Threat Object Classification in X-ray Images Using Transfer Learning

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***Abstract*—Automatic classification of threat objects in X-ray images is important because of terrorist incidents happening in every country especially in the Philippines. Manual inspection using X-ray machine is prone to human error due limited amount of time given to the operator to check the baggage. This task is also stressful because there are lots of objects to be identified and needs full attention. Over long period of time, the performance of human inspector decreases and the chance of missed detection increases. As a solution to the problem, this paper used the concept of transfer learning in classification of threat objects. The threat objects used in the experiment consists of 4 classes such as blade, gun, knife and shuriken. The dataset came from the GDXray database, a public database of X-ray images. Experiment results showed that by using the concept of transfer learning with data augmentation and fine-tuning, threat objects can be classified at 99.5% accuracy.**

Keywords— computer vision, convolutional neural networks, image classification, threat object, transfer learning, X-ray

I. Introduction

In every country, one of the highest priority is national security. Philippine government is continuously investing on weapons, and training of military personnel to keep the country secured from terrorist's attack. Based on the data from the Global Terrorism Database (GTD), Philippines was listed as rank 5 in the highest count of terrorist attacks [1]. The total number of incidents in 2016 was 633 with a total of 411 deaths and 720 injuries. Most of attacks was armed assault and bombing. To prevent unexpected incidents, entrance in airports, malls, and train stations have a security personnel and X-ray machine to check the bags of the person entering the area. But during rush hour, the likelihood of missed detection is big because the operator has only limited time to check the baggage. Another problem is that as time passed by, the performance of the operator will decrease due to tiredness. To solve this problem, this paper will use the concept of transfer learning to automatically classify threat objects in X-ray images.

The rest of the paper is organized as follows. Section II briefly discuss some related works about object classification in X-ray images. Section III explains the concept of transfer learning. Section IV presents the result of experiments. Section V is the conclusion.

II. Object Classification in X-ray Images

Classification of X-ray images is a challenging task in computer vision. The reason is that, images from X-ray are commonly occluded by other objects and cannot be recognized easily when rotated [2]. It is also hard to collect X-ray data because it will take 3-5 minutes just to scan an object and project it to the display. X-ray imaging is typically used in medicine to locate and identify fractured bones, dental radiography, food quality evaluation and baggage inspection. In baggage inspection, manual screening using X-ray machine is used in entrance of airports and train stations. The baggage is placed in a conveyor and the operator will observe the scanned baggage for any prohibited items in just a limited amount of time. With this, the probability of missed detection is big. To solve this problem, researchers proposed to automate the detection of threat objects. In [3], used adapted implicit shape model (AISM) to automatically recognize object in X-ray images. This is based on well-known implicit shaped model (ISM) which was originally developed for recognition of car, people, and animal photographs. In [4] presented an image classification technique for object detection in X-ray images using primed visual words in an SVM classifier framework. The proposed technique was evaluated in firearm recognition and mobile phone detection. Another paper in [5] used ensemble of exemplar-SVM in large scale classification of cargo images. In [6] evaluated modern computer vision techniques for baggage inspection such as bag of words (BoW's), sparse representations, codebooks and deep features. This is the first experiment in baggage inspection that uses deep learning. Their work shows that the highest recognition was achieved by methods based on visual vocabularies and deep features with 95% accuracy.

III. Transfer Learning

Transfer learning or knowledge transfer is a method of re-using a model trained from large dataset such as ImageNet [7] to solve another problem or task. This technique can be helpful when the available data is small and saves time labeling large amount of data. In [8] said that transfer learning allows the domains, tasks, and distributions used in training and testing to be different. The idea is that low level features like edges, colors, textures, shapes and lighting can be shared among different tasks. Training of data from scratch can be avoided by adopting a pre-trained network instead of random initialization of parameters and use it as a starting point of the training. In the work of [9] in medical image analysis, showed that sufficient fine-tuning of pre-trained deep convolutional neural network eliminates the need to train from scratch.

Transfer learning in image classification is used in many applications including medical [10], manufacturing [11] and baggage screening [12]. In [10] used multi-source transfer learning with convolutional neural network (CNN) for lung pattern analysis. In [11] used transfer learning in Mura (uneven screen display) defect classification. Lastly, [12] used transfer learning using AlexNet [13] and GoogleNet [14] to classify X-ray baggage images. Aside from image classification, transfer learning can be applied to object detection [15]. For this paper, VGG-16 model by [16] is

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used for image classification.

