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Research Article

Providing Faulty Thread Detection in Tie Rod End Grease Fittings with Machine Learning Method "YOLO" algorithm and "Smart-VS"

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Abstract **–** The tie rod end transmits the movement from the steering box to the wheels of the vehicle. The joint in the tie rod ends ensures that the pushing motion is transmitted in a mobile way. These joints must be lubricated with grease to reduce the friction force. In order to easily perform the lubrication process, there are greases that have an oily ball at the end and can be easily disassembled. Manufacturer-induced faults may occur in greasers. Frequently encountered tooth production errors can cause serious problems. A greaser with a thread defect can be fitted with a tight fit and disconnected from the assembly under fatigue. For this reason, greasers must be checked and separated during assembly. Defect control systems used in industry are generally carried out manually. At the same time, manual control varies according to operator competence and initiative. High efficiency, low cost and objectivity can be achieved with machine learning-based systems. One of the machine learning techniques, the deep learning algorithm YOLO (You Only Look Once) is extremely fast and sharp. In the supervised learning process, it is necessary to obtain the data that is desired to be determined, and to label and train the data. In this study, a detailed investigation of YOLO-based object detection with object detection methods designed in recent years, the effect of data labeling on detection results and Smart-VS Smart sensor performance comparisons were made.

Keywords – YOLO, Deep Learning, Object Detection, Grease Fitting, Labeling

I. INTRODUCTION

Vehicles consist of many systems working together. Suspension systems, one of the most important of these parts, move up and down independently of the chassis depending on changing road conditions, ensuring that the vehicle is not affected by road conditions as much as possible and ensures driving comfort and safety. The "tie rod end" part, one of the suspension system components, transmits the movement coming from the steering gear box to the tie rod shaft, tie rod end, axon and wheel, respectively. The tie rod end consists of several different components (Figure 1). These components are described as body, joint, plastic bearing and cover. Depending on the design and usage, some tie rod ends can be produced without plastic bearings. It is necessary to use grease fittings to reduce the friction force of the joint component of the tie rod end parts and to facilitate the lubrication operation for maintenance.

Grease fittings are mechanical components with a lubricated ball at one end and a mounting thread at the other end.

Fig. 1 AYD production tie rod end piece with greaser component

It is assumed that the rod part in the vehicles has not been subjected to any force before being tested and analyzed and that no permanent deformation has occurred. However, the tie rod part is exposed to different forces on the vehicle [1]. Due to the forces and fatigue they are exposed to, the grease fittings are mounted on the rod housing with threads. Errors in grease fittings may occur due to the manufacturer. Among these errors, the most common problem is dental errors. Thread manufacturing errors in grease fittings can cause serious problems. A grease fitting with a thread defect can only be assembled with a tight fit, it can be separated from the assembly as it is subjected to fatigue, or it can be separated from the assembly at the packaging stage without a tight fit. For this reason, grease fittings should be checked and separated during the assembly phase. Defect control systems are generally carried out manually. Manual control operation is subjective with high cost and low efficiency. This subjectivity may vary depending on operator competence and initiative. High efficiency, low cost and objectivity can be achieved with machine learning-based systems. There are many studies in the literature for deep learning-based defect detection. Deep learning, a subset of machine learning, emerged with the aim of making traditional techniques more efficient. Deep learning is called artificial neural networks created by models inspired by the human brain. This system, consisting of layers of interconnected and working together neurons, uses mathematical calculations.

It basically consists of 3 layers. These layers are divided into “Input Layer”, “Hidden Layer” and “Output Layer”. In deep learning, feature extraction and transformation operations are performed using non-linear layers. Each layer uses the previous result as input [2]. Essentially, deep learning is based on the process of learning from the representation of data. The concept called representation is summarized as follows; They are described as the vector of intensity values per pixel, that is, special shapes [3]. Choosing the right features is important in the quality of deep learning approaches [4]. In order to reveal these correct features, operations such as preprocessing and dimension reduction are performed. At this stage, getting rid of the dependency on features helps reduce the cost [5].

Güçlü et al. In the study conducted by [6], they first performed image processing and dataset augmentation for post-production detection of defects on the steel surface, and then made a comparative analysis using YOLOv5 and YOLOv7 algorithms. They proposed an embedded system that detects rolled steel defects. In this system using Jetson Nano, high FPS and real-time detection were achieved with 0.763mAP and 90% recall.

Duman et al. [7] presented a machine learning-based approach for defect detection and classification by monitoring powder bed images in additive manufacturing. They worked with VGG-16, Inception-v3 and DenseNet models and achieved the highest accuracy of 88.3% in the VGG-16 model by transfer learning.

Karaduman et al. [8] proposed a deep learning-based method for fault detection of insulators used in catenary systems. In this method, training and testing were carried out using ResNet34 architecture. They achieved 95.7% accuracy, 99% precision and 96.6% sensitivity results.

