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Milk Box Defect Detection using Deep CNN Model

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Abstract: Food packaging is a crucial issue in the food industry. In the milk and dairy industries, milk boxes must be in a good condition to preserve the freshness and quality of the milk. Any defect on the box is not compromised because milk will be spoiled and cause harm to the consumers. This paper focuses on the use of the deep CNN model in detecting the defect in the milk box. The work employed a pre-trained AlexNet model for the two-class classification problem, PERFECT and DEFECT. This work also aims to evaluate the box defect detection accuracy in terms of percentage through experiments on static images. 80 milk box images were used in this preliminary study, in which 40 images of perfect boxes and 40 images of the defect boxes. The result that is obtained by this project is 100% accuracy. It is concluded that the trained model can perform relatively well in classifying milk box images. However, in the future, more data could be used in the training to increase the accuracy of the model and avoid the occurrence of overfitting in the model. Further possible attempt also includes the use of milk box images from other imaging technologies in the training to give higher variability on the choice of dataset using which a deep learning model can train.

Keywords: Milk Box Defect, Defect Detection, Convolutional Neural Network (CNN)

1. Introduction

Packaging is the wrapping material around an item that helps to hold, protect, explain, market and keep the product clean. Good packaging reduces waste and ensures that the product maintains its target quality over time. Packaging is essential to every type of industry and crucial in the food business, clothes manufacturing and technology industry. Different industries will use different types of packaging, but the objective will remain the same to protect the product or item.

In food industries specifically in milk and dairy industries, milk boxes must be in a good condition with zero defects. Any defect on the box is not compromised because milk will be spoiled and cause harm to the consumers. Ultra-heat Treatment (UHT) milk, has a typical unrefrigerated shelf life of six

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to nine months if not opened and stored in dry and ambient conditions with low light. Therefore, an inspection of the milk boxes must be done carefully during the production process to preserve the freshness and quality of the milk.

There are many ways to inspect box defects. Instead of using a conventional method in which the inspection is done manually by the workers, deep learning is a new technology that has been used widely nowadays. In the fields of artificial intelligence (AI) and machine learning, deep learning models represent a novel learning paradigm. Recent breakthroughs in image processing and speech recognition have sparked a surge of interest in this area, owing to the possibility of applications in various other domains that produce large amounts of data [1]. Deep convolutional neural networks (CNN), for example, will automatically update the filters during training on large quantities of training data to learn a hierarchy of features from the raw image input. Deep Learning made a great success in object detection and developed rapidly.

For defect detection, the paper [2] introduced a new deep CNN architecture for defect detection that took all forms of defect-free and defective samples as input. Defect detection using image processing is a machine vision technology that is growing rapidly in a wide range of industries. It is used in manufacturing systems for high-throughput quality control, such as detecting flaws on manufactured surfaces like torn and smashed boxes. To overcome the limitations and improve the performance of conventional inspection systems that rely heavily on human inspectors, the concept is to create autonomous devices that automatically detect the defect box and analyse complex visual patterns from photographs.

Automatic defect detection has a lot of advantages, such as lower costs, high accuracy, and scalability. Automatic defect detection technology has clear advantages over manual detection. It also works in the long term with high efficiency and precision. Jin Yang has stated that defect-detection technology may lower production costs, increase production efficiency, and enhance product quality, while also laying a firm platform for the manufacturing industry's intelligent transition [3].

Therefore, this paper focuses on the use of the deep learning CNN model in detecting the defect in the milk boxes and assesses the performance of the CNN model for milk box defect detection in percentages.

2. Methodology

This work was run by using a device with a processor of Intel DualCore N3060. To detect the defect condition on the milk box, a milk box image is used to determine its condition. The defect on the milk box can be detected by using the AlexNet CNN architecture after the images have been trained using classification. The outcome of the result will be shown in terms of performance, training state, histogram error, confusion plot and receiver operating characteristic. Figure 1 shows the block diagram to represent the flow of the work.

