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OPTIMIZATION OF PREDICTION AND PREVENTION OF DEFECTS ON METAL BASED ON AI USING VGG16 ARCHITECTURE

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***Abstract*:** Manufacturing is one of the most valuable industries in the world, it can be automated without limits but still stuck in traditional manual and slow processes. Industry 4.0 is racing to define a new era in digital manufacturing through the implementation of Machine Learning methods. In this era, Machine learning has been widely applied to various fields and will certainly be very good applied in the manufacturing world. One of them is used to predict and prevent defects in metal. The process of predicting and preventing defects in metal is one of the important efforts in improving and maintaining production quality. Accuracy in predicting and preventing defects in metal can be an innovation and competitiveness in technology, both in production methods, and improving product safety and its users. Human operators and inspectors without digital assistance generally can spend a lot of time researching visual data, especially in high-volume production environments. For this reason, there needs to be research in developing Machine Learning technology in an effort to prevent the occurrence of defects in metal. And one of the development of this technology by using Convolutional Neural Network (CNN) architecture Visual Geometry Group 16 layer (VGG16). As for the metal defect dataset with 10 classes with details for training data as many as 17221, and test dataset as many as 4311, From the use of methods and datasets available, has been done training model used and produce very good accuracy, that is equal to 89% and testing with accuracy equal to 76%. And also done Interpreter process against new input data, to know metal defect type, prediction accuracy and appropriate action to prevent and overcome metal defect type result of Interpreter process application.

Keywords: *Defects on Metals, VGG16, Type of Defect Metals, prediction and prevention*

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Introduction

Sheet metal fabrication is one of the most popular processes for creating prototypes and parts in the industry. Ranging from low-volume prototypes to high-volume production parts. This process is often used in various industries, including automotive, aerospace, construction, manufacturing industry and other industries (Camacho, D.D., et al. 2018). The manufacturing industry, especially in the production and processing of metal materials, has a great challenge especially in maintaining the quality of a product. But the main problem that is commonly faced is the existence of defects on the surface of sheet metal as a result of the manufacturing manufacturer. The metal defects referred to can come from various factors, such as workmanship errors, instability of production parameters, and environmental influences. Considering that metal materials and their mixtures are basic materials that form solid crystals. The combination that forms the type of metal is a combination of aluminum, steel, titanium, and nickel. So it is impossible not to produce metal defects such as point defects, line defects, and plane defects (Gilbert, 2020).

Manual detection of metal defects by production operators has several limitations, including subjectivity and potential error from humans as manual labor. Therefore, a more sophisticated and automated approach is needed to address the problem. One approach that can be the best solution is to utilize image processing technology and Machine Learning to predict, and prevent possible defects on the surface of sheet metal.

Prediction and prevention of metal defects in the manufacturing industry are very important to do. Because manufacturing companies can quickly identify the possibility of defects in metal, allowing the manufacturing industry to take the necessary preventive actions quickly before metal production reaches the final production stage. This way this stage can improve the quality of the products produced. In addition, by predicting and preventing defects early, companies can avoid wasting time and resources associated with metal defects, so that the production process can run more efficiently.

Defects in metal not only affect the quality of a product, but also can increase production costs. Because if the metal has defects, it must be repeated or repaired, so it is possible to spend additional costs. But if prevention is done before there are defects in the metal, the cost can be minimized and can reduce waste of cost. The better or more accurate the ability to predict and prevent defects in metal, the better the quality of the product produced in this case is metal. Accuracy in predicting and preventing defects in metal can be an innovation and competitiveness in technology, both in production methods, and improving product safety and its users. Therefore, it is clear that the step will certainly be able to provide competitive advantages for companies or manufacturing industries.

Based on the background above, this research is expected to provide an overview of the importance of predicting and preventing defects in metal using technology that has developed mainly in the development of AI. This research still has room to be developed further and more effectively, so that it can contribute to improving product quality, metal product efficiency, and can have a positive impact on the manufacturing industry as a whole. By developing a prediction model based on Machine Learning, namely with the VGG16 algorithm that can recognize and predict defects in metal with high accuracy, it is expected to obtain high accuracy values, both in the training and testing processes so that they can provide prediction results and preventive measures that are good according to the production needs of the manufacturing industry. By combining the deep capabilities of the VGG16 architecture and production information, it is expected to be able to contribute significantly to improving the quality of metal products and effectiveness during the manufacturing production process.

Literature Review

In this chapter will be explained the introduction of theory as the basis for research. Such as the definition and types of defects in metal, prevention of defects in metal, Convolutional Neural Network (CNN) method, and VGG16 architecture. Each of which are:

1. Defects in metal

   Metal is the main raw material of products from the industry, and metal will definitely experience surface damage from the metal itself, such as scratches and deformations (Xu, Y. Zhang, & K. Wang, 2021). Likewise during the actual production process, damage to processing equipment or a harsh industrial environment will definitely cause certain quality problems of metal material products. According to Fang (2020) some surface defects are an important factor in determining the quality of industrial metal materials (Fang et al. 2020). In the world of metal industry found some metal defects that vary and complex, such as creasing, inclusion, patching, pitted surface, and scratches (Lv X, Duan F, Jiang JJ, Fu X, Gan L., 2020). Some types of metal defects in the manufacturing industry vary and complex, such as crease, inclusion, patching, pitted surface, and scratches which can be seen visually in figure 1.

