CHAPTER I
INTRODUCTION

1.1 Background

Lung cancer remains one of the world's major health problems due to its high mortality rate. This occurs because the disease is often only diagnosed when it has reached an advanced stage. According to the latest data from the World Health Organization (WHO) in 2025, lung cancer is the leading cause of cancer-related deaths globally, placing a significant burden on healthcare systems in various countries [1]. At the national level, according to data from the Global Cancer Observatory (GLOBOCAN) 2024, Indonesia recorded approximately 35,000 new lung cancer cases and over 30,000 deaths attributed to this disease in 2024 [2]. The disease typically presents no symptoms in its early stages; patients usually only experience general symptoms such as shortness of breath, frequent fatigue, and unexplained weight loss, and only develop severe symptoms once it progresses to an advanced stage Consequently, many patients only seek medical attention after the cancer cells have spread. Previous studies have also shown that artificial intelligence-based lung cancer detection systems utilizing medical imaging have proven effective in assisting early identification, thereby significantly increasing patients' survival rates [3]. Therefore, early detection is crucial for improving patients' survival chances and facilitating faster and more appropriate medical intervention. Early detection requires sensitive and accurate screening methods, as physical examinations alone are insufficient to detect small nodules in the lungs. Given the current advancements in medical technology, intelligent systems are needed to assist medical professionals in making faster and more accurate diagnoses. This necessity drives research into the development of Computer-Aided Diagnosis (CAD) systems to support the work of radiologists.

In the diagnostic process, Computed Tomography (CT-Scan) is widely recognized as the primary standard for lung imaging due to its ability to display anatomical structures in greater detail compared to conventional X-rays. CT-Scans produce cross-sectional images that allow physicians to view lung structures three-dimensionally without interference from ribs or other organs [4], [5]. The high spatial resolution of CT-Scans is crucial for distinguishing between small, irregularly shaped cancer cells and normal cells. Furthermore, research on the detection of lung cancer mutations in CT-Scan images has proven that the quality of the generated images significantly determines the success of automated analysis processes by computer systems [5]. However, manually examining hundreds of CT-Scan slices is an exhausting and time-consuming task for radiologists. Fatigue and physician subjectivity can also increase the risk of diagnostic errors, such as overlooking small nodules or misclassifying tissues. Therefore, the application of digital image processing technology and artificial intelligence serves as a vital solution to enable automated image analysis. The implementation of this automated system is expected to yield more objective results and reduce assessment variability among radiologists.

However, there are certain issues associated with CT-Scan examinations; despite its advanced technology, the resulting images are often not optimal for direct processing by artificial intelligence algorithms. One frequently encountered problem is the low contrast between cancerous tissue, lung structures, and the surrounding normal lung tissue, as they appear nearly identical [6]. Furthermore, to maintain patient safety, CT-Scans typically utilize a low radiation dose, which can introduce noise into the images, resulting in a grainy and blurred texture [7]. The quality of this input image significantly impacts the performance of machine learning models; if the input image lacks clarity, the model will struggle to learn essential features, consequently reducing prediction accuracy [6]. This is corroborated by several studies that specifically analyzed the impact of image enhancement on detection outcomes in lung medical images, proving that appropriate pre-processing stages can significantly improve model performance [8][9][10]. Therefore, the image pre-processing stage is a mandatory step in cancer detection systems. One of the commonly utilized techniques in this pre-processing stage is contrast enhancement.

Contrast enhancement techniques aim to readjust the distribution of pixel intensities within an image so that hidden details become more visible and easily distinguishable by both humans and computers. Several commonly used methods in contrast enhancement include Histogram Equalization (HE), which operates by globally flattening the histogram to improve the overall image contrast [11], [12]. However, this method has a drawback, as it can amplify noise in image regions with uniform backgrounds. To address this issue, the Contrast Limited Adaptive Histogram Equalization (CLAHE) method was developed. CLAHE operates locally on small image regions to ensure that contrast enhancement remains controlled without introducing additional noise [13]. Furthermore, the Gamma Correction method employs a non-linear transformation to adjust image brightness levels, making it highly effective for correcting images that are excessively dark or bright [14], [15]. Another technique is Contrast Stretching, which functions to stretch pixel intensity values to span the entire available dynamic range, resulting in sharper images [16], [17]. Each method possesses distinct characteristics and working principles; thus, their effectiveness requires systematic evaluation.

The importance of comparing these four contrast enhancement methods lies in the fact that each method possesses distinct characteristics in manipulating spatial distribution and pixel intensity. Although theoretically, HE and CLAHE methods might be superior in histogram distribution tasks, they carry different manipulation risks regarding the noise frequently present in low-dose CT-Scan images. Conversely, gamma correction and contrast stretching offer simpler linear and non-linear approaches that provide stability in maintaining the integrity of lung morphological features without inducing excessive visual artifacts. This comparative study facilitates determining whether the accuracy improvement in the classification model is attributed to sharp global contrast enhancement or the preservation of fine local details.

