Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 8, Number 2, April 2023
DOI : https://doi.org/10.33395/sinkron.v8i2.12394
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Detects Damage Car Body using YOLO Deep Learning Algorithm

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Submitted : Apr 1, 2023 | **Accepted** : Apr 14, 2023 | **Published** : May 2, 2023

Abstract: This journal presents a technique for detecting scratches, cracks and other damage to car bodies using machine learning methods. This method is used to improve process efficiency and checking accuracy and can also reduce the cost and time required for manual inspection. The method includes collecting image datasets of cars in good and damaged condition, followed by preprocessing and segmentation to separate damaged or damaged car parts. not broken. Then, it is followed by a deep learning algorithm, namely You Only Look Once, or Faster Region-based Convolutional Neural Networks, which is used to build a detection model. The model is trained and tuned using the collected data, then evaluated using the test data to measure the accuracy and precision of the detection results. The experimental results show that the proposed method achieves high accuracy and efficiency in detecting scratches, cracks, and other defects on the car body, with precision of an average of more than 70%. This method provides a promising approach to improving the car body inspection process which can be used by taxi companies to help inspect and maintain vehicles more quickly and accurately, to help with insurance, avoid accidents and so on.

Keywords: Deep Learning, Detection, Cracks, Car Body, Damage, Scratches

INTRODUCTION

In the automotive industry, vehicle maintenance is an important thing to do so that the vehicle can operate optimally and safely. One of the things that must be considered in vehicle maintenance is damage to the car body. Damage to the car body (van Ruitenbeek & Bhulai, 2022) can reduce the selling price of the vehicle and can also affect the safety of the driver. To detect damage to the car body, it is generally done by visually inspecting it or carrying out an inspection with a measuring device. However, this method has some limitations such as requiring a long time and requiring special expertise in interpreting inspection results. In recent years, the use of deep learning algorithms in the field of computer vision has demonstrated excellent capabilities in object detection and classification. Therefore, this study will use a deep learning algorithm to detect damage to the car body using images (Sze et al., 2022).

To maintain safety and comfort when operating a vehicle, a vehicle owner or the automotive industry (Hindarto et al., 2021) must inspect the condition of the car. In general, cars are frequently utilized and exposed to a variety of environmental elements that might harm the car's body parts. Therefore, it is crucial to have a reliable and precise procedure for identifying scratches, cracks, and other car body damage. To now, manually inspecting the cars' bodies has been labor- and money-

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intensive, and mistakes frequently result from carelessness. Every component of the car body is visually inspected throughout this process, and any damage discovered is noted. However, this approach is ineffective and extremely expensive, particularly in the automotive sector where there are a lot of cars.

Machine learning (Hadianto et al., 2023) approaches have been developed to streamline the automotive body inspection process to solve this issue. Deep learning algorithms such as YOLO (Xue et al., 2023), (Kong et al., 2022) and Faster R-CNN (Wang et al., 2021) show great results in detecting various types of damage to the car body. Damage to the car body is a common problem and can affect the performance of the car. Quick and accurate identification of damage to the car body can help speed up the repair process and reduce repair costs. To overcome this problem, a lot of research has been done to develop algorithms that can detect damage to the car body using deep learning. One of the deep learning algorithms used to detect damage to the car body is You Only Look Once (YOLO) (Lee et al., 2018), (Hindarto & Santoso, 2021). YOLO is a real-time object detection algorithm that can detect various types of objects in images and videos. This algorithm uses a convolutional neural network (CNN) to perform object detection. In detecting damage to the car body, the YOLO algorithm can distinguish various types of damage such as scratches, dents, and breaks on car body parts. Basically, the YOLO algorithm uses the input image to predict the bounding boxes surrounding the objects found in the image. Then, this algorithm assigns a label to the found objects such as "rubbing" or "damage". To do this, YOLO uses several convolutional layers and pooling layers in a CNN network. This layer helps the algorithm recognize specific features in the image, such as edges and corners in the image. After the CNN network performs feature extraction from the input image, the final layer generates bounding boxes and proper labels. In addition, another deep learning algorithm used to detect damage to the car body is the Faster R-CNN (Region-based Convolutional Neural Network). This algorithm also uses the CNN network to process the input image and predict the bounding box that surrounds the objects found in the image. However, this algorithm uses a more sophisticated region-based approach in recognizing objects. Faster R-CNN has two CNN networks, namely a network for feature extraction and a network for bounding box processing. First, the feature extraction network will produce relevant image features for detecting objects. Then, the network for bounding box processing will process these features and predict the bounding box that surrounds the object. The main advantage of deep learning algorithms such as YOLO and Faster R-CNN in detecting damage to the car body is their ability to process images in real-time and accurately. Both algorithms are able to detect various types of damage to the car body with a high degree of accuracy. In addition, these two algorithms can also be improved through training with more and more varied data to increase their accuracy and reliability.

This paper proposes a method for detecting scratches, cracks, and other damage to car bodies using machine learning techniques (Saputra et al., 2023). The proposed method involves collecting and preparing a dataset of car images, followed by preprocessing and segmentation to separate the damaged parts from the undamaged parts. Then, deep learning algorithms are used to build detection models, which are trained and evaluated using a test data set. The suggested approach is anticipated to offer a more effective and affordable automobile body inspection solution, particularly for the automotive sector, such as taxis, which must conduct routine vehicle inspections. The suggested method has the potential to reduce time and costs while improving the precision and consistency of inspection results by automating the inspection process. The results of this study can also be used to enhance the safety and maintainability of other kinds of vehicles, such as buses, trucks, and private cars. In all, YOLO uses complex convolutional neural networks and real-time spatial analysis techniques to provide real-time object detection in images and videos with a high degree of accuracy.

From the introductory description regarding the detection of car body damage, several Research Questions (RQ) arise for the topic Detects Car Body Damage using Deep Learning Algorithm
How to use Deep Learning algorithms to detect and repair damage to the car body? (RQ 1).
What sensor technologies can be used to detect car damage early? (RQ 2).
How to repair car body damage using Augmented Reality technology? (RQ 3).
What are the Deep Learning methods that can be used to speed up the process of detecting damage to cars? (RQ 4).

