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Evaluation of Top Pretrained Models Using Transfer Learning on Banknote Dataset with Quality Parameter

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ABSTRACT

Building a machine learning (ml) model for fast and accurate banknote classification is an open challenging problem. Image classification problems can be addressed in two ways: by building own model from scratch or by using the transfer learning technique. Building your model from scratch is time-consuming and does not guarantee the best results in the stipulated time. Transfer learning, on the other hand, is a popular technique used by many researchers to deploy ml models in less time with higher accuracy. This paper presents the evaluation of the top five pre-trained convolution neural network (CNN) models. This research aims to evaluate performance and find out the best suitable model from the available list for banknote classification with quality parameters. The model training was done on dataset of Indian banknote which included images from 16 classes, split into 8 classes for clean banknotes and 8 classes of spoilt banknotes. While performing the evaluations, we also consider the performance of models without fine-tuning and after fine-tuning.

1. INTRODUCTION

Vision impairment has a significant impact on the quality of life of adult populations [1]. It is challenging for them to carry out daily activities, such as reading, cooking, and even walking, which can lead to social isolation, depression, and anxiety. Banknote classification and identification is one of the challenges faced by visually impaired people in their day- to-day life. While doing financial transactions, there are greater chances of getting cheated due to vision impairment. Visually impaired people try to recognize the banknote denomination by its shape, size, or tactile marks, even if they are able to know the denomination, there is no mechanism to identify whether the bank note is soiled or damaged. They may receive mutilated/torn, soiled, or spoiled banknotes during money transactions with other people, but these damaged notes are not accepted by shopkeepers or vendors in the market and not even at private banks.

If a person wants to exchange spoiled banknotes, it has to be exchanged only at certain nationalized banks mentioned by the government. The banknotes are exchanged only if satisfies the rules for exchange given by the Government of India. Thus, it becomes very cumbersome even for a normal human being for doing financial transactions if he has cash, and few notes are spoiled. Globally, there are at least 2.2 billion people who are visually impaired and doing a financial transaction with spoiled banknotes becomes a difficult task for visually impaired people [1]. There are several researches have been done for the classification of banknotes as per their denomination, but there is a lack of mechanism for classification of banknotes as clean and spoiled.

Advancements in computer vision technology and modern technologies like deep learning, machine learning, and the Internet of Things (IoT) are used by researchers to solve complex problems like image classification and object detection. Many Android apps, web applications, and embedded applications using machine learning algorithms are developed and deployed successfully to solve complex problems that are time-intensive and resource intensive in the domains like agriculture, health care, banking sector, insurance, cyber security, fraud detection, etc. Many research work/ machine learning (ml) models have been published on fast and accurate image classification of banknotes as it is a very crucial application in many places. All these works/models are limited to classifying the banknotes into different denominations. As per the literature survey done, as far as we know, no dataset of clean and spoiled banknotes is available and that's the reason there is no known existing ML model able to classify/identify the spoiled notes as they are trained on the clean dataset.

Convolution neural network (CNN) architecture or model is built to classify the images. There are two ways to build CNN architecture/model. First, create your architecture from scratch. Second, we use the transfer learning (TL) technique to build CNN architecture. This research work presents our dataset consisting of clean and spoiled notes of both old and new banknotes (10, 20, 50, and 100) of India and evaluates the pretrained models, namely VGG16, VGG19, Xception, ResNet152V2, and InceptionV3 for the classification of Indian Banknotes as clean and spoiled banknotes. As per our findings, among the considered pretrained models, VGG16 performs best after fine tuning, giving 87.50 percent accuracy.

The structure of this article is as follows: The introduction to the topic is presented in section1, which describes the need for and importance of banknote image classification with clean and spoiled parameters. It also talks about how deep learning algorithms can be used to solve difficult problems. Transfer learning is a popular technique used while creating machine learning models with higher accuracy in less time. The next section 2 describes the literature survey and the research questions that this paper seeks to answer. Section 3 describes the dataset used in the experimentation. Section 4 describes the transfer learning technique used while creating CNN models in detail. Section 5 explains the experimentation and evaluation done by the pretrained models. The sixth section discusses the work's conclusions and future scope.