IV. Experiments and Discussion of Results

In this section, the dataset used in the experiment is described and how this data is preprocessed before feature extraction and fine-tuning followed by evaluation of results.

A. X-ray Dataset

The X-ray images used in this paper came from the GDXray database [17]. It is composed of 19,407 X-ray images and divided into five groups such as castings, welds, baggage, natural objects and settings. For threat object classification, X-ray images of baggage was used. Table I shows the training, validation and testing data used in the paper. The dataset was divided into 60% for training, 20% for validation and 20% for testing. Training data was used to train the threat object classifier. Validation data was used to tune the parameters. Testing data was used to measure the performance of the threat object classifier. The test accuracy of each class ($\boldsymbol{A_i}$) was computed using (1) where $\boldsymbol{i} = 1 \ldots m$, $\boldsymbol{m}$ = number of classes.

$$A_i = \frac{TP + TN}{P + N} \times 100\% \qquad (1)$$

The average accuracy ($\boldsymbol{A_{ave}}$) was computed using (2) to know the overall performance.

$$A_{ave} = \sum_{i=1}^{m} A_i \qquad (2)$$

Precision ($\boldsymbol{Pr}$) and recall ($\boldsymbol{Re}$) was also computed using (3) and (4) respectively. $\boldsymbol{Pr}$ calculates the predictive power of the model and $\boldsymbol{Re}$ calculates the hit rate or true positive rate.

$$Pr = \frac{TP}{TP + FP} \qquad (3)$$

$$Re = \frac{TP}{TP + FN} \qquad (4)$$

Where,

TP = true positive
TN = true negative
FP = false positive
FN = false negative
$P + N$ = total test data (positive and negative samples)

Another metric ($\boldsymbol{p}$) introduced by [6] was adopted to measure the detection performance using (5) and (6).

$$Q_i = \sqrt{Pr \times Pe} \qquad (5)$$

$$p = \frac{1}{m} \sum_{i=1}^{m} Q_i \times 100\,\% \qquad (6)$$

TABLE I. Number of X-ray Images Per Category

Threat Objects	Number of X-ray Images			
	Training	**Validation**	**Testing**	**Total**
Blade	150	50	50	**250**
Gun	150	50	50	**250**
Knife	150	50	50	**250**
Shuriken	150	50	50	**250**
Total	**600**	**200**	**200**	**1000**

B. Training of Threat Object Classification from Scratch

In order to show how transfer learning affects the performance of threat object classification, the dataset was first trained from scratch. The model was composed of 5 convolutional layers and 2 dense layers. The activation function used for the 1st up to 6th layer is ReLU (Rectified Linear Unit) which is zero for negative values and grows linearly for positive values. In the last layer of the network, softmax activation function was used. Softmax function squashes the output of each output units between 0 and 1. The value of each output unit corresponds to probability distribution of each classes with a total sum of 1. In the training, only 600 X-ray images of threat objects fed to the network. Using batch size = 20, the training takes 30 steps per epochs. Every steps were validated using validation data that has 200 X-ray images of threat objects. Fig. 1 shows the training and validation accuracy of the model. As we can see, after 5 epochs the model is overfitting.

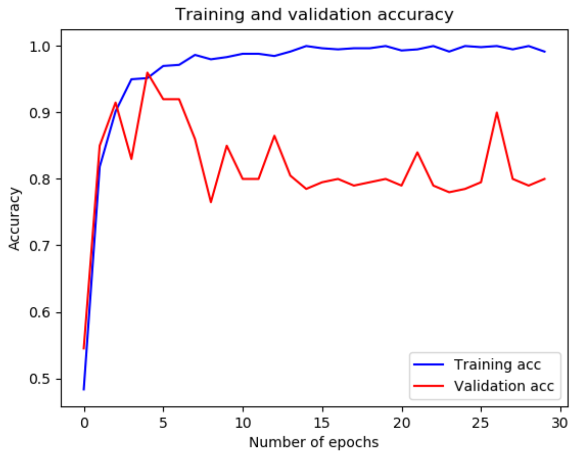

Fig. 1. Training and validation accuracy.