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LITERATURE REVIEW

Some of the literature discussed in this study is a paper that has discussed You Only Look Once (YOLO). You only look once: Unified, real-time object detection (Redmon et al., 2016). The basic YOLO model processes images in real time at 45 frames per second. The smaller online version, Fast YOLO, processes an incredible 155 frames per second and still achieves twice the map speed of other real-time detectors. Compared to advanced detection systems, YOLO has large localization errors but is less likely to predict false positives. Finally, YOLO is a common object representation. YOLO9000: Better, faster, stronger (Redmon & Farhadi, 2017). YOLO9000, a state-of-the-art, real-time object detection system that can detect over 9000 object categories. First, we propose various improvements to the YOLO detection method, both novel and drawn from prior work. The improved model, YOLOv2, is state-of-the-art on standard detection tasks like PASCAL VOC and COCO (Rostianingsih et al., 2020), (Tong & Wu, 2023), (Wedha, Helmi, et al., 2022). Using a novel, multi-scale training method the same YOLOv2 model can run at varying sizes, offering an easy tradeoff between speed and accuracy. At 67 FPS, YOLOv2 gets 76.8 mAP on VOC 2007. At 40 FPS, YOLOv2 gets 78.6 mAP, outperforming state-of-the-art methods like Faster R-CNN with ResNet and SSD while still running significantly faster. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks (Ren et al., 2017). Region Proposal Network (RPN) that shares full-image convolutional features with the detection network, thus enabling nearly cost-free region proposals. An RPN is a fully convolutional network that simultaneously predicts object bounds and objectness scores at each position. The RPN is trained end-to-end to generate high-quality region proposals, which are used by Fast R-CNN (Hindarto & Santoso, 2022) for detection. We further merge RPN and Fast R-CNN (Wedha, Karjadi, et al., 2022) into a single network by sharing their convolutional features - using the recently popular terminology of neural networks with 'attention' mechanisms, the RPN component tells the unified network where to look. For the very deep VGG-16 model (Bipin Nair et al., 2023), our detection system has a frame rate of 5 fps (including all steps) on a GPU, while achieving state-of-the-art object detection accuracy on PASCAL VOC 2007, 2012, and MS COCO datasets with only 300 proposals per image.

METHOD

You Only Look Once (YOLO) is a deep learning algorithm used to detect objects in images and videos with a high degree of accuracy. YOLO combines a deep convolution architecture and real-time spatial analysis techniques to deliver real-time object detection. YOLO uses a Convolutional Neural Network (CNN) that detects objects by dividing an image into several grid squares and then predicts the object in each square. This process is called grid cell classification. YOLO also uses bounding box regression to find the exact location of objects within each box. Mathematically, YOLO calculates the probability of an object class and the object's location in each grid. For each grid box, YOLO generates the probability of object class P(class) and bounding box given by 4 coordinates (x, y, w, h). Then, YOLO uses the following equation to calculate the probability score of each grid for all classes:

$$P\,(\text{class } i \mid \text{object}) \times P(\text{object}) \times IOU\,(\text{bounding box, ground truth}) \qquad (1)$$

where:

P (class i | object) is the probability that the object in the grid box is class i,
P(object) is the probability that there are objects in the grid box.
IOU (Intersection over Union) is a measure of how many bounding boxes are predicted to be adjacent to original bounding box. This probability score is used to determine whether an object is found in the grid box or not.

YOLO also uses non-maximum suppression (NMS) to address the problem of duplicate object detection in images. This process eliminates over-detection by setting a minimum distance limit between adjacent object bounding boxes. In all, YOLO uses complex convolutional neural networks and real-time spatial analysis techniques to provide real-time object detection in images and videos with a high degree of accuracy.

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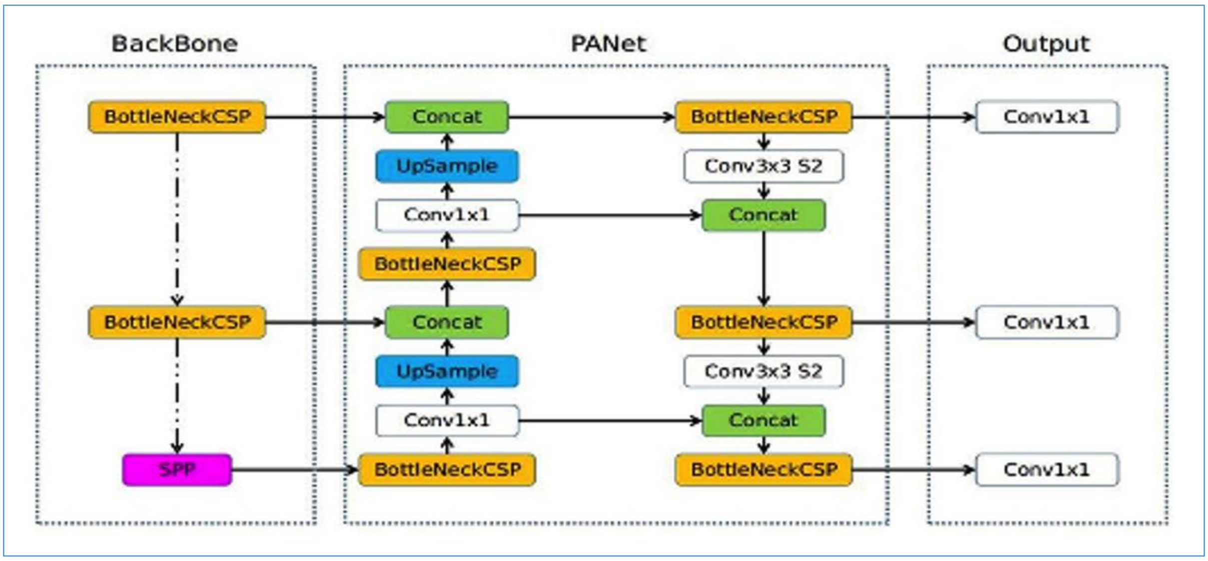

Figure 1. Model You Only Look Once (YOLO)
Source: Google Image

The architecture in Figure 1 is divided into Backbone, PANet and Output. Where the Backbone consists of BottleNeckCSP to SPP. Backbone in the context of Deep Learning refers to the neural network architecture used to perform feature extraction on the input data. In detecting car damage, the backbone is used to extract features from car images that will be used to detect damage. BottleNeckCSP is one of the layers used in the backbone. This layer aims to speed up the model training process and improve accuracy. You do this by combining several convolution layers into one BottleNeckCSP layer. Furthermore, there is the Spatial Pyramid Pooling (SPP) layer which allows Deep Learning models to detect objects of various sizes in a more efficient way. This layer works by pooling the features generated from the previous layer with different kernel sizes, so that it can produce a richer representation of the input image. The two layers are used together in the backbone to increase the efficiency and accuracy of detecting damage to cars.