2. LITERATURE SURVEY

Banknote classification is a very vital and challenging problem faced by visually impaired people. Visually impaired people have difficulty identifying banknotes. They usually recognize the denomination of banknotes by touching and feeling the tactile marks on the banknotes. Several researchers are working on banknote classification and identification. The classification of banknotes can be done for identifying the denomination, for checking the serial numbers on bank notes, for checking whether the banknotes are legitimate or fake, and for checking whether the banknotes are fit for transaction or not [2]. As per the literature survey, classification of banknotes is done using either image processing, machine learning, or deep techniques, or using computer vision and IoT-based techniques. The comprehensive literature survey of work done for banknote classification is as given below:

A device called Money talker that electronically recognizes the Australian banknotes from the way light reflects off of them, is proposed by Hinwood et al. [3] for visually impaired people. An artificial neural network-based banknote recognition system for identifying Bangladeshi bank notes has been proposed by Jahangir and Chowdhury [4]. For the classification of US dollars, Omatu et al. [5] presented a neural network-based system based on the principle component analysis (PCA) technique. Chae et al. [6] perform the Korean banknote classification based on RGB values and size of banknotes and the detection of counterfeit Korean banknotes by applying UV light to banknotes. Ahangaryan et al. [7] suggested system that makes use of wavelet transform and neural networks to recognize Persian banknotes.

A computer vision technique for the detection of US banknotes for blind people was used in Hasanuzzaman et al. [8]. By preprocessing the pictures to define the direction of the image to be classified and then using the k-means method to determine the class of banknotes using the features extracted by applying the PCA algorithm, whereas a system for the classification of US banknotes is suggested [9]. Although this classification technique improved the classification accuracy, additional time is required for pre-classification. A system to classify the currencies of 5 different countries as USD, CNY, KRW, RUB, and EUR is proposed [10]. The proposed system classified the CIS-captured banknote images on the basis of their size. A similarity map of key identifying locations on banknotes to suggest a system for classifying different types of currency was created by Pham et al. [11]. Classification is done using PCA based method and K-means algorithm.

Dunai Dunai et al. [12] proposed an IoT-based system consisting of wearable sunglasses for the recognition of euro banknotes. An infrared laser camera is used to capture the images. Although the recognition rate of banknotes is 97.5 percent, it is 69 percent when banknotes are crumpled. Pham et al. [13] used CNN based approach for classifying banknotes of multiple countries, but if the banknotes were damaged, it caused misclassification of banknotes.

A scheme to identify counterfeit Indian banknotes using image processing techniques and an SVM algorithm for classification is proposed [14]. Mittal and Mittal [15] presented a transfer learning-based deep learning strategy for identifying Indian banknotes. Sufri et al. [16] suggested a method based on deep learning and machine learning to construct a vision-based system enabling visually challenged people to recognize Malaysian currency. Choi et al. [17] proposed a machine learning-based system for the recognition of serial numbers on banknotes of Japan, Korea, and the Euro. Yadav et al. [18] compared six machine learning-based algorithms, namely, Decision tree, support vector machine, naive Bayes, logistic regression, random forest, and k-nearest neighbor for the detection of fake banknotes by applying them to the UCI ML repository banknote dataset. The naïve bias algorithm has less accuracy compared to other algorithms that they have compared. Swami et al. [19] suggested a deep learning-based algorithm to classify Indian banknote denominations that would be beneficial for those with visual impairments.

From the literature survey, it can be concluded that there is a lot of work done on 1) classification of currency and detection of fake banknotes, and 2) deep learning and machine learning approach is widely used for the classification of banknotes. Although there is a lot of work done, the literature review highlights that the work for the classification of banknotes as good and spoiled banknotes is still a neglected area and the dataset consisting of both spoiled and good banknotes is still limited. This lacuna motivated us first to create the dataset of good and spoiled banknotes of India and second to evaluate the top 5 pretrained models using transfer learning for checking the quality parameters of Indian banknotes, which would be further useful to other researchers working in the area of bank note classification.

Purpose of Research: This work concentrated to find the answers to the following questions during the multiclass classification procedure using eight class labels.

- Is classifying banknotes as a clean and spoiled a vital problem to address and is this the need of users?
- What are the lacunas in the available solutions for banknote classification?
- Is a dataset of banknotes with a clean and spoiled category available?
- How various popular pretrained image classification CNN models can be used in Transfer Learning to build fast and accurate banknote image classification?
- Which parameter should be considered to evaluate the pretrained models after training on our dataset?

Explanation:

a. Is classifying banknotes as a clean and spoilt a vital problem to address and is this the need of users?

Answer:

It is often seen that spoiled notes are refused by shopkeepers or vendors and thus it makes them of no use. The only option is to get them replaced by the bank. Many times, when you are accepting a large amount, you receive the cash bundle which may have spoiled notes. According to a WHO report, at least 2.2 billion individuals worldwide suffer from near- or farsightedness. The problem of identifying mutilated/torn, soiled, or spoiled banknotes is difficult for them and they might get cheated while doing mundane transactions. Hence, to summarize, classifying banknotes as clean and spoiled is an essential problem and there is an immediate need to address this problem.

b. What are the lacunas in the available solutions for banknote classification?

Answer:

As per the literature review, many mobile apps and research papers [2-23] were published by companies and researchers, but a common lacuna observed is that no research work addresses the important problem of classifying banknotes into clean and spoiled categories. No model is trained on such kind of dataset which is the biggest gap of all published work.

c. Is a dataset of banknotes in the clean and spoiled category available?

