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Realising Quality Control of Metal Products Used in Industry Through Deep Learning

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ABSTRACT

This study was carried out with the aim of detecting the defects on the surfaces of metallic products, which are frequently encountered in our daily lives and widely used in industry, with deep learning. Many metal products in the industry undergo different processes during the production phase. As a result of these processes, the detection of defects such as breakage, cracking, etc. on the surfaces of metal products is carried out by quality control personnel or production personnel. However, this error detection made by manpower both slows down production and causes overlooked errors. In order to easily detect these defects, in our study, we used a dataset consisting of 285 images in total with images of two different surface defects and images containing flawless metal parts and a CNN architecture, ResNet50 architecture, to defects. There are three classes in total in the dataset. Two of these classes consist of images of different types of defects on the surface of the metal piston part used in air conditioners, and one of them consists of images of perfect metal piston parts. Convolutional Neural Network (CNN) method was used to determine the features of the images. Precision, recall, F1-Score and accuracy metrics were used to measure the performance of the model. With the ResNet50 architecture, defects on the surfaces of metal piston parts are detected quickly and with high accuracy. As a result of the study, it was suggested that the proposed model can detect surface defects that occur in the usage areas of metal products in various sectors more quickly and accurately using deep learning. This shows that the quality control problems experienced in the industry can be reduced by using deep learning, saving time and manpower.

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1. Introduction

Metallic products are frequently used in people's daily lives and are produced in many regions of the world and are accepted as industrial products [1]. Metallic products undergo different processes such as bending, welding, assembly, printing during the production phase according to the sectors in which they will be used. And these production stages cause some surface defects due to factors such as the machines used, the temperature, weight used in these machines, and the quality of the welding wire if welding is performed. These surface defects occurring in metallic products are classified as cracking, curvature, tearing, scratching, etc. Surface defects occurring in industrial products are an important factor affecting the quality and working performance of these products. For manufacturers of industrial products, many methods are used to detect these defects. Generally, manufacturers currently perform quality control of these defects manually and this quality control process using manpower causes many defects occurring on the surfaces to be overlooked [2]. For this reason, different control systems have been developed in order to prevent these errors that may be overlooked. One of these processes is deep learning. Deep learning is now a widely used quality control process. It automatically detects the detection of errors and performs error detection and improvement in a shorter time [3]. In the literature, there are studies on fault detection with deep learning.

2. Literature Review

Silenzi et al. conducted a study to understand whether deep neural networks and transfer learning can be applied to flat images to classify surface defects in carbon-looking components made with carbon fibre reinforced polymers used in the automotive industry. They used a dataset of 400 images to test binary classification and 1500 images for multiple classification. They analysed these data by comparing ten models based on ten pre-trained deep CNNs in the ImageNet database. Accordingly, they suggested that the best model based on DenseNet121 has the capacity to distinguish 900 images of components with salvageable defects, unsalvageable defects and

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components without any defects with 97% accuracy [4]. Neuhauser et al. conducted a study on the classification and detection of surface defects in aluminium profiles, where a camera records extrusion profiles during production and a neural network can be used to distinguish between flawless surfaces and surfaces with various defects. They used a data set of 813 images. They analysed these data using a neural network. Accordingly, they obtained an accuracy of 0.98 in classification and an average precision of 0.47 in detection [5].

