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Philippine Banknote Counterfeit Detection through Domain Adaptive Deep Learning Model of the Convolutional Neural Network

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Abstract: Money counterfeiting is the illegal duplication of any currency for the use of deceiving any entity in exchange for a real-world value. Due to the advancements in computer vision in digital computing and the ill-effects of money counterfeiting, it had become one of the most prevalent issues in the fiscal system of any country that needs to be progressively solved. This paper investigated the use of AlexNet, VGG-16, and ResNet18 through transfer learning for the task of Philippine banknote counterfeit detection. The trained models of this paper achieved a testing accuracy of 81.25% for AlexNet, 95.96% for VGG-16, and 99.59% for ResNet-18. Despite achieving a lower testing accuracy, the trained ResNet-18 model of this study achieved a validation accuracy, specificity, precision, sensitivity, and F1-score of 100% on live testing through the developed web-based money counterfeit detection system..

Keywords: Philippine money counterfeit, transfer learning, deep learning, resnet18, domain adaptive learning, convolutional neural network.

1. Introduction

Money counterfeiting is the illegal duplication of currency to deceive recipients [1]. It is a prevalent threat and problem to any country's fiscal and economic system like the Philippines, with 51.3% of its citizens prefer to use the cash bills more than to go cashless as a payment method [2]. Counterfeited money deflates the value of a genuine currency, which inflates the prices of goods due to an unbalanced money distribution within the economy [3]. Due to the emergence of advanced technologies like computer vision and digital imaging in modern money counterfeiting, there is a need to design a solution in overcoming it using the same modern or more advanced technologies [1].

Among the many modern solutions in overcoming money counterfeit is through ultraviolet technologies [4]. Production of modern banknotes includes anti-copying features like unique lines and decorations that glow when exposed to ultraviolet light. Although this method is simple and effective at a small scale, it is tedious at a large scale. It heavily relies on manual labor and the subjective perception of the person towards counterfeited money [5].

Image processing techniques are among the most studied and proposed solutions in overcoming money counterfeiting [6]. One of these techniques is the Canny Edge Detection that processes a grayscale image to detect edges and suppress noise. Ballado et al [7] use this technique to compare the suspected bill image over an authentic reference image of the Philippine peso bill and check if the suspected bill is authentic or not. Similarly, Ankush Singh [8] improved the Canny Edge Detection technique by adding segmentation and feature extraction in counterfeit banknote detection. Although image processing. Although image processing techniques are effective for counterfeit money detection, they are computationally expensive or inefficient, tedious, and still rely on the subjective perception of humans for feature extraction.

The disadvantages of image processing for counterfeit money detection turned most of the recent studies towards using deep learning algorithms, particularly the convolutional neural network (CNN) [7], [9]. CNN is a deep learning technique that allows a system or model to learn from a large dataset through its heuristic approach [10]. Kamble et al [11] use CNN to model counterfeit money detection in Indian rupees. Their model achieved an accuracy of 86.5% by designing a handcrafted CNN architecture. The paper of Kumar et al [12] achieved an accuracy of 96.6% in detecting counterfeited Indian currency notes by adapting a three-layered CNN architecture. However, their methods are inadaptable to several currency platforms due to the scarce of well-studied banknote datasets. Furthermore, Larsen-Freeman [13] suggested using transfer learning or domain adaptive learning methods for classification modeling on a limited dataset.

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Transfer learning is a domain adaptive deep learning technique that reuses a pre-trained model of one task to a new task with a different or small dataset [13], [14]. In the process, transfer learning uses the upper layers of the convolutional neural network as feature extractors without changing the weights except for the class values in the lower-most layers [15].