In line with the increasing demand for fast and accurate diagnostic systems, the utilization of efficient Deep Learning architectures such as MobileNetV2 is an excellent choice. MobileNetV2 is designed as a lightweight model utilizing depthwise separable convolutions and inverted residual blocks, enabling it to operate rapidly even on devices with limited specifications [18]. This advantage is highly beneficial for deployment in regions with low computational resources, such as community health centers or small hospitals, which still require reliable cancer detection tools. Recent studies indicate that MobileNetV2 can achieve competitive accuracy compared to larger models, provided that the input data is of high quality

[19]. However, lightweight models of this nature are highly sensitive to noise in the input images, making the role of contrast enhancement critical. Without appropriate contrast enhancement, the model may fail to recognize fine details in cancerous nodules, ultimately resulting in high loss values and low accuracy during both the training and testing phases.

Although numerous studies have discussed contrast enhancement techniques and classification using Convolutional Neural Networks (CNN) separately, there is still a research gap regarding the comparison of these four techniques specifically on the MobileNetV2 architecture. Most previous studies have only compared two methods, such as HE and CLAHE [19], or focused on developing new algorithms without testing their impact on lightweight models like MobileNetV2 [15]. Few studies have specifically analyzed how HE, CLAHE, Gamma Correction, and Contrast Stretching affect the training results (loss values) and the final accuracy of the MobileNetV2 model on lung cancer CT-Scan datasets. This lack of technical guidance makes it difficult for CAD system developers to select the most optimal pre-processing method for this case. Therefore, systematically conducted experimental research is required to determine which contrast enhancement method best aligns with the characteristics of MobileNetV2.

Based on these issues, this study aims to compare the performance results of the four contrast enhancement techniques in improving lung cancer classification accuracy. The focus of this research is to evaluate the effect of each pre-processing technique on the accuracy and loss evaluation metrics generated by the MobileNetV2 model. By comparing the resulting images from HE, CLAHE, Gamma Correction, and Contrast Stretching against the original images, this study is expected to determine the best and most effective method for improving image feature quality. The results of this research will serve as a foundation for building a lung cancer classification system that is computationally efficient and possesses a high level of accuracy. It is hoped that this contribution will support the development of advanced medical technologies for lung cancer detection and treatment in the future.

1.2. Problem Statements

Based on the background of the problem described above, the problem statements addressed in this study are formulated as follows:

1. How do the visual quality characteristics of lung CT-Scan images change after the application of four different contrast enhancement techniques, namely HE, CLAHE, Gamma Correction, and Contrast Stretching?
2. How does the performance of the MobileNetV2 model compare (in terms of accuracy and loss values) in classifying lung cancer on CT-Scan image datasets that have been pre-processed using each of the respective contrast enhancement techniques?

1.3. Objectives

In line with the stated research problems, this study has the following objectives to be achieved, which are outlined as follows :

1. To analyze the effect of applying four contrast enhancement techniques HE, CLAHE, Gamma Correction, and Contrast Stretching on the visual quality and the clarity of feature details in lung CT-Scan images.
2. To evaluate and compare the performance of the MobileNetV2 architecture in classifying cancerous and normal lung CT-Scan images, by considering the accuracy and loss evaluation metrics, after undergoing pre-processing with the four proposed contrast enhancement techniques.

1.4. Benefits of the Research

This research is expected to provide a tangible impact on the development of healthcare technology and artificial intelligence, with the following benefits:

1. To determine which contrast enhancement technique is the most effective in assisting lightweight deep learning models to better analyze medical images.
2. To explain in detail how pre-processing image quality improvements can make lung cancer detection more accurate and minimize detection errors.
3. To provide recommendations regarding the most optimal and efficient contrast enhancement technique to be implemented in MobileNetV2-based Computer-Aided Diagnosis (CAD) systems.

4. To offer an alternative early detection solution for lung cancer that is computationally efficient, enabling its implementation on devices with limited specifications in primary healthcare facilities.
5. To support medical professionals and radiologists in reducing the risk of diagnostic errors caused by poor image quality, thereby facilitating faster and more accurate decision-making processes.

1.5. Scope of the Research

To ensure the focus and scope of this research remain well-directed, this study is limited to the following aspects:

1. The research object used is lung CT-Scan (Computed Tomography) medical images, focused on a two-class classification, namely normal lungs and cancerous lungs.
2. This study does not include the lung nodule segmentation process and focuses solely on the classification of lung CT-Scan images.
3. The Deep Learning architecture utilized is restricted to MobileNetV2 as a lightweight model for image classification.
4. The Contrast Enhancement techniques compared only include four methods: Histogram Equalization, Contrast Limited Adaptive Histogram Equalization (CLAHE), Gamma Correction, and Contrast Stretching.