Konovalenko et al. conducted a study to detect and classify three different surface defects on the rolled metal surface. In this study, they used a total of 18,723 data sets, including 1820 1st class damaged images, 14,576 2nd class damaged images and 2,327 3rd class damaged images. They analysed this dataset used during the classification of surface images in ImageNet (ResNet50) database. They suggested that the best model of the classifier based on ResNet50 showed an average classification accuracy of 0.9691 based on all damage types [6].Wang et al. conducted a study on a method that combines faster convolutional neural networks developed using ResNet50, which has a high accuracy rate and short running time for automatic detection of surface defects in steel materials. In their study, they used a total of 50,272 data sets, including 37,080 flawless photographs, 12,876 photographs with a single defect and 316 photographs containing more than one defect. They used CNN, a neural network used to detect and locate the features of the surface images of steel sheets and analysed the data set on CNN. They used binary image classification and object detection at the same time to increase accuracy and reduce working time. As a result of their study, they concluded that the pitted surface defects are not obvious because they are small and the accuracy of the detection of the crack defect, which has a narrow, long image, is not high, and they suggested that the best result was obtained by combining the Faster R-CNN object detection model developed using the ResNet classification model. They claim that the accuracy value varies from 0.975 for single classification and from 0.972 to 0.for object detection model and the running time of the model is reduced [7].Adibhatla et al. a study on a deep learning algorithm that works with a single look-once (YOLO) approach while performing quality inspection on printed circuit boards (PCB). In the process of their study, they used 11,000 images as a data set. In order to detect defects in PCBs, they used a network consisting of 24 convolutional layers and 2 fully connected layers in the YOLO/CNN database. They detected an error of 98.79% in PCBs with a batch size of 32. As a result of these studies, they concluded that the CNN algorithm combined with Tiny-YOLO-V2 can detect defects in PCBs with an accuracy of 98.82%. They suggest that other CNN object detection algorithms such as Rateninet, GoogleNet, ResNet should be implemented using GPU hardware to increase the learning speed [8]. Zhao et al. Zhao et al. made innovations on the basis of YOLOv4 architecture in order to solve the problem of low accuracy and location detection rate in the detection of defects on the surfaces of metal materials and examined the effect of pyramid network addition to different positions of the model. In this application, Zhao et al. used 720 images as a data set. And they ran this data set they used in the YOLOv4 database. As a result, when compared with the traditional YOLOv4 network, they obtained results that the recognition accuracy of the new model reached 92.5% and the recognition accuracy improved [9].

Su et al. They conducted a study to solve the problems encountered in the fault detection of metal gear tips due to various gear types, inhomogeneity of the tip surface structure, small size and multi-scale defects. In this study, they used 710 images containing metal gear end face defects. They processed this data set on SR-ResNetYOLO, a cascaded combination detection method. They concluded that this method performed well in terms of mAP and recall rates of 96.66% and 97.07%, respectively, and the computation time of detection per image was 0.12 s [10]. Noroozi et al. Noroozi et al. carried out a study to overcome errors such as overheating, incorrect welding process or power supply failure, etc. occur during soldering on printed circuit boards. They used 309 images taken from different distances and angles, 270 of which were defective and 39 of which were perfect, as a data set. They used the YOLOR model to analyse these data sets. As a result, they concluded that the YOLOR model performs much better in precision and recall than single and two-stage detector models and has a faster extraction time [11]. Baumgartl et al. They carried out a study to detect printing defects. As a data set, they used thermographic images of H13 steel samples during in-situ off-axis monitoring during the printing process. They used Grad-CAM to analyse these data in a gradient-weighted class activation map. They concluded that a convolutional deep neural network can detect defects at the time of printing with an accuracy of 96.8% and can be used to identify them [12]. Gui et al. They determined a quantitative criterion for classifying surface quality according to surface smoothness and conducted a study to show that different surface qualities contain different types of internal defects. They used carbon steel S30C alloy powder prepared by gas atomisation method for PBF- EB. They used LS230, Beckman Coulter USA, for particle size analysis of the powder and SEM, a scanning electron microscope, to examine the surface morphology of the S30C alloy powder: JEOL JCM-6000. They used 3D non-destructive testing techniques to classify the types of internal defects. Logistic regression, support vector machine, decision tree, naive Bayes and XGBoost algorithms were used in the optimisation of PBF-EB process parameters. They concluded that the support vector machine has the highest model performance. They proposed a new framework for creating process maps of parts produced with PBF-EB [13]. Fang et al. conducted a study on both 2D and 3D surface defect detection technologies for some metal planes consisting of steel, copper plates, aluminium and strips. In this study, they analysed more than 160 publications. According to these papers, they suggested that defect detection methods in metal planar materials can be examined in 4 different ways: statistical-based methods, spectrum- based methods, model-based methods and machine learning-based methods. As a result, they concluded that machine learning prevents data imbalance in the detection of visual defects, GAN is successful in generating defect samples, but it is necessary to create a rich and diversified database of surface defects in metal planar materials [14].

