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Multilabel image analysis on Polyethylene Terephthalate bottle images using PETNet Convolution Architecture

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Abstract
Packaging is most of the important aspects of the product. Good packaging can increase the competitiveness of a product. Therefore, to maintain the quality control of the packaging of a product, it is necessary to have a visual inspection. Furthermore, an automatic visual inspection can reduce the occurrence of human errors in the manual inspection process. This research will use the convolution network to detect and classify PET (Polyethylene Terephthalate) bottles. The Convolutional Neural Network (CNN) method is one approach that can be used to detect and classify PET bottle packaging. This research was conducted by comparing seven transfer learning models of CNN, namely VGG-16, Inception V3, MobileNet V2, Xception, Inception ResNet V2, Depthwise Separable Convolution (DSC), and PETNet, which is the architectural model proposed in this study. The results of this study indicate that the PETNet model gives the best results compared to other models, with a test score of 96.04%, by detecting and classifying 461 of 480 images with an average test time of 0.0016 seconds.

Keywords:
Convolutional Neural Network (CNN);
Polyethylene Terephthalate Network (PETNet);
Quality Control;
Transfer Learning Model;
Visual Inspection;

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INTRODUCTION

In the product packaging process that uses bottles as containers for the product, several stages must be passed before it becomes a finished product (a finished good), including filling, labeling, capping, and others [1][2]. Of course, these stages cannot be separated from errors in the product packaging process [3]. Moreover, when defective products are distributed to consumers, they may generate complaints or even product returns [4][5]. Therefore, manufacturers must use a quality control system to reduce financial risk and reputational damage [6]. Thorough testing of products is required before shipment [7].

As a result, in order to maintain production quality, a visual inspection of the product is required to ensure that the results are in accordance with the established rules. One of the most common procedures in the industry is the visual approach to defect detection [8]. Most bottle inspections are hand-picked by operators using eye checks [9]. But currently, due to increased production capacity, an industry cannot use human labor to sort a product [10]. Therefore, many industries have recently incorporated artificial intelligence (AI) algorithms into their manufacturing processes [11][12]. In particular, AI approaches within the industry are always needed to reduce machine failures and improve quality control products automatically [13]. Intelligent production planning systems will increase industry efficiency and productivity [14].

One of the numerous digital image classification methods available today that can be used for visual sorting is the Artificial Neural Network (ANN) method. An ANN is a traditional structure comprising three layers: input, output, and hidden. There are a different number of neuron elements in each layer [15]. Multi-Layer Perceptron (MLP) is the name given to this type of ANN model with many layers (MLP). In terms of classification, MLP is extremely accurate. MLP, on the other hand, has a weakness in digital image classification. To address this problem, MLP, specifically the Convolutional Neural Network

(CNN), has been developed. CNN is generally used for image data identification and classification [16]. CNNs have a layered architecture with shared weights, sparse connections, and pooling operations that can identify both short-term and long-term patterns occurring in different parts of the time series [17]. However, CNN has produced numerous new breakthroughs in various applications, including segmentation, object recognition, and detection [18].

CNN has numerous architectures, including LeNet, AlexNet, ResNet, and GoogleNet [19]. GoogleNet is a CNN-based architecture that was introduced in 2014 and won the ImageNet LargeScale Visual Recognition Challenge 2014 (ILSVRC14) contest on image data classification. In addition to GoogleNet, ResNet (Residual Network) is a type of deep transfer learning based on network residuals. ResNet-50 consists of 16 residues, each with a convolution size of 1x1, 3x3, and 1x1 and function diagrams (64, 128, 256, 512, and 1024) [20]. There is also AlexNet, which is a different model. AlexNet is a deep convolutional neural network version with a large variety of hidden layers, consisting of an enter layer, five convolutional layers, three pooling layers, and three fully connected layers [21]. Then there's MobileNet. MobileNet is a CNN architectural model that employs two sets of hyperparameters for an efficient design, allowing for the creation of very small, low-latency models that can be easily implemented to meet the needs of mobile and embedded applications [22]. To reduce computation in the initial layer, MobileNet is built on depth wise separable convolutions [23].

By comparing several Convolutional Neural Networks (CNN) models, this study proposes some of the best models for classifying Polyethylene Terephthalate (PET) bottle images. The contents, caps, and labels on the bottles were the parameters detected in this study. This study used more class labels and datasets than previous studies. Because the trained model is an optimal convolutional neural network model, it has a high accuracy level in classifying PET bottle images.

