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Pakistani Currency Recognition to Assist Blind Person Based on Convolutional Neural Network

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ABSTRACT

A visually impaired person faces many difficulties in their daily life, such as having trouble finding their ways, or recognizing the person and objects. One of the crucial problems is to recognize the currencies for a blind or visually impaired person. In this research article, we have proposed a system to recognize a Pakistani currency for a blind or visually impaired person based on Convolutional Neural Network (CNN) and Support Vector Machine (SVM). In the proposed system, seven different Pakistani paper currency notes (Rs.10, 20, 50, 100,500, 1000 and 5000) are used for training and testing. Experimental results show that the proposed system can recognize seven notes of Pakistan's Currency (Rs. 10, 20, 50, 100, 500, 1000, 5000) successfully with an accuracy of 96.85%.

1. Introduction

Meanwhile, technology is growing fast day-by-day. Through the use of technology, people solve their problems in the small passage of time. Modern automation systems in the real world require a system for currency recognition. There is some possible application which is used in real life such as currency counting machine, currency monitoring systems, currency exchange machine, currency recognition system to assist for a visually impaired person. Vision not only helps us to perform daily activities but also affects the behavior of the person. Blindness affects the psychological behavior of a human being; a person has impaired vision or a person with normal vision likely having less depression than a blind person.

They have a lack of social relationships and also more likely to suffer from anxiety. One of the main problems for blind people is to recognize the real-world object around them. The human can detect and recognize objects, then they meet their need for security and can trust their environment. For blind or visually impaired persons, one of the major problems is to recognize the banknote. A normal person can easily identify the Currency value, but for a blind person or visually impaired person, it's a difficult task to recognize currency accurately. Blind and visually impaired persons need to recognize the currency also differentiates between the currencies.

According to the World Health Organization (WHO), approximately 2.2 billion people suffer from vision impairment problems.188.5 million people have a mild vision impairment, 826 million people have near vision impairment. In comparison, 217 million people have moderate to serve vision impairment, and 36 million people are blind, the majority of people who has a visually impaired problem over 50 years of age. The main cause of visual impairment is uncorrected refractive errors, cataract, age-related macular degeneration, glaucoma, diabetic retinopathy, corneal opacity, and trachoma (Ali & Manzoor).

Many people used a different kind of technique for currency recognition, such as textures, sizes, and color of a currency note. Today's computational power and availability of the camera make it easy for us to build an efficient system that recognizes the Pakistani currencies. There are seven denominations of Pakistan's currency, which differ in size and color. The proposed method can recognize the different Pakistani currency [10, 20, 50, 100, 500, 1000, and 5000], which convert the output into the voice of the currency type to blind or visually impaired person.

2. Literature Review

(Doush, Sahar, & Sciences, 2017) design a smartphone currency recognition system for Jordanian currencies. The Jordanian currency dataset has been used for currency recognition based on the SIFT algorithm. The currency paper and coin are recognized with the help of a smartphone by using (SIFT) algorithm. The color feature is extracted from the currencies, which help the matching task and object description process. Comparing both color SIFT and Grey SIFT for currency recognition, where color scale-invariant features provide better accuracy then (grey SIFT). The accuracy of the proposed system achieved 71% for paper currency.

Yousry, Taha, & Selim (2018) Proposed a Currency Recognition System based on Oriented FAST and rotated BRIEF (ORB) algorithm. The Artificial Neural Network is used to classify the four different country's currencies. The preprocessing techniques are performed on Currency paper, from the background of input images to extract the ROI. The ORB algorithm has been used for extracted features from the currency notes. Finally, the Hamming Distance is used for matching the binary descriptors, which is obtained from feature extraction. The experimental result shows that the system achieves an accuracy rate of 96% with a running time of 0.682s.

(Jyothi, SundaraKrishna, & SrinivasaRao, 2016) designed a system to recognize the United Kingdom ("Pound"), Japan ("yen"), and European ("euro") country currencies. During the designing of currency, every currency has different dimensions, Color luminance, Edge histogram. The max Sobel gradient, correlations have been used for feature extraction. The radial basis Function networks are utilized for developing an intelligent system that can recognize the paper currency.

