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Banknotes Counterfeit Detection Using Deep Transfer Learning Approach

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ABSTRACT

Financial institutions in Bosnia and Herzegovina have adopted and implemented various security measures in preventing production of counterfeited banknotes as well as security measures in detecting counterfeited banknotes. Despite that, there are still many cases of money counterfeiting being reported in this specific country. This happen due to various reasons for instance not thorough attention given to the appearance of the banknote during money transactions. Based on 2017 and 2018 annual report by the Central Bank of Bosnia and Herzegovina, there were 691 and 535 registered cases of banknotes counterfeiting for the convertible mark (KM). The most denomination's banknotes as counterfeited were 100 KM followed by 20 KM and 50 KM. Hence this study proposed deep learning technique in detecting the counterfeited BAM banknotes utilizing CNN models. Initially results showed that the proposed method could be used for counterfeit money detection with 99.88% using VGG16 as the highest accuracy.

Key words: Deep Transfer Learning, AlexNet, GoogLeNet, VGG16, Banknotes, Counterfeit

1. INTRODUCTION

With the tremendous technological development, the society are facing immense amount of counterfeit money that varies due to low-quality printer-based to high quality banknotes. Despite the widespread online as well as electronics payments, utilizing banknotes still remain essential for most people. Aditionally, electronic payments concept in the context of fighting against money counterfeiting is indeed a major role since the payments are much safer since governments are able to control the origin of the money [1]. Considering this issue, it is vital to efficiently and correctly detect and distinguish counterfeit banknotes from the genuine notes. As we know, manual detection is time-consuming, slow and inefficient as compared to automatic techniques. With the current printing technology, even for aesthetic of home purposes are so advanced that the quality of pictures are astonishing with details in the images which may not be seen by the human eyes. Although Ultraviolet (UV) recognition technology is already in existence, however with the development of counterfeiting technology, this technology is insufficient in identifying counterfeit currency notes, thus more advanced deception techniques are required [2]. Note that the aim of each counterfeit detection method is to recognize bank notes correctly from both sides by inspecting the color, design features and specific data of currency. Thus, there is plenty of specific identification methods based on image recognition for data argumentation [2], [3], [4].

On the other hand, the official monetary unit of Bosnia and Herzegovina is ‘Convertible Mark’ (KM). One Bosnia and Herzegovina convertible mark (BAM) is divided into 100 fenings. The denominations of banknotes in usage are 10 KM, 20 KM, 50 KM and 200 KM, besides the coins of 0.05, 0.10, 0.20, 0.50, 1, 2, and 5 KM. Financial institutions in Bosnia and Herzegovina have adopted and implemented various security measures to prevent counterfeited banknotes production. Further, based on the Annual Report by the Central Bank of Bosnia and Herzegovina (CBBH), in 1998 there were no counterfeits detected but in 1999 there were 142,485 counterfeited BAM banknotes found. In the year of 2000, there were 230,204 counterfeits detected (Central Bank of Bosnia and Herzegovina) [5]. According to the annual report in year 2017, 691 registered as counterfeited banknotes of the convertible mark (KM) (Central Bank of Bosnia and Herzegovina) [6]. In 2018, there were 535 registered as counterfeits of the Convertible Mark by the Central Bank of Bosnia and Herzegovina. By the denomination's structure, the most banknotes that were detected as counterfeited were denominations of 100 KM with 214 pieces, followed by 20 KM with 149 pieces and 50 KM with 138 pieces. The rest of the detections were in the coin KM counterfeits [7]. Conversely, in 2017 the CBBH registered 2994 counterfeited banknotes and coins [6], out of which there were 2303 coins or 77% and the balance is 691 banknotes specifically 23%. Coins held an approximate market value of 3,000 BAM while banknotes with approximate value of more than 30,000 BAM therefore this study focused on banknotes due to the significant difference in values of banknotes versus coins.