Recently published banknote counterfeit detection and recognition studies utilized transfer learning as their main method. One of these is the paper of Pachon et al [16] that utilizes the pre-trained (a)AlexNet, (b)SqueezeNet, (c)ResNet-18, (d)Inception-v3, and (e)customized CNN architecture for Colombian banknote counterfeit detection. Their transfer learning method achieved a validation and training accuracy of (a)99.86%, (b)99.88%, (c)100.00%, (d)99.97%, and (e)99.86% respectively. The transfer learning methods of Linkon et al [17] uses the pre-trained (a)ResNet-152-v2, (b)MobileNet, (c)NASNetMobile for Bangladeshi banknote counterfeit detection and achieved a testing/validation accuracy of (a)98.88%, (b)88.65%, and (c)100.00% accordingly. Rajendran and Anithaashi [18] uses transfer learning on pre-trained (a)AlexNet, (b)GoogLeNet, and (c)VGG-16 for Indian banknote counterfeit detection. Their method achieved a validation/testing accuracy of (a)95.00%, (b)88.00%, and (c)100.00%. Similarly, the papers of Yildiz et al [19] and Almisreb and Saleh [20] use the same pre-trained architectures on transfer learning for Bosnian Mark banknote counterfeit detection.The works of Yildiz et al achieved a validation/testing accuracy of (a)99.68%, (b)97.36%, and©)99.88%, while the works of Almisreb and Saleh achieved a validation/testing accuracy of (a)95.24%, (b)88.65%, and (c)100.00%. Pham et al [21] use the pre-trained (a)AlexNet and (b)ResNet-18 on transfer learning for the detection of the counterfeited Indian rupee, Korean won, and U.S. dollar bills. Their study achieved a validation/testing accuracy of (a)97.93% and (b)97.69%. Schulte et al [22] use transfer learning with pre-trained Inception-v3 to detect counterfeited Euro bills on several training configurations. Their paper achieved a validation/testing accuracy of 100.00%. Although these studies show promising results, no studies use the transfer learning method on Philippine banknotes and real-time counterfeited money detection and application. Moreover, there is no existing study or published dataset that contains Philippine peso bills.

This paper explored AlexNet, VGG-16, and ResNet-18 for a counterfeited money detection system through a limited image-set and domain adaptive learning method in the context of the Philippine banknotes. The main goal of this paper is to determine the adequacy of AlexNet, VGG-16, and ResNet18 for Philippine banknote counterfeit detection. Specifically, this study aimed to (1) produce a banknote image-set consisting of five-hundred and one-thousand Philippine peso bills; (2) investigate CNN in the context of counterfeited Philippine banknote detection through transfer learning with the pre-trained AlexNet, VGG-16, and ResNet-18 models; (3) determine the training and validation accuracy of the CNN model for counterfeited Philippine banknote detection and; (4) determine the testing/validation accuracy, specificity, precision, sensitivity, and F1-score of the best performing trained model on a real-time counterfeited Philippine banknote detection system or application, and (5) provide a fair comparison of the transfer learning method of this study in terms of testing/validation accuracy over the recently published transfer learning methods in [16], [17], [18], [19], [20], [21], [22].

TABLE I. Comparison of CNN Architecture by layers and parameter size.

CNN Architecture	No. of Layers	Parameters (millions)
AlexNet	8	60
VGG-16	16	138
Inception-v3	42	27
MobileNet-v2	28	3.37
ResNet-18	18	11

2. CNN and the Transfer Learning Approach

A. *Convolutional Neural Network (CNN)*

Convolutional Neural Network or CNN is a deep learning algorithm that gained momentum and popularity in several studies and applications due to its capacity to learn relevant features from input images at different convolutional levels similar to the human eyes and brain capacity. Developed CNN architectures can efficiently solve complex problems with high accuracy and lower error rate [23]. These CNN architectures generally consist of activation functions, convolutional, pooling, and fully connected layers. The most used and well-performing beyond human of these architectures are the AlexNet, VGGNet, Inception-v3, MobileNet, and ResNet [24]. Table I shows the comparison of these CNN architectures in terms of their layer number and parameter size.

The AlexNet, VGG-16, and MobileNet-v2 are among the notable CNN architecture with AlexNet consisted of eight layers with 60 million parameters, VGG-16 has 16 layers and 138 million parameters, and MobileNet-v2 is having 28 layers with 3.37 million parameters. The Inception-v3 and ResNet-18 architectures are among the CNN architectures that exceed human eyes and brain, with Inception-v3 consisted of 42 layers and 27 million parameters while ResNet-18 has 18 layers and 11 million parameters. Furthermore, this paper uses the AlexNet, VGG-16, and ResNet-18 architectures to investigate the adequacy of CNN in detecting counterfeited Philippine bills due to their suitability with the study's goal. This paper used the pre-trained weights of these architectures on the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) dataset [25] during the training.