Liu et al. conducted a study on defect detection for the metal base of a TO-can packaged laser diode. They used 1051 original images of TO-can base defects from a semiconductor laser manufacturer as a dataset. They compared these data sets on YOLO-SO, Faster R-CNN, SSD and YOLO-V4 algorithms. Based on their experiments, they concluded that the YOLO-SO model reaches 84.0% mAP, which is 5.5% higher than the YOLO-V5 algorithm, and that the advantages of the YOLO-SO model are the smallest weight size and the detection speed of 25 FPS, and for these reasons, the YOLO-SO model is more suitable for real-time detection of metal TO- can base defects [15]. Abagiu et al. conducted a study on the detection of defects occurring during machining in an engine block in the piston chamber. They implemented the application on Python. They concluded that the weakness of the application is dependent on an adequate and accurate data set and the advantage is that applications such as communication, HMI, logging and others can be abstracted and used in new applications [16].Wang et al. conducted a study on improving the accuracy of quality control of reciprocating compressors. After their study, they proposed the Extreme Gradient Boosting Outlier Detection (XGBOD) algorithm. They suggested that the false decision rate of this algorithm is lower than other algorithms [17]. Chaudhari et al. conducted a study on the analysis of steel surface defects. Kaggle Severstal: Steel Defect Detection steel defect detection dataset. They tested this dataset on Random Forest classifier using GLCM (Grey Level Co-occurrence Matrix), Gabor Wawelet and Histogram of Oriented Gradients (HOG). As a result of their study, they obtained advantages such as automatic examination of surface faults, reduction of labour cost, removal of operators' judgement and creation of a database. And with this study, they suggested that the SVM classifier achieved a maximum accuracy of 95% [18].

As a result of the researches in the literature, it is seen that the defects occurring on the surfaces of metallic products used in the industry can be detected quickly and with more accuracy with deep learning. Considering these studies, in this study, the classification of defects occurring on metallic surfaces with CNN using images of metallic surfaces was performed. Classification process was performed using ResNet50 architecture. The contributions of the study to the literature are as follows.

Defects on the surfaces of metal products are detected and the images are classified with CNN architecture.

Two different defects were identified and a dataset containing a total of 285 metallic surface images in 3 different folders, including separate images for these defects and images without defects, was used.

Accuracy metric was used for training and performance evaluation of the CNN model.

It is suggested that the proposed model can quickly and accurately detect surface defects occurring in the usage areas of metal products in various sectors.

The remaining stages of the article are planned as follows. In the second section, information about the method and data set used in the study is given. In the third section, information about the studies conducted is given. In the fourth section, the results and recommendations obtained as a result of the article are shared.

3. Material and Method

In this section of the paper, the CNN architecture, dataset, performance metrics, validation and training methods are explained.

3.1. Metal Piston Part used in air conditioners

In this article, the images of the metal piston part in the air conditioners used in Mechanic Component Images (Normal / Defected) were used as a data set [19].

The data set used consists of images of a metal piston part used in air conditioners. In these images, which are divided into three different groups, two of the groups show two different defects. The other group contains various images of the metal piston part without defects.

Figure 1 and Figure 2 show images of the defect classified in group 1. In these images, a stain on the surface of the metal piston part is exemplified.