Sevi et al. [9] proposed a deep learning-based ensemble learning method for detecting defects on the rail surface in their study. YOLO-v5 architecture is used. The detection of classes in the data set with 8 different defects was successfully achieved and over 80% success was achieved.

Aktaş et al. [10] proposed a deep learning model for detecting tactile parquet surfaces. They used deep learning and image processing algorithms together in their studies. YOLO-v3 architecture and DenseNet model were combined to create the YOLOv3-Dense model. They carried out training and testing with

YOLO-v2, YOLO-v3 and YOLOv3-Dense architectures on the same data set. As a result, they achieved 89% F1-Score, 92% average sensitivity and 82% IoU.

Ozel et al. [11] proposed a deep learning-based YOLO-v4 model in their study to perform instantaneous crack tracking of the automobile suspension part during dynamic testing. As a result of training with YOLO-v2, YOLO-v3 and YOLO-v4, they achieved 96.3% mAP success.

II. MATERIALS AND METHOD

The initial phase in machine learning first involves collecting original data. Following the data collection phase, a model is selected and trained on the collected data. The trained model is then used to make predictions. When the model encounters new data during the training process, it begins to learn, makes predictions, and receives feedback on the accuracy of these predictions. Thanks to the feedback obtained, errors made are corrected step by step [12].

Deep learning made a huge impact in the scientific world in 2012. The basic architecture of deep learning, considered as Convolutional Neural Network (ESA), started the rise in this field by winning the ImageNet competition. In subsequent years, participants often designed their models in line with deep learning architecture. These models are considered the cornerstones of the deep learning world. AlexNet architecture has achieved great success by reducing the error rate of computerized object recognition from 26.2% to 15.4%. This architecture consists of 5 convolution layers, pooling layers and 3 fully connected layers. It is designed to classify 1000 objects in total. The size of the filters was determined as 11x11 and the number of step shifts was 4. GoogLeNet architecture has a complex structure, especially known for its Inception modules. This architecture, consisting of 22 layers, won the ImageNet 2014 competition with an error rate of 5.7%. GoogLeNet is one of the first CNN architectures to offer a design other than traditional sequential convolution and pooling layers. ResNet is one of the deepest architectures ever designed. This architecture, consisting of 152 layers, won the ImageNet 2015 competition with an error rate of 3.6%. This rate generally varies between 5-10%, depending on human skills and expertise. R-CNN (Region-CNN) is a model developed specifically for object recognition. This architecture consists of 4 parts: In the first part, images are taken, in the second part, region suggestions are made with Selective Search (SA), in the third part, each region suggestion is processed with an AlexNet-like ESA architecture, and finally, if the ESA output is determined as an object, the area detected by SA is Arrangements are made in the region and the final result is produced [13].

YOLO (You Only Look Once) uses a variation of Darknet, a 53-layer network trained on ImageNet. This architecture is extended with a 106-layer fully convolutional structure for the detection task. Darknet-53 provides better performance and 1.5% faster processing compared to ResNet. Darknet-53 with shortcut links also features feature map sampling and merging. YOLO algorithm is an effective method that has attracted attention in object detection problems due to its ability to obtain fast results and has been preferred in many studies. When traditional and modern deep learning algorithms are examined, it is seen that especially multilayer CNN-based architectures are used in various scientific fields. The CNN model is a network structure that stands out with its success in image feature extraction and is preferred in object detection problems (Figure 2).

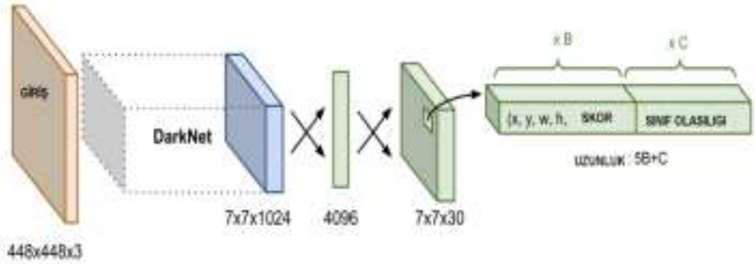

Fig. 2 DarkNet53 backbone

In YOLO, the input image is passed through the convolutional neural network only once, and bounding boxes are created for objects in the image. The objects in these boxes are first examined in terms of whether they are objects or not and which class they belong to. Thus, object detection is achieved. Inside each bounding box, object detection is indicated by its confidence score. In this approach, Redmon and his team showed that by approaching the object detection problem as a regression problem, results can be obtained at a lower cost with a single convolutional pass. YOLO architecture detects and classifies objects in the image by processing the input image with convolution layers and feature extraction layer[14]. YOLOv7 basically consists of four main components (Figure 3).