1) *AlexNet*

AlexNet is the CNN architecture developed by Alex Krizhevesky that popularized convolutional neural networks in various areas of research and application [26]. AlexNet is the first state-of-the-art CNN architecture that outperformed standard computer vision techniques regarding recognition and accuracy [27]. It is the most researched CNN architecture because of its importance in most image identification and classification problems [28]. The standard structure of AlexNet consisted of

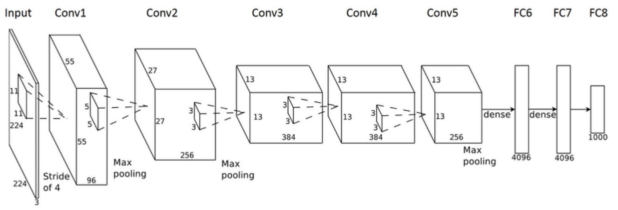

Figure 1. AlexNet Architecture

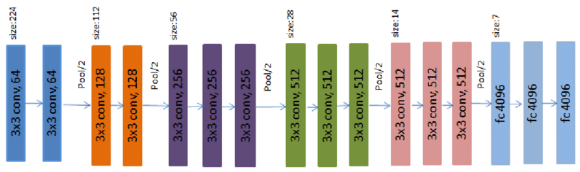

Figure 2. VGG-16 Architecture

five convolutional layers with max-pooling, two fully connected layers, and a SoftMax layer. Figure 1 shows the diagram of AlexNet architecture borrowed from Pedraza et al [29] and as used in this paper.

2) VGG-16

VGG-16, also known as OxfordNet, is a CNN architecture developed by Simonyan et al [23] that achieved a top-5 test accuracy of 92.7% in ILSVRC-2014. It is like AlexNet but developed based on learning through deeper convolutions yet optimum parameter size. The structure of VGG-16 consisted of five blocks of two to three convolutional layers, a block of fully connected layers, and a SoftMax layer. Figure 2 shows the diagram of VGG-16 borrowed from Gopalakrishnan et al [30] and as used in this paper.

3) ResNet-18

ResNet-18 is a variation of the ResNet architecture developed by He et al [31] that can manage degradation of image recognition or classification accuracy as the convolutional layer deepens by introducing a series of residual blocks. These residual blocks allow the input images to skip several convolutional layers and enhance the weights generated by these skipped convolutional layers in the output layer. The paper of He et al [32] proved that ResNet architecture performs better than other CNN architecture for recognition and classification. The structure of ResNet-18 consisted of 17 convolutional layers, eight residual blocks, a fully connected layer, and SoftMax. Figure 3 shows the original ResNet-18 architecture diagram borrowed from Ramzan et al [33] and used in this paper.

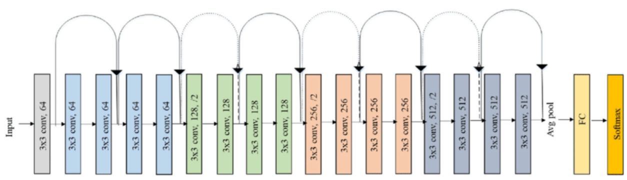

Figure 3. ResNet-18 Architecture

B. Transfer Learning

Transfer learning in the context of deep learning is a deep learning approach that allows the development of a network model using a dataset of fewer than 10000 samples but on top of the pre-trained model architecture [34]. In transfer learning, the network uses the information from primary tasks to enhance the generalization about a new task. Moreover, the last few layers of the trained network are replaced with new layers in transfer learning, such as the fully connected layer and a SoftMax classification layer, to learn only the features of the new dataset and its classes. Figure 4 shows the transfer learning pipeline as used in the context of this paper.

