Development of a Sequential Neural Network Model for Bottle-Fill Level Detection and Classification

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ORIGINAL RESEARCH

Abstract- Machine vision is one of the cutting-edge technologies that can assist human operators in tasks such as bottle-fill level detection and classification, resulting in increased efficiency in the bottling industry. Although pre-trained models such as the MobileNet, ResNet-50, and VGG-19 for bottle-fill level detection and classification exist, their accuracy is dependent on the similarity of their trained data to the application domain. As a result, this paper describes how to create a sequential neural network model for bottle-fill level detection and classification in Python 3.8.3. The proposed model is evaluated and compared to the MobileNet, ResNet-50, and VGG-19 models in a multiclass problem (correctly filled, overfilled, and underfilled). Furthermore, a confusion matrix was used to assess the performance of the proposed model in the correctly filled, overfilled, and underfilled categories of filled bottles. In comparison to the MobileNet, ResNet50, and VGG-19 models, the proposed model had a training and testing dataset accuracy of 98%, while the MobileNet had 73%, ResNet50 had 76%, and VGG-19 had 75%. The accuracy of the confusion matrix on 40 sample sizes for each class of the filled level was 97%. Finally, in the application domain, the proposed model outperforms the MobileNet, ResNet50, and VGG-19 models. As a result, the method used in the neural network layer structuring of the sequential neural network model should be considered a viable alternative in similar applications.

Keywords- Bottle Fill Level, Classification, CNN, Detection, Sequential neural network.

1 Introduction

Incorporation of advanced technology, such as machine vision, into the manufacturing process, streamlines the process by reducing operator input, which reduces errors; enhances production speed, improves quality, reduces costs, and simplifies the manufacturing process. Incorporating advanced technology, such as machine vision, into the manufacturing process streamlines the process by eliminating operator input, which reduces errors; increases production speed, improves quality, reduces costs, and simplifies the manufacturing process. Bottles are widely used in industries such as beverages, medications, and other chemical items. According to (Anush *et al.*, 2021), one of the important criteria evaluated during production in these sectors is the detection of the level of bottle fill in real time.

Diverse methods for detecting bottle fill levels have been employed, including sensor-based systems, which are difficult to set up, and human inspectors, who are slower, and their efficiency is affected by fatigue and other associated situations. Machine vision is one of the methods of artificial intelligence applied to automate the level of bottle filling in the industry (Kumar *et al.*, 2015; Peilin *et al.*, 2017). The machine vision system processes images and implements rules and parameters designed to support manufacturing applications such as quality assurance (Akundi and Reyna, 2021). For image processing, machine vision employs convolutional neural network (CNN), which has applications in a variety of domains (Tao et al., 2018; Bahaghigat *et al.*, 2019).

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Ismail and Malik (2021) developed a system based on machine vision and deep learning techniques for the inspection of grades of fruit based on their outer appearance or freshness. Various deep learning methods were applied, ResNet50, MobileNet V2, DenseNet-121, NASNet-A, EfficientNet-B0, EfficientNet-B1, and EfficientNet-B2. The outcome of their study shows that Efficient Net CNN models and their stacked combinations have the highest accuracy in grading the test set and samples, as compared to the other deep learning models. Parakontan and Sawangsri (2019), proposed the development of a machine vision for automated inspection of PCB assembly. The outcome of the application shows the real-time analysis and inspection of micro size defects in PCB, such as copper leakage was a success. However, this developed application is only suitable for lab-scale testing, as it has not been applied in the industry.

Akundi and Reyna (2021), proposed a machine vision system for product dimensional analysis, which could be used in an automated quality control system. The system could identify defects in cubes, cylinders and sinusoidal objects and it could also identify minute defects in objects. The outcome of the proposed system shows that it performs well for items with an entirely uniform cross-section. However, it is unable to inspect items with varying cross-sections. Bahaghigat *et al.*, (2019) proposed a vision inspection system based on end-to-end deep learning technique. In their proposed work, the VSS network, and the VGG 19 are the deep learning classifier used to recognize defective bottles on the product line.