PANet (Path Aggregation Network) is a neural network architecture used for object detection in images. PANet is used as part of the YOLOv4 object detection system.

PANet consists of several layers, namely:

1. Concat: This layer is used to combine the features produced by several layers earlier in the architecture.
2. UpSample: This layer is used to perform upsampling operations on features that have been combined on the Concat layer. The upsampling operation is carried out with the aim of increasing the feature size so that it can be integrated with the features in the previous layer.
3. Conv: This layer is used to convolve features that have been upsample by the previous layer. Convolution is performed to obtain more complex and abstract features.
4. BottleNeckCSP: This layer is the main layer in PANet. BottleNeckCSP is used to compress the features that have been produced by the previous Conv layer. This aims to reduce the computational load and speed up the object detection process.
5. SPP: This layer is used to obtain different feature representations of images of different sizes. This feature representation can be used to improve the quality of object detection in images with different resolutions.

After going through a series of layers, PANet produces Conv 1x1 output which is used to classify objects in images. The output contains information about the location, size, and class of objects in the image.

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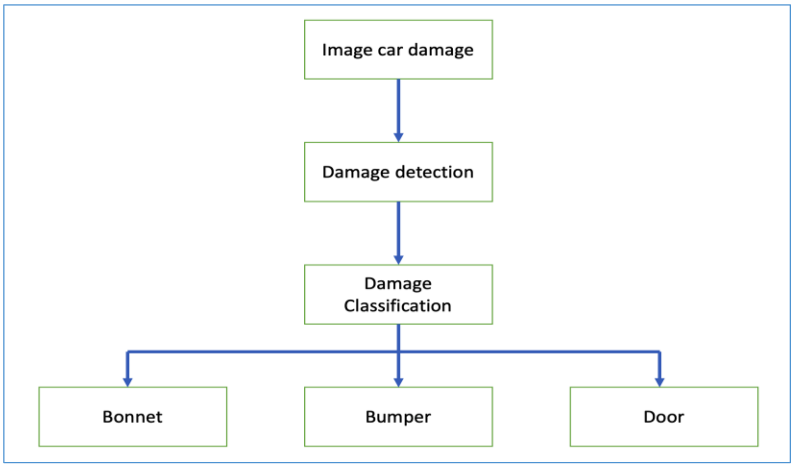

Figure 2. Model You Only Look Once (YOLO)
Source: Researcher Property

Figure 2 YOLO algorithm will detect for bonnet, bumper and door. Where later the image dataset will be trained as shown in Figure 1. The results of the training or model from YOLO will later be used as detection on objects or car images. Damage detection as a model in detecting image car damage. Later it will be classified as a bonnet, bumper, or door. The YOLO (You Only Look Once) algorithm is a deep learning algorithm that is often used in object detection tasks in images. In this study, the YOLO algorithm was used to detect damage to the car body, namely on the bonnet, bumpers, and doors. Before it can be used to detect damage to the car body, the YOLO model needs to be trained using an image dataset. The image dataset used in this study consists of images of healthy cars and images of damaged cars on the bonnet, bumpers, and doors. This dataset will be used to train the YOLO model to recognize damage to the car body with high accuracy. After the training process is complete, the YOLO model can be used as a detection on objects or car images. When used to detect damage to the car body, the YOLO model will provide output in the form of the location of the damage in the car image. Furthermore, the output given by the YOLO model will be further processed to classify the type of damage to the car body, namely the bonnet, bumper, or doors. This is done by using a model that has been previously trained to classify the types of damage to the car body. By utilizing the YOLO algorithm (Chirgaiya & Rajavat, 2023) and the damage classification model for the car body, technicians can easily and quickly detect and identify car damage with high accuracy. This technology can help improve the efficiency and quality of car maintenance services, as well as reduce the costs required for car maintenance and repair.

RESULT

Figure 3, Detection results using YOLO for bonnets, doors and bumpers can be very accurate depending on the quality of the training data and the model used. In general, after going through the training process on the training data, the YOLO model will understand the visual characteristics of each object and can detect objects with high accuracy in new images. In the case of car damage detection, the YOLO model can be used to detect damage to bonnet, door, and bumper parts by recognizing the visual pattern of damage in each of these parts. For example, if there is a scratch or dent on the bonnet, the YOLO model can recognize this visual pattern and provide detection results that the bonnet is damaged. Likewise, if there is damage to the door or bumper, the YOLO model will be able to detect it with high accuracy and provide appropriate detection results. However, keep in mind that the detection results from the YOLO model are not always perfect and can be affected by the quality of the training data and the model used. Therefore, it is important to continuously develop and update the car damage detection model used to improve detection accuracy and performance.

