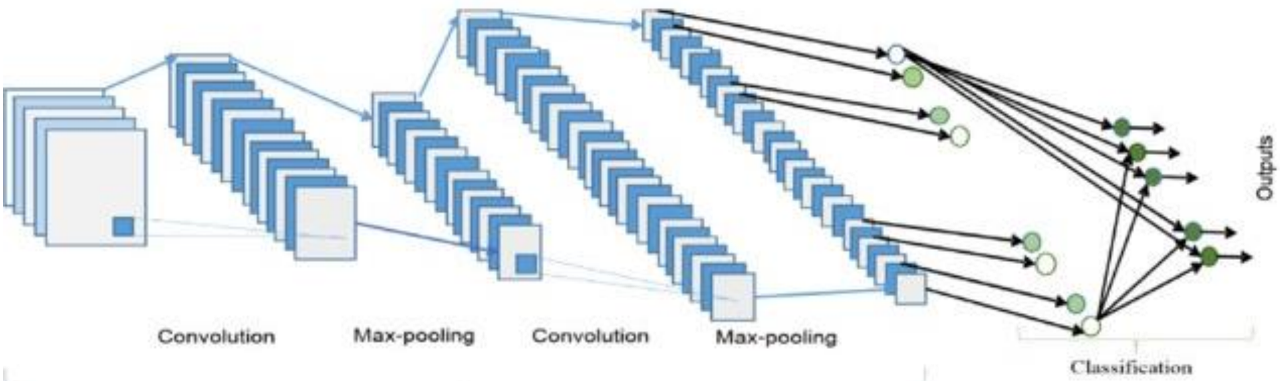


Figure 7. Confusion matrix of $Dataset_2$

Table 1. Obtained performance of the second system on $Dataset_3$

Category	No. of images $Dataset_3$		Correctly recognize as real banknote	Correctly recognize as fake banknote	Accuracy in %
	Training	Test			
1 Dinar	81	20+7	21	6	96.3
5 Dinar	81	21+6	21	6	100
10 Dinar	81	22+5	22	5	100
20 Dinar	81	23+4	23	4	100
50 Dinar	81	24+3	24	3	100
A total average accuracy of					**99.26**



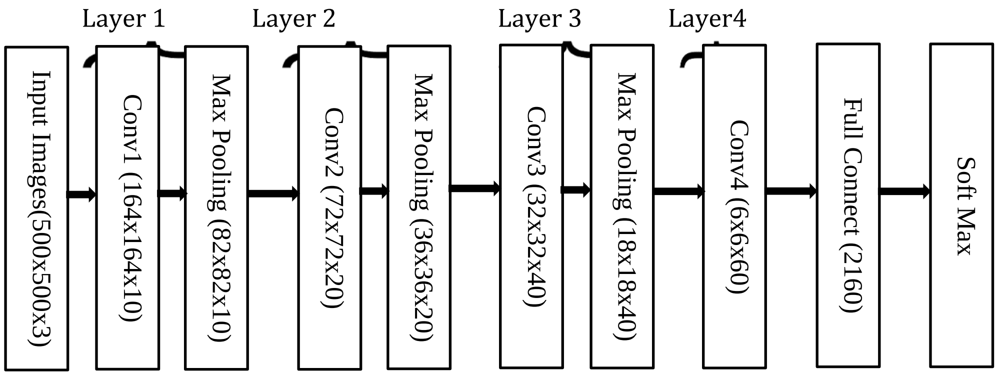


Figure 8. The structure of the trained convolution neural network

6. Conclusion

The two proposed systems are applied using different number of convolutional layers and their optimal parameter until a better result was obtained. From the experimental results of the first system, better results were obtained at CNN architecture using four numbers of convolutional layers, ReLU, dropout, and batch normalization techniques. Where the used learned filter sizes were 11x11, 11x11, 5x5 and 3x3. This system is working in effective to recognize the Libyan banknote categories. While, the second system was designed to generate images having the same features of real Libyan banknotes. This system was generated the $dataset_2$ and was correctly classified the test division of the $Dataset_2$ as real banknote images. In order to ensure the efficiency of the second system for recognizing fake banknotes, some strange banknote images were added to test division of the $Dataset_3$. It was found that this system was correctly classified all real and strange images, except one image from the strange images was misclassified. This system is powerful, it can detect counterfeiting with high accuracy.

7. Future work

In this work, experiments were presented that demonstrate the importance of training GAN in the process of generating the Libyan banknote and the importance of CNN used in the process of GAN and classification. Where the results show the capabilities of GAN in recognition of the Libyan banknote with the generation of increasing the images for the available real training images, as it achieved an amazing result in the classification process in the least possible time than the previous recognition systems.

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