CHAPTER 1
INTRODUCTION

1.1 Background

Trains are public transportation that has existed since the 18th century in Indonesia and are included in transportation that can be used for daily needs in traveling and transporting goods in the form of raw materials, materials, and others. Trains are transportation that runs on a rail track that has been provided so that it cannot run outside the designated track. The railway track that is always passed by trains will certainly require a period of use and maintenance so that the train can run properly on its track. There are various types of maintenance carried out so that trains can operate properly, including engine maintenance, wheel maintenance, and maintenance on railroad tracks. One of the priorities in railroad maintenance is checking the surface of the rail that has been damaged due to erosion that occurs when the train wheels rub against the railroad tracks. In particular, routine maintenance carried out on railroad tracks is always carried out every day to maintain the stability and mobility of train travel so that it continues to run well and avoids various potential accidents. The most important maintenance on railroad tracks is checking the surface of the rails for unevenness or defects that can affect the shaking and smoothness of the train that passes through it. Rail surface defects are a type of defect that often occurs on railroad tracks [7]. There are many methods of railway maintenance, such as traditional maintenance using the human eye or detection methods using ultrasonic sensors [8] [9]. Even now, practitioners have developed many detection methods using Deep Learning and Computer Vision [10] [11], Several methods have been tested based on Computer Vision such as strip detection on steel [12], Defect detection on railway tracks [7], The You Only Look Once (YOLO) model can detect train track defects in real-time.

In recent years, there has been a lot of research related to detecting damage on the surface of railroad tracks using the deep learning method, even having varying test results with various dataset training methods, one of the deep learning training uses a limited dataset to detect defects on the surface of railroad tracks [7] with research results for precision and recall still below average so that it can be applied to real-time detection objects, The objective was to train the method with a limited number of datasets and determine the defect detection results on the `y-axis` pixels.

Usually, Deep learning training requires a large number of datasets to achieve the level of accuracy in predicting it. This is actually an obstacle for us because the discovery of defects on the railroad tracks is random and requires energy sources, materials, and experts in sampling. With a limited dataset, we conducted training with several variations of the You Only Look Once (YOLO) model to improve the accuracy of detecting defects on the surface of the railroad tracks.

Our task here is to use several variations of the You Only Look Once (YOLO) model: YOLOv6, YOLOv7, YOLOv8, and YOLO-NAS to determine defects on railroad tracks at the pixel level to verify the types of defects on public railroad tracks and on high-speed railroad tracks. The main focus of this study is on the accuracy of detecting defects by using dataset RSDDs including 2 types of railroads consisting of high-speed rail (type1) and heavy rail (type2). Then compare the training results of each YOLO variation that has been tested with the same dataset whether the limited RSDDs dataset can achieve detection accuracy even for minor damage.

1.2 Statement of Problem

The problem formulation based on the above background is:

With various deep learning models to detect defects on railway tracks, what if applied in real-time, is the average precision level in detection capable of detecting defects on railway tracks at image transfer speeds? The YOLO model has been used with various image datasets to perform real-time image detection and has a mAP (mean Average Precision) above average with fairly low latency. Now it will be tested with a limited number of datasets against defect objects on the surface of high-speed railway tracks or heavy trains. In this study, it should be noted that the sub-problems faced are as follows:

1. How can YOLO model variants achieve training results with good precision and latency with a limited dataset?
2. How are each training result able to detect damaged objects with new image data types? It needs to be customized.
3. Can metrics of Precision, Recall, and Latency be a key point to implementing real-time damaged object detection?

Based on the existing problems, this research must be limited. The limitations of the problem in this research are:

1. Training for this object detection uses a limited existing dataset of RSDDs for detecting defects on high-speed trains and Heavy rail.
2. The training results focus on performance metrics of Precision, Recall, and computational speed/latency parameters.

1.3 Research objectives

The goal of this research is to produce a object detection system that is capable of classifying damage on the surface of conventional railway tracks and on the surface of express railway tracks, where the parameters to achieve this goal require high Mean Average Precision `(mAP)` results and fast computing speed.