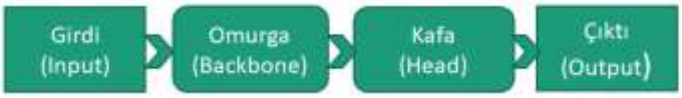

Fig. 3 YOLO algorithm

Input includes images or videos that the model will process. Backbone is a pre-trained network used to extract features from the input image. Convolution layers include E-ELAN (Extended Efficient Layer Aggregation Networks) layer and MP (Maximum Pooling) layers. The head is used to perform operations in the final stage. It applies bounding boxes to feature maps, producing the final output containing object labels, bounding box plots, and object detection scores. The output shows the detection results. In this way, YOLOv7 offers an architecture that can detect objects quickly and effectively.

A. *Mechanical Design*

The part feeding system in automation devices is extremely important for the production and processing processes to occur efficiently, uninterruptedly and accurately. Drum feeding system is a widely used technology in material handling and feeding processes used in many industrial applications. In the drum feeding system design, it is important to first determine the properties of the material to be transported (Figure 4). Factors such as material type, size, density, flow characteristics form the basis for sizing the drum and selecting system components. The flow rate and capacity required by the material to be transported in the system are effective in determining the drum size, drive power and other components [15].

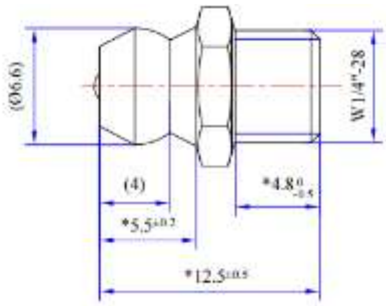

Fig. 4 Grease fitting part technical drawing

These parameters must be appropriate to the production rate and business processes. Selection of the drive system that will enable the drum to rotate is important. Engine power must be determined by taking into account the size and weight of the drum, the properties of the material and the operating conditions of the system. The parts feeding system increases production speed by automating manual parts handling and placement. In this way, production processes occur faster and more efficiently. The parts feeding system ensures that materials or parts are continuously fed into the device. This ensures an uninterrupted production flow on the production line and reduces production line stoppages and waiting times. The parts feeding system ensures that parts are placed accurately at designated positions and angles. This ensures higher accuracy and repeatability in operations and helps minimize errors. Manual parts handling and placement can be time-consuming and increase labor costs. By using an automatic parts feeding system, you can reduce labor costs and allow workers to focus on higher value tasks. As a result, the parts feeding system in automation devices is an indispensable component to optimize production processes, increase efficiency, minimize errors and reduce labor costs.

The values of the grease fittings in the inventory for the system were determined and the design was provided modularly according to the variety of grease fittings (Figure 5).

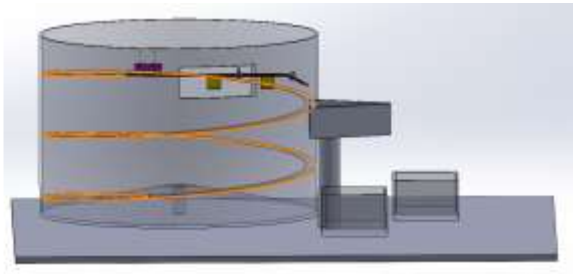

Fig. 5 Mechanical design

With the feeding system designed within the scope of this study, 50 – 60 pieces/min. will feed. The upper bowls are made of stainless 304 quality sheet metal. There is a single way output at the sorter exit. A maximum of 2.5 kg of product is loaded into the feeding unit.

B. *Control and Electronic Design*

The material selections of the system, the laser sensor to be used, the pneumatic motor for the separator, the industrial type camera and the Raspberry, PLC and HMI as the controller were determined (Figure 6). Grease fitting checks are carried out with deep learning algorithms. Faulty and approved parts are kept in memory.

Fig. 6 Electronic equipment's

C. *Data Collecting and Labeling*

The biggest need in deep learning models is big data. Data were collected in a unique way, deformed or incorrectly supplied grease fitting parts were recorded on different backgrounds (Figure 7).

Fig. 7 OK/NOK grease fitting parts

The recorded data were collected in the "Grease_Data" folder as "acceptance" and "rejection" data (Figure 8). A total of 5000 data have been recorded, 2850 "acceptance" and 2150 "rejection" data.

Fig. 8 Grease fitting data collection

Data labeling is one of the important processes required for training the model. Labeling the data correctly can directly affect the detection results. Labeling process refers to determining the coordinate values of the part to be detected. The labeling process can be carried out in a web-based format compatible with YOLO via Theos AI or MakeSense AI. The format suitable for YOLO is the process of scaling the labelled coordinate values between 0 and 1. Theos AI platform was preferred in the study. The values in the labelled data output show the label number and the start and end points in the x coordinate, and the start and end points in the y coordinate. Each data is labelled in 3 different formats (Figure 9). In this study, in addition to the sorting process of grease fitting parts, the effect of versions and algorithms on the detection results, comparison of their performance with the SmartVS system, and the effect of the data labeling process on the detection results were examined.