Answer:

To the best of our knowledge, no open access dataset of clean and damaged banknotes is available. Hence, two new datasets were created and published on IEEE Dataport and Mendley, respectively, which are available for the research community. The first dataset [24] consists of clean images whereas the second dataset [25] consists of only spoiled banknotes of Indian currency (total 8 classes).

d. How various popular pretrained image classification CNN models can be used in Transfer Learning to build fast and accurate banknote image classification?

Answer:

After studying many research articles [26-30], it is observed that transfer learning is the foolproof and the preferred method used while creating a machine learning model. In this technique, the weights of already published pretrained models are used while creating a new model. This technique guarantees deploying a more accurate model in less time. The same technique can be used while creating a classification model for banknotes in clean and spoiled categories.

e. Which parameter should be considered to evaluate the pretrained models after training on our dataset?

Answer:

The pretrained models can be evaluated using a variety of parameters, such as the F1 score, MCC (Matthew's correlation coefficient), and Cohen's kappa (K), Top-1, Top-5, Accuracy, Loss, time taken for training, etc. This research work considers only one parameter, i.e., accuracy of the model before fine-tuning and after fine-tuning. After deploying any ml model in a real-world application, how accurately a model classifies the images is considered, thus "accuracy" as an evaluation parameter is considered in our evaluations. The research is conducted as per the following steps:

a. Create own dataset.
b. Select the pretrained model from Keras. Applications list which has higher accuracy. All of these pretrained models were trained using the publicly accessible ImageNet dataset.
c. Use the Keras preprocessing layers, which help to convert the raw data on disk to tf.data.Daset objects that can be used to train or test the model.
d. Evaluate the top 5 pretrained models on the dataset in two phases without fine-tuning and after fine-tuning.
e. Compare the models based on their accuracy results.

3. DATASET

Developing an ML model for classification of an image or object, it is usually difficult to find the precise required dataset with tidy and clean images [31]. The lack of data, the inability to find data in the needed format, the poor quality of the data, the possibility that the data may contain extraneous features, etc. were problems that researchers had to deal with. Many researchers have created their datasets and made them available for other researchers to solve complex problems in their domain. A few open-access banknote datasets of different currencies are also available with different denominations. In our research, no dataset of Indian banknotes with categories of clean and spoiled dataset was available. We created and published two datasets on IEEE-Dataport and Mendeley. The IEEE-Dataport consists of the dataset which has clean banknotes of India and the dataset on Mendeley consists of the dataset which has spoiled banknotes of India. For experimentation, we merged both the clean and spoiled bank notes of India to create a dataset consisting of a total of 16 classes with old and new denominations. Table 1 describes the dataset with sample images.

As per Meshram et al. [32], the images of banknotes of India were captured using the mobile camera in different environments and different lighting conditions, like dark and illuminated. Additionally, the pictures are rotated, taken from the front and back, and photographed from various perspectives and backgrounds while being in a chaotic setting with folded and obscured banknotes. The dataset for experimentation consists of a total of 3200 images consisting of both clean and spoiled banknotes of India.

4. RESULTS AND DISCUSSION

The evaluation of pretrained models using transfer learning on our dataset of clean and spoiled banknotes of India is performed. A machine learning-based strategy called transfer learning is frequently employed to address computer vision issues. Transfer learning is a popular method in computer vision because it enables the speedy construction of exact models [33]. Transfer learning involves starting from patterns that have been discovered when resolving previous problems rather than from scratch. Pre-trained models are commonly used in computer vision to express transfer learning. In order to resolve an issue resembling the one we are attempting to solve, a pretrained model is developed on a sizable benchmark dataset. Large benchmarking datasets like Imagenet are used to train the pretrained models. It consists of more than 15 million high-resolution images, which are labeled and classified into approximately 22000 classes. Five pretrained models, namely, VGG16, VGG19, Xception, ResNet152V2, and InceptionV3, are considered for evaluation. These models are selected by referring to list of pretrained models given by Keras application [3].

The evaluation of pretrained models was performed on our dataset consisting of 3200 images. It consists of clean and spoiled images of banknotes with denominations 10, 20, 50, and 100. Evaluation of each selected model is done using transfer learning without fine-tuning and with fine-tuning. The subsequent actions are carried out while utilising pretrained models with transfer learning on the banknote dataset:

Table 1. Indian banknote dataset

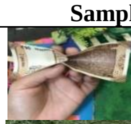
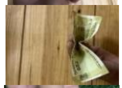
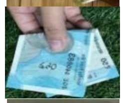
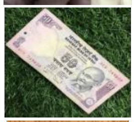
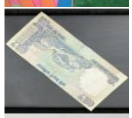
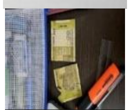
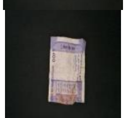
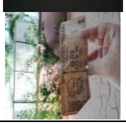
Sr No.	Class	Total no of images	Resolution	Dataset available at	Sample images	
1	Clean New 10	200	225 × 225	IEEDataPort		
2	Clean New 20	200	225 × 225	IEEDataPort		
3	Clean New 50	200	225 × 225	IEEDataPort		
4	Clean New 100	200	225 × 225	IEEDataPort		
5	Clean Old 10	200	225 × 225	IEEDataPort		
6	Clean Old 20	200	225 × 225	IEEDataPort		
7	Clean Old 50	200	225 × 225	IEEDataPort		
8	Clean Old 100	200	225 × 225	IEEDataPort		
9	Spoilt New 10	200	225 × 225	Mendeley		
10	Spoilt New 20	200	225 × 225	Mendeley		
11	Spoilt New 50	200	225 × 225	Mendeley		
12	Spoilt New 100	200	225 × 225	Mendeley		
13	Spoilt Old 10	200	225 × 225	Mendeley		
14	Spoilt Old 20	200	225 × 225	Mendeley		
15	Spoilt Old 50	200	225 × 225	Mendeley		
16	Spoilt Old 100	200	225 × 225	Mendeley		

Table 2. Comparison of pre-trained models

Sr. No.	Name of the pre-trained model	Data augm-entation	Epoch	Keras pre-processing	Hyperparameter				Wall time taken by model for training	Accuracy	
					Batch size	Optimizer	Learning rate	Activation function		Without fine-tuning	With fine-tuning
1	VGG16	Yes	30	Yes	32	rmsprop	0.001	relu	42m 56s	67.50%	87.50%
2	VGG19	Yes	30	Yes	32	rmsprop	0.001	relu	47m 55s	67.34%	85.47%
3	Xception	Yes	30	Yes	32	rmsprop	0.001	relu	51m 41s	60.31%	60.31%
4	ResNet 152V2	Yes	30	Yes	32	rmsprop	0.001	relu	39m 49s	67.50%	67.81%
5	InceptionV3	Yes	30	Yes	32	rmsprop	0.001	relu	45m 55s	59.69%	60.62%