3. Methodology

This study's methodology consisted of four successive phases: (1) Dataset and Input Data, (2) Data Preprocessing, (3) Training and Modeling, and (4) Classification, as shown in figure 5. The following subsections below briefly discuss each of these phases as used in this study.

A. Dataset and Input Data

Dataset and Input Data is the first phase of the methodology of this study. The dataset of this study consisted of 782 raw colored front and back images with 391 each are genuine and counterfeited five-hundred and one-thousand Philippine peso bills. This paper manually extracted and collected these colored images of random sizes as JPEG from the web or taken using the camera of a standard smartphone or web camera. Figure 6 shows a sample raw image of the used dataset's genuine and counterfeited Philippine peso bills. Additionally, Figure 7 show and highlight the security features of the current genuine Philippine peso bill.

Another process performed in this phase is dataset splitting and labeling. This study randomly partitioned the used dataset by 80% training or 626 images and 20% testing/validation dataset or 212 images. Each partitioned image-set contains an equal number of authentic and counterfeited images of the 500- and 1000-peso Philippine banknotes, either a front or back image of these real or fake bills. This study labeled the images in a CSV file which contains the filenames of the images and their respective classes. Counterfeited images are represented by zero (0), while authentic images are represented by one (1). The output of this phase is the labeled training and testing dataset of the used dataset.

B. Data Preprocessing

Data preprocessing is the second phase of the methodology of this paper. As inspired by the data augmentation processes of Pachon et al [16], this paper's data preprocess consisted of image cropping, resizing, rotating, and image normalization. This paper used these processes on the training dataset while only the normalization in the testing/validation dataset.

1) Image Cropping

The image cropping of this study aimed to eliminate all the unwanted information or pixels of the images in the dataset. This paper automatically eliminated these unwanted pixels of each Philippine bill image using the

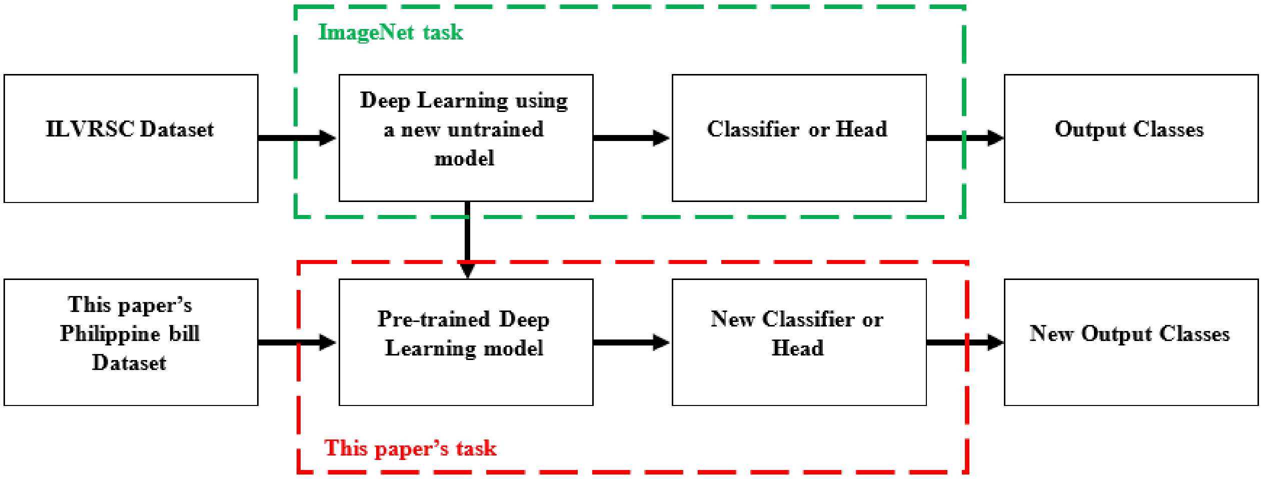

Figure 4. Transfer Learning Pipeline of this paper.