METHOD

Several steps must be taken in this study to get the best results regarding PET bottle classification. Figure 1 shows the stages carried out in this research.

Figure 1. Research Stages

Data Collection

The dataset used in this study is PET bottle image data, taken using a digital camera and totalling 4800 images. Large datasets are needed to create better results.

This study divides the dataset into eight label classes (empty fill, less fill, missing label, broken label, faulty label, missing cap, broken cap, and faulty cap) with 48 possible label classes on the image. It is broadly divided into three types: predicted label class, predicted label classes, and predicted label classes. To avoid an imbalance in the data that can result in poor model predictions, the authors generalize the mix of data, using 100 images for each possibility. Figure 2 is an example of the dataset used in this study: an image with one label class, two label classes, and three label classes.

Program Implementation

The data that has been collected will be pre-processed first with the steps shown in Figure 3. Based on Figure 3, in the pre-processed image stage, the first step is to transform the image to 200 x 200 pixels with 3 RGB channels, and then the image will be converted into an array that represents the value of each pixel in the image. After that, the value of the array will be changed to its value range from 0-255 to 0-1 so that the value is not too large and to make it easier during the training process.

After the image has been pre-processed, the next step is determining the architectural model. In particular, the following models have been used: Depthwise Separable Convolution, Xception, VGG-16, MobileNetV2, Inception V3, Inception ResNet V2 and PETNet. The proposed model architecture (PETNet) is presented in Figure 4.

The proposed model (PETNet) is divided into two parts, namely the feature learning layer and the fully connected layer. Feature learning is a pattern recognition process in images with several stages. First, the image dataset is inserted into the convolution layer + ReLu, so the output is a feature set. The next stage is max pooling, which is used to simplify the feature set data.

After that, a technique called batch normalization is used to normalize the output so that the PETNet training process can be optimized and accelerated.

Figure 2. Sample Dataset

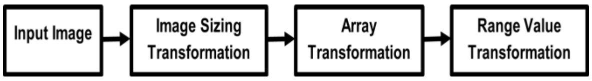

Figure 3. Image Pre-Processed Steps

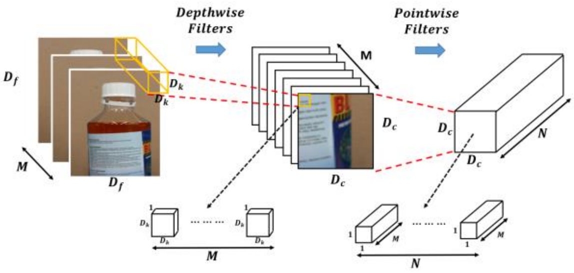

Figure 4. Proposed Model Architecture

The last stage in the feature learning process is dropout regularization, which aims to prevent the model from being overfitted by randomly deactivating some neurons in the layer.

Based on Figure 4, there are 5 Conv2D layers in the proposed model, which can be calculated using (1) and five max-pooling layers, which can be calculated using (2) and (3), as follows [24, 25, 26, 27]:

$$y_{w^{l+1},h^{l+1},d} = \sum_{w=0}^{W}\sum_{h=0}^{H}\sum_{d=0}^{D} f_{w,h,d} \times x^{l}_{h^{l+1}+h,w^{l+1}+w,d} \qquad (1)$$

where ($x^{l}_{i^{l+1}}$) is an input tensor which contains height (h^l), width (w^l), and depth (d^l). The spatial location of (h^l, w^l) is utilized from the bank filter of f and d^l is a receptive field x^l. Therefore, the total trainable parameters of the feature extraction represented as kernel formalized as [24, 25, 26, 27]:

$$y_{k^{l+1},c^{l+1}} = D_k^2 \times D_c^2 \times M \times N \qquad (2)$$

The PETNet and DSC models have been optimized for hyperparameter selection (for example, the number of convolution layers and filters in each layer, the dropout parameters, and the number of neurons in the fully connected layer).

Models with pre-trained weights in ImageNet were fine-tuned to classify bottle defects based on the datasets collected, while PETNet and DSC models were trained from the beginning. DSC consists of a depthwise filter and a pointwise filter, which are formalized as [24, 25, 26, 27]:

$$y_{w^{l+1},h^{l+1},d} = \sum_{d=0}^{D} f_d \times \sum_{h=0}^{H}\sum_{w=0}^{W} f_{w,h} \times x^{l}_{h^{l+1}+h,w^{l+1}+w} \qquad (3)$$

where f_d denotes as 1×1 convolution, namely pointwise filter. Therefore, the total trainable parameter of the DSC layer is formulized as [24, 25, 26, 27]:

$$y'_{k^{l+1},c^{l+1}} = (D_c^2 \times M)(D_k^2 + N) \qquad (4)$$

Therefore (2) and (4) show the DSC architecture reduced the trainable parameters of the convolution process.