Therefore this study examines the problem of counterfeit banknotes in Bosnia and Herzegovina using Deep learning technique namely Convolutional Neural Networks (CNN) model. Deep Learning method is proven to be highly efficient in solving practical problems, where the level of complexity and layers becomes simpler as the number of data increases. This makes deep learning is being used widely as one of the mainstreaming technology in computing. Further, this study will elaborate the deep transfer learning models for predicting the genuineness of the banknotes. The purpose is to develop an efficient and accurate method for checking the genuineness of the banknotes via fine- tuning the pre-trained Convolutional Neural Networks (CNN) and comparing the obtained results with the given conditions.

2. LITERATURE REVIEW

Numerous work have been done in the area of automatic fake banknote detection and recognition that have proposed various methods in improving the recognition process as well as reducing the time of detection. As reported in [8] and [9], statistical approach is utilized by computing the mean, variance, and Pearson correlation coefficients. Eleven features are incorporated by different countries to prevent the usage of spurious banknotes. Eleven different world's currencies were tested and analyzed in identifying the significant features to improve the most optimum process in counterfeit detection. In addition, findings by [10], [11] and [12] applied Neural Networks (NN) for suspected banknote classification. The authors of [15] presented a review on currency recognition and classification techniques.

Some of the proposed method were able to recognize rapidly and precisely even the old and dirty banknotes amongst the original and not counterfeit. Counterfeit banknote recognition via NN began by converting the image of the note into gray scale followed by image compression. Then, this image served as inputs to the ensemble NN for classification of the banknotes. Combined Artificial Neural Network (ANN), Gene Algorithm (GA) and some other well known machine learning approach were used in image processing as reported by [13], [14], [27] & [28] resulting in short training time and high recognition speed. Here, eight features were tested and recognized successfully.

As reported in [16], a texture-based recognition technique was developed by three different approaches namely statistical, structural, and spectral. Some of the texture features considered were Tamura features, Multi Resolution Simultaneous Auto Regressive (MRSAR), edge histogram, Gabor texture feature, pyramid-structured and tree-structured wavelet transform. In this research, the focused was on spurious coins and 94% accuracy attained based on the proposed methodology. Even higher accuracy was achieved using pattern-based recognition techniques as reported in [17], [18] & [19] resulting in 100% and 97% accuracy rates. Many authors proposed their methods based on image processing namely histogram [20]. Recall that histogram described the global color distribution in the image, by counting the number of pixels of each color [15]. The scanned image is usually processed by resizing and converting the image into gray scale followed by comparing the image to the normalized histogram of counterfeit banknote. Consequently, histogram is further used in Neuro-Fuzzy based (Adaptive Neuro-Fuzzy Inference System) counterfeit detection techniques as described in [21].

On the other hand, detection via digital image processing has been widely used. As discussed and reported in [22] and [23], bit-plane slicing technique is utilized for counterfeit currency detection [22]. After that ,the image is decomposed into grayscale with higher order bit levels were evaluated using Canny edge detection and higher improvement in CPU time performance is recorded as compared to work done by [24] where the Canny edge detector was applied too on the original image rather it is sliced. Further, in [25], application of image processing that include feature extraction, HSV color space using MATLAB was done for fake currency note detection technique.

3. METHODOLOGY

This section will discussed in detail the proposed method developed for this research.

3.1 Dataset Acquisition

The very first step in currency recognition through image processing is database or dataset acquisition. Hence in this research, 189 genuine banknotes are collected whilst 173 as counterfeited banknotes as dataset based on Table 1 below:

Table 1: Category of Banknotes as Database

Currency Type	Genuine	Counterfeited
10 BAM	26	23
20 BAM	32	31
50 BAM	67	70
100 BAM	64	49

All raw data was extracted from genuine BAM banknote images. The images were captured using Samsung's Galaxy S7 Duos SM-G930FD mobile phone primary camera with 12 MP, f/1.7 and 26mm lens (GSM arena). The raw banknotes database are collected by capturing the image of the banknote in controlled environment specifically approximately 20 centimeters vertical distance from the target object. Next, external lightning device was used. Some sample of raw images of BAM banknote are as shown in

Error! Reference source not found.1 for both fake and genuine banknote.