The outcome of the proposed model shows the superiority of the deep learning technique to the HSV colour space and threshold values technique for decision-making. Zhou *et al.*, (2019) proposed a multiscale filtering method which is adopted to search for defects in the annular panel region. For the annular texture region, we combine template matching with multiscale filtering to detect defects. In comparison with some conventional procedures, the experimental findings show that the proposed methods yield a better outcome. Nazim and Sattar (2020) designed an automated water tap controlling system using machine vision. This system employs image processing techniques to reduce water waste at the faucets. The devised system detects the object as a hand or a bottle, and if the detected object is a bottle, the water level is displayed. The detection accuracy for the hand is 85.71 %, and the detection accuracy for the bottle is 77.77 %. The proposed technology will provide an automated way for water conservation.

Wang *et al*., (2019) proposed machine vision intelligence for product defect inspection based on deep learning and Hough transform. The identification module is built using a convolutional neural network, with an inverted residual block included as the fundamental block to achieve a good balance between identification accuracy and processing efficiency. Superior inspection performance is attained by employing the proposed method on a large dataset of defective and defect-free bottle photos. Koodtalang *et al.*, (2019) designed a glass bottle bottom inspection based on image processing and deep learning. This research describes an image processing and deep learning-based glass bottle bottom inspection system. The results of the experiments demonstrate that the accuracies of bottom locating and defect detection are 99% and 98.5%, respectively. Rong *et al.*, (2020), present impurity detection of Juglans using deep learning and machine vision with two-stage convolutional networks to perform picture segmentation and impurity detection in Juglans images in real-time. The suggested technique is capable of successfully segmenting 99.4% of object areas in test photos, classifying 96.5% of foreign objects in validation images, and detecting 100.0 % of test images. From the literature, it is evident that dedicated deep learning models achieved better results than the pertained models.

Therefore, this paper demonstrates how to build, implement, and test a sequential neural network model for bottle fill-level detection. Python 3.8.3 was used to design and implement the proposed method. The problem is modelled as a multiclass problem (correctly filled, overfilled, and underfilled), with sample sizes for each class in testing and training datasets. In the training and testing datasets, the proposed model is checked and its performance is compared with the MobileNet, ResNet50, and VGG-19 models. Furthermore, the confusion matrix was employed with a sample size of 40 to evaluate the proposed model's real-world performance in the correctly filled, overfilled, and underfilled classes of filled bottles overfilled, and underfilled classes of filled bottles.

2 Material Method

CNNs are a popular type of neural network for image identification and classification. The data set is technically classed into 0.7 training data set and 0.3 testing data set. The training set is used to train the model, while the testing set is used to assess and optimize the model's performance. The input images (dataset) are processed and to classify the classes, a series of convolution layers with filters (Kernals), pooling, fully connected layers (FC), and the Softmax function are used.

2.1 CNN Model Architecture

The sequential CNN model is proposed in this work. Its performance in detection and classification is compared with MobileNet, ResNet50, and VGG-19 models.

2.1.1 Sequential Model

A sequenced model is appropriate for a simple layer stack with precisely one input and one output tensor. The Concurrent API gradually adds layers to the model (hence the name Sequential). The sequenced API is straightforward to use. Keras and the Sequential() class are used to create the Sequential model. Layers will be added to the model sequentially using the add() method. The Conv2D() class is used to create each convolutional layer in a CNN, which simply performs the convolution operation in a 2D space. In Keras, a convolutional layer is referred to as a Conv2D layer. The pooling layer is created after the convolutional layer has been created. Layers of convolution and pooling are used in combination. Maximum pooling and average pooling are the two types of pooling operations.