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Figure 3, Detection results using YOLO for bonnets, doors, and bumper.
Source: Researcher property

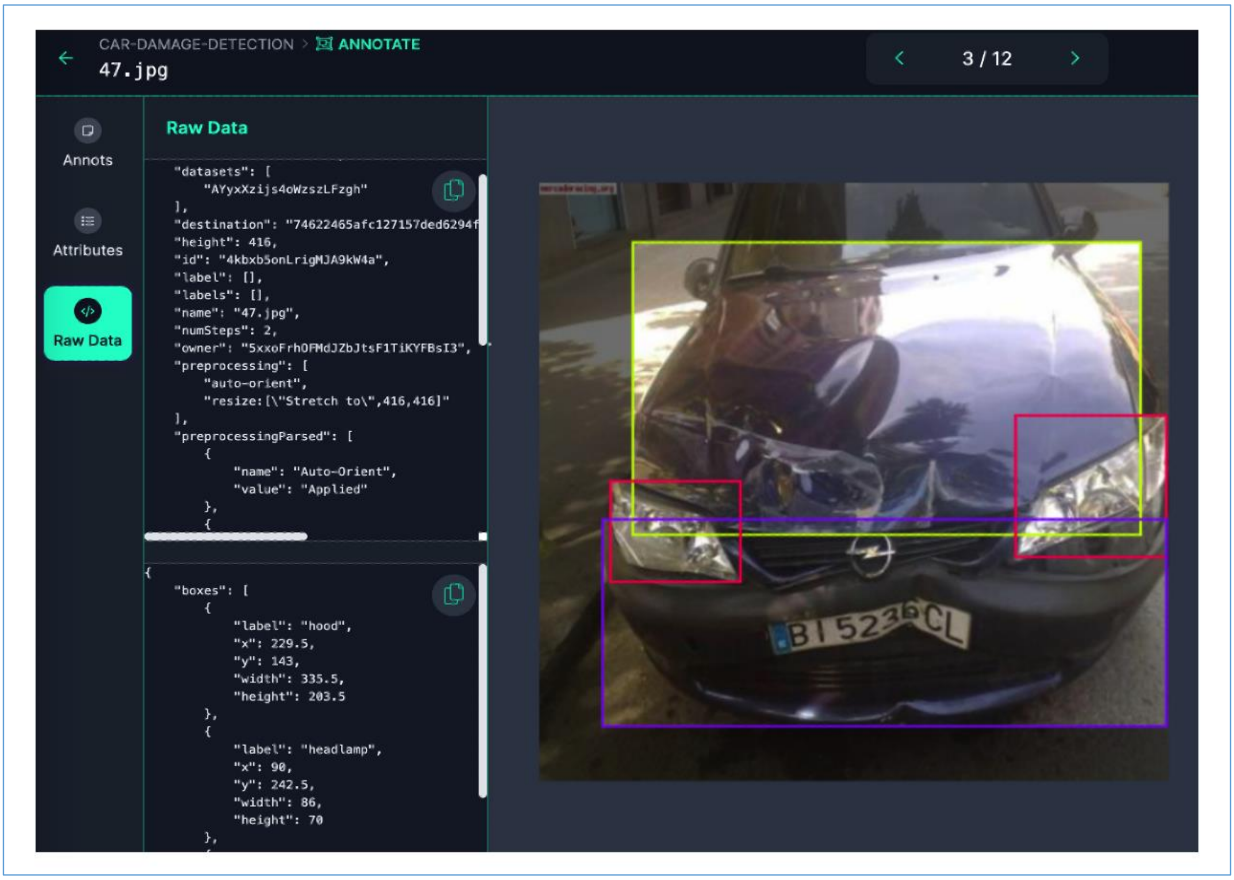

Figure 4. Notation image with annotate tool.
Source: Roboflow image dataset

Figure 4, Notation image with annotate tool is the process of adding annotations or marks to digital images to provide additional information or explanations about objects or parts of the image. These annotations can be text, lines, boxes, or other symbols placed at relevant locations with objects or parts of the image. To do image notation, you can use various available tools or applications, such as Adobe Photoshop, GIMP, Paint, and others. Several special tools or applications are also available for image notation, such as LabelImg and RectLabel. In the context of detecting damage to cars, image notation with annotate tools is very important to improve the quality of the dataset. These annotations enable Deep Learning models to better learn about crash locations and improve detection accuracy.

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Table 1. Result testing

Experiment	Precision	Recall	mAP_0.5
1	0.659	0.311	0.363
2	0.572	0.610	0.519

Table 1. Result testing, after testing it produces an average Precision of 61.55%, an average Recall of 46.05%, and an average mAP of 0.441. The test results show the performance of the model in detecting damage to car images. Precision measures how accurately the model predicts the correct objects, while recall measures how many of the detected objects are correct from the actual number of objects. In this case, the average precision of 61.55% indicates that the model successfully predicts 61.55% of objects correctly from all detected objects. While the average recall of 46.05% indicates that the model can only detect 46.05% of all objects that exist. Meanwhile, mAP or Mean Average Precision is the average precision value of all detected object classes. In this case, the average mAP of 0.441 indicates that the model has sufficient performance in detecting defects in car images in general. However, the performance of this model can still be improved by optimizing the parameters and techniques in the model training and testing process. In addition, using a larger and more diverse dataset can also improve the performance of damage detection on cars using deep learning algorithms such as YOLO.