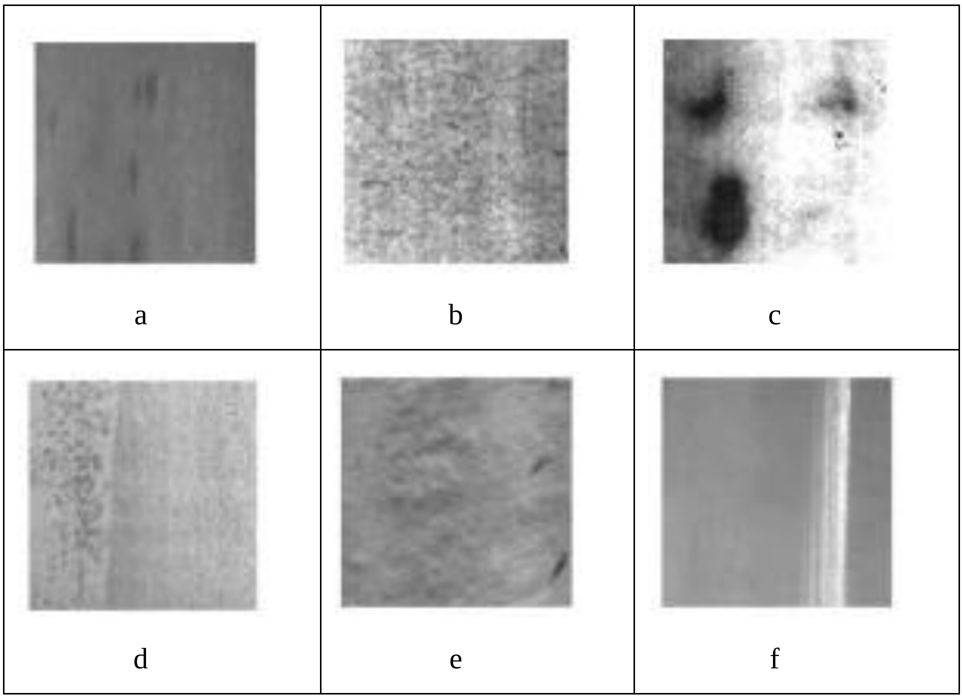

Figure 1. Examples of metal surface defects. (a) Crasing, (b) inclusion, (c) Patches, (d) Pitted surface, (e) Rolled in scale, (f) Scratches.

According to Lv X (2020), there are 10 types of defects or damage to metal that are often found in the manufacturing industry. The explanation is as follows:

1.1. Crease

Crease It is a phenomenon that produces fine crack networks on the surface of a material. The main cause of Crease type defects is generally related to uneven pressure or inappropriate deformation distribution during the forming or rolling process. And the pressure or deformation leads to the formation of microvoids and small cracks. If pressure is applied to the metal surface continuously, the cracks in the metal will elongate and break. Crazing generally occurs almost on metal including on metal that has corrosion resistance. Crease prevention involves careful setting in paying attention to the parameters used during the forming or rolling process, using the right tools, good pressure control, and careful deformation monitoring are some steps that can be taken to prevent the formation of crease defects on metal.

1.2. Crescent Gap

Crescent gap or can be termed as a crescent gap on metal occurs due to various factors in the manufacturing and processing of metal. Some factors that can cause the formation of crescent gaps include: cutting process, material stiffness, mechanical deformation, humidity and heating, quality of equipment and machines used in the manufacturing process, such as cutting or rolling can also cause the formation of crescent-shaped gaps. In an effort to prevent and overcome Crescent Gap (Cg), it is important to conduct strict quality control and supervision throughout the manufacturing process, as well as ensure that the machines, equipment, and production parameters are set correctly.

1.3. Inclusion (In)

Inclusion is a metal defect with a relatively small size that can be particles or material trapped in the metal surface during the forming or production process of metal. This defect occurs due to imperfections in raw materials or production processes. Prevention of metal defects in the form of inclusion on metal is an important part in the manufacturing process to maintain quality and material integrity. Some prevention efforts that can be done include: selecting quality raw materials, supervision and maintenance of equipment, cleaning materials, optimizing manufacturing processes, early detection and monitoring, using filters, training employees periodically on materials and final products which are certainly important steps in helping to identify inclusions or other defects quickly, so that corrective actions can be taken earlier.

1.4. Oil spot

This defect occurs due to contamination of the metal surface by lubricant or mechanical oil during the production process. Lubricants or mechanical oils are used in the manufacturing industry to reduce friction between the metal surface and equipment or tools used in the production process. But if not managed properly, lubricants or oils can cause problems on the surface of the metal being processed. In general, there are oil spot type metal defects due to lubricant or oil contamination on the metal surface. To prevent and overcome this oil spot defect, some actions can be taken including: using appropriate lubricants, controlling lubricant or oil applications carefully, cleaning surfaces to keep them clean before and after lubricant or oil applications, and testing quality periodically on metal products to detect this oil spot defect.

1.5. Punching hole

Metal punching hole defect is a type of defect that occurs due to holes or gaps on the metal surface. This defect generally occurs due to a workmanship or production process of metal that involves cutting or drilling techniques with certain machines or tools. The hole or gap can appear with various sizes and shapes, depending on the cutting technique used and the characteristics of the metal material processed. To prevent and overcome punching hole defects, some actions can be taken including: selecting the right tools for cutting or drilling that match the type of metal material processed, accurate cutting techniques, machine supervision by ensuring that the machine or tool used in the cutting or drilling process is in good condition, and quality inspection on metal products after the cutting or drilling process is done.