Classification

Training and validation are the next steps. The TensorFlow library is used to test and train models. Figure 4 represent the proposed PETNet architecture containing depthwise and pointwise layer. The vector multiplication among the pointwise and depthwise shown in equation (3) represent the optimization of the conventional CNN architecture. Therefore, the PETNet is able to reduce the computational cost by lowering the number of the PETNet trainable parameters.

In order to maintain the transfer learning model performance, this research provides the hyperparameter. Table 1 shows the hyperparameter.

The training and validation process can be seen in Figure 5. In the training and validation process, the first stage carried out before the model is trained is dividing the dataset into datasets for training and datasets for validation. Then each model will be trained and validated. At this stage, each model's accuracy and training validation values will be calculated.

Table 1. Hyperparameter

Description	Parameters
Models	*PETNet, DSC, VGG16, MobileNet V2, InceptionV3, Xception, Inception ResNetV2*
Dataset	Image PET Bottle
Batch size	64
Epochs	100
Image Size	200 x 200
Learning Rate	0.001
Optimizer	Adam

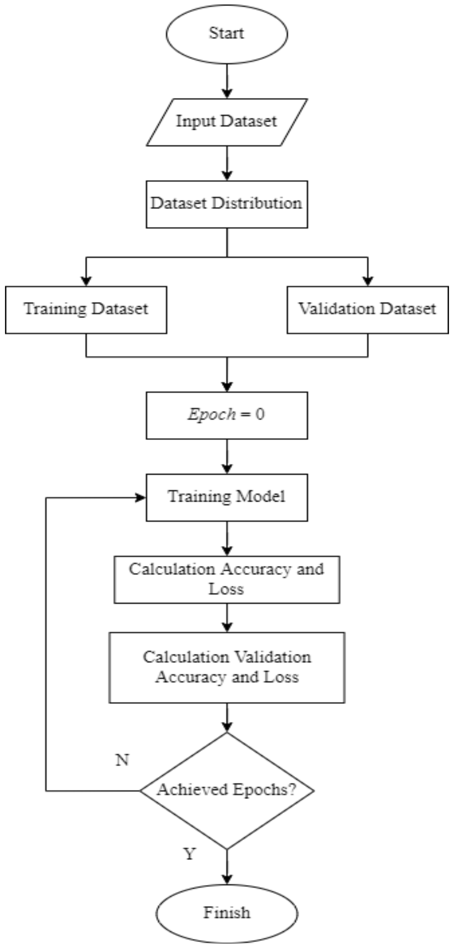

Figure 5. Training and Validation Stages

RESULTS AND DISCUSSION

Each model in this study was performed using an Intel® Core(TM) i3-6006U CPU @ 2.00GHz (4 CPUs), ~2.0GHz, GPU NVIDIA GeForce 920MX, and 4 Gb RAM. Figure 6 depicts the results of each model's training and validation.

Figure 6(a) shows that each model's average accuracy and loss are almost identical. In contrast, the lowest accuracy among these models is Xception, with an average accuracy value of 0.8635. The seven models have the same trend: the higher accuracy value and the increased number of epochs.

The proposed model, namely PETNet, has the highest accuracy compared to other models, with an average accuracy value of 0.8913. Meanwhile Figure 6 (b), the training loss results from each model have a fairly good loss value and will gradually decrease as the number of epochs increases.

The seven models have the same trend even though there are differences in the average values. The proposed model has the lowest average loss value compared to other models, namely 0.1966.

This study used a confusion matrix to evaluate each model [22]. Table 2 shows the results of the confusion matrix model. Based on Table 2, it can be seen that each model has a fairly good average value for the confusion matrix. For example, the proposed model has the same average value for each matrix as the VGG-16 model, which is 100%.

However, in matrix accuracy, the proposed model has a value greater than the VGG-16 model, which is 99%. Meanwhile, the model that has the lowest average matrix precision, recall, and f1-score is the Xception model.