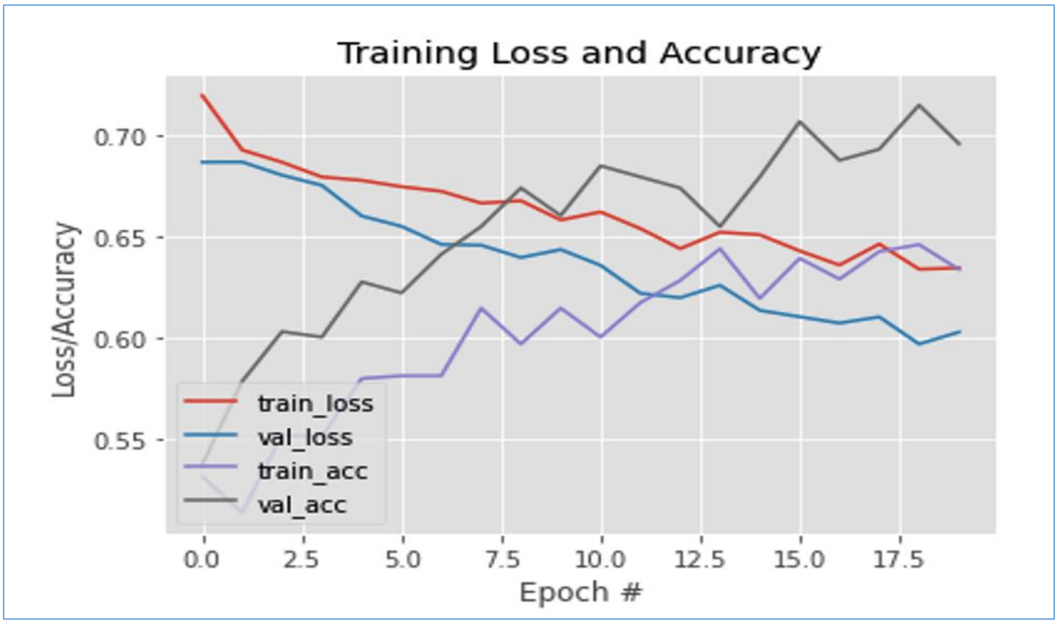

Figure 5. Training loss and accuracy

Figure 5, Training loss and accuracy are the two main metrics in the Deep Learning model training process. Training loss measures the difference between the model's predicted value and the ground truth of the training data. Lower training loss values indicate that the model has learned to predict training data with better accuracy. However, keep in mind that low training loss does not always guarantee good model quality, because the model can learn too much from the training data by overfitting. Meanwhile, training accuracy measures how accurately the model predicts the training data. The higher the training accuracy value, the better the model is in learning the training data. However, as with training loss, high training accuracy values also do not guarantee good model quality if the model learns too much from the training data by overfitting. In the model training process, the aim is to optimally achieve low training loss values and high training accuracy. However, the final assessment of the quality of the model should be carried out using validation or test data that is not used in the training process.

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DISCUSSIONS

How to use Deep Learning algorithms to detect and repair damage to the car body? (RQ 1)

To use the Deep Learning algorithm to detect and repair damage to the car body, the steps that can be taken are as follows:

1. Collect and prepare data: Collect a dataset of images depicting damage to the car body, as well as images of the car in normal condition. Make sure the dataset is balanced and representative. When collecting and preparing data for use in Deep Learning algorithms to detect and repair damage to the car body. Choose the type of damage you want to detect: There are many types of damage that can happen to a car body, such as scratches, dents, rust, and so on. Make sure you select the type of damage you want to detect and collect the appropriate images. Collect a balanced dataset: Make sure you collect a balanced number of images between damaged cars and normal cars. This will ensure that the Deep Learning algorithm does not become biased towards any of the categories. Collect a representative dataset: Make sure the dataset you collect represents the actual condition of the car. This can be done by taking pictures from various sources and different situations, such as on the road, in the workshop, and so on. Data annotation: Once you have collected your dataset, you need to tag or annotate each image with the appropriate label. This allows Deep Learning algorithms to differentiate between damaged and normal cars. Data preprocessing: After the dataset has been collected and annotated, the next step is to preprocess the data. This process can include resizing, cropping, and normalizing images so that they are ready for use in Deep Learning algorithms. Using a Deep Learning algorithm to detect and repair damage to the car body, a representative, balanced and properly annotated image dataset is required so that the algorithm can distinguish between damaged and normal car conditions. Furthermore, the data will be preprocessed so that it is ready to be used in the Deep Learning algorithm.
2. Data annotation: Annotate the dataset by marking the location and type of damage on the car image. These annotations will be used as labels on the data to train the deep learning model. Collecting a balanced dataset is essential in building an accurate Deep Learning model. An imbalance in the number of images between the normal class and the damaged class can cause the model to tend to classify images into the majority class, resulting in poor performance in identifying the minority class. To ensure that the dataset is balanced, it is necessary to collect an equal number of images of damaged cars and normal cars. One way to achieve this is to take pictures from different sources, such as searching the internet for pictures of damaged and normal cars or taking pictures of normal and damaged cars from different sources. In addition, it is also important to choose images that are representative of each category. Images must represent the various types of damage to the car body and include a variety of lighting conditions and backgrounds. In this case, data augmentation technology can help to increase the number of representative images from each category by changing existing images into various variations such as changing colors, rotating, cropping, and others. Finally, the resulting dataset must be tested to ensure a balanced number of images between damaged and normal cars before being used in training a Deep Learning model.
3. Model training: Use deep learning algorithms such as YOLO or Faster R-CNN to train models with annotated datasets. At this stage, the model will learn to recognize and distinguish between damage to the car body and normal conditions.
4. Model validation: After the model is trained, validate the model using different datasets. This will test the extent to which the model can estimate damage to the car body with high accuracy. Model implementation: Implement the model in the system to detect damage to the car body in real-time. The model can be applied to CCTV in workshops or to cars equipped with cameras. After getting the dataset and creating the right Deep Learning model, the next step is to implement the model in the system to detect damage to the car body in real-time. There are several ways to implement a Deep Learning model, depending on the environment and available resources. Using CCTV in workshops: The model can be applied to existing CCTV in workshops to detect damage to cars that are being repaired. When the car enters the workshop, the CCTV will take pictures of the car and the model will process the image to detect whether there is any damage to the car body. If there is damage, the repair shop technician can immediately repair the damage. Using a camera in a car:

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Some cars are equipped with cameras installed in various parts of the car. Models can be applied to these cameras to monitor car conditions in real-time. When the car is in use, the camera will continue to take pictures and the model will process the images to detect damage to the car body. If there is damage, the car driver will be notified to immediately repair the damage. Implementation of the Deep Learning model in a system for detecting damage to the car body in real-time requires fast and accurate data processing. Therefore, adequate computing resources and a fast network are needed to ensure the system can work properly. In addition, it is also necessary to carry out regular evaluation and maintenance to ensure that the system can run properly and is accurate in detecting damage to the car body.

5. Bug fixes: Once a crash is detected, the next step is to fix the crash. Deep learning models can help identify the type of damage and provide recommendations for improvement.

By using Deep Learning algorithms such as YOLO and Faster R-CNN, detection of damage to the car body can be done efficiently and accurately. This can help reduce repair costs and speed up the repair time for damaged cars.