3.2 Data Augmentation

Due to the fact that counterfeit money is recognized in a variety of conditions, this research aims to train the neural network model to deliver the best accuracy in counterfeited banknote detection. Data augmentation could inflate the dataset with various transformations and invariant instances that further increase the accuracy of the model. Thus, this research utilized data augmentation through both traditional and automated methods. The traditional approach implies five different modifications via Adobe Photoshop "Patch" tool specifically removing the left and right side of the banknote, removing the symbols of the banknote, removing the upper and lower part of the banknote as well as rotating the banknote by 180 degrees as depicted in Figure 2 (a), (b), (c), (d) and (e). Note that the traditional augmentation methods were based on manual rotating, cropping or cutting that are indeed time consuming, therefore in this research, automated data augmentation methods are used as well. These methods include running the scripts written in Python programming language along with OpenCV libraries through Command Line Prompt (CMD), in ensuring consistency in data augmentation as well as time efficient. Sample of images using this automated augmentation method is further as shown in Figure 2(f) through (j).

Figure 1: Example of raw dataset image for fake banknote (top) and genuine banknote (bottom).

In addition, data augmentation methods that comprised of seven different types of data altering using OpenCV library are as listed below:

i. In terms of contrast, based on color look up table;
ii. Image burning;
iii. Image saturation altering;
iv. Image augmentation is based on adding more black pixels in order to change the hue;
v. Image blurring;
vi. Change of Red Green Blue (RGB) picture into gray image;
vii. Inserting the noise with the combination of Numpy library and OpenCV libraries.

3.3 Fine Tuning of the CNN models

Transfer learning uses pre-trained model that was prepared on a huge benchmark dataset to handle issues that is th most optimum to be able to provide the best accuracy [26], [29], [30], [31] and [32]. In addition, fine tuning of the CNN models include excluding the softmax layer of the pre-trained network and replace with the softmax layer that is relevant to the explored problem. Next is to begin with smaller learning rate. Pre-trained weights are normaly highly accurate as compared to the initially randomly set weights.

A. AlexNet Fine Tuning

The first step of fine tuning was to replace the last three layers in the pre-trained AlexNet to be able to recognize only four category of banknotes as tabulated in Table 1. A Rectified Linear Unit (ReLU) layer was added to improve the non-linear problem-solving ability. Furthermore, another fully connected layer is added with an output of size 4.

B. GoogLeNet Fine Tuning

In order to retrain GoogLeNet to classify new images, the fine tuning is replaced with the last three layers of this neural network. Fine tuning is done by adding three new layers, the first one is the fully connected layer, next is the Softmax layer and the last one is the classification output layer.

C. VGG16 Fine Tuning

Here, the CNN VGG16 has the first layer that correlated all the images with the input layer by resizing these images into 224x224x3. Upon completion of correlation, the first fine tuning method is conducted followed by the addition of a fully connected layer with filter size of 64x64. The next fine tuning is additional of Softmax layer similar to AlexNet CNN. The last fine tuning of the VGG16 is adding of the classification output layer.

4. EXPERIMENTAL RESULTS AND DISCUSSION

This section will detail the experimental conducted as well as the results attained based on the proposed methodology.

4.1 Dataset

Upon completion of data augmentation as described earlier, note that the dataset consist of 189 genuine banknotes and 173 counterfeit banknotes. Next, synthesize dataset is generated and the size of database is increased to 3360 of genuine and 2412 counterfeited banknotes respectively. The graphical illustrations that showed the impact of data augmentation are as in Figure 3.

4.2 Experimental Platform

As mentioned earlier, MATLAB framework is used for data processing. Further, an additional tool namely Deep Learning with specific function 'Execution Environment', was included in MATLAB environment in ensuring appropriate implementation and processing Deep Learning algorithms. Firstly, only the CPU was used followed by the second option with only the GPU used and final option both resources with the parallel pool were used. The fastest approach for huge computations would be the one that involved both the CPU and GPU with a parallel pool. This parallel pool was design in such a way that only specific GPU's were supported. Further, AMD, Radeon made GPU, was used thus the limitation raised was the GPU was not in the list of the supported GPU's for MATLAB's Deep Learning Tool. This limitation reduced the training computations in MATLAB.