Furthermore, testing of the previously trained model using the image dataset that has been prepared is carried out. The model testing in this study uses a new image dataset that is different from the one used during the training and validation processes. Testing using the new dataset aims to determine the model's performance when it is entered with data that is different from the training data. To find out the performance of the model, it will calculate the accuracy value based on the prediction results of the model on the new image input. Here, the author prepares 480 image data files used for testing. Table 3 shows the effect of model testing.

Table 3 shows that the best models in terms of image classification of PET bottle portraits are PETNet with 461 correct predictions, VGG-16 with 458 correct predictions, and MobileNet V2 with 448 correct predictions, and InceptionResNet V2 with 448 correct predictions. The number of correct predictions is the same for all 443 images: Inception V3 with 434 correct predictions and Xception with 389 correct predictions. It can be said that the prediction results from the model used to classify the PET bottle portrait images using the new dataset are quite good. An example of the test results of the proposed model can be seen in Figure 7.

Figure 7(a) is an image of a dataset with 1 class label "faulty cap". When the image is predicted, the model successfully detects an error in the image. The prediction results are in accordance with the class, which is "faulty cap" with a value of 0.986 (98.6%), while for other classes, the model does not detect any errors or damage to other classes.

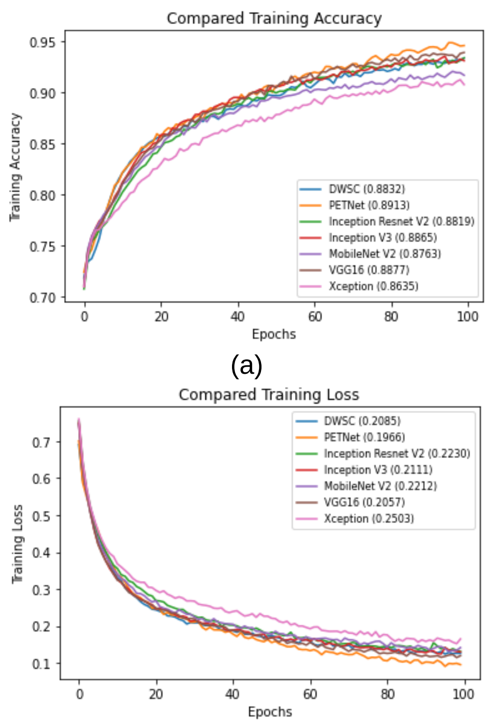

Figure 6. (a) Model Accuracy Comparison and (b) Model Loss Comparison

Table 2. Confusion Matrix Model Performance

Model	**Recall (%)**	**Precision (%)**	**F1-Score (%)**	**Accuracy (%)**
DSC	97	99	99	92
VGG16	100	100	100	98
Xception	99	99	99	97
Inception V3	99	99	99	96
MobileNet V2	100	99	99	97
Inception ResNet V2	99	99	99	97
PETNet	**100**	**100**	**100**	**99**

Table 3. Result of Model Testing

Model	**Correct Prediction**	**Incorrect Prediction**	**Accuracy (%)**
PETNet	**461**	**19**	**96.04**
DSC	417	63	86.88
VGG-16	458	22	95.42
MobileNetV2	440	40	93.33
Inception V3	435	45	90.42
Xception	436	44	81.04
Inception ResNet V2	443	37	92.30

Figure 7(b) is an image of a dataset that has the class "broken cap" and "faulty label". When the image was predicted, the model managed to detect damage to the bottle cap and a label error in the image. The results of the prediction are following the class, namely "broken cap" with a value of 0.974 (97.4%) and "faulty label" with a value of 0.998 (99.8%). While for other classes, the model detects no errors or damage to other classes.

Figure 7(c) is an image of a dataset that has the classes "less fill", "broken cap", and "faulty label". When the image is predicted, the model successfully detects that there are mismatches in the contents, damage to the bottle cap, and label errors in the image. The results of these predictions are in accordance with the class, namely "less fill" with a value of 1.0 (100%), "broken cap" with a value of 0.997 (99.7%) and "faulty label" with a value of 0.999 (99.9%). While for other classes, the model detects no errors or damage to other classes. The computational time performance of each model used for training is calculated in minutes and for testing in seconds, as can be seen in Figure 8 [28, 29, 30, 31].