Ali and Manzoor (2013) aims to build an intelligent system for Pakistani currencies note which recognize the currencies precisely. They take five different currencies notes (Rs 10, 50, 100, 500, 100). They scan 100 images of Pakistani Currencies; 20 images of each class pass for feature extraction by using the proposed system. If the image matched with the features which are presented in a MAT-file, it returns the class name to recognize the Pakistani currency accurately. Experimental results show that the proposed system classified the Pakistani Currency Accurately.

(Semary, Fadl, Essa, & Gad, 2015) propose a system for the Egyptian Currency Note recognition. The system is based on the image processing utilities that ensure performing the process as speedy and robust. The system is used the basic image processing technique such as segmentation foreground, histogram enhancement, and region of interest (ROI) algorithm and finally matched the captured image taken from the camera with the dataset. The experimental result shows that the proposed system recognizes the Egyptian currencies with high accuracy of 86% and a short time.

Dunai Dunai, Chillarón Pérez, Peris-Fajarnés, & Lengua Lengua (2017) aim to develop a portable system for a blind person to recognize the euro banknote currency for a blind or visually impaired person. The proposed system is based on the electronic device Raspberry Pi and the Raspberry Pi camera, PINoIR (no infrared filter); these instruments are fixed into the pair glasses which allow the blind and visually impaired person to recognize the Euro banknote currency, especially when currency is given or taken from someone. The system detects the euro currency by using the modified Viola-Jones algorithm, and the recognition of the euro banknote is based on the speed-up robust feature (SURF) technique. Accuracy of the banknote detection is 86%.

(García-Lamont, Cervantes, & López, 2012) aims to introduce the recognition method of Mexican currency paper by using computer vision. The Mexican banknote is based on color and texture feature technique, with the RGB space and Local binary pattern (LBP). The classification technique is applied to Mexican banknotes, which shows the accuracy is low.

(Youn, Choi, Baek, & Lee, 2015) Currency is different from each other such as size or color that provides essential information in their recognition. The proposed system used a fast and efficient algorithm to recognize the multi-national currency note images. The algorithm is tested on 55 currencies of 30 individual classes, which belong to 5 countries EUR, KRW, RUB, CNY, and USD. The experimental results of the proposed system perform well in accuracy for typical banknotes and spiled banknotes (Youn, Choi, Baek, & Lee, 2015).

Guo, Zhao, and Cai (2010) used upgraded Local Binary Pattern (LBP) known as the block Local Binary Pattern (block LBP) algorithm. The problem in LBP was unable to extract high-quality features from currency paper. The proposed system was uncomplicated and fast. The experimental result from the upgrade technique shows a high accuracy rate from 92% (Yousry, Taha & Selim, 2018).

3. Methodology

The proposed system is a real-world application that recognizes the Pakistani currency for a blind and visually impaired person in real-time based on deep Neural networks using Alex-Net architecture. The pre-trained Alex-Net architecture is used as a feature descriptor to extract deep features from images. The input images are passed to the Alex-net Model, which has 227 x 227 x 3 dimension, defined by the first layer of Alex-Net. The intermediate five layers are the sequence convolution and three are dense layers. In this proposed system, we train our model using the pre-train Alex-Net model on Pakistani Currencies having six different classes.

3.1 CNN features

Deep learning CNN (Convolutional Neural Network) is a powerful learning technique. CNN's, like neural networks, are made up of neurons with learnable weights and biases. Each neuron receives several inputs, takes a weighted sum over them, passes it through an activation function and responds with an output. CNN is a convolutional neural network that contains multiple convolutions, regularization, downsampling and fully connected layers. There are different CNN models, each with different architecture. CNN extracts the deep semantic feature from the image data, which classifies and detects image data more precisely. In our proposed method, the Alex Net model has been suggested as a feature descriptor.

3.1.1 Alex-Net Architecture

Alex-Net is a type convolutional neural network designed to extract deep feature for image data for classification of complex images which cannot classify with simple handcrafted features. The network had a very similar architecture as LeNet. It consisted of 11x11, 5x5,3x3, convolutions, max pooling, dropout, data augmentation, ReLU activations, SGD with momentum. Alex Net applies a different mathematical operation on input image such as convolution, pooling. Alex Net regularization has three-down samplings, five convolutional and three fully connected layers. To remove non-linearity from the feature maps, Alex-Net uses a rectified linear unit called ReLU, which performs regularization to regularize the value of feature maps after applying convolution. To reduce the dimensionality and remove scarcity, a dropout layer is placed after a fully connected layer before sending it to the last fully connected layer fc8. Alex-Net Architecture is discussed detail in below:

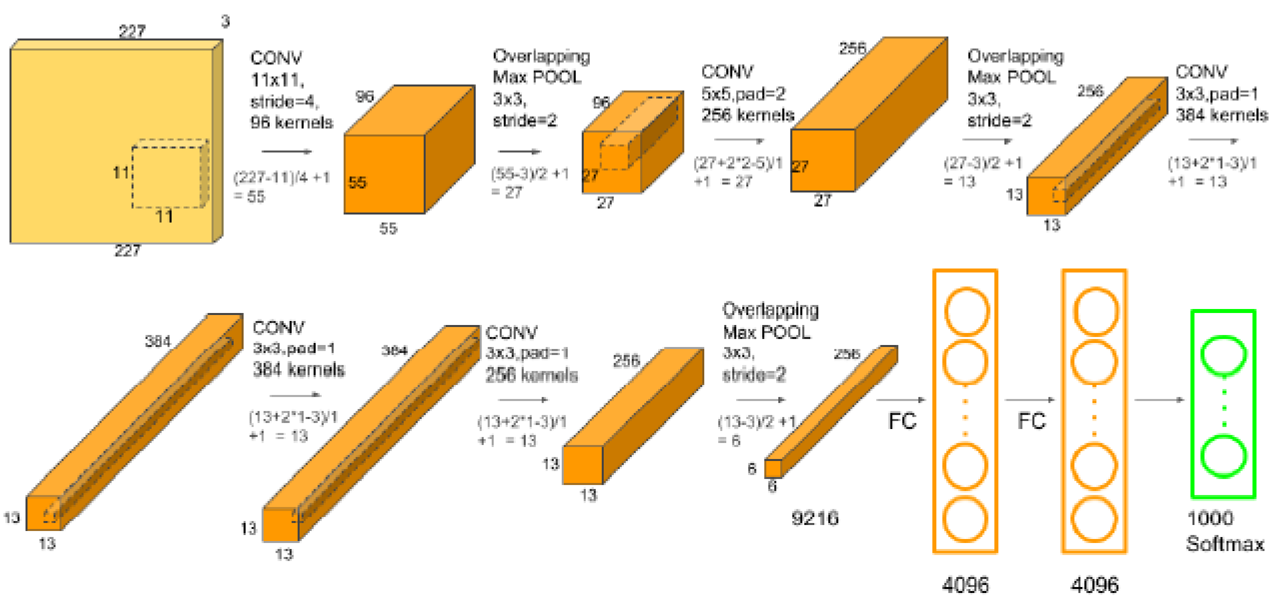

Fig. 1. Alex-Net Architecture

3.1.2 Proposed Framework

The main idea of this work is to input video from the camera. If there is a currency in the input video, the proposed system recognizes it belongs to a class.

There are seven classes:

1. Note-10
2. Note-20

3. Note-50
4. Note-100
5. Note-500
6. Note-1000
7. Note-5000

First, the preprocessing steps apply to datasets, such as rotation, scaling, addition, and blur. In the next step, the augmented data is used for our proposed CNN pre-trained Alex-Net model, which extracts deep features from the last fully connected layer fc8, which is 1000 dimensional.

Finally, the model is trained on a pre-train Alex-Net architecture through which the recognition of the currency takes place. The input from the camera and video streaming extract the frames. Then each frame extract from a video uses to train the model and classifies the currency that belongs to exactly which class.
The framework of the proposed system is discussed in detail below:

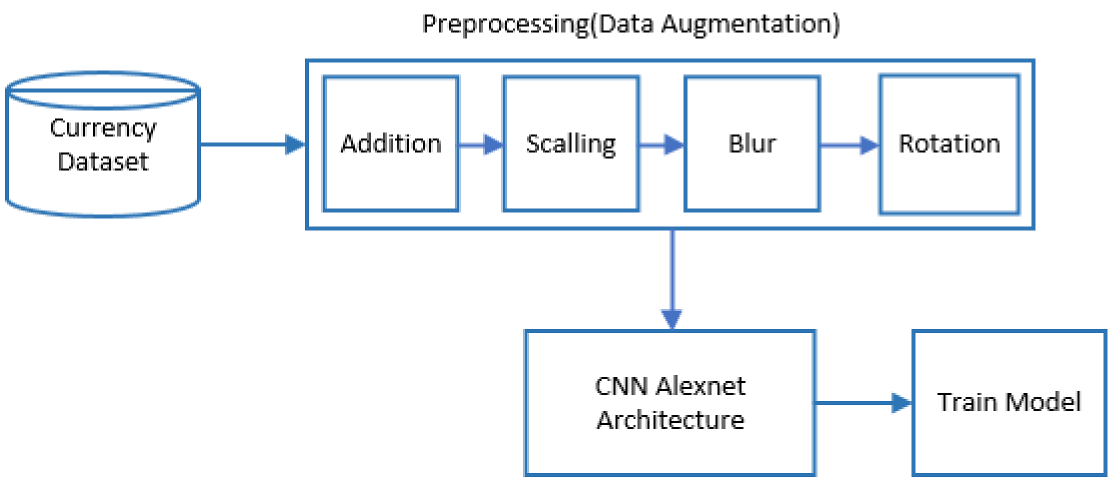

Fig. 2. Training Framework

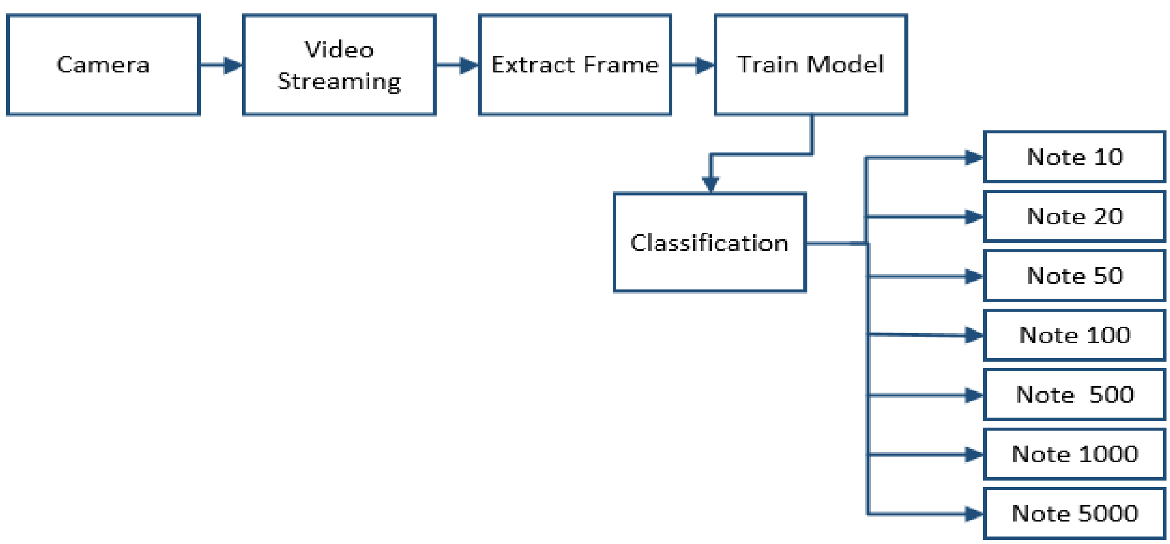

Fig. 3. Classification Framework

3.1.3 Support Vector Machine (SVM)
SVM is a supervised machine learning algorithm that draws the line between different classes and defines their boundaries by differentiating the classes between different categories. The hyperplane is used to separate the two classes.

3.1.4 Histogram of Oriented Gradients (HOG)
HOG is a feature descriptor technique that is used to extract the discriminant feature from the currency image for the classification.

4. Results and Discussion
4.1 Dataset Description
The datasets that have been created so far are the Pakistani Note Currencies [Note 10, 20, 50,100, 500, 1000, and 5000].