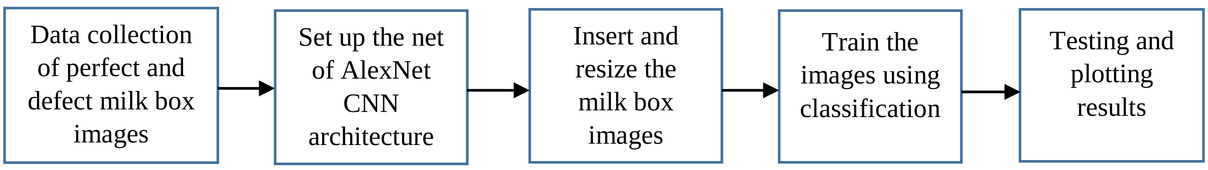

Figure 1: Flow of the work

2.1 Data collection of perfect and defective milk box images

The milk box images of perfect and defect were captured by using a Poco X3 NFC phone. There are about 80 milk box images used for training. Among the images of milk boxes, 40 were perfect images of milk boxes and the rest were defective milk boxes. Figure 2 shows some of the milk box images that are used as the input to the network. The images are divided into 2 classes, the “Pbox” named files are for perfect milk box images while the “Dbox” named files are for defect milk box images.

Figure 2: The sample images for perfect and defect milk box

2.2 Setup the net of Alexnet CNN architecture

The architecture used for the network is AlexNet. The AlexNet consists of layers to determine the desired output. For this work, the layers in the network as shown in Figure 3. AlexNet’s architecture design is where the filters are repeated because of the way it was created.

2.3 Milk box images insertion and resizing

There are 80 milk box images used for the network,40 perfect boxes, and 40 defect box images. All of the milk box image files in both categories are uploaded in the same folder to make it more convenient for the network to read the files. MATLAB reads the milk box image files by their name and their type of 22 files. In the network, the perfect box images are named PBox1, PBox2, PBox3, and till Pbox40. As for the defect box images, the file names are Dbox41, DBox42, and Dbox43 and the list goes on until it reaches Dbox80. The images are set to 277 277 pixels in size because AlexNet expects them to be that size. Varying architectural designs necessitate different picture sizes, however the photographs must be at a set size by the architecture. The AlexNet needs a size of 277 277 pixels.

1	*1x1 ImageInputLayer*
2	*1x1 Convolution2DLayer*
3	*1x1 ReLULayer*
4	*1x1 CrossChannelNormalizationLayer*
5	*1x1 MaxPooling2DLayer*
6	*1x1 GroupedConvolution2DLayer*
7	*1x1 ReLULayer*
8	*1x1 CrossChannelNormalizationLayer*
9	*1x1 MaxPooling2DLayer*
10	*1x1 Convolution2DLayer*
11	*1x1 ReLULayer*
12	*1x1 GroupedConvolution2DLayer*
13	*1x1 ReLULayer*
14	*1x1 GroupedConvolution2DLayer*
15	*1x1 ReLULayer*
16	*1x1 MaxPooling2DLayer*
17	*1x1 FullyConnectedLayer*
18	*1x1 ReLULayer*
19	*1x1 DropoutLayer*
20	*1x1 FullyConnectedLayer*
21	*1x1 ReLULayer*
22	*1x1 DropoutLayer*
23	*1x1 FullyConnectedLayer*
24	*1x1 SoftmaxLayer*
25	*1x1 ClassificationOutputLayer*

Figure 3: The layers of the system

2.4 Images Training by Using Classification Technique

Image classification is where the images from image processing are fed into the system. In this part, the system will learn how to differentiate between perfect and defective milk boxes. The images are inserted by the user into the classification system according to the defect or class that occurs in the milk box images. After inserting all of the images according to their class, the network will be able to learn by the train features of the neural network. Image classification is very important because it will determine the result that the network will produce. Figure 4 shows the flowchart of the system in detail to determine whether the milk box images are perfect or defect.

The work is started by planning the project and determining the possible outcome of the project. Next, the milk box images that have defects and are perfect are collected as the input of the neural network. AlexNet architecture is set up with the details such as the size and name of the files in the coding required by the models. After the input and CNN architecture are created, the database is considered done and can be used for processing. The database went through a classifying process to determine the images that have a defect or perfect milk box images. The result of 1 will be defect box and 0 for perfect box images in the “Image class”.The program ends after it can determine the class of the images.