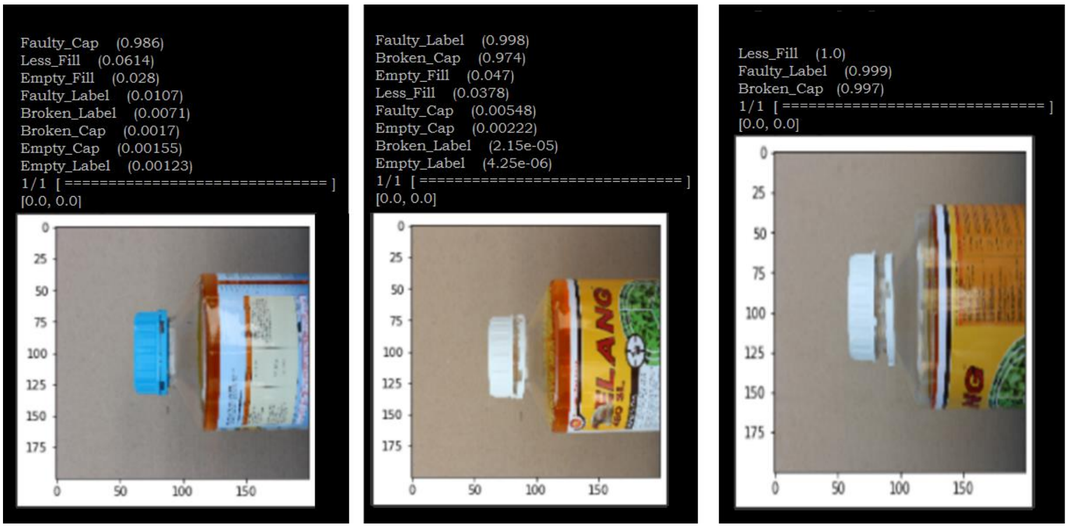

Figure 7. (a) Results of One Class Label Detected (b) Two Class Label Detected and (c) Three Class Label Detected

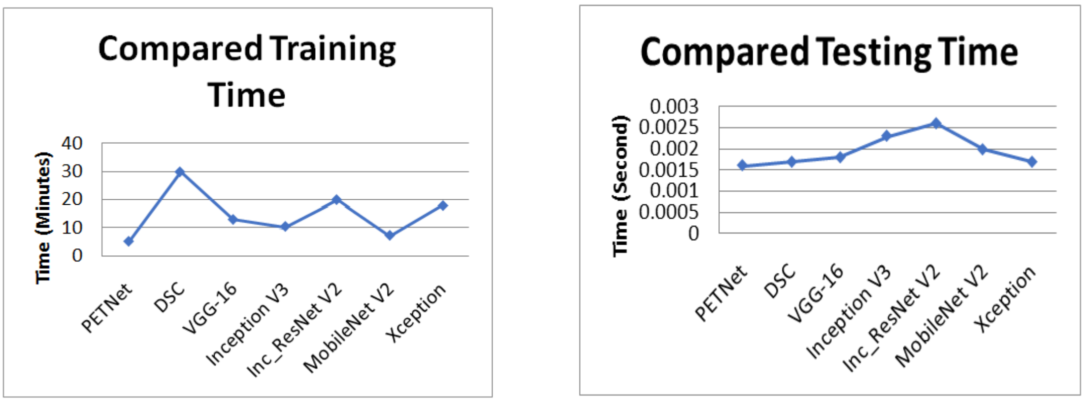

Figure 8. (a) Training Time Comparison and (b) Testing Time Comparison

The computational time performance of each model used for training is calculated in minutes and for testing in seconds, as can be seen in Figure 8. Figure 8(a) shows that the proposed model has the fastest training computation time, with a training computation time of 5 minutes. Meanwhile, the model with the longest computation time is DSC, with a computation time of 30 minutes. Figure 8(b) shows that the proposed model has the fastest computational testing time, with a test computation time of 0.0016 seconds. Meanwhile, the model with the longest computation time is Inception ResNet V2, with a computation time of 0.0025 seconds.

CONCLUSION

Based on the analysis in this study, it was found that PETNet has the best performance in terms of classifying PET bottles into eight classes, namely "empty fill", "less fill", "missing label", "broken label", "faulty label", "missing cap", "broken cap" and "faulty cap". The PETNet architecture was successfully implemented with high performance matrices, which represent the training accuracy and the confusion matrices (precision, recall, and F1-score, respectively). Moreover, the PETNet model, in testing a new dataset that was not used in the training process, succeeded in predicting the most images, namely 461 of 480 images, with a percentage of 96%. Therefore, the reduction of the hyperparameter concluded that the PETNet is the fastest model, which, by testing time compared to other models, is 0.0016 s.

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