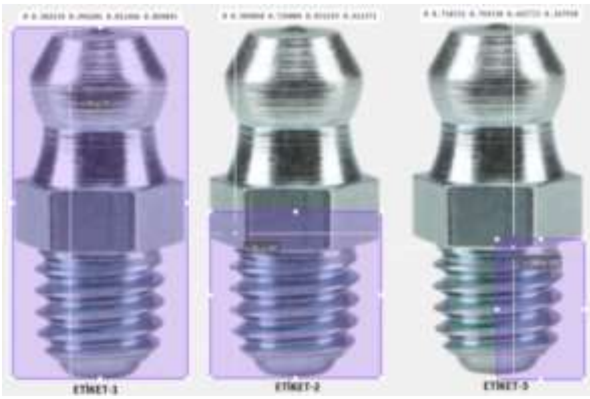

Fig. 9 Different region labeling example

D. *Train and Test*

The image files of the obtained data and the files containing the label data were clustered separately for training and testing. It is important that there is no training data in the test data. Training data was determined as 70%, validation data as 15% and test data as 15%. The training process was carried out with 4 YOLO v7 algorithms and 4 YOLO v5 algorithms through the system. Training results trials were conducted for acceptance and rejection parts (Figure 10). Each test result is recorded.

Fig. 10 Algorithm demonstration

III. Results

Training results were achieved with a total of 8 different algorithms, including version 7 and version 5 algorithms. Success was achieved for each algorithm in version trials. The number of errors was determined according to the acceptance and rejection data obtained. The most important criteria to be evaluated among the algorithms are mAP/FPS and number of errors. Evaluations were made according to the labeling size and a comparison was made with SmartVS (Table 1).

Table 1. Version Trials

Algoritma	Versiyon	İsim	Etiket	mAP/FPS	Toplam	Onay	Ret	Hata
YOLO	v5	Small	150x300	0,82/1,1	2650	2605	45	34
		Medium		0,79/1,5	2650	2571	79	36
		Large		0,77/1,4	2650	2576	74	35
		XLarge		0,81/0,7	2650	2579	71	31
		Small	150x150	0,91/1,1	2650	2587	63	21
		Medium		0,89/1,5	2650	2589	61	26
		Large		0,86/1,4	2650	2581	69	23
		XLarge		0,88/0,7	2650	2587	63	24
		Small	75x150	0,75/1,1	2650	2583	67	41
		Medium		0,73/1,5	2650	2567	83	48
		Large		0,79/1,4	2650	2565	85	42
		XLarge		0,74/0,7	2650	2559	91	53
	v7	W6	150x300	0,89/4	2650	2577	73	31
		X		0,91/1,3	2650	2575	75	30
		Default		0,90/2,5	2650	2582	68	32
		Tiny		0,86/3,1	2650	2576	74	30
		W6	**150x150**	**0.92/4**	**2650**	**2613**	**37**	**1**
		X		0,93/1,3	2650	2610	40	8
		Default		0,91/2,5	2650	2608	42	9
		Tiny		0,91/3,1	2650	2613	37	11
		W6	75x150	0,85/4	2650	2596	54	32
		X		0,88/1,3	2650	2605	45	30
		Default		0,86/2,5	2650	2608	42	34
		Tiny		0,84/3,1	2650	2585	65	36
SmartVS			150x300		2650	2636	14	22
			150x150		2650	2608	42	6
			75x150		2650	2584	66	30

IV. CONCLUSION

In this study, fault detection of the grease fitting part was successfully carried out. With YOLO, 4 different algorithms were determined for 2 different versions, the effects of 3 different label processes were examined and SmartVS performance comparisons were made. It is observed that the effects of the labeling process are high and error rates vary depending on the labeling region. The label must bear the attributes desired to be detected in a part and must be detailed. For this reason, the W6 model of the YOLOv7 algorithm achieved success with a high mAP/FPS rate in the 150x150 label field and a minimum error rate was achieved. In the SmartVS system, the minimum error value was obtained in the 150x150 label area. It was concluded that the effect of the label area should be to see the entire thread area of the grease fitting part rather than looking at the entire part. Regional examination in the dental area causes an increase in the error rate. The system's YOLOv7/W6 algorithm started working with the weight buddy trained on the 150x150 label area (Figure 11), and although it remained lower than SmartVS in terms of FPS performance, more successful results were obtained in the SmartVS 150x150 label area in terms of error performance. It is thought that in future studies, the low FPS can be increased with a higher GPU and processor.

Fig. 11 Machine final

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