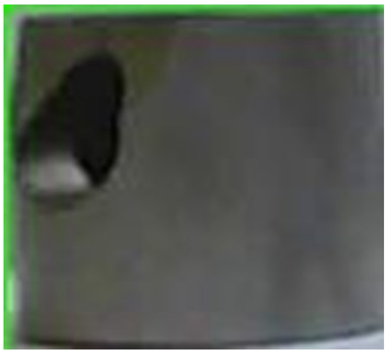

Figure 1. On the surface of the metal piston part.

Figure 2. Image of a stain on the surface image of the stain that occurs.

Figure 3 shows a visual of the defect classified in the 2nd group. This image is a visual of a peeling or cracking defect on the metal piston surface.

Figure 3. An image of the peeling defect on the surface of the metal piston part.

Figure 4 shows the image of the metal piston part with no defects on the surface.

Figure 4. An error-free image of the metal piston part

3.2. Methods Used

In this study, deep learning is used and ResNet50 architecture is used to detect various defects occurring on the surface of the metal piston part used in air conditioners quickly and with the highest accuracy rate.

3.2.1. ResNet50

ResNet was introduced in 2015 in the paper "Deep Residual Learning for Image Recognition". It is a deep learning architecture that won an award in the ILSVRC 2015 competition.

ResNet50 is a pre-trained model of ResNet containing 50 layers. Firstly, the ResNet50 model was loaded into the study. Then the pre-trained weights of the model were frozen. Relevant lines were added to the study so that these layers would not be updated during training. This process preserves the pre-trained feature extraction capabilities of ResNet50. And it allows us to add new custom classification layers on top of these features. In this study, we have added a special classification layer on top of ResNet50. This is an important convolution based model that forms the CNN architecture.

3.2.2. Performance Metrics

Two performance metrics, Accuracy and Categorical Crossentropy, are used in this study. These two metrics are monitored and evaluated during model training. Accuracy shows the correct classification rate of the model. It is a metric that expresses the ratio of correctly classified samples to the total number of samples. Categorical Cross Entropy is a common function used for multiclass classification. It calculates the difference between the probability distribution predicted by the model and the actual labels. The lower the difference, the better the model performance.

3.2.3. Cross Validation

Cross validation is a model evaluation technique used in machine learning. Cross validation randomly divides the dataset into two different clusters, training and validation. It performs training and evaluation on these clusters. In each evaluation and training cycle, the model is trained and on the remaining clusters. These tests are averaged and the overall model performance is obtained. Cross validation helps us to obtain advantages such as obtaining more reliable results and more efficient use of data sets. In this study, the dataset was not used directly in the cross validation method. Part of the dataset was used for training and part for validation. This separation was achieved by using the ImageDataGenerator class. In the study, 30% of the dataset was used for validation. The rest of the data set was used for training.

4. Experimental Results

In this study, ResNet50 architecture was used to classify the defects on the surface of metal parts using image processing algorithm with a dataset consisting of images of the piston part used in air conditioners in order to detect defects on the surface of metal parts. This study is configured with Intel(R) Core(TM) i7-9750H CPU @ 2.60GHz 2.59 GHz, 16 GB RAM, NVIDIA

GeForce GTX 1660 Ti GPU and Windows 11 (64 bit) operating system. Python programming language was used in this study.

ResNet50 model was used with TensorFlow package. In the ResNet50 method, the optimiser parameter is used to optimise the model and the metrics parameter is used to determine the metrics to be used to evaluate the model. In this study, the accuracy metric was used. For ImageData Generator, the subset parameter was also included in the study in order to separate the training and validation sets. Training and validation values were used to separate the training and validation sets. The layers of ResNet50 were kept constant during training and Flatten, Dense and Dropout layers were added after the output of ResNet50. Finally, a softmax layer was added for the three classes. The model is compiled with RMSrop optimisation algorithm, categorical_crossentrop loss function and accuracy metric.