Fig. 2 shows the confusion matrix of the trained model. An ideal confusion matrix has diagonal values equal to the test data which is 50 X-ray images per class. The model was able to identify 50 images of gun, blade, and shuriken but failed to identify 46 images of knife. 46 knifes was predicted as gun based on the figure.

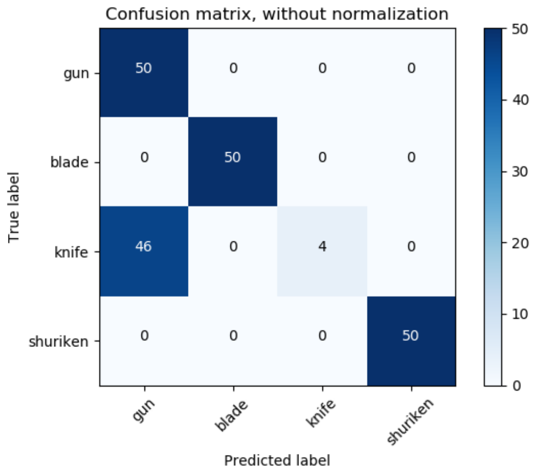

Fig. 2. Confusion matrix.

In another experiment, data augmentation was applied to the images to generate more training data from existing training examples which is only 600 images. In data augmentation, random transformations were implemented to the images such as random rotation, shearing, random zooming, and flipping. Fig. 3 shows the sample generated images of gun using data augmentation.

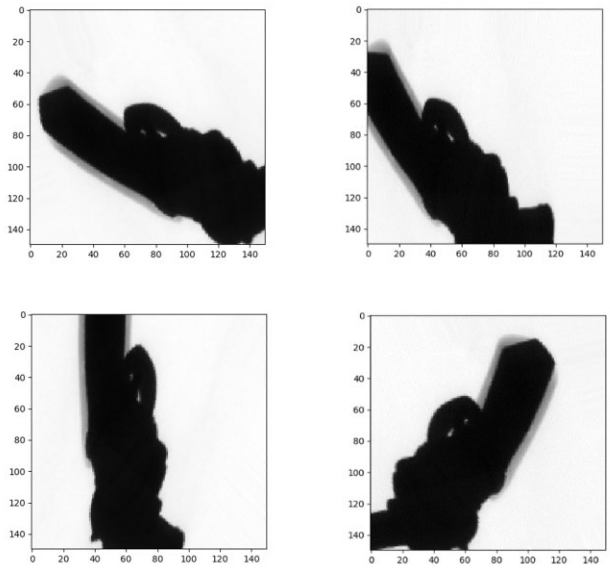

Fig. 3. Generated images of gun using data augmentation.

Fig. 4 shows the training and validation accuracy of the model with data augmentation. As we can see, the validation accuracy starts at an accuracy of 72.5% and keeps increasing in each number of epochs up to 95.5% without overfitting. The data augmentation helps the model with a small training data to prevent overfitting.

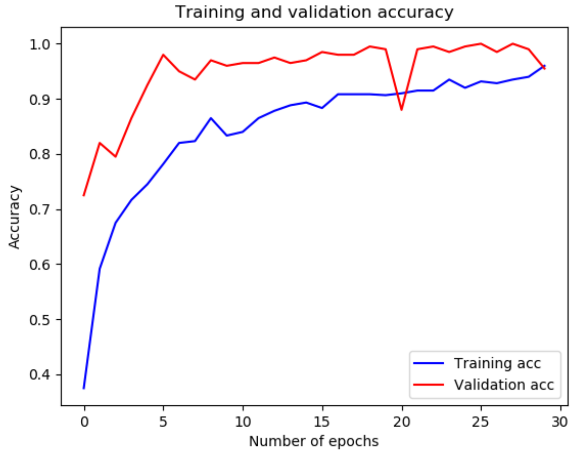

Fig. 4. Training and validation accuracy. (with data augmentation)

Fig. 5 shows the confusion matrix of the trained model with data augmentation. The model successfully identified the knife and shuriken but failed to identify 4 guns and 2 blades. 4 guns was predicted as knife and 2 blades was predicted as shuriken.