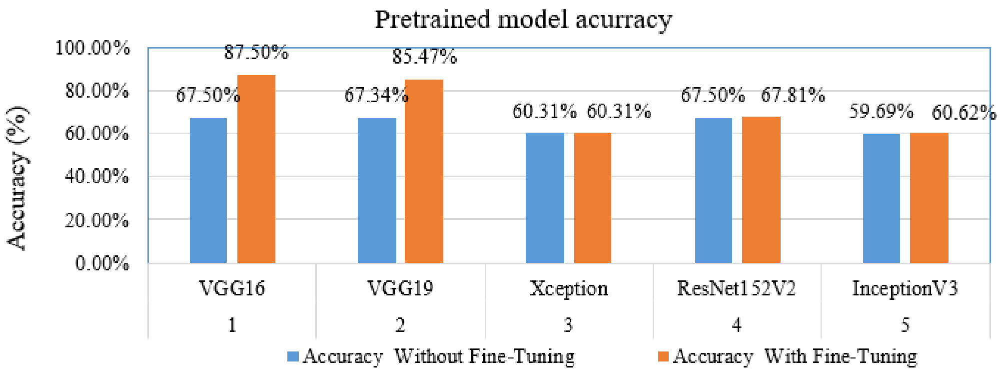


Figure 1. Accuracy of pre-trained models considered

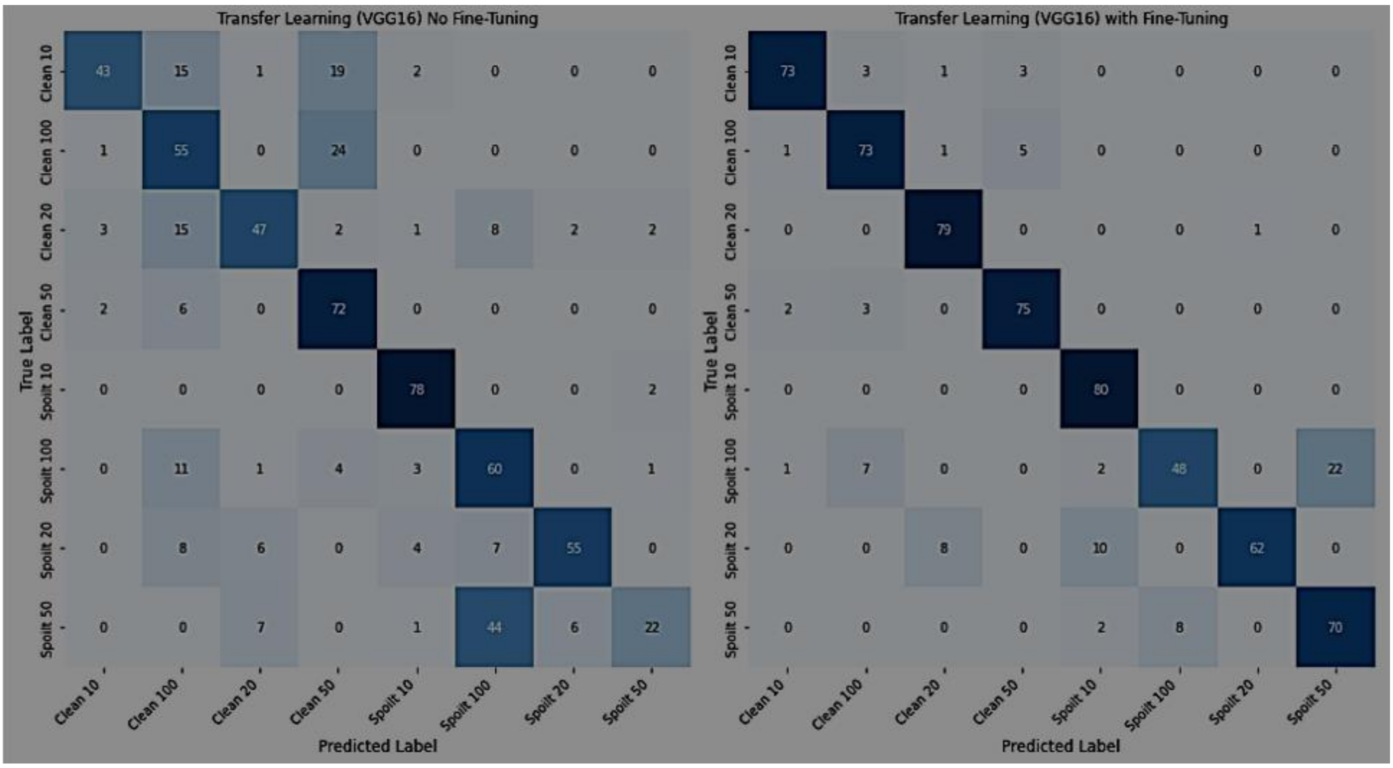


Figure 2. VGG16

1. Earlier CONV layers in the original network should be frozen.
2. Replace the fully connected (FC) nodes of the original architecture with newly initialized nodes.
3. Begin training, but only for the FC layer heads.
4. Unfreeze some or all CONV layers in the original network and run a second pass of training.

So, while experimenting, the fully connected layers were replaced and placed on top of the original architecture of the model. The FC layers were trained first by freezing the original layers and the second time by fine-tuning, two layers from the original architecture were unfrozen and again the FC layers were trained. The output layer consists of parameters for a number_of_classes and the activation function. The number_of_classes was initialized to 8 and the activation function was initialized to Softmax. The results of each selected model with and without fine-tuning are shown in Table 2. From the table it can be derived VGG16 performs best among the five models compared.

Figure 1 shows the accuracy of each pretrained model considered, with and without finetuning. It can be derived after comparison of five models that without finetuning, both VGG16 and ResNet52V2 have the same accuracy, i.e., 67.50, but after fine tuning VGG16 performs best among the five pretrained models with 87.50 % accuracy.

The confusion matrix with and without finetuning for the classification of banknotes for each evaluated model is shown in Figures 2-6, respectively.

The classification accuracy of the models is displayed using the confusion matrix of each pretrained model taken into consideration. The model is run with a batch size of 32, having 8 classes, with 30 epochs. An architecture for improving the quality parameters for fruit detection proposed by Meshram et al. [30] is considered to check whether the quality parameter classification of banknotes is improved or not the MNet architecture is used. The author has used inception V2 for their architecture, but after pretrained models were evaluated on the banknote dataset VGG16 performs more accurately, thus the MNet architecture using VGG16 is evaluated for quality classification of banknotes. The MNet architecture for the banknote dataset with VGG16 was run for 30 epochs with finetuning. For fine-tuning, 5 convolution layers of the VGG16 model are unfreeze. The results of MNET architecture with VGG16 for banknote classification and banknote quality classification are presented in Figure 7 (a and b), respectively. From the confusion matrix, the accuracy of MNET architecture with VGG16 for banknote classification is 99.68 percent, and the accuracy for banknote quality classification is 100 percent.