1.6. Rolled pit

Rolled pit metal defect is a type of defect that occurs on the metal surface in the form of protrusions or small depressions that are spread periodically. This defect is generally seen as protrusions or depressions that are shaped like dots, flakes, or ribbon shapes. Rolled pit defects are formed as a result of the forming or rolling process of metal that involves compression and deformation of metal material on a microscopic scale. To prevent and overcome Rolled pit defects, there are several actions that can be done, such as: good roller/roll maintenance, strict process supervision during the rolling or forming process of metal, quality inspection on metal products after the rolling process to detect the presence of rolled pit defects, and optimization of process parameters.

1.7. Silk spot

Silk spot metal defect is a type of defect that appears as an area of metal surface that has a appearance like stains or plaques shaped like local or continuous waves. This defect often appears on the top or bottom surface of the metal sheet and tends to have imperfections in its density distribution along the length of the sheet. Silk spot defects often interfere with the visual appearance of metal products and can damage the aesthetic value and quality of the metal surface. To prevent and overcome silk spot defects, there are several actions that can be done: process optimization by optimizing temperature, pressure, and deformation parameters during the forming or processing process of metal, maintenance of rollers/rolls used in the forming process in good condition and not experiencing significant tilt or deformation, visual inspection, and quality control.

1.8. Waist folding

Waist folding metal defect is a type of defect that occurs on the metal surface that results in folds either vertically or horizontally and these folds look like wrinkles on the metal sheet. This defect often occurs on the edge or edge of the metal sheet and can reduce the quality and visual appearance of metal products. There are several actions that can be done for prevention and handling that can be taken namely: selection of metal materials that have good resistance, process optimization, tool maintenance and visual inspection.

1.9. Water spot

Water spot is one of the types of defects on the metal surface that occurs due to the presence of water stains or spots. This defect appears during the metal production process that involves water, such as cooling or cleaning with water. Water spot can reduce the aesthetic and functional quality of metal products, especially if the products are used in environments that require a clean and free appearance from metal defects visually. In addition, water spot can also be the starting point for the occurrence of corrosion or other damage on the metal surface. To avoid and reduce metal defects of water spot type, manufacturing companies generally will consider some preventive measures, such as using high-quality water that has little minerals or contaminants, drying the metal surface efficiently after the cleaning or cooling process, and avoiding excessive use of water which can leave residues of water.

1.10. Welding line

Welding line type metal defect occurs as a result of the process of joining two parts of metal with welding technique. Although this welding technique is an important part of many manufacturing processes, but sometimes the joint area can show differences in structure and material properties. So it will look like a line or area called welding line. To avoid this problem, it is important to use the right welding technique and optimize the welding parameters so that the joint area has material properties that match the other parts of the metal. And if needed, surface treatment or smoothing can be done to reduce the visual or functional impact of welding line.

2. Convolutional Neural Network Method

Convolutional neural network (CNN) is a development of multilayer perceptron (MLP) that is designed to process two-dimensional data. CNN belongs to the type of Deep Neural Network because of the high network depth and is widely applied to image data (Suartika, E.P.I. et al. 2016). There are several common CNN architectures. The architectures include: LeNet, AlexNet, ZF Net, GoogleNet, VGGnet, and ResNet (Setiadi E., & Wibowo, A. 2021). CNN is known for its ability in end-to-end learning, which means that the model on CNN can be learned from raw data until it can provide relevant output. The model or network that is created can provide the intended result, by training the network using supervised learning method by minimizing the loss function such as Cross-Entropy loss, Mean Squared error (MSE), Huber loss, Hinge loss (Margin Loss) and so on depending on the type of task being faced or to be solved. Because each loss function has different characteristics and effects on model learning, and some functions can be more suitable than others, depending on the data and objectives to be obtained (Yulianto, Y. & Wibowo, A., 2023).

3. VGG16

VGG16 is an abbreviation of Visual Geometric Group developed by Oxford University. VGG16 means that there are 16 Layers contained in the visual geometric group. Where VGG16 is one of the configuration architectures in Convolutional Neural Network (CNN) (Simonyan, K & Zisserman, A., 2015). In general VGG16 uses 5 convolutional blocks that are then connected to 3 MLP classifiers. The output layer uses Sigmoid activation function if there are 2 or less categories, and softmax activation function if there are 3 or more categories from the dataset used (Hridayami et al. 2019).

Research Methodology

In the research of optimization of prediction and prevention of metal defects based on Machine Learning: the development of VGG16 architecture is proposed as a solution to overcome the problem in recognizing metal defects and preventive actions and appropriate approaches to overcome the problem, as well as to improve the quality of metal production and reduce the risk of defects that may occur. So to get the expected results, there needs to be a process of design and implementation gradually. The research stages are presented in figure 1 below.