Fig. 4. Dataset

4.2 Data splitting
We design our local dataset by collecting different images of Pakistani currency's notes and perform Data Augmentation on images. As we know, this is the primary rule of deep learning to separate the data into two parts training and cross-validation because during the training phase model is check to wither it's going right on the dataset or not. We categorize our original dataset into two subparts training part and cross-validation part:

Table 1: Dataset Description

No	Class	Total images	Training	Cross Validation
1	Note-10	22,069	16551	5517
2	Note-20	22,069	16551	5517
3	Note-50	22,069	16551	5517
4	Note-100	22,069	16551	5517
5	Note-500	22,069	16551	5517
6	Note-1000	22,069	16551	5517
7	Note-5000	22,069	16551	5517
Total		**154483**	**115857 (75%)**	**38619 (25%)**

4.3 Model Training

The proposed system model is trained on the pre-train coffee Alex-Net model, which has the best validation accuracy. The validation accuracy of the model during training is 99.9614% and has a loss validation of 0.0013%. As shown in the below graph.

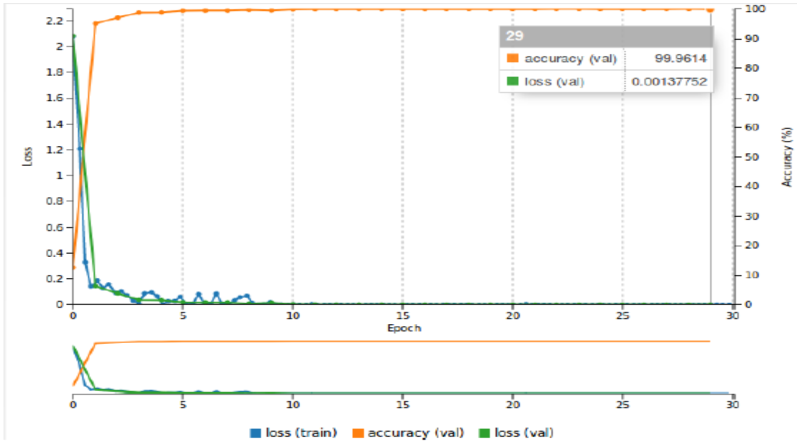

Fig. 5. Loss and Cross-Validation Accuracy

4.4 Experimental setup

The platform used for testing of the proposed method is CONVNE using python (Geany 1.33) running over own laptop machine supporting an Intel(R) Core(TM) i5-4200 M fourth-generation processor is clocked at 2.50GHz, with Windows-10 64 bit-version operating system.

4.5 Experimental Result

The experimental results are evolved by classifying the test data on our proposed method. There are seven different categories of test images. Each category contains 100 images, which is classified by our suggested technique as below.

Table 2: Accuracy of each category

Category	Accuracy
Note-10	97%
Note-20	96%
Note-50	97%
Note-100	100%
Note-500	95%
Note-1000	94%
Note-5000	99%

4.6 Overall Accuracy

To compute the overall accuracy of over proposed system, we calculate the different measurement factor of accuracy first we calculate the accuracy of each class in next step we sum up all these accuracies and then divided the sum up accuracy by total classes, so we get the overall accuracy of our proposed system.

$$\text{Overall accuracy} = \frac{\text{Summation of all Categories Accuracy}}{\text{Total Classes}}$$

Table 3: Overall Accuracy of Proposed System

Category	Accuracy
Note-10	97%
Note-20	96%
Note-50	97%
Note-100	100%
Note-500	95%
Note-1000	94%
Note-5000	99%
Overall Accuracy	96.85%

4.7 Over All Accuracy on SVM (Pakistani Coins)

The proposed system has also been performing by using SVM to recognize the Pakistani Currencies Notes and coins. The highest accuracy of this proposed system used as a baseline for recognition of Pakistani coins is 76.19%.

Table 4: Overall Accuracy of Notes (SVM)

HOG Parameters			SVM Parameters		
Window Size	Block Size	Cell Size	Gamma	Cost	Accuracy
128,128	16,16	8,8	0.1	100	74
128, 128	16,16	8,8	1	100	0.3968
128, 128	16,16	8,8	0.001	100	0.7619
128,128	16,16	8,8	0.001	10	0.70
128,128	16,16	8,8	0.001	1	0.6150
128,128	16,16	8,8	0.1	1	0.7103
128,128	16,16	8,8	1	1	0.3888
128,128	16,16	8,8	12.5	12.5	0.3253
128,128	16,16	4,4	0.001	100	0.7539
128,128	32,32	4,4	0.001	100	0.7460
128,128	32,32	8,8	0.001	100	0.75
128,128	32,32	16,16	0.001	100	0.75
64,128	16,16	8,8	0.001	100	0.6785
64,64	16,16	8,8	0.001	100	0.6190
64,64	16,16	8,8	0.1	100	0.6626
64,64	16,16	8,8	1	100	0.6706
64,64	16,16	8,8	1	10	0.6626
64,64	16,16	8,8	0.1	0.01	0.4722

4.8 Over All Accuracy on SVM (Pakistani Note)

The highest accuracy of this proposed system used as a baseline for recognition of Pakistani Currencies Note is 82.04%.