1.4 Hypothesis

Based on the existing knowledge and background, the results of this study can contribute to conducting training in detecting defects on fast train tracks and public trains in real time. Detecting damage in real-time on fast train tracks or heavy train tracks. Proving that the performance metric obtained with the proposed model is better than the previous object detection model

1.5 Methodology

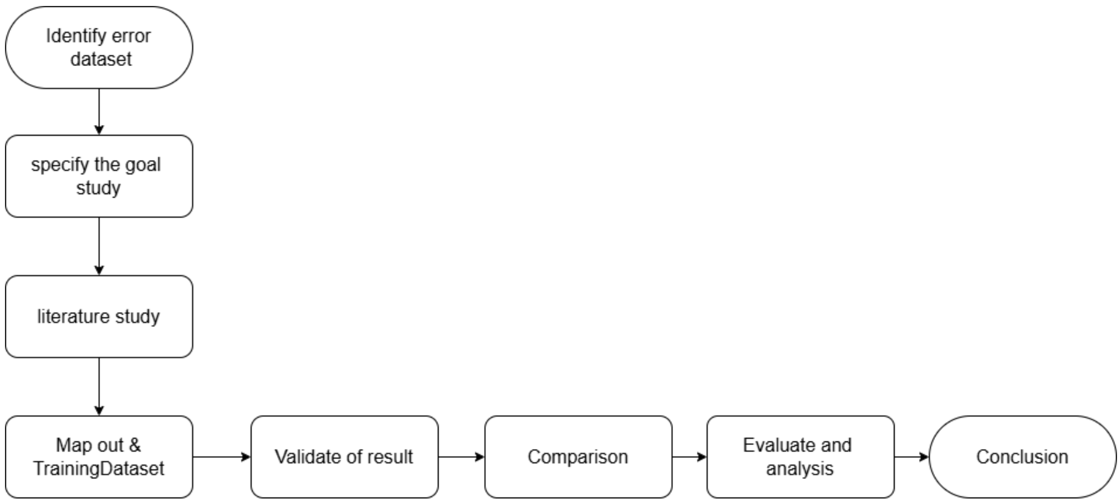

Fig. 1.1 The methodological steps used in this research

The methodological steps used in this research are as follows:

a. Identify error dataset
   Identifying the problems found in the dataset to determine the direction of the research topic taken and determining the objectives to be achieved in conducting this research.

b. Specify the goal study
   Determine the objective of the research after identifying the problems in the dataset.

c. Literature study
   Collection of model data and object detection methods based on literature studies, journals, and other readings related to the research as references and further understanding related to the topic being researched.

d. Map out & Training Dataset
   Then, using the related literature and journals, continue to design the model that has been determined to carry out dataset training and carry out training on existing datasets.

e. Validate of Result
   After the model design and training are carried out, the next step is to test the results of the previous dataset training with several trial samples to determine the map and latency obtained.

f. Comparison
   After the trial results with the proposed model are obtained, the results of the trial are then compared with other models with the same dataset.

g. Evaluate and analysis
   Next, the trial and implementation are carried out and also compared with other models, The evaluation of the implementation results regarding the shortcomings and advantages of the proposed model.

h. Conclusion
   From all the steps that have been taken, conclusions are drawn from the results of the research that has been carried out and continued with suggestions related to the research results.

1.6 Research Method

In this study, the method used is to use the YOLO-NAS and previous YOLO version detection object models as a comparison for the detection results of defective objects on the surface of fast/heavy railway tracks.YOLO-NAS is a variation of the new model released in 2023 by Deci [1] and has never been used for training damage detection on the surface of railway tracks. It has been used for training on the Foggia dataset to detect early fires in forests. The state of the art can be seen in the table 1.1

The last research on defects on railway track surfaces used 2 deep learning models, namely OC-TD and OC-IAN to classify crack areas on high-speed train tracks and general/heavy trains [7], This method is used as a comparison against the results of precision defect detection on the surface of fast/heavy railway tracks with the proposed detection model. The scheme used for this study is to be able to detect defects on the surface of fast railway tracks or general/heavy railway tracks. Here the YOLO detection object model is used to be able to accurately detect each type of defect.