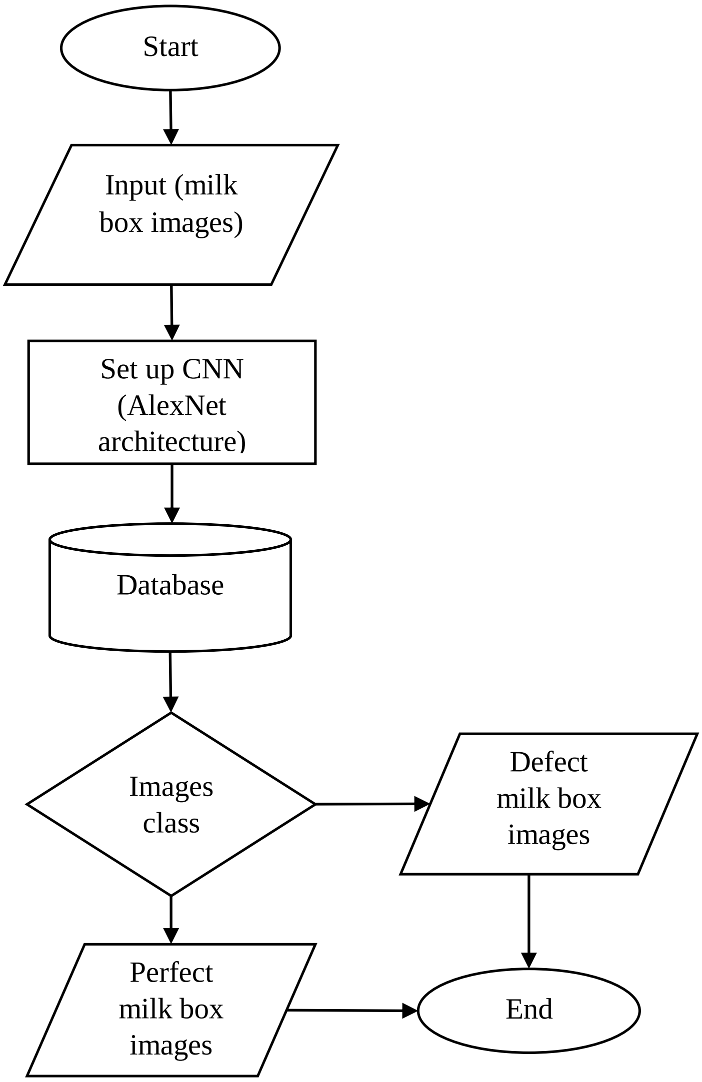

Figure 4: The flowchart of the system

2.5 Testing and Plotting Results

The CNN requires input and output for the network. The input images are inserted into the CNN network and go through the process that was mentioned in Figure 1. To obtain the outcome of the project, testing and plotting must be done by generating the neural network train tools or nntraintools that will use the classification data from the database and generate the plot for results. This part shows the accuracy, percentage, and graph of the project results. The AlexNet architecture's categorized pictures are used in the Neural Network Training or nntraintools. Figure 4 shows the flowchart of the system.

3. Results and Discussion

The Neural Network Training supplied by MATLAB is used to create the work's results. Data on performance, training state, error, and confusion may be retrieved in the form of a graph or percentage data using the nntraintools or Neural Network Training.

3.1 Performance

The performance plot is really important to indicate if the training, test and validation had encountered a problem or not. Figure 5 illustrates the performance plot for this work, which reveals that the highest performance is at epoch 37, which was obtained at the epoch with the lowest validation error. The total number of epochs produced by nntraintool is 37, with epoch 37 being the best since the training and testing data sets decrease. The network must come to a halt at epoch 37 since it begins to overfit beyond that. After a few prior epochs with close to 0% dynamic fluctuation, the nntraintools will automatically stop.

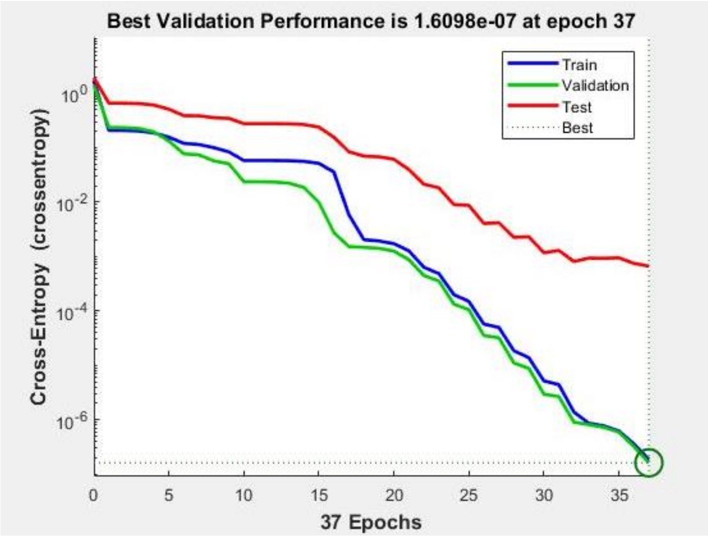

Figure 5: The network performance plot

3.2 Training state

The training state displays the current progress or status of the training; this section will provide the best performance as well as the number of predecessors that have not improved after 6 epochs. From Figure 6, the result shows an error at validation 6 at epoch 37 synchronized with Figure 5. To identify the optimal validation, the system will always stop after 6 validation errors in which the value does not change. At epoch 37, when the system starts to exhibit a large drop, the network performs optimally. The last bottom of the curve in the plot shows the number of precedents that did not improve after 6 successive epochs, then the training stopped. For this network, the training stops at epochs 37.