Table 5: Overall Accuracy of Coins(SVM)

HOG Parameters			SVM Parameters		
Window Size	**Block Size**	**Cell Size**	**Gamma**	**Cost**	**Accuracy**
128,128	16,16	8,8	0.1	100	0.8142
128,128	16,16	8,8	0.01	100	0.8204
128,128	16,16	8,8	0.001	100	0.7889
128,128	16,16	8,8	0.001	10	0.7224
128,128	16,16	8,8	1	100	0.31454
128,128	16,16	8,8	0.125	1	0.76048
128,128	16,16	8,8	0.125	0.125	0.45052
64,64	16,16	8,8	0.01	100	0.58748
64,64	16,16	8,8	0.001	100	0.74541
64,64	16,16	8,8	0.001	10	0.47673
64,64	16,16	8,8	1	10	0.48820
64,64	16,16	4,4	0.001	100	0.61009
64,64	32,32	4,4	0.001	100	0.53538
64,64	32,32	16,16	0.001	100	0.48099
64,64	16,16	8,8	0.125	1	0.74049
64,64	16,16	8,8	0.125	0.125	0.50131
64,64	16,16	8,8	0.1	10	0.77064
64,64	16,16	8,8	12.5	12.5	0.30504

5. Conclusion and Future work

In this study, we presented a novel method for the recognition of Pakistani Currencies Note. The features from images are extracted using a deep convolution neural network. This structure consists of two steps: in the first step, we train our model by using a pre-train Alex-Net architecture. In a second phase, we use the webcam, which performs video streaming and from that video streaming, we extract the frames and pass our model to train on the pre-train Alex-Net architecture, which recognizes the currency with the accuracy of 96.85%. As the proposed technique more efficiently and effectively recognize the Pakistani Currencies Note, so the proposed framework can be further extendable for future work in this particular area. More advancement in the current framework would the more efficient in recognizing even complex Pakistani Currencies Note.

References

[1] Ali, A., & Manzoor, M. J. W. A. S. J. (2013). Recognition system for Pakistani paper currency. *28*(12), 2069-2075.

[2] Doush, I. A., Sahar, A.-B. J. J. o. K. S. U.-C., & Sciences, I. (2017). Currency recognition using a smartphone: Comparison between color SIFT and gray scale SIFT algorithms. *29*(4), 484-492.

[3] Dunai Dunai, L., Chillarón Pérez, M., Peris-Fajarnés, G., & Lengua Lengua, I. J. S. (2017). Euro banknote recognition system for blind people. *17*(1), 184.

[4] García-Lamont, F., Cervantes, J., & López, A. J. E. S. w. A. (2012). Recognition of Mexican banknotes via their color and texture features. *39*(10), 9651-9660.

[5] Guo, J., Zhao, Y., & Cai, A. (2010). *A reliable method for paper currency recognition based on LBP.* Paper presented at the 2010 2nd IEEE InternationalConference on Network Infrastructure and Digital Content.

[6] Jyothi, C. R., SundaraKrishna, Y., & SrinivasaRao, V. (2016). *Paper currency recognition for color images based on Artificial Neural Network.* Paper presented at the 2016 International Conference on Electrical, Electronics, and Optimization Techniques (ICEEOT).

[7] Semary, N. A., Fadl, S. M., Essa, M. S., & Gad, A. F. (2015). *Currency recognition system for visually impaired: Egyptian banknote as a study case.* Paper presented at the 2015 5th International Conference on Information & Communication Technology and Accessibility (ICTA).

[8] Youn, S., Choi, E., Baek, Y., & Lee, C. J. N. (2015). Efficient multi-currency classification of CIS banknotes. *156*, 22-32.

[9] Yousry, A., Taha, M., & Selim, M. M. J. I. A. J. e. T. (2018). Currency Recognition System for Blind people using ORB Algorithm. *5*(1), 34-40.