CHAPTER I

INTRODUCTION

1.1 Research Background

The oil and gas industry which is actively engaged in doing business operations in Indonesia's borders is presently grappling with serious and pressing issues regarding the safety and dependability of its pipeline system of distribution. Various incidents that have surfaced and which have been reported by Milenia (2021) clearly outline the severity and magnitude of this precarious scenario; one such incident included extensive corrosion which had been discovered in the injection pipe, which eventually caused a leak to take place in a pipeline belonging to Pertamina, which is in the area of Jambi. Additionally, Nugroho (2021) shed light on another such case in Bojonegoro where: a leak in an old crude oil pipeline, parts of which have remained operational since Dutch colonial times in the country, had taken place. Such disturbing events serve to highlight the very real and present danger that pipeline corrosion presents to the integrity and dependability of infrastructure, thus making such timely and powerful action necessary to stem and correct this present state of affairs.

Corrosion is a very serious issue that is deeply ingrained and exercises a significantly detrimental effect upon oil pipelines, which are undoubtedly an important component of the overall infrastructure that we all use in our everyday lives. This common problem threatens to trigger widespread leaks, which compromise not only health, security, and safety of towns and communities in direct association with these pipelines but also inflict huge damage upon surrounding natural habitats that are necessary for health, security, and livelihoods of all those who are dependent upon them. Such leaks have far-reaching consequences, causing long-lived damage to our natural environment, and can also trigger calamitous events in the form of fire and explosion, along with many other secondary issues that would necessarily follow from such breakdowns. In addition to these high stakes, the economic costs of corrosion are extremely high; in addition to incurring huge money losses in terms of product loss and wastage, corrosion requires costly repairs to fix and restore damage triggered by corrosion, along with generating reduced productivity due to inevitable idle time created by corrosion in our essential infrastructure systems. PT Pertamina, as the main operator of oil pipelines in Indonesia, is subjected to large financial costs arising from the environment compensation required and the expensive replacement of damaged pipelines.

Traditional methods that use standard procedure for manual inspection and thickness measurement, which have traditionally been used for assessment work, have turned out to be quite ineffective in ensuring detailed and extensive evaluation. But with the advent and usage of latest AI-based semantic segmentation technology that not only makes inspections quicker but also more organized and accurate in nature over vast surfaces, a much more efficient solution is available. Motivated by the promise of this revolutionary strategy, the research paper termed "COMPARATIVE ANALYSIS OF MULTI-CLASS SEMANTIC SEGMENTATION MODELS FOR PIPELINE CORROSION DETECTION" aims to provide models that are compatible with handheld devices, thus making inspections of essential infrastructure at a cost that is feasible and reasonable.

Specifically tailored deep neural networks that have been specially designed and created for the specific function of semantic segmentation have shown an impressive degree of power and capacity far over that of more conventional techniques and methods. This is especially true in the case of accurate identification and determination of corrosion zones affected. Such ability to such an outstanding magnitude has been validated and supported by extensive research studies carried out by Kumar et al. (2021). In their breakthrough work, they used multi-class segmentation, which is highly adept at distinguishing and recognizing features of importance to various objects present in an image. Such an outstanding rate of separation is based upon the use of various colors assigned to labeling all different classes, as demonstrated by research conducted by Chen et al. (2020). Use of such an advanced segmentation method makes differentiation in a clear and straightforward way based upon different represented classes, which is of unlimited value in determining with accuracy zones that have undergone corrosion impact. Therefore, such an ability makes damage analysis lesser in difficulty, which makes all such an activity significantly easier. Additionally, use of such novel techniques also holds huge promises to lessen significantly their dependency upon manual inspection techniques, together with accelerating entire decision-making processes involved in dealing with corrosion-related problems as well as managing them in an appropriate way.

This technique, referred to as multi-class segmentation, using the sophisticated framework of Convolutional Neural Networks (CNN) is decisively proven to be the most successful and powerful technique used in performing segmentation of images when viewed from the perspective of Deep Learning techniques. The architecture of CNN is particularly capable of handling complex and intricate features embedded in multi-class images with impressive performance at an accuracy rate of 78.4%. This impressive performance is far superior to binary classification techniques, which have reportedly performed at an accuracy rate of merely 75%, as presented in research by Jawale et al. in 2019. With such outstanding abilities and performance, such segmentation is highly appropriate for use in various applications that require an extensive and in-depth examination of all those various images' features and attributes.

The evidence presented in a highly detailed manner by Daffa et al. (2023) clearly shows and proves that deep learning techniques have much higher levels of accuracy in their ability to identify and analyze complex data patterns in comparison to conventional machine techniques. In the context of deep networks, Convolutional Neural Network, also known as CNN, is a particular type with unique features, thus giving it an exceptional capacity to automatically choose important features from large datasets with minimal configurations at setup stages (Rokhana et al., 2019). The main contribution that CNN offers is functionality, which allows it to identify local features with minimal levels of difficulty; this is through the novel use of convolutional layers combined with max-pooling layers, which are used to simplify and speed up various computations (Rokhana et al., 2019). For health applications, CNN has attained an impressive optimal rate of accuracy at 95.3% when used to classify US B-mode images, which clearly shows their exceptional functionality in this specific context (Rokhana et al., 2019). Additionally, CNNs have an exceptional capacity to optimize with regard to incoming new data since their deep architecture is specially crafted to learn with high levels of adaptability in various levels of features, thus resulting in improved overall performance (Rokhana et al., 2019). In comparison, traditional machine techniques have great difficulties when dealing with automatic feature selection as well as handling transformations in data, particularly in complex applications such as corrosion detection, where complex visual patterns bring high levels of extra challenges.