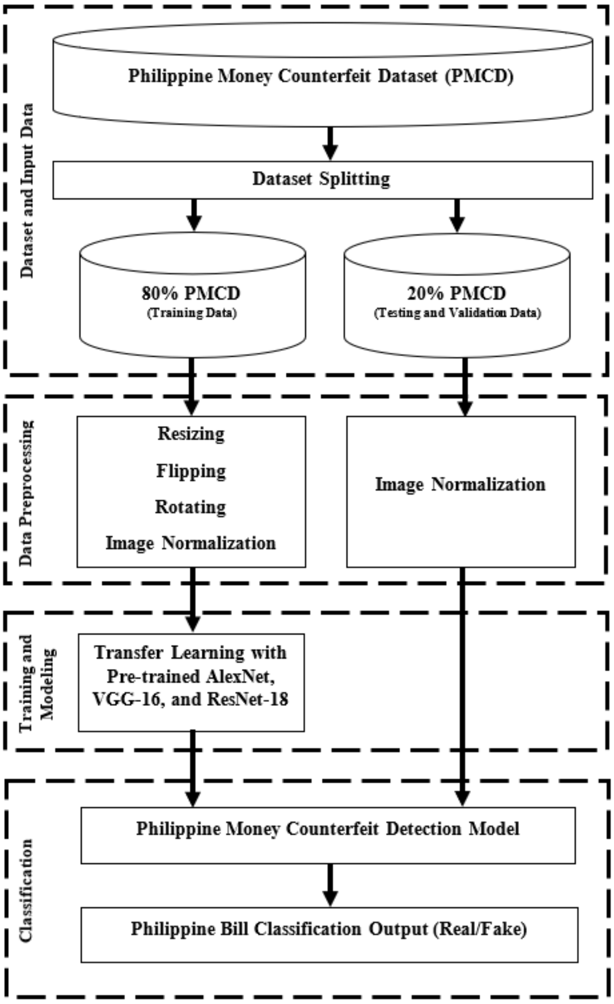

Figure 5. Deep learning Pipeline of this paper.

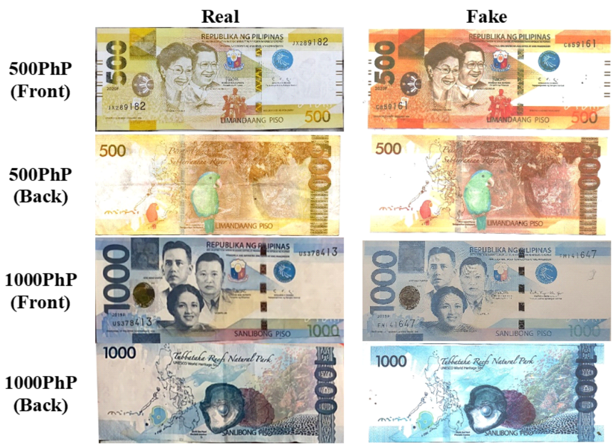

Figure 6. Samples of Real and Fake Philippine 500 and 1000 peso bills.

Figure 7. Security Features of modern Philippine bills: Front (top: 1. Watermark, 2. Baybayin script, and 3. Security thread) and back (bottom).

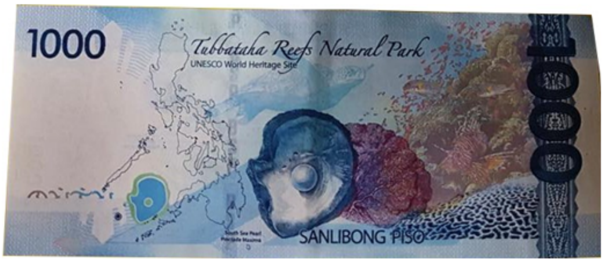

Figure 8. Philippine banknote after image cropping.

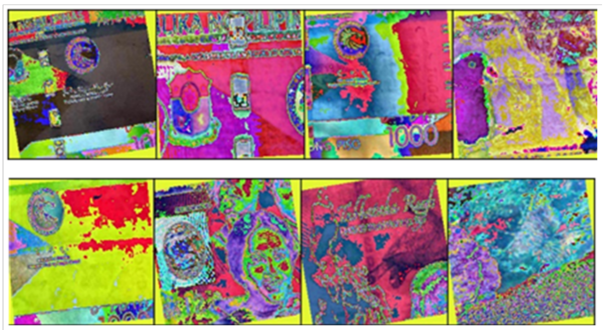

Figure 9. Philippine banknote after normalization.