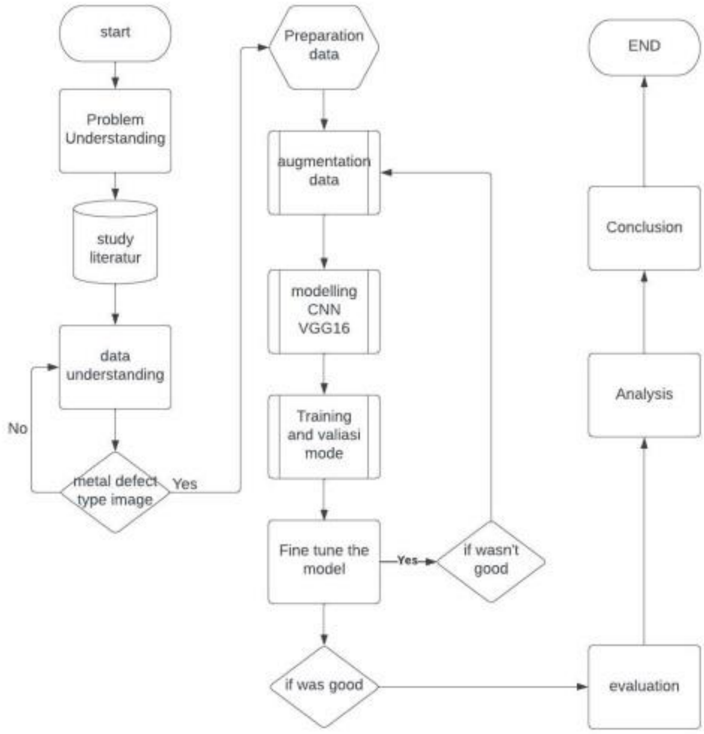

Figure 1. Flow Chart

The workflow of this research starts from understanding the importance of knowing the stages in detecting the types of metal defects, understanding the differences of the types of metal defects in morphology, selecting sample data that is used as input for training, validation and testing data. Then designing a network with CNN VGG16 method to perform classification and detection on new input images of metal defect types. The CNN VGG16 network design is applied with the process of training the model using training data. So that the network that is created can learn to study and recognize input objects. If the network learning obtains good results in distinguishing metal defect types, then the network is then tested against validation data. If the validation data also shows good results then the network can be used for testing process in the form of classification and detection on test data.

1. Data collection

Data collection The collection of metal defect data used is in the form of types and classes which consist of 10 types of metal defects. They are crease, crescent_gap, inclusion, oil_spot, punching_hole, rolled_pit, silk_spot, waist folding, water_spot, and welding_line. We took the data from the kaggle catalog1. Where the total number of data that we use in applying this system is 2360 images. Where the images consist of 52 images of crease metal defects, 226 images of crescent_gap metal defects, 216 images of inclusion metal defects, 204 images of oil_spot metal defects, 219 images of punching_hole metal defects, 31 images of rolled_pit metal defects, 650 images of silk_spot metal defects, 146 images of waist folding metal defects, 289 images of water_spot metal defects, and 273 metal defects of welding_line type. The examples of images in each image can be seen in figure 2 below.

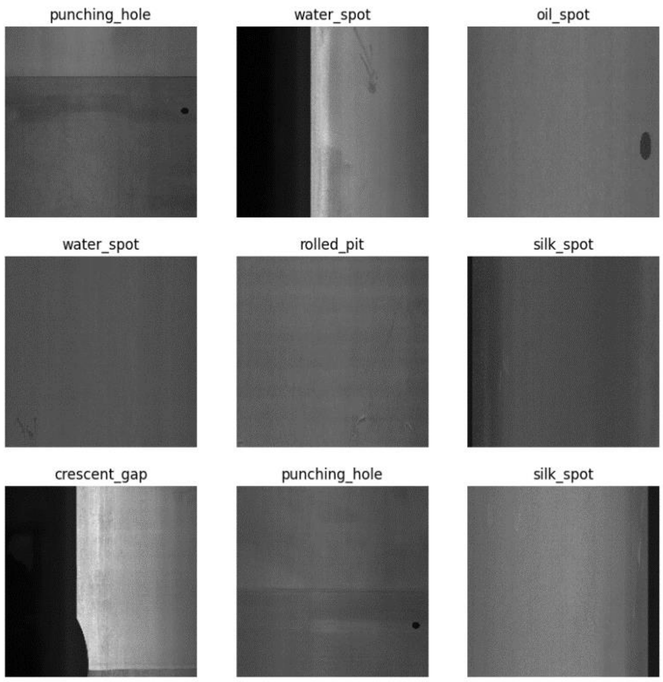

Figure 2. is an example of an image for training data

However, because the amount of data is relatively small and the imbalance between the amount of data for each class, then synthetic data augmentation is performed. Synthetic data itself has the purpose of producing a large and diverse set of data that can be used for purposes, such as training and testing models on Machine Learning methods to conducting research studies without sacrificing the privacy or security of individuals or organizations (watanabe & ishumaru, 2016). And from the results of the synthetic data creation process, the total amount of data becomes 21532 files. Which each class is roughly 2000 image data.

From all the data above, we divide it into training and test data. Which training data is used to train the model, while test data is used to test how well the model works on data that has not been seen before. The number of each training and test data is 5062 images for training and 1268 for test. The details can be seen in table 1 below.