In the first stage of the study, the name of each class in the data set and the sample numbers of these classes were collected with the os.listdir function. This function is used to loop the list of files in the specified directory and to get the subclasses of the data set. After this stage, random images from three different classes in the data set were selected and visualised as a 3x3 matrix. Then, the number of instances of each class was calculated and lists containing the name of each class and the number of instances of that class were created. A bar graph showing the number of instances of each class was created using the barplot function of the seaborn library. The bar chart is shown in Figure 5.

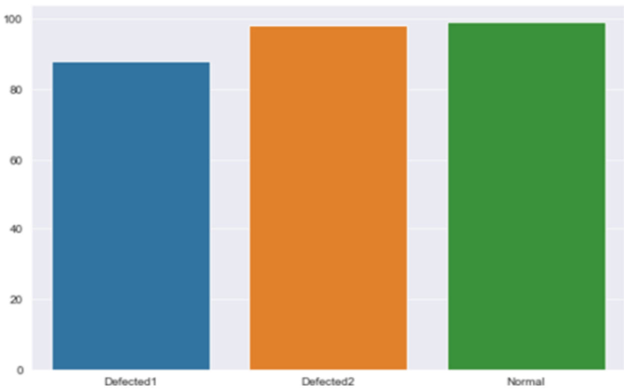

Figure 5. Bar chart showing the names of the classes used in the dataset and the number of instances belonging to those classes

In the rest of the study, the plt.subplots function was used to visualise the random samples of each class. With this function, a 3x3 graph layout was created to display the images. Each subplot will be used to visualise one image. The overall size of the subplots was determined with the Figsize parameter.

This parameter value is set to (9,8). The function 'for j in range(3)' was used to start a loop with three different examples from each class. After the selected image was read with cv2.imread function, the colour channels of the image were converted to RGB format. The generated subgraph is shown in Figure 6.

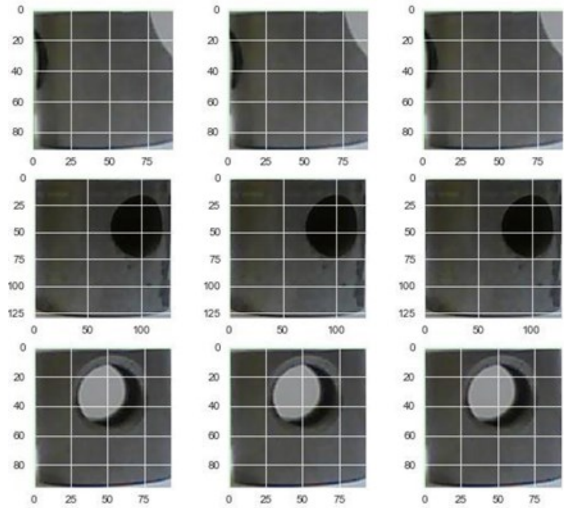

Figure 6. Three randomly selected images from each class shown in subgraphs

In the next part of the study, data augmentation is performed using ImageDataGenerator. This allows the model to be trained with different images. At this stage, 30% of the dataset is reserved as validation data. In the rest of the study, the deep learning model is trained. During training, the model weights are recorded and overfitting is prevented. ModelCheckpoint parameter is used to determine the best model weights. If the model fails validation, EarlyStopping is used to stop the training process so that this failure does not continue. Model compilation was performed with the model.compile function to determine the optimisation algorithm, loss function and metrics. The accuracy metric was determined as the metric.

Confusion Matrix was used to evaluate the accuracy of the model. This matrix shows the number of correct and incorrect classifications. Each cell shows how accurately the model predicts the samples belonging to which class.

Figure 7 shows the graph of the Confusion Matrix used to evaluate the accuracy of the model.