(a) Traditional Augmentation of the banknote with left side cut off

(b) Traditional Augmentation of the banknote with right side cut off

(c) Traditional Augmentation of the banknote with symbols cut off

(d) Traditional Augmentation of the banknote with lower part cut off

(e) Traditional Augmentation with the banknote flip

(f) Automated augmentation based on contrast effect

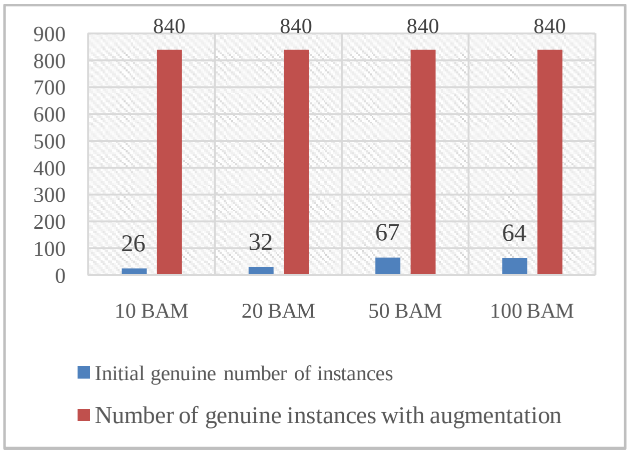
(g) Automated augmentation based on Hue effect

(h) Automated augmentation based on Blur effect

(i) Automated augmentation based on Grayscale effect

(j) Automated augmentation based on Noise effect

Figure 2: Example of both traditional and automated augmented banknotes based on each method used



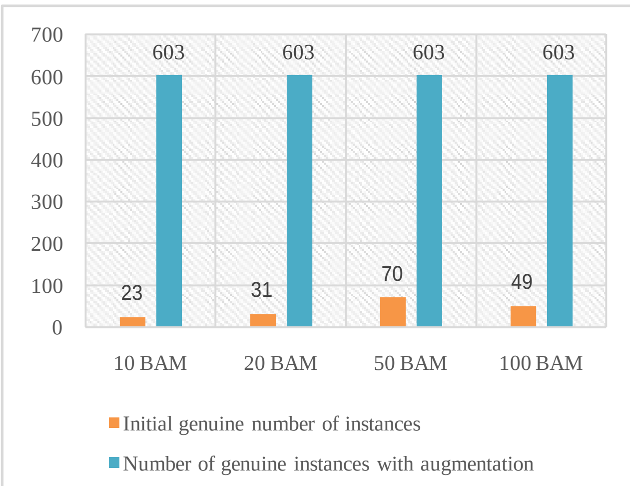


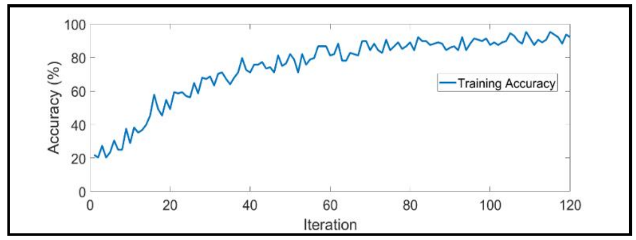
Figure 3: Plots for comparison of genuine banknotes with and without augmentation process (Top) and counterfeited banknotes with and without augmentation process (Bottom)

4.3 The Training Results

In this research, the experimental training was divided into testing and real-run phases. During the testing phase, size of dataset input images along with some other factors like epochs, mini batch sizes, validations, frequencies areevaluated and validated. Conversely, the purpose of the testing phase was to introduce approximate outcomes of the training data as well as the approximate time of the training itself. Since one of the objectives of this study is to test various neural networks, the best way to compare their strengths in terms of effectiveness and accuracy is by giving them the same training and validating conditions. Thus, this research was based on the following factors that were used in the real-run phases.

4.4 Testing phase results for AlexNet

The first testing phase was done in MATLAB using AlexNet CNN. This testing included only counterfeited banknotes. Therefore, this run can be seen as a banknote value checker rather than a counterfeited-genuine checker since there were nil genuine banknotes. The initial run was on a dataset consisting of 603 instances out of which 400 were used for training and 200 for validation. This runs on a miniBatch of 128 and 10 epochs. Each epoch had 12 iterations thus resulting in a total of 120 iterations. The training progress with validation can be seen in Figure 4. The final achieved accuracy in this run was 94.46%. The purpose of the second testing phase is to check if the hardware affects the time needed for the complete process to finish.