This work selected two models for Deep Learning: BiSeNetV3 with an EfficientNetB1 backbone, and Mobile U-Net. Mobile U-Net was used since it is efficient with maintaining high accuracy, thus is excellent for usage in devices with limited resources. Yoon et al. in their work in 2021 demonstrated that Mobile U-Net is capable of an average segmentation accuracy of 89.9% with an inference of just 13 ms, which is ideal for usage in real-time.

BiSeNetV3 uses a special kind of convolution that is also quicker. STDC-2 is the core component that accepts an input size of 768 x 1536. BiSeNetV3 achieves an mIoU score of 79.0% with an execution speed of 93.8 frames per second. The design is excellent since segmentation accuracy is enhanced while keeping computing power efficient. This is excellent for usage on computing devices with minimal computing power, such as edge computers and smart phones (Tsai & Tseng, 2023).

Standard Convolutional Neural Network (CNN) classifies images very effectively but is ineffective in detailed segmentations. To address this issue, Mobile U-Net and BiSeNetV3 have been put forward to maximize segmentation accuracy. One such model was examined by Kumar et al. (2021), but in this paper, two other architectures are examined to identify the optimal means to detect corrosion in oil pipelines.

This work makes corrosion detection in oil pipelines more efficient and accurate. The work also offers a comparison of how various Deep Learning models detect corrosion. The results of this work will help aid in providing a more efficient and effective corrosion detection system for the oil and gas industry.

1.2 Problem Identification

Based on this background, several problems have been identified, namely:

1. Corrosion of oil distribution pipelines can easily cause leaks detrimental to the community and agencies.
2. Manual identification of corrosion requires more time and resources.
3. A technology is needed to help detect corrosion in image-based pipes.

1.3 Problem Scopes

The construction of the model in this study is determined by several problem restrictions so that the discussion remains focused and does not spread, as follows:

1. The segmentation model used is only Mobile U-Net and BiSeNetV3 with EfficientNetB1 as the backbone.

2. The datasets totaled 112 images from public datasets such as Google Image, Roboflow, Kaggle, and live photos.
3. This study focuses on determining an efficient model for corrosion detection in oil and gas pipelines.
4. The image resolution used in the model training process is 256x256 pixels.
5. Applying traditional augmentation techniques to enrich the dataset.
6. The segmentation class consists of three categories: corrosion (red), pipe (blue), and background (green).
7. The model evaluation method uses mIoU and Dice Coefficient as the primary metrics.
8. This research only covers analysis up to detecting the percentage of corrosion area pixels.

1.4 Research Problem Statements

The following is the formulation of the problem that is the focus of this research:

1. How does implementing Mobile U-Net and BiSeNetV3 models with EfficientNetB1 backbone detect corrosion in pipes?
2. How can traditional augmentation improve corrosion image segmentation performance and support efficiency evaluation between Mobile U-Net and BiSeNetV3 based on EfficientNetB1 in detecting pipeline corrosion?
3. How can the accurate percentage of corrosion area pixels be calculated to support the corrosion detection system of oil and gas pipelines?

1.5 Research Objectives

The main objectives of this research are as follows:

1. Developed a segmentation model based on Mobile U-Net and BiSeNetV3 with EfficientNetB1 backbone that can detect corrosion in pipes.
2. Analyze and evaluate the effect of traditional augmentation techniques on improving corrosion image segmentation performance, and compare the efficiency of the EfficientNetB1-based Mobile U-Net and BiSeNetV3 models in detecting pipeline corrosion.
3. Determine the percentage of corrosion area pixels as the final segmentation result to support detection on oil and gas pipelines.

1.6 Research Result Benefits

1. For Authors
   a) Deepen knowledge and skills in applying deep learning models Mobile U-Net and BiSeNetV3 with an EfficientNetB1 backbone to image segmentation, especially in corrosion images.
   b) Improved understanding of the implementation of traditional augmentation on the influence of datasets in image segmentation.
   c) Gain practical experience in scientific research and development of deep learning-based solutions that can be applied to real problems in the industrial world.

2. For Industrial Sector
    a) Providing technology-based solutions to monitor pipeline conditions, especially oil pipeline distribution, against corrosion to prevent operational losses due to pipeline leakage.
    b) Assist field workers, especially in inspection, in identifying corrosion-detected pipeline areas in report generation.
3. For University
    a) Make a scientific contribution to developing multi-class semantic segmentation technology using the Mobile U-Net architecture BiSeNetV3 and EfficientNetB1.
    b) Provides references and opportunities for further research in the field of image segmentation, especially on pipe corrosion in the industrial field.