Table 1. Distribution of Research Data

Type of metal defects	Amount of training data	Amount of validation data	Amount of test data
crease	1335	320	414
crescent_gap	1399	364	129
inclusion	1356	343	425
oil_spot	1338	333	418
punching_hole	1568	412	496
rolled_pit	1328	356	422
silk_spot	1452	335	447
waist folding	1336	332	418
water_spot	1361	304	417
welding_line	1304	345	413
total	13777	3444	4311

Training data is used to perform network learning process, then evaluated. If the accuracy of the network model training process has not increased, it is necessary to modify the CNN layer with VGG16 architecture, network parameters and on its sample data. If the accuracy result is good then the next process is testing with validation data. Validation data is data that is not used in the training process. The network validation process uses 1012 data to test the network or model that is created with the number of image images in each class roughly the same that is 100 images. If the accuracy of this validation data is not good, there is a possibility of overfitting, therefore the network needs to be modified again by doing augmentation steps. So that the results are good or there is an increase then this network can be used to process test data. Test data contains a set of sample data that want to know its classification type.

2. Data preprocessing

Data preprocessing includes a series of steps that are performed before the data is entered into the model for training. The data preprocessing stage is done by changing the size of the metal defect image from a length and width of 250 pixels to a size of 200 pixels in each image for the width and length of the image, shifting the metal defect image, cropping, and other stages that are used to create a larger variation of data. Such a process is called the augmentation process. The data augmentation process is an important part of the data preprocessing process during model training in

Machine Learning. In general, this process is done to prevent overfitting and enrich the variation of data available for the model. By using this process, the model is expected to learn better and become more general in recognizing various variations in real data. The next step is to divide the collected data into two, namely training and testing data. Followed by the labeling process on each image data according to each class of metal defect types. Where the labeling results are done using numbers 0 to 10. Number 0 for crease image label, number 1 for crescent_gap image label, number 2 for inclusion image label, number 3 for oil_spot image label, number 4 for punching_hole image label, number 5 for rolled_pit image label, number 6 for silk_spot image label, number 7 for waist folding image label, number 8 for water_spot image label and number 9 for welding_line image label.

3. CNN Design of VGG16 Architecture

This research proposes a method for detecting metal defect types based on the shape and characteristics of metal defects consisting of 10 classes as explained in the previous chapter. In the detection process, the convolution layer is performed on the server until it is finished. The image or dataset will be retrained to obtain a good CNN model with VGG16 architecture that will be used to generalize and make good predictions on new data, such as kernel size, filter and layer.

Table 2 VGG16 Model Structure

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 200, 200, 64)	1792
conv2d_1 (Conv2D)	(None, 200, 200, 64)	36928
max_pooling2d (MaxPooling2D)	(None, 100, 100, 64)	0
conv2d_2 (Conv2D)	(None, 100, 100, 128)	73856
conv2d_3 (Conv2D)	(None, 100, 100, 128)	147584
max_pooling2d_1 (MaxPooling 2D)	(None, 50, 50, 128)	0
conv2d_4 (Conv2D)	(None, 50, 50, 256)	295168
conv2d_5 (Conv2D)	(None, 50, 50, 256)	590080
conv2d_6 (Conv2D)	(None, 50, 50, 256)	590080
max_pooling2d_2 (MaxPooling 2D)	(None, 25, 25, 256)	0

conv2d_7 (Conv2D)	(None, 25, 25, 512)	1180160
conv2d_8 (Conv2D)	(None, 25, 25, 512)	2359808
conv2d_9 (Conv2D)	(None, 25, 25, 512)	2359808
max_pooling2d_3 (MaxPooling 2D)	(None, 12, 12, 512)	0
conv2d_10 (Conv2D)	(None, 12, 12, 512)	2359808
conv2d_11 (Conv2D)	(None, 12, 12, 512)	2359808
conv2d_12 (Conv2D)	(None, 12, 12, 512)	2359808
max_pooling2d_4 (MaxPooling 2D)	(None, 6, 6, 512)	0
flatten (Flatten)	(None, 18432)	0
dense (Dense)	(None, 4096)	75501568
dense_1 (Dense)	(None, 4096)	16781312
dropout (Dropout)	(None, 4096)	0
dense_2 (Dense)	(None, 10)	40970

===
Total params: 107,038,538
Trainable params: 107,038,538
Non-trainable params: 0

On the input layer, the data used is training data. Then the input data is processed on the first convolution layer by using maxpooling and ReLu activation function. The output on the first convolution layer is used as input on the second convolution process. Then the results of the convolution process are collected on the fully connected layer. On this layer, features that have correlation with certain classes are determined so that the final result of this process is features that are classified into ten classes.

Research Results and Discussion

1. CNN Implementation of VGG16 Architecture

There are three stages in implementing CNN with VGG16 architecture after preparing the dataset that will be used in this research, namely training, validation and testing. The training stage is the main stage to train the model or network in learning the input data. This model will learn from the training dataset or data to adjust the parameters or patterns in the data so that it can make accurate predictions. Then the performance of the model or learning algorithm is measured and evaluated using validation data to get how well the model generalizes on data that has never been seen before. With the hope that the model that has been created becomes accurate and reliable. During the training and validation process, hyperparameter adjustment of the model such as learning rate, number of layers and convolution filter size is done to get better model performance. After the model is considered good enough, based on the evaluation on the validation dataset, the next step is to evaluate the model using the test dataset to test the final performance of the model that has been created. This evaluation will give an overview of how well the model can generalize on new data that has never been seen.