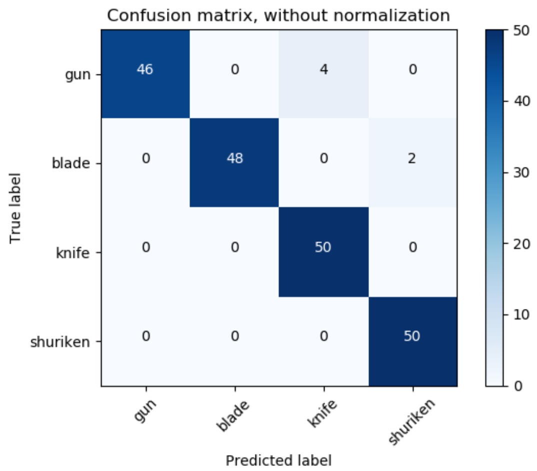

Fig. 5. Confusion matrix. (with data augmentation)

C. *Applying Transfer Learning for Small Dataset*

In the next experiment, data augmentation and transfer learning was applied using pre-trained model from large database which is the VGG-16. This is a 16 layer deep neural network design by [16] trained in 1000 different classes on ImageNet [7]. VGG-16 model has a total of 14,714,688 parameters with 5 convolutional blocks. The model was used as a feature extractor to extract generic features like edges, colors and textures. In applying transfer learning, the convolutional base is frozen to preserve generic features learned from previous training. Fig. 6 shows the training and validation accuracy after applying transfer learning. As we can see, the validation accuracy starts at 95% instantly at first epoch and 99% at 30 epochs. The combination of data augmentation and transfer learning improves the accuracy of the threat object classifier.

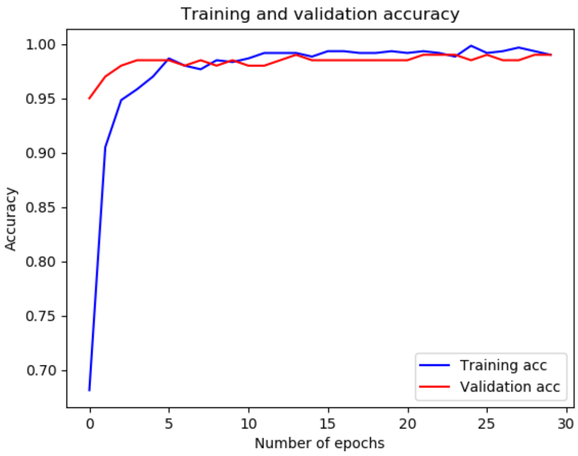

Fig. 6. Training and validation accuracy. (transfer learning with data augmentation)

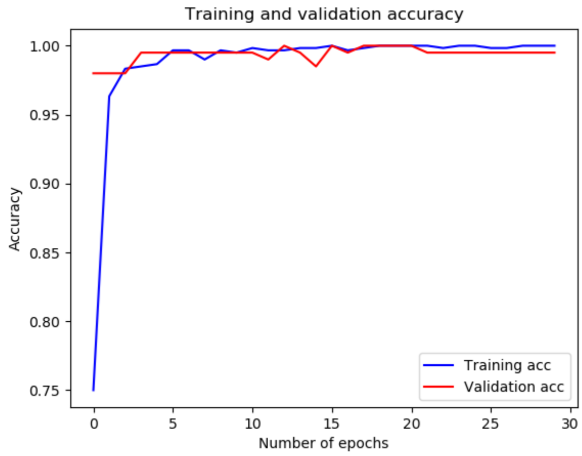

Fig. 8. Training and validation accuracy. (fine-tuned model)

Fig. 7 shows the confusion matrix of the trained model with data augmentation and transfer learning. The model successfully identified the blade, knife and shuriken but failed to identify 4 guns. 4 guns was predicted as blade in the test data.