OpenCV library on Python. Figure 8 shows a Philippine banknote after image cropping. the output of this process is banknote images without unnecessary pixels.

2) Image Resizing

This study resized the training dataset by 229×229 pixels, cropped in all sections by 224×224 pixels to satisfy the input requirements of ResNet-18 architecture, randomly rotated by 1 to 10 degrees with default, and normalize each using the standard ImageNet normalization values. Figure 9 shows the sample output of these processes. The output of this phase is a preprocessed training, testing, and validation dataset.

C. Training and Modeling

This study uses the pre-trained AlexNet, VGG-16, and ResNet-18 to develop a Philippine banknote counterfeit detection model through the domain adaptive approach of CNN or transfer learning and identify the most suitable model among these architectures for the current task. This study accomplished this phase by feeding the training dataset onto the defined architectures and replacing the last fully connected layer and softmax of each thus, allowing the networks to learn only the features and security information of the used Philippine money counterfeit dataset. Moreover, Table II shows the configuration used in this paper to train these CNN architectures on Google Colab-GPU with Python programming language and Tensorflow2.0/Keras. The output of this phase are the Philippine money counterfeit detection models of AlexNet, VGG-16, and ResNet-18.This study labeled the images in a CSV file which contains the filenames of the images and their respective classes. Counterfeited images

TABLE II. Modeling Configuration

Training Parameter	Configuration Setting
Batch size	8
Max epoch	15
Learning rate	0.001
Shuffle	True
Training function	Adam

are represented by zero (0), while authentic images are represented by one (1). This study uses Google Colab, Python programming language, and Microsoft Excel to accomplish this process.

D. Classification and the Web-based Applicaton

The classification phase of this study consisted of two procedures: (1) validation and (2) testing. This phase aimed to determine the performance of the developed Philippine banknote counterfeit detection model using the 156 testing and validation images. This study determined the testing accuracy of the developed model coincidentally of the model training. In contrast, this study determined the validation accuracy using the output generated from the developed application with the developed model embedded in it and confusion matrix scores by Equations 1 to 5; where P is the actual number of real Philippine money, N is the actual number of fake Philippine money, TP and FP are the statistics of correctly detected real and fake Philippine money, and PN and FN are the statistics of misclassified real and fake Philippine money by the model.

$$Accuracy = \frac{TP + TN}{P + N} \quad (1)$$

$$Specificity = \frac{TF}{FP + TN} \quad (2)$$

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (4)$$

$$F1 - score = \frac{2 * TP}{2 * TP + FP + FN} \quad (5)$$

The developed counterfeit money detection system is a web-based application that can run on any camera-equipped computing device and detect the security features of the Philippine money as shown in figure 7 above. The authors chose to develop a web application due to its versatility in several computing platforms instead of the traditional desktop/mobile applications. The proponents of this study developed the web application using HTML, Python programming language, and Flask. This paper used the developed web application to verify the trained models' task performance in real-world scenarios using the test dataset or an image captured by an embed-

Figure 10. Developed application to validate the trained Philippine counterfeit money detection model.

ded camera. Furthermore, this paper uses the validation dataset to assess the trained models on the developed system and the actual premise. Figure 10 shows the interface of the developed web application of this study.

E. Results and Discussion

1) Training and Testing Result

This study took 11 minutes and 44 seconds to train and model the Philippine banknote counterfeit detection using the training dataset on ResNet-18 model, nine minutes on AlexNet model, and 14 minutes and 36 seconds on the VGG-16 model. All the trained CNN models achieved a training accuracy of 100.00% but individually achieved a testing accuracy: 81.25% on AlexNet, 95.96% on VGG-16, and 99.59% on ResNet-18 – which is the highest among AlexNet and VGG-16. These statistics, regardless of the currency of the used dataset, are lower than the best performing models of the papers of Pachon et al [16], Linkon et al [17], Rajendran and Anithaashri [18], Yildiz et al [19], Almisreb and Saleh [20] , Pham et al [21], and Schulte et al [22], as shown in Table III. The 99.59% testing accuracy of ResNet-18 is higher than the 96.67% test result of the image processing method of Ballado et al [7]; hence, proving that deep learning approach performs better than image processing techniques. Additionally, each of the trained models took less than one to two minutes, depending on the image size, to test the authenticity of one Philippine banknote.