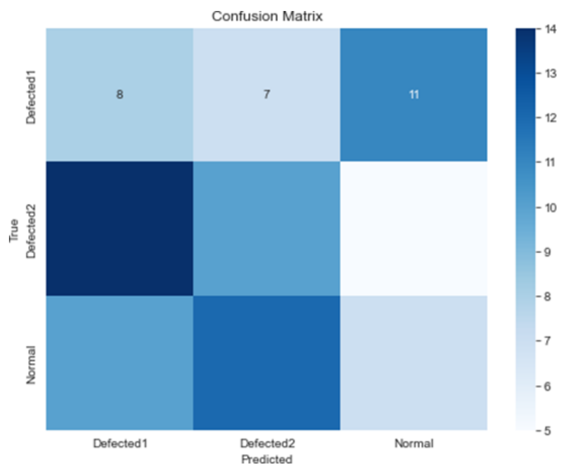

Figure 7. Image of the confusion matrix graph.

Then classification report was used to calculate the metrics of the model such as accuracy, precision, recall and F1-score for each class.

In Figure 8, the curve graph showing Precision, Recall and F1-score metrics is shared.

Figure 8. Curve graph showing Precision, Recall and F1-score values.

Table 1. Performance Metrics (Precision, Recall, and F1-Score) for Different Classes

Classes	Precision	Recall	F1 Score
0	0.29	0.35	0.32
1	0.38	0.38	0.38
2	0.38	0.31	0.34

During training of the model, cross entropy was used to measure the difference between the predicted probabilities and the actual labels. The graph showing the output values of the loss function used is shown in Figure 9.

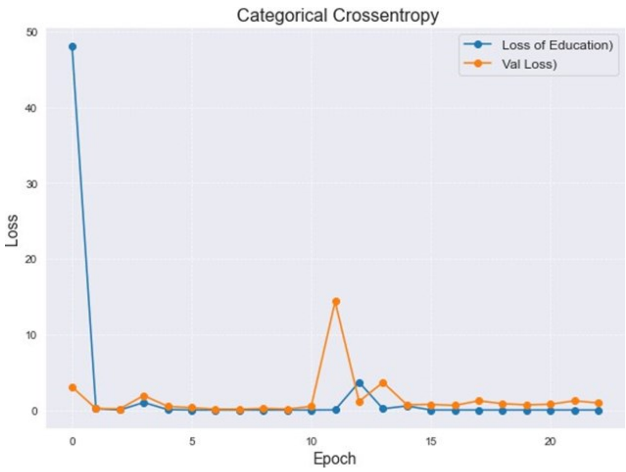

Figure 9. Graph showing the cross entropy loss.

The training accuracy of this model trained with ResNet50 method was 1 out of 50 values. And the trained model was saved in a file with .h5 extension.

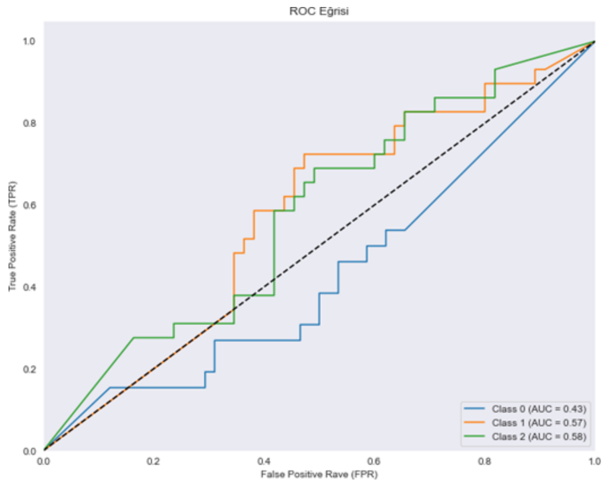

Figure 10. ROC of ResNet50 for all classes

Figure 10 shows the ROC graph and AUC values of the ResNet50 model according to the classes.

The processes and stages throughout the whole study are shown in the flow diagram in Figure 11.