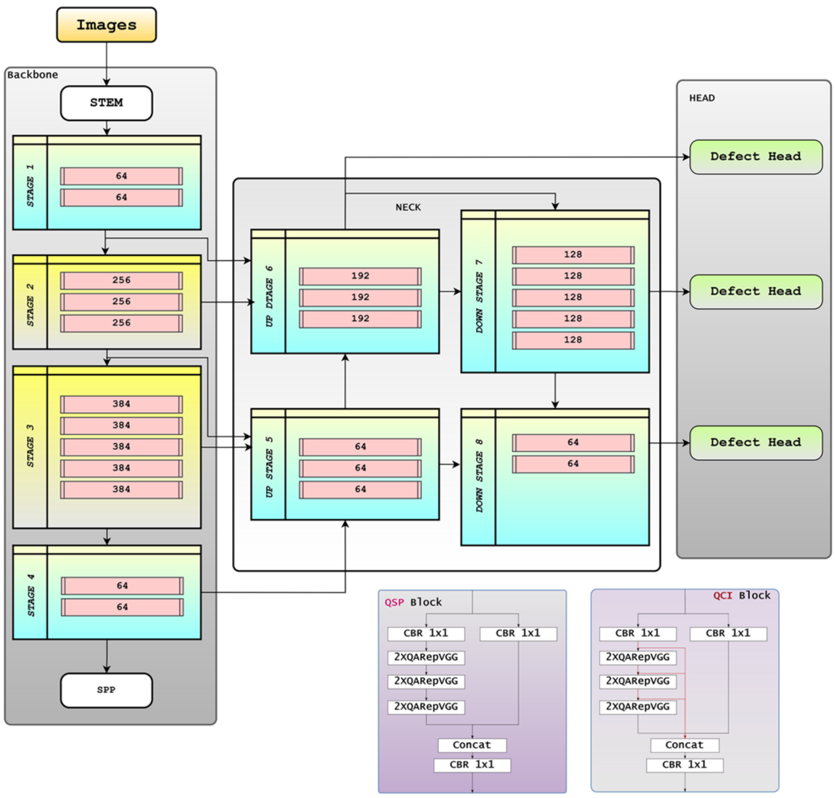

Fig. 1.2 YOLO-NAS architecture [1]. The architecture is automatically discovered through a Neural Architecture Search (NAS) system called AutoNAC to balance latency vs throughput.

1.7 Scheduling Activity

The following is an estimated schedule of activities for completing this research, which is expected to follow the activity plan so that this research runs smoothly.

Table 1.2 Research Milestone

No	Activity	2024		2025					
		Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
1	Proposal Research								
2	Seminar of Proposal								
3	Technical Analysis								
4	Thesis Monitoring								
5	Journal Submission								
6	Thesis Defence								

Table 1.1 State of the art of paper related

state of the art				
Title	Author	Approach	Dataset	Conclusion
Two Deep Learning Networks for Rail Surface Defect Inspection of Limited Samples With Line-Level Label [7]	Defu Zhang, Kechen Song, Qi Wang, Yu He, Xin Wen, and Yunhui Yan	OC-IAN and OC TD	RSDDs	Based author's purpose, OC-IAN and OC-TD were designed for inspecting express rail defects and common/heavy rail defects, respectively. Experimental results demonstrated that the author's methods were effective and achieved good results.
Assessing the Effectiveness of YOLO Architectures for Smoke and Wildfire Detection [13]	EDMUNDO CASAS, LEO RAMOS, EDUARDO BENDEK, AND FRANCK-LIN RIVAS-ECHEVERRÍA	YOLO	Foggia Dataset	Author said the YOLO-NAS variants stood out by achieving the highest recall scores among all models.
A Comprehensive Review of YOLO Architectures in Computer Vision: From YOLOv1 to YOLOv8 and YOLO-NAS [1]	Juan Terven, Diana-Margarita Córdova-Esparza, Julio-Alejandro Romero-González	YOLO-NAS	COCO 2017	Based on the author's results, the YOLO-NAS model was pre-trained on Objects365, three YOLO-NAS models have been released in FP32, FP16, and INT8 precision, which achieve an AP of 52.2% on MS COCO with 16-bit precision.