In this case, max-pooling will be used. Each pooling layer in a CNN is created using the MaxPooling2D() class, which performs the Max-pooling operation in a 2D space. In Keras, a Max-pooling layer is known as a Max-Pooling 2D layer. A CNN's final layers are fully (densely) connected layers. Keras' Dense() class is used to create these layers. A CNN's Multilayer Perceptron (MLP) component is made up of multiple fully connected layers. A fully connected layer is referred to as a dense layer in Keras. The Sequential CNN architecture proposed here is as follows:

- Two convolutional layers: first layer: 32 filters and second layer: 16 filters. The activation function used for both layers is the Rectified Linear Unit (ReLU).
- Max-pooling is used in two pooling layers.
- A flattening layer exists between the last pooling layer and the initial dense layer.
- Dense layer (Two): The first layer has 8 units and the second layer has 3 units. Softmax activation in the last layer and ReLU activation in the first layer.

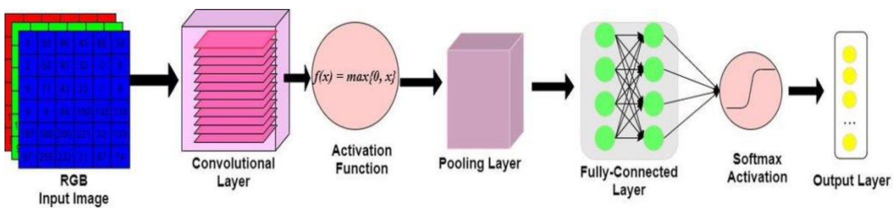

Fig. 1: Image of the CNN process (McDermott, 2022)

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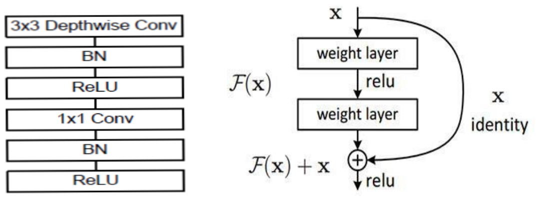
2.1.2 MobileNet Model

MobileNet uses separable convolutions. Depth-wise convolution in MobileNets uses one filter for each input channel. The depth-wise convolution outputs are then merged through the use of an 11 convolution by the point-wise convnet. In one step, a convention filters and mixes inputs to produce a new set of outputs. The separable depth-wise convolution divides this into two layers: one for filtering and one for combining. The chief distinction between MobileNet architecture and traditional CNN structure is division of the convolution into a 3x3 depth-wise Convolution and a 1x1 point-wise Convolution, replacing the traditional CNN model's single 3x3 convolution layer followed by the batch norm and ReLU. The MobileNet architecture is shown in Figure 2a.

2.1.3 ResNet-50 Model

The ResNet-50 structure follows two basic design concepts. First, layers have an equal number of filters irrespective of the size of the output feature map. Second, reducing the size of the feature map in half necessitates the use of twice as many filters to maintain the complexity of the time of each layer. ResNet-50 is a 50-layer (CNN). The network accepts 224-by-224 image input. ResNets, on the other hand, have fewer filters and are less complex than VGGNets. The ResNet-50 architecture is depicted in Figure 2b.



a. MobileNet architecture b. ResNet-50 Architecture

Fig. 2: MobileNet and ResNet-50 architecture (Shrivastav, 2022)

2.1.4 VGG-19 Model

VGG-19 is a 19-layer (CNN). There are sixteen convolution layers, three layers that are fully connected, five Max-Pool layers, and one SoftMax layer in total. Figure 3 shows the structure of VGG-19. The sequential model differs from the MobileNet, VGG-19, and ResNet-50 in that they are pre-trained models with distinct architecture. The data set used in this study was created taking into account the measurement of a liquid filled in a generic bottle. A threshold measure was chosen to be correctly filled. The dataset includes 3000 images that were created which consists of 1000 images each for the overfilled bottle, correctly filled bottle, and underfilled bottle respectively. This data set was also spliced into 70:30 training and testing data sets. Cropping, scaling, and normalizing are some of the pre-processing performed on the images before feeding them into a CNN network. The supervised learning approach was used to train the Sequential, MobileNet, ResNet-50, and VGG-19 CNN models individually. Figure 4 presents images of the dataset classes.