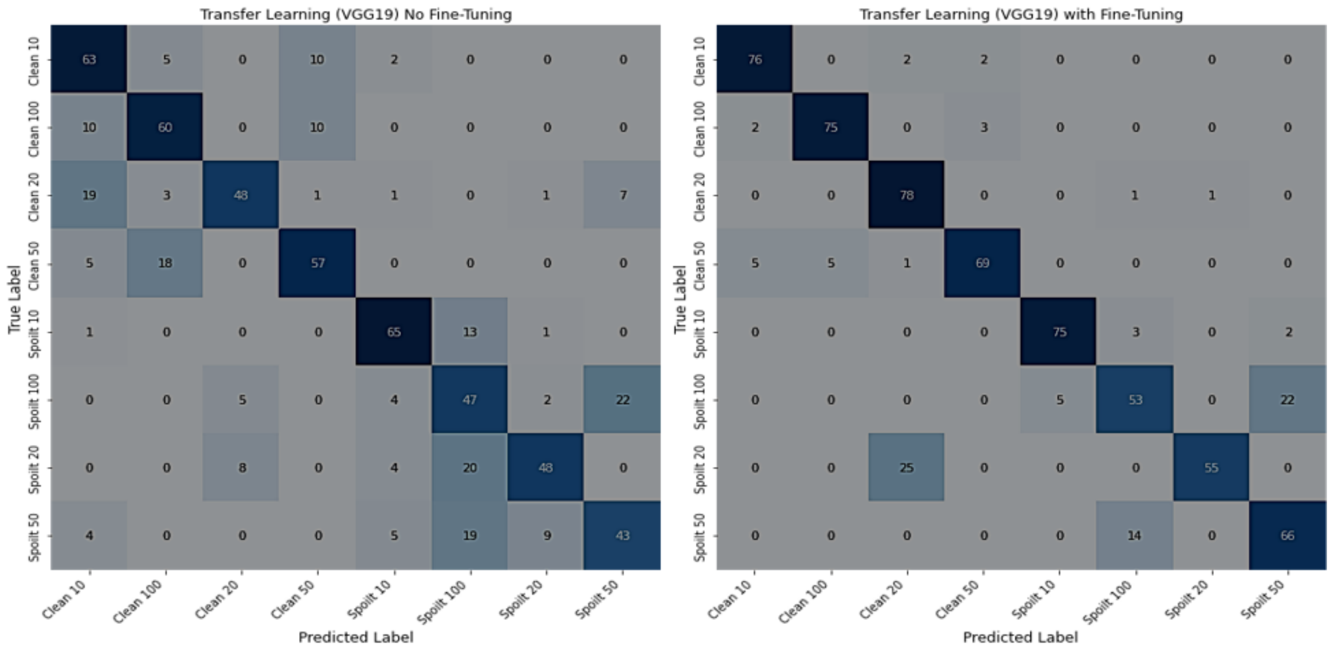


Figure 3. VGG19

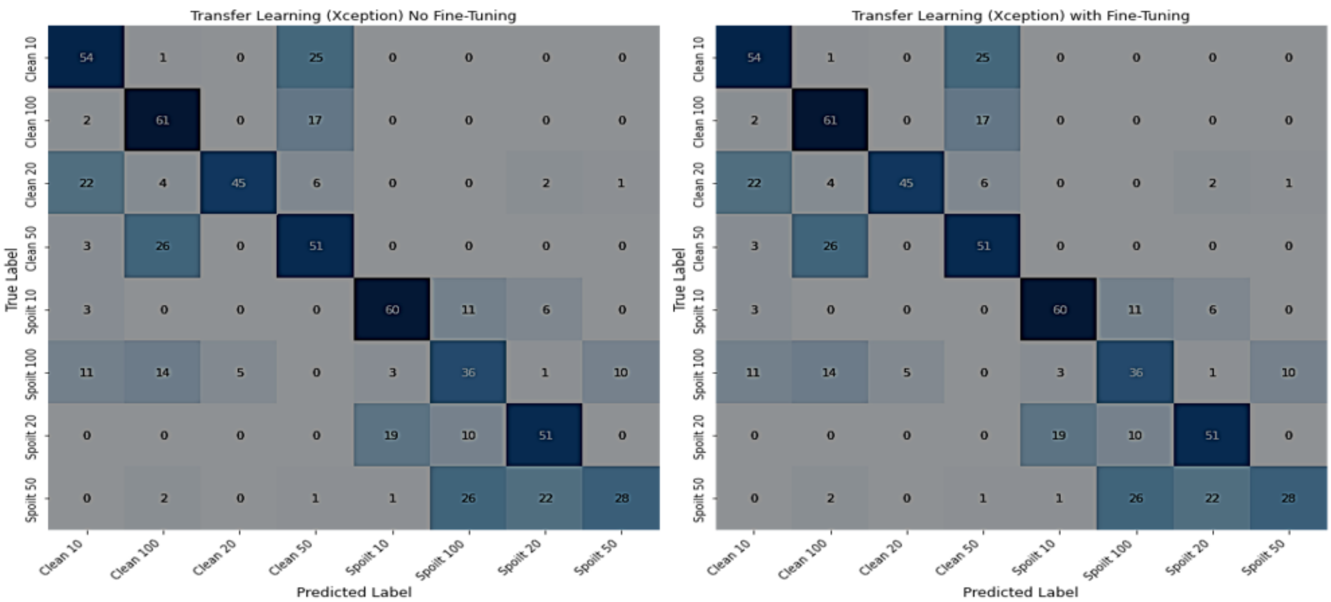


Figure 4. Xception

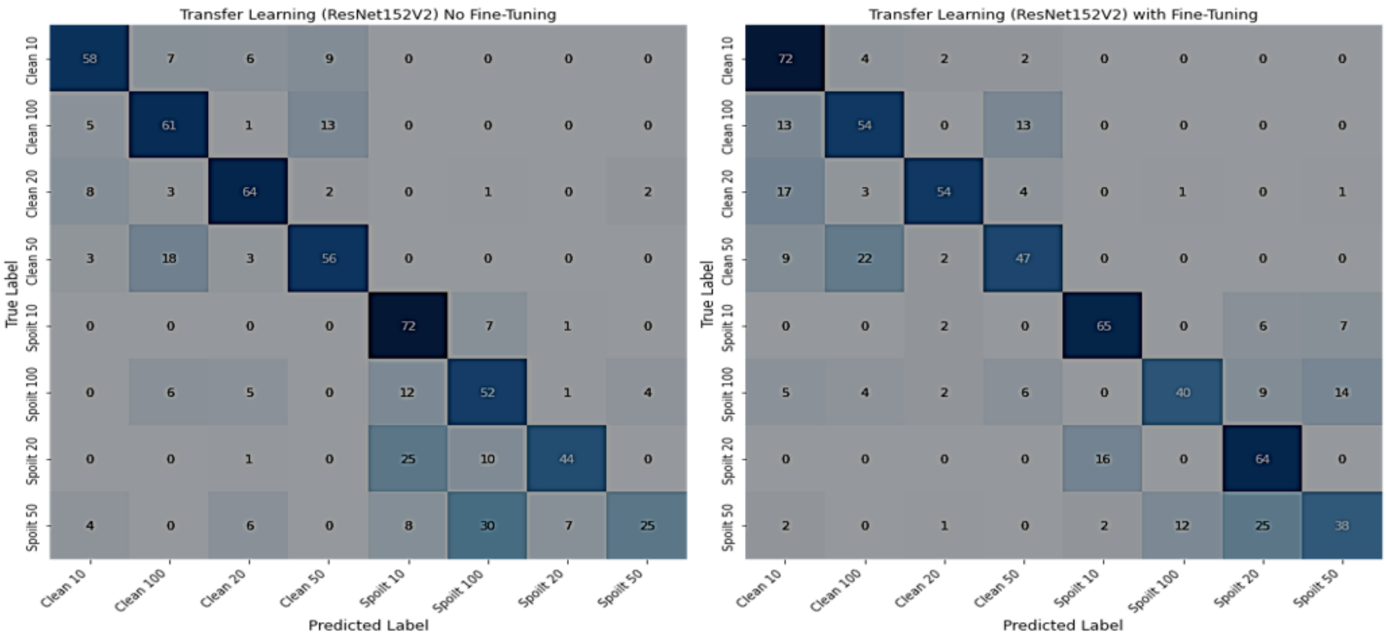


Figure 5. ResNet152V2

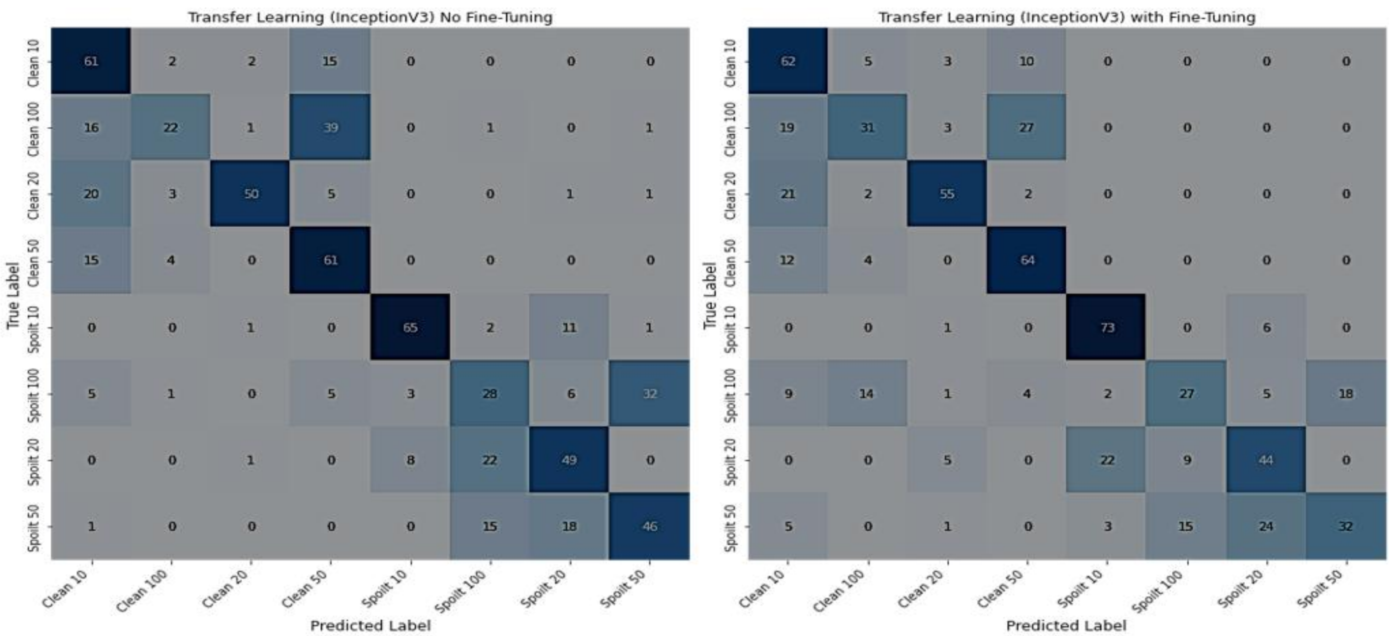
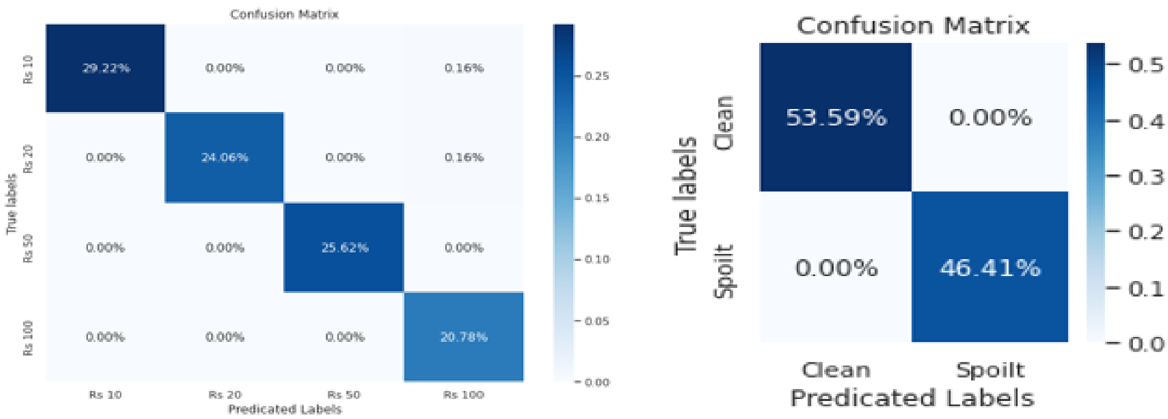


Figure 6. InceptionV3



(a) (b)

Figure 7. (a) Banknote classification using Mnet; (b) Banknote quality classification using MNet

5. CONCLUSION

The presented work has performed the evaluation of pretrained models, namely, VGG16, VGG19, Xception, ResNet152V2, and InceptionV3 on our banknote dataset, consisting of 8 classes, 4 for clean banknotes of 10, 20, 50,100, and 4 for spoiled banknotes of 10, 20, 50, and 100. Among the considered pretrained models, VGG16 performed best, giving an accuracy of 87. 50 percent for the classification of banknotes. Further, to improve the classification accuracy considering the quality parameters of banknotes, MNET architecture was evaluated. This Mnet architecture gives 99.68 percent accuracy for the classification of Indian banknotes and 100% accuracy for banknote quality classification.

Although several researchers have done ample amount of work for banknote classification and identification of fake banknotes, the area of classification of banknotes along with the quality parameters of banknotes has remained untouched. Moreover, there is no existing dataset which has both good and bad quality of Indian Banknotes. Thus, a banknote dataset with Both good and bad quality Indian banknotes were created, and transfer learning using pretrained models is done for classification of Indian banknotes along with their quality is done. Although there are several other pretrained models available, as a part of the research selected pretrained models are evaluated and our own dataset of clean and spoiled banknotes of India is used for evaluating classification accuracy of models. Other pretained models can be evaluated and their accuracy can be checked. The MNET architecture using VGG16 pretrained model provides 100 percent accuracy for banknote quality classification. Hence, this architecture can be integrated with a mobile app, as a further enhancement, also this architecture can be used for the quality classification of banknotes of other countries, provided there is availability of dataset consisting of good and spoiled banknotes of other nations.

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