What sensor technologies can be used to detect car damage early? (RQ 2)

There are several sensor technologies that can be used to detect car damage since. Tire Pressure Sensor: This sensor is installed on each car tire and can detect the air pressure in the tire. If there is a significant difference in pressure between the tires on one side and the other, the sensor will give a warning. This can help prevent accidents due to underinflated tires. Engine Condition Sensor: This sensor is installed in the car engine and can detect various problems in the engine such as excessive temperature, abnormal vibration, or fuel problems. This sensor can also provide an early warning so that vehicle owners can make repairs before the problem becomes more severe. Brake Sensor: This sensor can detect the performance of the car's brakes and provide a warning if there is a problem with the brake system. This can help prevent accidents due to malfunctioning brakes. Camera Sensor: Camera sensors can be used to detect visual damage to the car body such as scratches, cracks, or other damage. By using Deep Learning and computer vision technology, camera sensors can be trained to detect damage automatically and provide early warning. All these sensors can be integrated into a larger system to provide vehicle owners or technicians with real-time vehicle health information. With the right sensor technology, damage to a car can be detected early so it can be repaired before it becomes a more serious and dangerous problem.

How to repair car body damage using Augmented Reality technology? (RQ 3)

Augmented Reality (AR) technology can assist car technicians in repairing damage to the car body by displaying a 3D visualization of the car and accurately identifying the location of damage to the car body. Here are the steps to repair car body damage using AR technology:

Choose the appropriate AR platform: Choose the AR platform that suits your needs. AR platforms can be applications that can be installed on smartphones or tablets, or they can be specialized hardware devices designed for this purpose. AR application on a smartphone or tablet: The most used AR platform is through an AR application on a smartphone or tablet. Some examples of AR applications that can be used to repair car body damage are AR Body Shop and AR Smart Repair. The application can allow users to view car models in AR and pinpoint damage to the car body that needs to be repaired. In addition, this application can also provide a step-by-step guide to fixing the damage. Dedicated AR hardware: Other AR platforms that can be used are dedicated AR hardware such as HoloLens and Magic Leap. This device can provide a more immersive and more interactive AR experience in repairing car body damage. Users can view car models in AR and take corrective actions directly on the device. Selection of the appropriate AR platform must be adjusted to the needs and available budget. AR apps on smartphones or tablets can be a more affordable option, while dedicated AR hardware can provide a more interactive and immersive experience.

Scan a car using AR technology: Use AR technology to scan a car and create a 3D model of the car. Scan the car from multiple angles to ensure that the resulting 3D model is accurate. To scan a car using Augmented Reality technology, you first need suitable hardware such as a camera or 3D sensor. Then, the appropriate AR application needs to be installed on the device. After that, the steps that need to be taken are as follows: Prepare the car: Make sure the car is clean and there are no obstructions blocking the view of the camera or sensors. Position the AR device: Position the AR device at the

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p-ISSN : 2541-044X

right distance from the car so that the object can be scanned properly. Ensure that sufficient light is available to produce a clear image. Scan a car: Launch the AR app and point the camera or sensor at the car. Scan the car from multiple angles to ensure the resulting 3D model is accurate. Make sure every corner of the car is well scanned. Create 3D model: After the car has been scanned, the AR app will generate a 3D model of the car. Make sure the model is accurate and that no car parts are missing. After the 3D model has been created, AR technology can be used to repair damage to the car body. For example, AR technology can be used to overlay an image over a 3D model of a car indicating the parts that need repair. AR technology can also be used to display step-by-step repair instructions on the device screen, so technicians can repair damage more easily and quickly.

Identification of damage locations: After a 3D model of the car has been created, use AR technology to identify the location of damage on the car body. AR technology can assist car technicians in knowing the location of damage accurately and in detail. After the 3D model of the car is created, AR technology can be used to identify the location of damage to the car body. Here are the steps: Open the AR application on your device and activate scan mode. Point the device camera at the pre-built 3D model of the car. The device displays a 3D model of the car in a real-time environment. Technicians can zoom in and out of the car model, and move it as desired. Technicians can then identify damage to the car body by observing the 3D model from various angles and examining the details. Technicians can zoom in on the affected area to examine the damage in more detail and accurately. Technicians can mark the location of the damage on the 3D model and add notes about the type of damage and the corrective steps needed. By using AR technology to identify damage to the car body, technicians can see damage more clearly and in detail, so they can repair damage more quickly and accurately. In addition, AR technology can also assist technicians in estimating repair costs and showing repair results virtually before carrying out physical repairs to the car. Make repairs: After the location of the damage is identified, the car technician can make repairs to the car body. AR technology can assist technicians in repairing damage accurately and efficiently. Repair verification: After the repair has been completed, use AR technology to verify that the defect has been properly repaired. AR technology can assist car technicians in ensuring that the car has been repaired properly. AR technology can improve accuracy and efficiency in repairing damage to the car body. By using AR technology, car technicians can repair damage more quickly and accurately, thereby saving repair time and costs.

What are the Deep Learning methods that can be used to speed up the process of detecting damage to cars? (RQ 4). Several Deep Learning methods that can be used to speed up the process of detecting damage to cars include:

Transfer Learning: Transfer Learning is a Deep Learning technique that takes advantage of a pre-trained model and adapts it to a new dataset. By using Transfer Learning, the time and resources needed to train the model become more efficient because the model used already has previous knowledge and experience. For example, we can use a pre-trained model like the VGG16 or ResNet50 to detect damage to a car. VGG16 and ResNet50 are two examples of deep learning models that are popular in the field of computer vision. Both are used in image recognition and object classification tasks. VGG16 is a deep learning model that is trained on ImageNet datasets consisting of over a million images and 1000 object categories. This model uses a Convolutional Neural Network (CNN) architecture with 16 layers and has a good ability to recognize objects in images. VGG16 consists of several convolution layers which aim to extract features from images, followed by several fully connected layers which aim to classify. VGG16 has more than 138 million parameters and requires considerable computational resources to train. ResNet50 is a deep learning model that also trains on ImageNet datasets. This model uses a Residual Neural Network (ResNet) architecture with 50 layers and solves a problem called "vanishing gradient". In the ResNet architecture, there are identity blocks that allow information to flow more quickly through the network and reduce the chance of information loss. ResNet50 has more than 23 million parameters and requires less computational resources than VGG16. Both can be used as a basic model for object recognition or image classification tasks. However, ResNet50 is faster and more efficient than VGG16. Although both are quite accurate in object recognition tasks, ResNet50 is preferred because of its size and lower complexity, and higher

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Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 8, Number 2, April 2023
DOI : https://doi.org/10.33395/sinkron.v8i2.12394
e-ISSN : 2541-2019
p-ISSN : 2541-044X

computational efficiency. However, the selection of the model depends on the goals and specific needs of the given task.