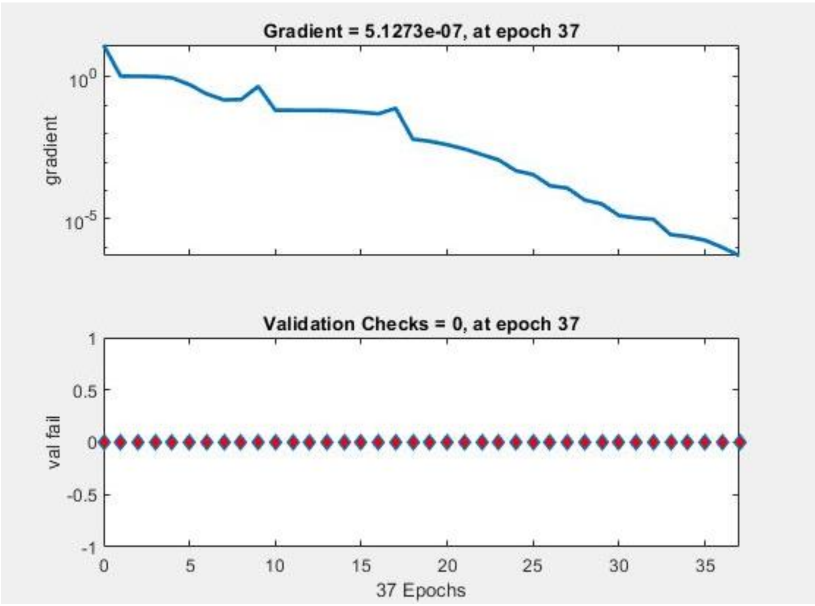

Figure 6*:* The image of the training state graph

3.3 Histogram error

The Neural Network Training error histogram is generated to indicate the histogram of error between the target values and predicted values after the Neural Network Training. Figure 7 shows the Histogram Error of Neural Network Training. The error indicates how different the input and its output are; in this network, the classified image and the output had an error in 20 Bins. Bins are the number of vertical bars that are observed in the graph. The Y-axis represents the dataset which is the milk box Image. The X-axis indicates the Zero Error value which is at 0.0000 where most of the data sets are processed.

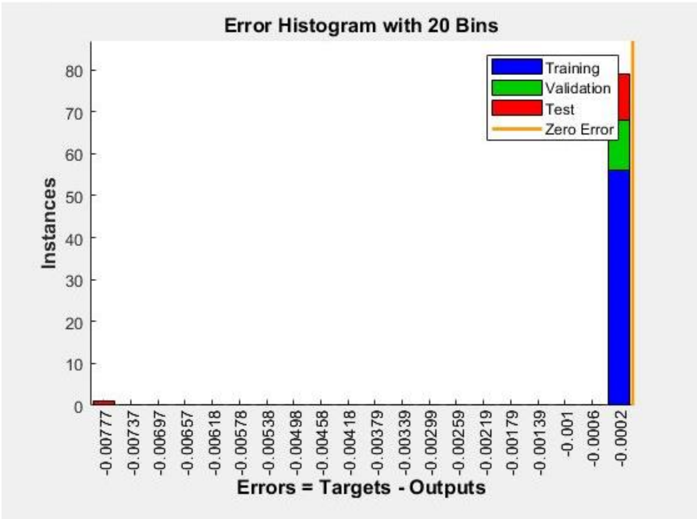

Figure 7: The image of the Histogram plot

3.4 Confusion plot

The confusion plot was generated to summarize the classification output of the neural network performance. The confusion plot was also used to evaluate the performance of the CNN model created. Figure 8 shows the image of the confusion plot generated by using MATLAB. The rows of the confusion matrix correspond to the output class and columns correspond to the target class. In the graph plot, the diagonal cells are correctly classified and off-diagonal cells are incorrectly classified.