2) Validation Result

This study validated the trained ResNet-18 based Philippine banknote counterfeit detection model using nine random counterfeited bill images (N or the total number of negatives) and 11 authentic bill images (P or the total number of positives) in the validation dataset and uploaded each onto the developed web application. The trained model achieved a perfect true positive (TP) and negative (TN) score of nine and 11, respectively. In extension, the trained model achieved a score of 100% in terms of validation accuracy, specificity, precision, sensitivity, and F1-score despite having a lower testing accuracy than the results of relevant literature. Figure 11 show the samples of the actual validation results using the developed web application of this study. Unless authentic, the trained model of this paper marked the Philippine bill samples as "fake" when it does not satisfy the learned security features of an authentic Philippine bill. Moreover, and unless real, the developed web application will provide reasons explaining how the factors that marked the Philippine bill sample as "fake".

4. Conclusion

The performance disadvantages of previous approaches and the absence of studies utilizing deep learning and well-studied Philippine money counterfeit datasets, this paper presented the use of domain adaptive deep learning approaches for the detection of Philippine Counterfeited Money. This paper investigated the use of transfer learning through AlexNet, VGG-16, and ResNet-18. The results of this paper show that ResNet-18 is the best performing model for the task and achieved a training and testing accuracy of 100.00% and 99.59%. This study also determined that the trained model scored 100% on validation accuracy, specificity, precision, sensitivity, and F1-score while using a web application. Overall, ResNet18 is adequate for Philippine banknote counterfeit detection despite having a lower testing result than the other relevant studies. This paper also proved that deep learning works better for the money counterfeit task than with image processing techniques.

For further studies, investigating the same method using other pre-trained CNN architectures and transformer networks using the same Philippine banknotes dataset and alike should be explored. It is also recommended to conduct the same study that employs several training configurations. Additionally, the scarce Philippine money counterfeit dataset hinders other researchers from conducting further the same study; hence, there is a need to establish a dataset consisting of different banknote images of each country.

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TABLE III. Comparative testing accuracy results of this study over the other studies' results.

Transfer Learning Method		Currency	Statistics (%)
This study	(a)AlexNet (b)VGG16 (c)ResNet18	Philippine peso	(a)81.25 (b)95.96 (c)99.59
Pachon et al. [16]	(a)AlexNet (b)SqueezeNet (c)ResNet18 (d)InceptionV3 (e)Custom	Colombian peso	(a)99.86 (b)99.88 (c)100.00 (d)99.97 (e)99.86
Linkon et al. [17]	(a)ResNet152v2 (b)MobileNet (c)NASNetMobile	Bangladeshi banknote	(a)98.88 (b)100.00 (c)97.77
Rajendran and Anithaashri [18]	(a)AlexNet (b)GoogLeNet (c)VGG-16	Indian rupee	(a)95.00 (b)88.00 (c)100.00
Yildiz et al. [19]	(a)AlexNet (b)GoogLeNet (c)VGG-16	Bosnian mark	(a)99.68 (b)97.36 (c)99.88
Almisreb and Saleh [20]	(a)AlexNet (b)GoogLeNet (c)VGG-16	Bosnian mark	(a)95.24 (b)88.65 (c)100.00
Pham et al. [21]	(a)AlexNet (b)ResNet18	Indian rupee, Korean won, U.S. dollar	(a)97.93. (b)97.69
Schulte et al. [22]	Inception-v3	Euro banknotes	100.00

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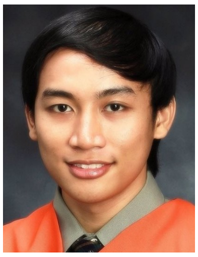

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