BAB 1. INTRODUCTION

The formation of potholes on road surfaces is a significant issue that impacts road safety and traffic flow, especially in developing countries. These potholes, caused by water penetration into road cracks due to wear, extreme weather conditions, heavy traffic, and poor drainage, contribute to discomfort, steering misalignment, and loss of vehicle control. They are a major factor in road accidents, leading to fatalities and injuries, and cause delays, increased emissions, and higher operating costs for vehicles. Moreover, potholes contribute to congestion and driver frustration, which can lead to hazardous driving behavior [1].

Manual maintenance and road repairs often require a long time and high costs, while damage detection still relies on reports from the public or physical inspections that are not always accurate and fast. In addition, road damage is often detected late due to extreme weather factors and high traffic volumes [2]. Therefore, although road repair efforts continue to be carried out, major challenges remain in terms of early detection and efficient handling of potholes. This study aims to offer a faster and more accurate solution by using deep learning-based automatic detection technology, such as YOLOv9, YOLOv10, and YOLOv11, which are expected to improve the efficiency of pothole detection and support the government's efforts to maintain driver safety and improve road infrastructure. In the previous study [3], the YOLOv5 model has been implemented to automatically detect potholes. And from the modeling results obtained, the precision value is 90.4% and the recall score is 81.2%. Then in this study, a case was found where there was a decrease in the box loss score during model learning in the training and validation sets.

In another study [4], a model was developed for detecting highway potholes using CNN and transfer learning. The CNN model performed better compared to transfer learning; however, the inception V3 model, which had been pretrained on a large number of images from ImageNet, outperformed the CNN model. The study noted anomalies during the testing phase where small potholes were sometimes overlooked. Thus, the dataset's quality and uniformity across all images were deemed crucial for effective training and validation.

Additionally, in study [6], a performance comparison was conducted for various models used for real-time pothole detection, including SSD, HOG, CNN, and YOLO.. Based on this performance, YOLO demonstrated faster processing capabilities, enabling real-time pothole detection with an accuracy of 82%.

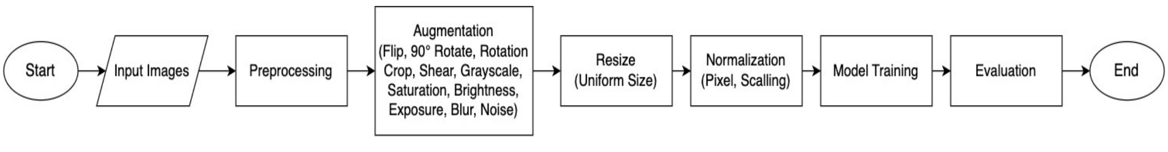

Fig. 1. Pothole detection flow process

In this research, we propose a sophisticated approach to pothole detection using state-of-the-art object detection techniques. The proposed method involves a multi-step process to effectively identify and localize potholes under real-world conditions. First, we employ three latest versions of YOLO models (YOLOv9, YOLOv10, and YOLOv11) for pothole detection in images and models are evaluated in varius metrics such as mAP50, mAP 50-95, and inference speed.

The novelty of this research lies in its comprehensive approach that addresses several key limitations of previous studies. While prior research has shown progress in automated pothole detection using models such as YOLOv5, CNN, and SSD, these approaches often face challenges related to dataset quality, detection under diverse environmental conditions, and model efficiency in real-time applications. For instance, research using YOLOv5 [3][5] achieved promising results with precision scores above 80% but reported issues such as declining box loss scores during training and validation, as well as difficulties in detecting small potholes. Similarly, CNN-based methods [4] demonstrated better accuracy compared to transfer learning but tended to miss small potholes and heavily relied on high-quality, uniform datasets.

Our research directly addresses these gaps by introducing a comparative analysis of YOLOv9, YOLOv10, and YOLOv11, which are designed to overcome the limitations of previous YOLO versions and other deep learning models. Unlike previous research, our study utilizes a highly diverse dataset encompassing both close-range and distant image captures, as well as roads with varying degrees of damage (smooth, slightly damaged, and severely damaged). By systematically tuning hyperparameters for each model, we ensure that the detection process is optimized for specific challenges, including low visibility and detection of small or partially obscured potholes.