2.2 Performance Evaluation

The problem was modelled as a multiclassification problem. The training data set was used to train Sequential, MobileNet, ResNet-50, and VGG-19, which were then tested using the test data set. The proposed model is evaluated and its performance in a multiclass problem (correctly filled, overfilled, and underfilled) is compared to the MobileNet, ResNet-50, and VGG-19 models using accuracy, precision, recall, and F1 Score.

a. Overfilled class b. Correctly filled class c. Underfilled class

Fig. 4: Image of the Data set

In addition, the confusion matrix was used to assess the performance advantage for correctly filled, overfilled, and underfilled bottles.

2.2.1 Confusion matrix

It explains how a classifier algorithm performs on a set of test data with known true values. It is a tabular representation of actual versus predicted values, as shown in Figure 5.

		Predictions	
		Class 1	Class 2
Actual	Class 1	TP	FN
	Class 2	FP	TN

Fig. 5: Confusion matrix

The confusion matrix as given by [20] is presented in Equation 1 below

$$C_{Matrix} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Where TP is truly positive, TN is truly negative, FP is false negative, and FP is false positive. NOTE: TP + TN + FP + FN must be equal to the total number of observations.
True positive: actual positive instances that the algorithm predicted correctly. True negative: actual negative instances that the algorithm predicted as negative. False positive: actual positive instances that the algorithm predicted as negative. False negative: actual negative instances that the algorithm predicted as positive.

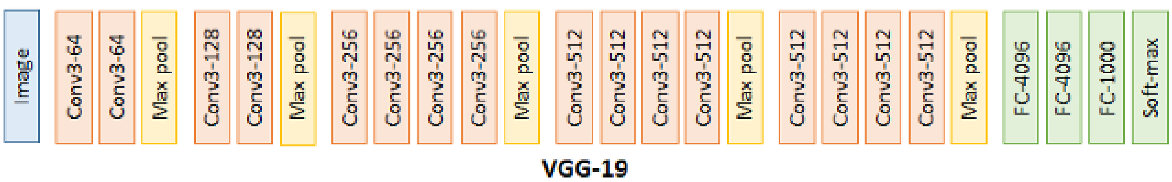


Fig. 3: VGG-19 architecture (Source: Shrivastav, 2022)

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2.2.2 Precision

Measures of accuracy achieved in the true prediction. In other words, it indicates how many positive predictions are made of all positive predictions (Shalev-Schwartz, 2014)

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

2.2.3 Recall

True observations are accurately predicted, that is, how many positive observations are correctly predicted as positive. It is also known as Sensitivity (Shalev-Shwartz, 2014; Opeyemi and Oyeyemi, 2023).

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

2.2.4 F1 score

The F1 score, which ranges from 0 to 1, represents the natural logarithm of precision and recall. Because, unlike simple averages, the harmonic mean is not susceptible to extremely large values (Shalev-Schwartz, 2014)

$$F1\ score = \frac{2}{\frac{1}{Precision}+\frac{1}{Recall}} = \frac{2*(Precision*Recall)}{(Precision+Recall)} \quad (4)$$

3 Results and Discussion

The performance of the sequenced CNN model on the training data set is depicted in Figure 6. Figure 7 contrasts the sequenced CNN model to the MobileNet, ResNet50, and VGG-19 CNN models in the areas of accuracy, F1 score, recall, and precision in the train and test data sets.