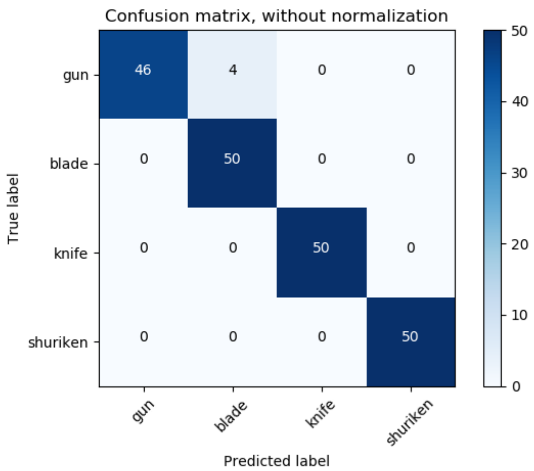

Fig. 7. Confusion matrix. (transfer learning with data augmentation)

D. *Fine-Tuning the Model*

After implementation of transfer learning with data augmentation, the threat object detection classifier was fine-tuned by unfreezing few top layers of the pre-trained model which is the fifth convolutional block of VGG-16 and trained it jointly with 2 dense layers. Based on literature, fine tuning upper layers of the pre-trained model has positive effect on the classification performance. The fifth convolutional block is composed of 3 convolutional layers and 1 pooling layer. The total number of parameters of the model is 16,813,124 including 2 dense layers at top of the network. Fig. 8 shows the results the training and validation accuracy of the fine-tuned model. As we can see, the validation accuracy starts instantly at 98% and at some epochs (e.g. epoch = 13), has an accuracy of 100%. In the last epoch, the accuracy decreased slightly at 99.5%

Fig. 9 shows the confusion matrix of the fine-tuned model. The model successfully identified the blade, knife and shuriken but failed to identify 1 gun. 1 gun was predicted as blade in the test data.

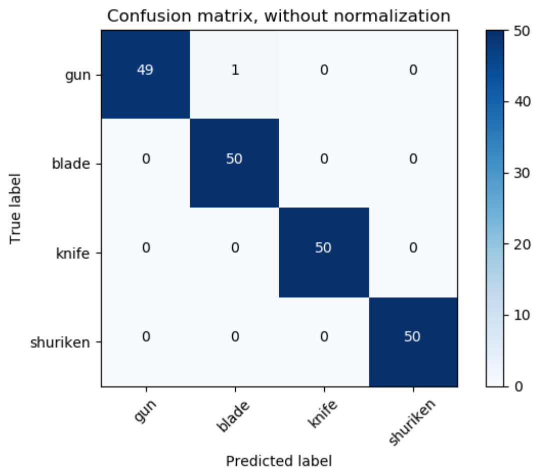

Fig. 9. Confusion matrix. (fine-tuned model)

Table II shows the performance summary of threat object classifier in test data. It shows that the maximum accuracy was achieved using fine-tuned model at 99.5%. The lowest accuracy from the customized model which is trained from scratch achieved 77% only. Table III shows the $\boldsymbol{Pr}$ and $\boldsymbol{Re}$ values of each classifier as well as the $\boldsymbol{p}$ values. Again, the fine-tuned model achieved the highest value which is 99.5%.

TABLE II. PERFORMANCE OF THREAT OBJECT CLASSIFIER

Model	$\boldsymbol{A_i}$				$\boldsymbol{A_{ave}}$
	gun	**blade**	**knife**	**shuriken**	
Customized model	100.0	100.0	8.0	100.0	77.0
Customized model with data augmentation	92.0	96.0	100.0	100.0	97.0
Transfer learning with data augmentation	92.0	100.0	100.0	100.0	98.0
Fine-tuned model	98.0	100.0	100.0	100.0	99.5

TABLE III. PRECISION AND RECALL OF EACH CLASSIFIER

Model	gun		blade		knife		shuriken		p
	Pr	Re	Pr	Re	Pr	Re	Pr	Re	
Customized model	0.52	1.00	1.00	1.00	1.00	0.08	1.00	1.00	75.1
Customized model with data augmentation	1.00	0.92	1.00	0.96	0.93	1.00	0.96	1.00	97.1
Transfer learning with data augmentation	1.00	0.92	0.93	1.00	1.00	1.00	1.00	1.00	98.1
Fine-tuned model	1.00	0.98	0.98	1.00	1.00	1.00	1.00	1.00	99.5

V. CONCLUSION

Threat object classification in X-ray images using transfer learning was successfully implemented in a small dataset consisting of 250 images per threat objects. Experiment result shows that the use of transfer learning with data augmentation and fine-tuning for threat classification improves the performance of the model.

For future work, the transfer learning will be experimented using own X-ray dataset to detect improvised explosive devices (IED's) and will be deployed to a bomb disposal robot.

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