Deep Reinforcement Learning: Deep Reinforcement Learning is a Deep Learning method that utilizes a reward system to teach models how to speed up the crash detection process. In this case, the Deep Learning model will be rewarded when it detects damage to the car quickly and accurately. By providing rewards, the Deep Learning model will learn to find more efficient ways to detect damage to cars. Reinforcement Learning is a Deep Learning method that uses a reward system to teach a model or agent how to speed up the crash detection process. This method is used to study agent behavior in complex and dynamic environments, where agents must make the right decisions to achieve their goals. Basically, Deep Reinforcement Learning involves two main components: agent and environment. Agents are entities that learn from the environment, while the environment is the situation that occurs around the agent and provides the information needed to make decisions. For agents to learn, reward systems are used to provide positive or negative feedback on the actions of agents in the environment. In car crash detection applications, Deep Reinforcement Learning can be used to teach models or agents how to speed up the crash detection process. Models or agents can be programmed to locate damage to cars in the most efficient and accurate way and will be rewarded when they find the damage. Rewards can be positive numerical values, while punishments or penalties can be negative numerical values. In the context of car damage detection, Deep Reinforcement Learning can help reduce the time it takes to find a fault, thereby speeding up the car repair process. This is especially important in the automotive industry, where the time it takes to repair a car can affect repair shop productivity and customer satisfaction.

Multi-task Learning: Multi-task Learning is a Deep Learning method that allows us to train a model to perform multiple tasks at once. In terms of detecting damage to cars, for example we can train a model to detect several types of car damage simultaneously. In this way, the process of detecting damage to cars can be done more quickly and efficiently. Multi-task Learning is a Deep Learning technique in which one learning model is used to study several tasks or problems at once. In the context of detecting car damage, this technique can be used to train a model to simultaneously detect several types of damage to a car, such as damage to tires, body, glass, and so on. One of the main advantages of Multi-task Learning is the ability of the model to utilize the information contained in several tasks simultaneously to improve performance on each task learned. In this case, the information learned in one task can provide an advantage in learning another task. In addition, Multi-task Learning can also help reduce overfitting of the training data, because the model is created to study the information contained in several tasks, thereby reducing the possibility of the model to be too specialized in one task. There are several network architectures that can be used to train models with Multi-task Learning, such as the Shared Bottom-Up Top-Down (SBUTD) architecture and the Multiple-Input Multiple-Output (MIMO) architecture. In the SBUTD architecture, several tasks are studied simultaneously by using the same lower layers, while the upper layers vary according to the task being studied. Whereas in the MIMO architecture, each task has its own input and output, and each input and output is connected by layers between them. In the case of car damage detection, Multi-task Learning can be used to speed up the detection process, because the model only needs to be trained once to detect several types of damage, thereby reducing model training time and costs. In addition, models trained with Multi-task Learning can also be used to repair several types of damage to a car simultaneously, thereby increasing repair efficiency and speeding up car repair time.

Parallel Computing: Parallel Computing is a data processing technique that utilizes several computers or processors to process data simultaneously. In terms of detecting damage to cars, this technique can be used to speed up the process of training and testing Deep Learning models. By using multiple computers or processors simultaneously, the time needed to train Deep Learning models can be significantly reduced. Parallel Computing is a data processing technique that utilizes multiple computers or processors to process data simultaneously. This technique enables the processing of large amounts of data in less time and can help speed up the training and testing process of Deep Learning models. In the case of detecting car damage using Deep Learning, parallel computing can be used to speed up the process of model training and testing. Deep Learning model training requires a large amount of time and computational resources, and by leveraging parallel computing, training time can

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e-ISSN : 2541-2019
p-ISSN : 2541-044X

be significantly reduced. By using multiple computers or processors simultaneously, Deep Learning models can be processed more quickly and efficiently. There are several technologies and tools that can be used to implement parallel computing in detecting car damage using Deep Learning. One popular technology used is GPU (Graphics Processing Unit) technology which allows parallel use in data processing. In this case, the GPU can be used to process large amounts of data in parallel, thereby speeding up the model training and testing process. In addition, Cloud Computing technology can also be used to speed up the Deep Learning model training process. In this technology, the training process can be carried out on a cloud server which has bigger and stronger computing capacity and resources. By utilizing Cloud Computing technology, the time and costs required to develop Deep Learning models can be reduced significantly. In testing Deep Learning models, parallel computing can also be used to speed up the process of testing models on larger data. By utilizing multiple computers or processors simultaneously, model testing can be carried out more quickly and efficiently, thereby enabling the use of Deep Learning models on larger data. Overall, parallel computing is a very important and effective technique in accelerating the process of training and testing Deep Learning models for car damage detection. In this case, the use of GPU and Cloud Computing technology can help speed up the process of training and testing models significantly, thereby enabling the development of more accurate and efficient Deep Learning models for detecting car damage. In choosing the right Deep Learning method to speed up the process of detecting damage to cars, it is necessary to consider various factors such as resource availability, dataset size, problem complexity, and so on. In addition, it is also necessary to carry out periodic testing and evaluation to ensure that the method used can provide optimal results in speeding up the process of detecting damage to cars.