2. Training network or Model

The model training process is done using training data. The percentage of training data used is 80% of the total data available. In this data, there is also data used for the validation process and this data is separate from the training data. From the training data 80% for the training process and 20% for the validation process. In detail, the number of data used for the training process is about 500 images, and 100 images are used for the validation process. While the computation process is done using single GPU mode. The training process uses the following parameters:

Model Optimizers : Adam
Learning rate : 0.0001
Mini-batch size : 16
Epoch : 7

The training results are presented in table 3. The network training gives good accuracy. The graph of accuracy and error of the training process is presented in figure 3.

Table 3 CNN network Training Results

```
accuracy
      training          (min:    0.257, max:    0.942, cur:    0.942)
      validation        (min:    0.347, max:    0.798, cur:    0.969)
Loss
      training          (min:    0.173, max:    1.920, cur:    0.173)
      validation        (min:    0.679, max:    1.704, cur:    0.855)
862/862 [==============================] - 187s 216ms/step - loss:
0.1733 - accuracy: 0.9419 - val_loss: 0.88863 - val_accuracy: 0.7654
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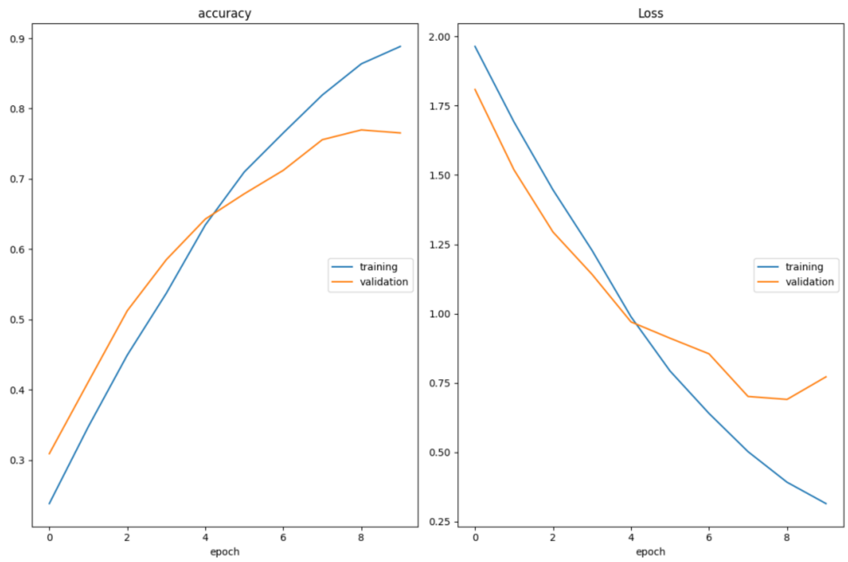

Figure 3 Graph of Accuracy and Training Error

3. Model testing

Interpreter is a stage in the process of testing data by entering sample data that want to know the type of classification on the network, then the network will output the label of metal defect type and the percentage of accuracy of the input data. The result of this interpreter is very influenced by the model training on the training data and the validation process. The classification results that come out of the network, can be used as a consideration to determine the type of metal defect, and determine some actions that can be done for prevention and handling based on the results of metal defect detection. In the test data testing stage using data as much as 4311 data with the number of each class according to the description in table 1. This test produces good accuracy that is 76.5% with the correct number as much as 3299 data. So if the total number of test data is 4311 then there are 1012 data that are wrong predictions. From the wrong prediction data, the most errors in predicting metal defect types are