Figure 8: The image of the Confusion plot

For validation, the images taken from the dataset are 12 milk box images. The true positive rate in Table 1 represents the perfect milk box image classification, and it shows that the accuracy is 100 %. The false-negative rate is the defect milk box images classification and it shows that the accuracy is 100 %. The false-positive and negative rate shows the incorrectly classified class of the images, and the percentage is 0%, respectively.

Table 1 The validation performance

No	Parameters Performance	Percentage Performance %
1	True Positive Rate	100%
2	False Positive Rate	0%
3	True Negative Rate	100%
4	False Negative Rate	0%
5	Accuracy	100%

3.5 Receiver Operating Characteristics

The neural network Receiver Operating Characteristic was carried out to show the quality of the classifiers from the network. ROC is very important because it is used to prove the performance of the classification of the Neural Network. For this work, the Training, Validation, Test and Overall had a result that was more to True Positive and Negative Rate that shows that the network has a good classification accuracy. Figure 9, shows that the curves in the graph are at the left top edges of the plot, hence showing that the Neural Network classification has a high percentage of accuracy. The percentage error for this project is 0%. Datasets are successfully classified.

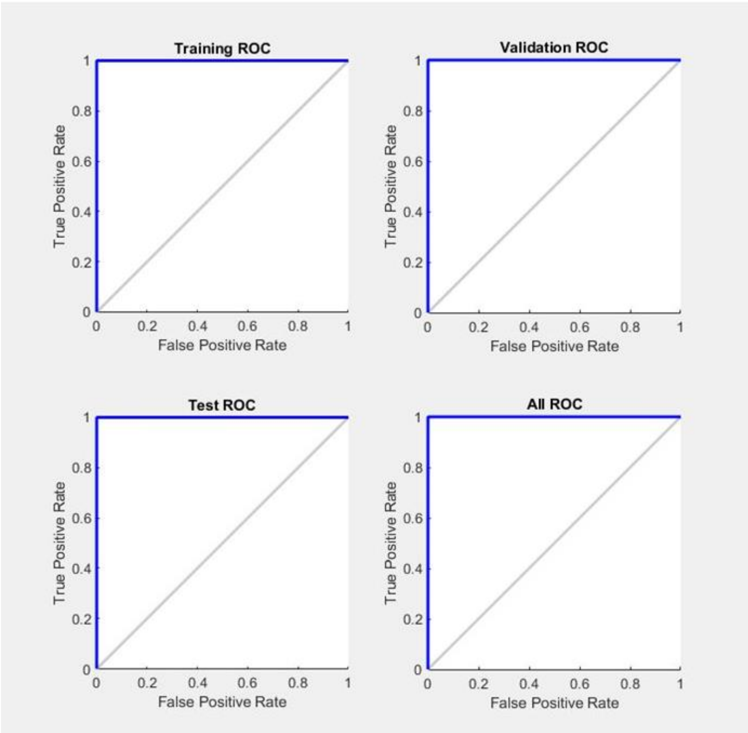

Figure 9: The image of Receiver Operating Characteristic

4. Conclusion

The deep learning and the architecture used in this work can produce a significant result. The AlexNet which consists of 8 layers produced a result with 100% of accuracy in classifying the milk box class. However, in the future, more data could be used in the training to increase the accuracy of the model and avoid the occurrence of overfitting in the model. Further possible attempt also includes the use of milk box images from other imaging technologies in the training to give higher variability on the choice of dataset using which a deep learning model can train.

The use of AlexNet as the architecture of the neural network has produced a great result in terms of the accuracy of the network and the factory should consider using this system that will benefit their quality of production and bring improvement to the management of the production or any department. The use of Deep Learning should be much wider and not just determining the defect in the milk box, but it should also be used in many parts of the production system that still have a lot of weaknesses to this day to improve the quality of the product.

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References

[1] Ahsan, M., Ibrahimy, M., Khalifa, O., & Ullah, M. (2012). VHDL Modeling of EMG Signal Classification using Artificial Neural Network. Journal of Applied Sciences, 12(3), 244–253. https://doi.org/10.3923/jas.2012.244.253

[2] EMG Signal Processing for Hand Motion Pattern Recognition Using Machine Learning Algorithms. (2020). Archives of Orthopaedics, 1. https://doi.org/10.33696/orthopaedics.1.005

[3] Yang, J., Li, S., Wang, Z., Dong, H., Wang, J., & Tang, S. (2020). Using Deep Learning to Detect Defects in Manufacturing: A Comprehensive Survey and Current Challenges. Materials, 13(24), 5755. https://doi.org/10.3390/ma13245755