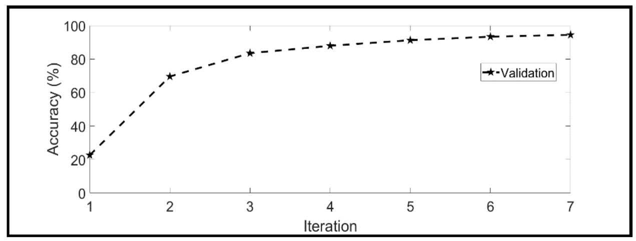


Figure 4: Training progress plots using initial AlexNet: training accuracy (Top) and validation (Bottom).

To verify this, the initial test phase was re-run with only modification of the execution environment. Instead of the initial parallel environment which created a parallel pool, this execution environment did not create a parallel pool and the result can be seen in Figure 5. With additional testing, it is ensured that one training and validation run in MATLAB can have different validation accuracy because of the randomize function that is used in image-picking. Due to this fact, accuracy was not taken into consideration in the second phase and the time was the only factor that was observed to conclude which option will be used for the upcoming runs. As final testing runs for AlexNet, an accuracy of 99.51% is attained as shown in Figure 6. This indicated that the model trained using counterfeited banknotes solely upon completion of 50 epochs was able to recognize from the image as 10, 20, 50, or 100 BAM banknote. This accuracy was satisfactory for testing phases, hence this configuration was used as a basis for the following runs. There were many attempts to run the VGG16 in the same manner as the previous networks in comfirming the performance with AlexNet and GoogLeNet. Here, the miniBatch number was reduced from 128 to 64, then to 32, 16, and finally as 8 but none of these configurations performed well by blocking the training and validation process each time. The size of the dataset was reduced from 400 to 300, and then to 150 and 50 but just like miniBatch configuration however CNN was not able to complete the process successfully even after two epochs, all other configurations need to be analyzed.

4.5 Real- run Phase Results

Next, recall that in this research the dataset of counterfeited banknotes have 603 instances, hence genuine banknotes with similar database size is to be used in the training and validation process using similar quantity for each 10, 20, 50 and 100 genuine banknotes in this stage totaling 603 instances.

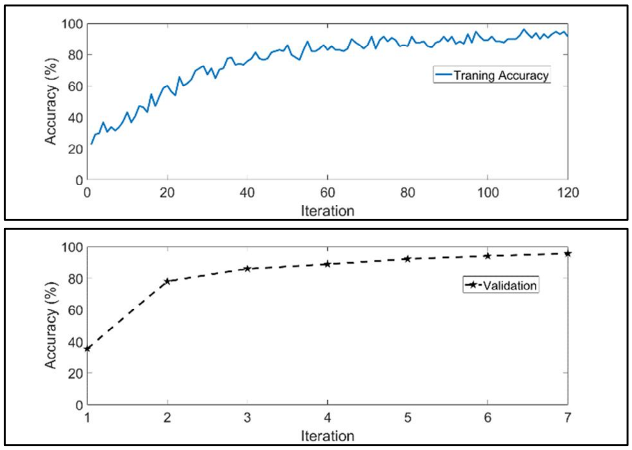


Figure 5: Training progress plots for second AlexNet run: training accuracy (Top) and validation (Bottom).

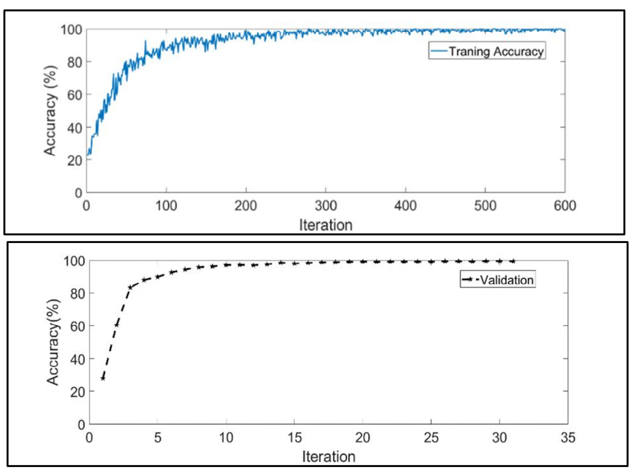


Figure 6 Training progress plots for second AlexNet run: training accuracy (Top) and validation (Bottom).