on rolled_pit type. From the number of data that actually rolled_pit is 422 files, the number that is correct 233 and the number that is wrong 189 files. With details 39 images predicted as waist folding type, 37 as punching hole metal defect type, 18 as crease metal defect type, and 10 as oil spot metal defect type. This happens because the rolled_pit metal defect type has similarities visually both size characteristics, shape that is almost similar to waist folding and punching hole metal defect types. The complete accuracy results of classification on test data can be seen in confusion matrix in figure 42, and semantic classification results for new input data that have not been used either in train data, validation data or test data we also tested to obtain information detection results on a particular image, so that from the findings of metal defect types can be determined appropriate actions to overcome and prevent certain types of metal defects. The results of detection through interpreter process are as shown in figure 5.

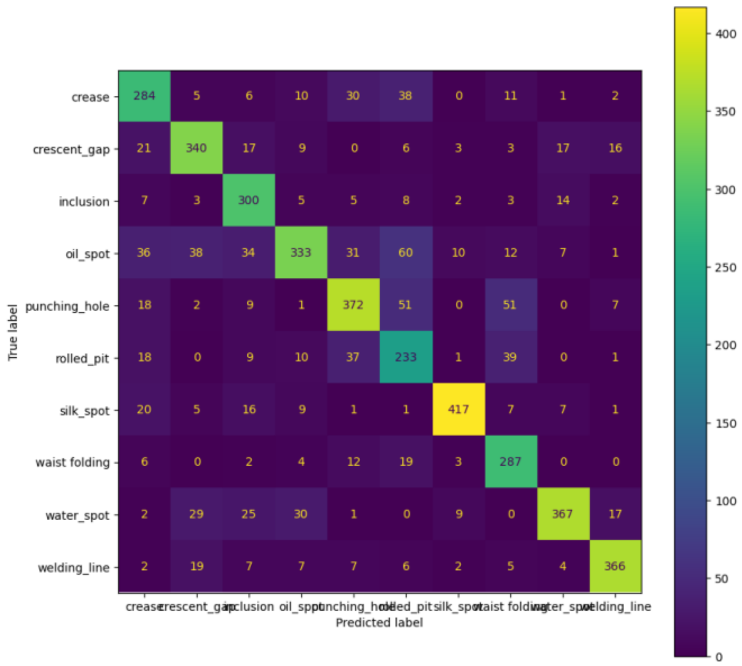

Figure 4 Confusion Matrix From Test Data

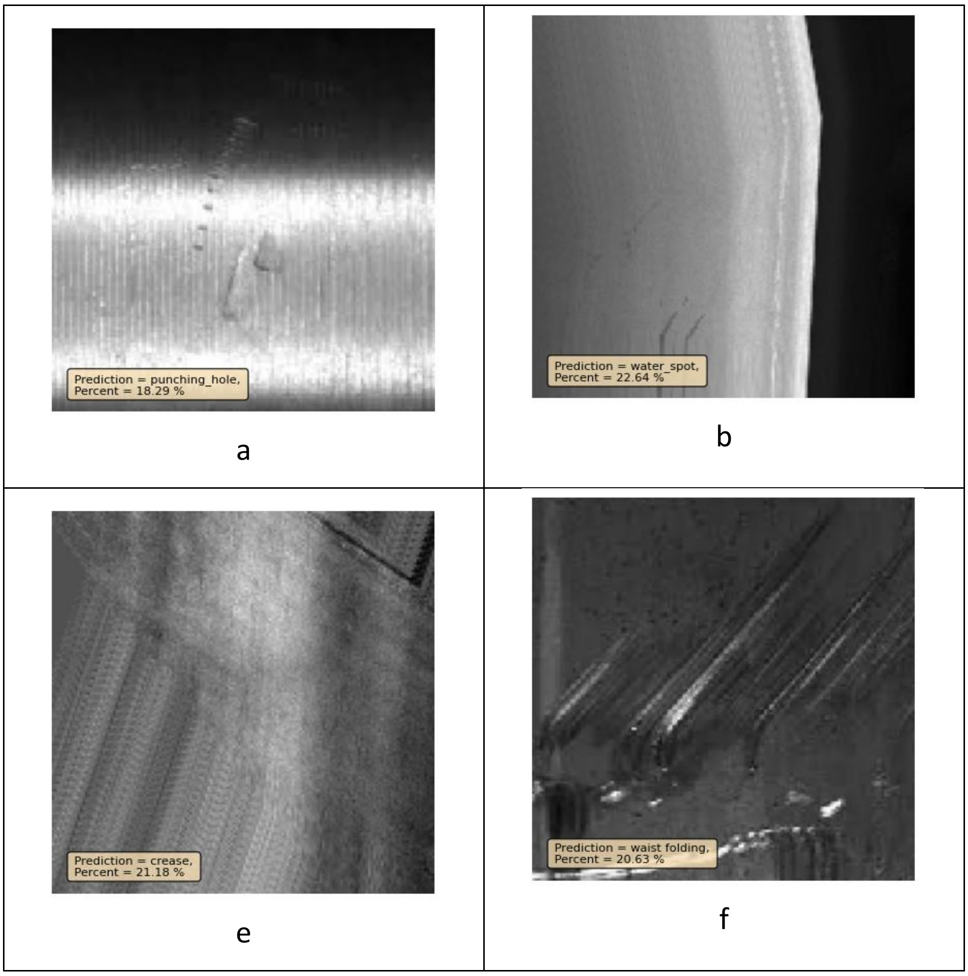

Figure 5 Semantic classification results on test data and test data samples on some data.

Figure 5 is the result of the interpreter process on new input data. Where from the picture it can be concluded that the detection and classification results and the right steps to prevent and take appropriate actions in dealing with metal defect types that are recognized, can be seen in table 4 below.

No	Name of image	Classification result	Accuration percentage	Preventive action
1	a	Punching hole	18,29%	• Selecting the cutting or drilling tool that is suitable for the type of metal material • Accurate cutting technique • Machine supervision by ensuring that the machine or tool for cutting or drilling is in good condition • Quality inspection on metal products after the cutting process before mass production
2	b	Water spot	22,64%	• Using water with high quality that has little mineral or contaminant • Efficient drying of metal surface after cleaning or cooling process • Avoiding excessive water use
3	c	Crease	21,18%	• Careful adjustment in paying attention to the parameters used during the forming or rolling process • Using the right tool • Good pressure control • Careful monitoring of deformation
4	d	Waist folding	20,63%	• Selecting metal material that has good resistance • Process optimization • Tool maintenance • Visual inspection