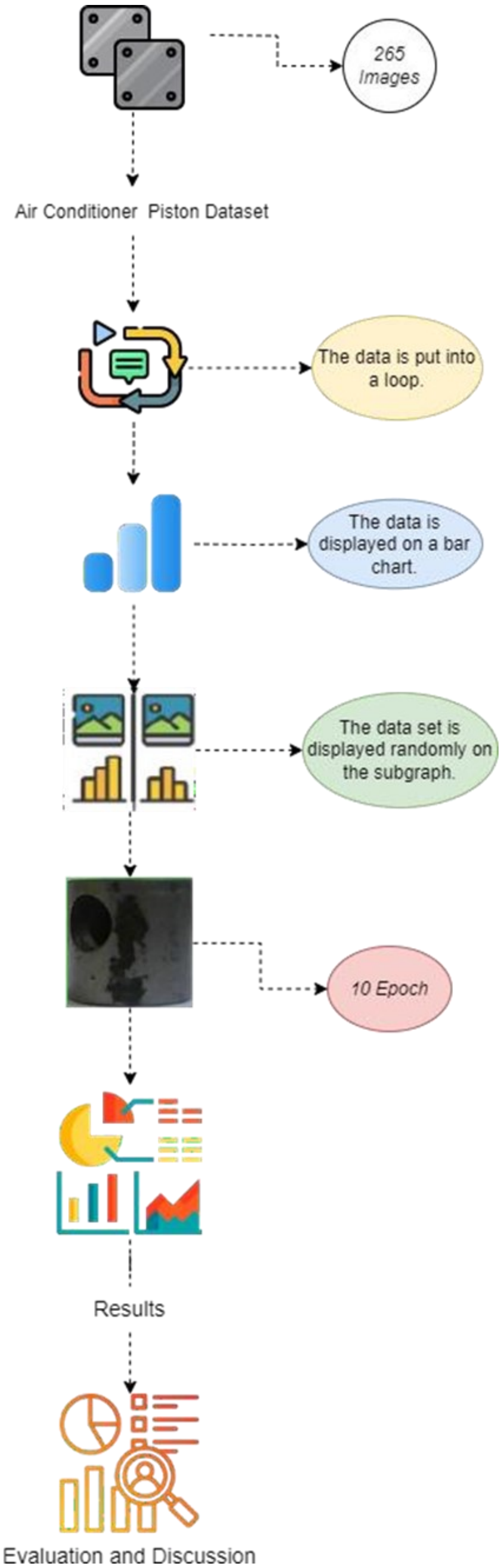

Figure 11. Flow Showing the Stages of the Study for the Detection of Defects Occurring on the Surface of the Metal Piston Part in Air Conditioners with Resnet50 Model Diagram

5. Results

In this study, a deep learning based approach is used to detect defects on the surfaces of metal piston parts in air conditioners and to ensure quality control. Using ResNet50 architecture, the process of classifying the defects on the surfaces of metal piston parts in air conditioners has been successfully performed. As a result, it is seen that the model used in the study provides a faster and more accurate solution compared to the manual and personnel-based control methods currently used in quality control processes in the industry. The accuracy rates obtained as a result of the study reveal that the model has a very high rate of detecting surface defects occurring on the surfaces of metal products during the production process. It is also an example of how deep learning methods can be used in quality control processes in the industry.

Future studies on this subject can increase the efficiency in this field by determining the detection of different types of errors with extended data sets and using them in real-time systems as a target.

6. Discussion and Suggestions

The data set used in this study is limited. However, it is thought that classification success can be increased by using a data set containing more images. By using different feature extraction models and different machine learning methods, it is thought that the process of classifying and distinguishing the defects formed on metal surfaces after the processes they undergo in production networks will be performed more successfully.

The proposed feature extraction and classification model is thought to be able to perform quality control and sorting processes in a non-contact manner with image processing and imaging systems in automation systems to detect defects and defects occurring on the surfaces of metal products.

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