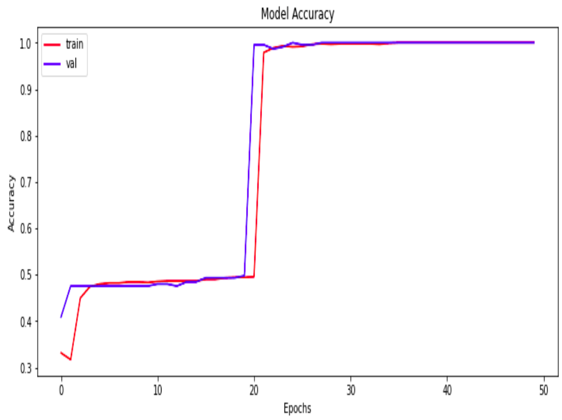

Fig. 6: Sequential model accuracy in the training and testing data set

Figure 6 shows that the sequential model accuracy attained the 90% Mark around the 20th epoch indicating the robustness of the model to quickly learn the pattern in the database.

Figure 7 indicates the sequential CNN Model in this work outperforms the MobileNet, ResNe-50, and VGG-19 CNN models on the training and testing datasets in terms of accuracy, F1-Score, Recall, and Precision as presented. Furthermore, a real-time test of the system was performed using a sample size of 40 for each class of underfilled, overfilled, and correctly filled bottles and the result is presented in Figure 8.

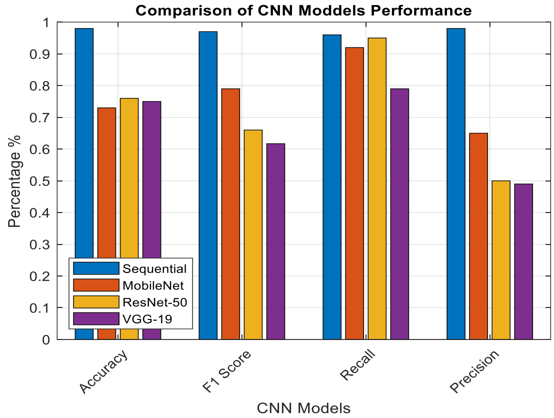

Fig. 7: Comparison of the performance of CNN models

		Predictions		
		CORRECTLY FILLED	OVER FILLED	UNDER FILLED
Actual Values	Correctly Filled	39	0	1
	over filled	2	38	0
	UNDER FILLED	2	1	37

Fig. 8: Confusion matrix result for the multiclass problem using a sample size of 40 final version

True Positive (TP) = 39 + 38 + 37 = 114
True Negative (TN) = 76 + 79 + 79 = 234
False Positive (FP) = 1 + 2 + 3 = 6
False Negative (FN) = 4 + 1 + 1 = 6
From the confusion Matrix presented in Figure 8 the accuracy, precision, recall and F1 score were obtained using Equations 1-4. Table 1 presents the results.

Table 1. Confusion matrix result for Sequential model on real-time classification

CNN Model	Accuracy	F1 Score	Recall	Precision
Sequential	0.97	0.95	0.95	0.95

According to Figure 8 and Table 1, the sequential model performs well in the real-time classification of the level of the filled bottle for the three classes.

4 Conclusion

This article explains the design and execution of a sequenced CNN model for real-time detection and classification of filling bottle levels. The study compares the proposed model to the MobileNet, ResNet50, and VGG-19 CNN models. In the multiclass problem under consideration, the presented findings demonstrate that the proposed CNN model outperforms the MobileNet, ResNet50, and VGG-19 CNN models in terms of efficiency and superiority. It performs well in terms of Accuracy, F1-Score, recall, and Precision on data sets for training, testing, and real-time applications. This demonstrates that the model is a useful classification system for fill-bottle-level classification. The Sequential CNN Model Architecture has demonstrated its ability to perform efficient classification. As a result, the architecture used in the design of the Sequential CNN model should be considered when designing and implementing CNN models for classification problems.

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CONFLICTS OF INTEREST
No conflict of interest was declared by the authors.

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