```
              precision    recall  f1-score   support

      crease       0.69      0.73      0.71       387
crescent_gap       0.77      0.79      0.78       432
   inclusion       0.71      0.86      0.78       349
    oil_spot       0.80      0.59      0.68       562
punching_hole      0.75      0.73      0.74       511
  rolled_pit       0.55      0.67      0.61       348
   silk_spot       0.93      0.86      0.90       484
waist folding      0.69      0.86      0.76       333
  water_spot       0.88      0.76      0.82       480
welding_line       0.89      0.86      0.87       425

    accuracy                           0.77      4311
   macro avg       0.76      0.77      0.76      4311
weighted avg       0.78      0.77      0.77      4311
```

Gambar 6 Clasification report

In the report of the classification model that has been made as shown in figure 6, it can be concluded that the model has good performance with an accuracy rate of about 76% for the test dataset consisting of 4311 samples. This is reinforced by the high f1-score values for each class that can show that the model can recognize various classes quite well.

Conclusion

The results of the implementation of the CNN method with the VGG16 architecture to identify the type of defect in metal show that the CNN architecture with the VGG16 architecture can identify 10 types of varieties quite well. The evaluation of the training results on the network architecture or VGG16 architecture on the train data resulted in an accuracy of 88% and a validation accuracy of 76%. While the results of the testing process on the test data resulted in an accuracy of 76% For the test data scenario with 10 classes tested as many as 4311 samples. Although there are errors in identifying the type of metal defect, the errors in predicting are not too significant. From the testing process, it was found that the highest prediction error for the type of metal defect was the rolled_pit type. Of the 422 images owned by the rolled_pit type, the number of correct predictions was 233 and the number of incorrect ones was 189 files. With details, 39 images were predicted as waist folding type, 37 as metal defect punching hole type, 18 as metal defect crease type, and 10 as metal defect oil spot type. The occurrence of errors in identifying or detecting is caused by visual characteristics, variations in data for each class, complexity in classifying types of defects mainly on rolled_pit types, waist folding and crease.

To overcome this, it is better to try using a different model, further handling is needed in terms of doing approaches such as strengthening data by increasing the number of images used both for needs during the training and validation process, doing augmentation process to create more variations in training dataset especially on data that has a high error rate.

In addition to testing the data in the test data, this study also tried to detect and classify types of metal defects on new input data, which have not been recognized by the network or model used. From the results of detection and classification on new input data, it can be concluded that the network is able to recognize each new input image of metal defects very well too. Although it has a relatively low percentage, but the testing process is able to detect very precisely. To overcome this, it is better to try using a different model, further handling is needed in terms of doing approaches such as strengthening data by increasing the number of images used both for needs during the training and validation process, doing augmentation process to create more variations in training dataset, model change.

Reference

Camacho, D.D., et al. 2018. Applications of additive manufacturing in the construction industry – A forward-looking review. Automation in Construction. Vol. 89, 2018, 110-119, DOI: https://doi.org/10.1016/j.autcon.2017.12.031.

Endang, S. & Wibowo, A. 2023. Klasifikasi dan deteksi keretakan pada trotoar menggunakan metode convolutional neural network. JTSC, Vol. 4, No. 1, 412-427, DOI: https://doi.org/10.51988/jtsc.v4i1.116.

Fang, X.; Luo, Q.; Zhou, B.; Li, C.; Tian, L. Kemajuan Penelitian Deteksi Cacat Permukaan Visual Otomatis untuk Material Planar Logam Industri. Sensor 2020 , 20 , 5136. DOI: https://doi.org/10.3390/s20185136

Gilbert JL (2020) Metals: basic principles, biomaterials science, 4th edn. pp 205–228.e1

Hridayami, P., Putra, I., & Wibawa, K., (2019). Fish species recognition using VGG16 deep convolutional neural network. Journal of computing science and engineering, 13(3), 124-130, DOI: https://doi.org/10.5626/JCSE.2019.13.3.124

Lv X, Duan F, Jiang JJ, Fu X, Gan L. Deep Metallic Surface Defect Detection: The New Benchmark and Detection Network. Sensors (Basel). 2020 Mar 11;20(6):1562. DOI: 10.3390/s20061562.

Simonyan, K. and Zisserman, A. 2015. Very deep convolutional networks for large-scale image recognition. 3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings. (2015), 1–14.

Suartika, I.W., et al. 2016. Klasifikasi citra menggunakan Convolutional Neural Network (CNN) pada Caltech 101. Jurnal Teknik ITS. Vol. 5, No. 1 (2016), 2301-9271.

Watanabe, T., & Ishimaru, T. (2016). A Least Median of Squares Method Based on Fuzzy Reinforcement Learning for Modeling of Computer Vision Applications. 2016 Joint 8th International Conference on Soft Computing and Intelligent Systems (SCIS) and 17th International Symposium on Advanced Intelligent Systems (ISIS), 65–71. https://doi.org/10.1109/SCISISIS.2016.0027

Wibowo, A. & Putra, M. 2021. Pemanfaatan kamera DSLR Canon 1200D untuk pengamatan fotometri bintang variabel. Seminar Panorama Antariksa 2021, 978, 78-81, 2022.

Wibowo, A. & Lusiana. 2022. Budidaya Tanaman Aren Sebagai Langkah Strategis Mewujudkan Hutan Lestari Di Subang. Sadeli: Jurnal Pengabdian kepada Masyarakat, Vol. 2, No. 216-24, 2022.

Yulianto, Y. & Wibowo, A. 2023. Deteksi keretakan perkerasan jalan aspal menggunakan metode convolutional neural network. JTSC, Vol. 4, No. 2, 581-593, DOI: https://doi.org/10.51988/jtsc.v4i2.

Xu, Y.; Zhang, K.; Wang, L. Deteksi Cacat Permukaan Logam Menggunakan Modifikasi YOLO. *Algoritma* 2021 , *14* , 257. https://doi.org/10.3390/a14090257