A. AlexNet

The first real-run in MATLAB was done with AlexNet CNN as shown in **Error! Reference source not found.**7. The total time taken was 1256 minutes and 26 seconds with accuracy of 99.38%. With a total of 50 epochs and 25 iterations per epoch, this run made 1250 iterations for complete run.

B. GoogLeNet

The second real-run was based on GoogLeNet CNN. Using this neural network, training and validation process spanned longer than the AlexNet. As depicted in Figure 8, the GoogLeNet took 1751 minutes and 11 seconds. With this amount of time, the GoogLeNet needed approximately 500 minutes more to complete the process using similar set up conditions and configurations as AlexNet, however as for accuracy the GoogLeNet CNN achieved accuracy of 97.36% that was 2.02% percent lower than the AlexNet CNN as in Figure 8.

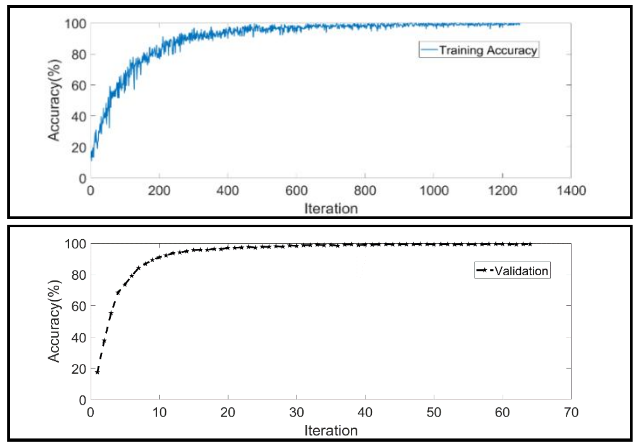


Figure 7: Real-run progress plots for AlexNet: training accuracy (Top) and validation (Bottom).

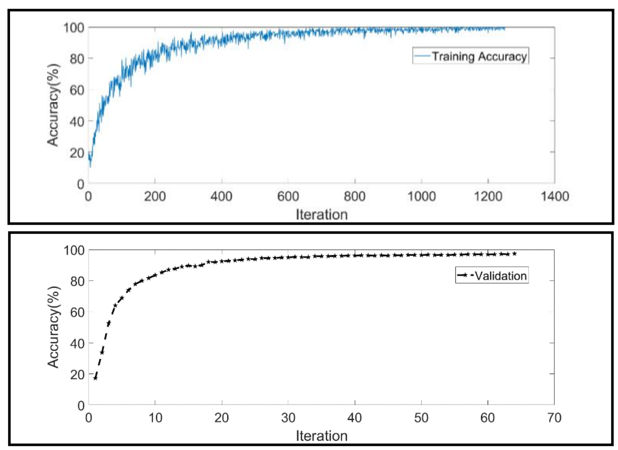


Figure 8: Real-run progress plots for GoogleNet: training accuracy (Top) and validation (Bottom).

C. VGG16

The final real-run was done with VGG16. The configuration of VGG16 network was set on different hardware. This change in the setting should not affect the result of the run. In addition, based on the experiments in the training phase; the run could take more time to complete. As shown in Figure 9, the VGG16 achieved 99.88% accuracy upon completion namely higher than CNN. On the other hand, CNN process took a longer time to complete the training. The complete process was 3404 minutes and 53 seconds, which is approximately doubled the time as compared to GoogLeNet CNN and approximately three times longer than the AlexNet CNN.