CONCLUSION

Based on research on "Detects Car Body Damage using Deep Learning Algorithm", it can be concluded that the use of Deep Learning algorithms YOLO has very good results in detecting various types of damage to the car body, such as scratches, tinkles, cracks, etc. In the early stages, collecting a balanced and representative dataset is very important in training a Deep Learning model. In addition, sensor technology such as vibration sensors and optical sensors can also be used to detect damage to the car early on. Furthermore, Augmented Reality technology can be used to repair damage to the car body in a more efficient way. The process of scanning a car using AR technology can help car technicians identify the location of damage accurately and in detail. In addition, there are several Deep Learning methods such as Deep Reinforcement Learning, Multi-task Learning, and Parallel Computing that can be used to speed up the process of detecting damage to cars. Thus, the Deep Learning algorithm can be used as a tool in detecting and repairing damage to the car body in a way that is faster, more efficient, and more accurate. This research has carried out the implementation of the Deep Learning model using YOLO to detect damage to cars through images but has not yet utilized Augmented Reality and Internet of Things technology that uses cameras to repair damage. In this research, several Deep Learning methods were also used, such as transfer learning and data augmentation to speed up the model training process. Nonetheless, this research provides an overview of how Deep Learning technology can be used to detect damage to cars quickly and effectively.

REFERENCES

Bipin Nair, B. J., Aadith Raj, K., Kedar, M., Vaishak, S. P., & Sreejil, E. (2023). Ancient Epic Manuscript Binarization and Classification Using False Color Spectralization and VGG-16 Model. *Procedia Computer Science*, *218*, 631–643. https://doi.org/10.1016/j.procs.2023.01.045

Chirgaiya, S., & Rajavat, A. (2023). Tiny object detection model based on competitive multi-layer neural network (TOD-CMLNN). *Intelligent Systems with Applications*, *18*(September 2022), 200217. https://doi.org/10.1016/j.iswa.2023.200217

Hadianto, E., Amanda, D., Hindarto, D., Makmur, A., & Santoso, H. (2023). Design and Development of Coffee Machine Control System Using Fuzzy Logic. *Sinkron*, *8*(1), 130–138. https://doi.org/10.33395/sinkron.v8i1.11917

Hindarto, D., Indrajit, R. E., & Dazki, E. (2021). Sustainability of Implementing Enterprise Architecture in the Solar Power Generation Manufacturing Industry. *Sinkron*, *6*(1), 13–24.

https://jurnal.polgan.ac.id/index.php/sinkron/article/view/11115

Hindarto, D., & Santoso, H. (2021). Plat Nomor Kendaraan dengan Convolution Neural Network. *Jurnal Inovasi Informatika*, *6*(2), 1–12. https://doi.org/10.51170/jii.v6i2.202

Hindarto, D., & Santoso, H. (2022). PERFORMANCE COMPARISON OF SUPERVISED LEARNING USING NON-NEURAL NETWORK AND NEURAL NETWORK. *Janapati*, *11*, 49–62.

Kong, L., Wang, J., & Zhao, P. (2022). YOLO-G: A Lightweight Network Model for Improving the Performance of Military Targets Detection. *IEEE Access*, *10*, 55546–55564. https://doi.org/10.1109/ACCESS.2022.3177628

Lee, Y., Yun, J., Hong, Y., Lee, J., & Jeon, M. (2018). Accurate License Plate Recognition and Super-Resolution Using a Generative Adversarial Networks on Traffic Surveillance Video. *2018 IEEE International Conference on Consumer Electronics - Asia, ICCE-Asia 2018*, *June 2018*, 1–4. https://doi.org/10.1109/ICCE-ASIA.2018.8552121

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, *2016-December*, 779–788. https://doi.org/10.1109/CVPR.2016.91

Redmon, J., & Farhadi, A. (2017). YOLO9000: Better, faster, stronger. *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017*, *2017-January*, 6517–6525. https://doi.org/10.1109/CVPR.2017.690

Ren, S., He, K., Girshick, R., & Sun, J. (2017). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *39*(6), 1137–1149. https://doi.org/10.1109/TPAMI.2016.2577031

Rostianingsih, S., Setiawan, A., & Halim, C. I. (2020). COCO (Creating Common Object in Context) Dataset for Chemistry Apparatus. *Procedia Computer Science*, *171*(2019), 2445–2452. https://doi.org/10.1016/j.procs.2020.04.264

Saputra, A. D., Hindarto, D., & Santoso, H. (2023). Disease Classification on Rice Leaves using DenseNet121, DenseNet169, DenseNet201. *Sinkron*, *8*(1), 48–55. https://doi.org/10.33395/sinkron.v8i1.11906

Sze, E., Santoso, H., & Hindarto, D. (2022). *Review Star Hotels Using Convolutional Neural Network*. *7*(1), 2469–2477.

Tong, K., & Wu, Y. (2023). Rethinking PASCAL-VOC and MS-COCO dataset for small object detection. *Journal of Visual Communication and Image Representation*, 103830. https://doi.org/10.1016/J.JVCIR.2023.103830

van Ruitenbeek, R. E., & Bhulai, S. (2022). Convolutional Neural Networks for vehicle damage detection. *Machine Learning with Applications*, *9*(December 2021), 100332. https://doi.org/10.1016/j.mlwa.2022.100332

Wang, S., Xia, X., Ye, L., & Yang, B. (2021). Automatic detection and classification of steel surface defect using deep convolutional neural networks. *Metals*, *11*(3), 1–23. https://doi.org/10.3390/met11030388

Wedha, B. Y., Helmi, H., Dazki, E., & Indrajit, R. E. (2022). Adopsi IoT Pada Core Process Trucking di Indonesia Dengan Menggunakan TOGAF Framework. *JATISI (Jurnal Teknik Informatika Dan Sistem Informasi)*, *9*(1), 230–243. https://doi.org/10.35957/jatisi.v9i1.1980

Wedha, B. Y., Karjadi, D. A., Wedha, A. E. P. B., & Santoso, H. (2022). Style Transfer Generator for Dataset Testing Classification. *SinkrOn*, *7*(2), 448–454. https://doi.org/10.33395/sinkron.v7i2.11375

Xue, G., Li, S., Hou, P., Gao, S., & Tan, R. (2023). Research on lightweight Yolo coal gangue detection algorithm based on resnet18 backbone feature network. *Internet of Things (Netherlands)*, *22*(March), 100762. https://doi.org/10.1016/j.iot.2023.100762

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