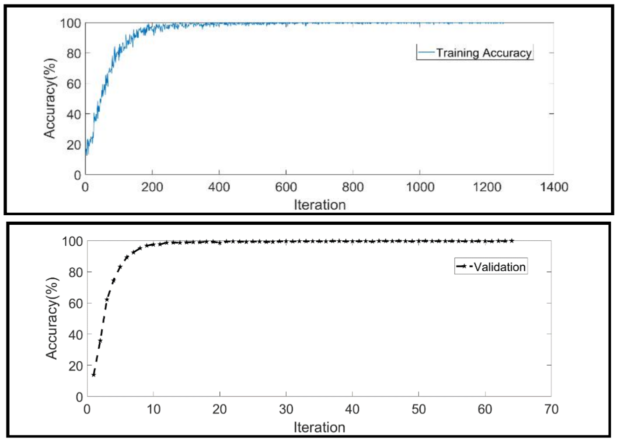


Figure 9: Real-run progress plots for VGG16: training accuracy (Top) and validation (Bottom).

Note that in this research different CNN configuration are used to detect the genuine of each banknotes. To the extend of our knowledge, this specific banknotes namely Bosnian and Herzegovinian banknotes has never been analyzed using Deep Learning technique as compared to some other foreign banknotes, thus it is proposed to be utilized for detection of counterfeiting. The primary concern of this study was to evaluate and validate CNN models for predicting the authenticity and genuineness of the BAM banknotes. Furthermore, it is also to test the possibility of using trained CNN's in real-time scenario in distinguishing the genuine on the counterfeit BAM banknotes. The results from the training and validation checking is as depicted in Figure 10.

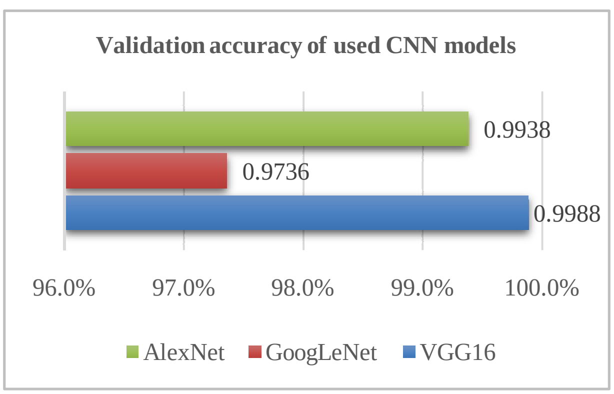


Figure 10: Validation of accuracy using all three proposed models

It is observed that the AlexNet CNN achieved 99.38% accuracy while the GoogLeNet's accuracy was 97.36% and VGG16's with 99.88% accuracy. Considering that the training process for all three mentioned CNN's used 603 dataset images during training and testing, the obtained results are considered satisfactory. Fine tuning helped to configure the CNN's to perform in the best possible manner based on results attained. It is seen that CNN can reach even higher accuracy with more data samples or with additional fine tuning of the CNN's. Therefore it is proven that applied CNN technique is suitable to be used in BAM banknote genuine prediction with high accuracy. Since the accuracy rate achieved were 99.38%, 97.36%, and 99.88% respectively, it can be confirmed that the models were trained well and the application can be widespread.

5. CONCLUSION

As a conclusion, the purpose of this research was to carry out BAM currency recognition. Recognition includes the denomination of the currency along with genuineness checking. Reall that three different CNN models were used, train, and validate based on the dataset. Further, results achieved from the proposed method were highly satisfactory. CNN AlexNet was fine-tuned by replacing the last three layers in the pre-trained AlexNet with 99.38% accuracy. GoogLeNet was modified with three layers 'loss3-classifier', 'prob', and 'output' replaced with new layers achieved a fair accuracy of 97.36%, but it was the lowest among the used three CNN's architecrture examined. Finally, the VGG16 was modified almost the same as AlexNet, but recorded the best accuracy against the other two CNN's architectures with a score of 99.88%. The final results received from all three CNN's were proven satisfactory. The overall performance of deep learning networks delivers better results as compared to traditional methods. Future work include additional fine tuning of CNN's for possible higher detection accuracy. In addition, the proposed algorithms can be used in automatic payments, money exchangers or mobile application development that may lead banknote detection genuineness through an image taken from the mobile phone. Nevertheless, this work could be also improved in terms of real-time banknote inspection.

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