CHAPTER V
CONCLUSIONS AND SUGGESTIONS

5.1 Conclusions

Based on the results of this study, which discusses the application of contrast enhancement methods in the lung cancer classification case study using lung CT-Scan images based on MobileNetV2, it can be concluded that the four contrast enhancement techniques each produced different visual characteristic changes to the quality of the original images (baseline). The application of the Histogram Equalization (HE) method produced visual changes that globally and extremely equalized the color spectrum, making object boundaries appear very clearly. However, this method has the drawback of sacrificing the naturalness of the medical image by introducing artificial noise in healthy lung areas. Meanwhile, the application of the Contrast Limited Adaptive Histogram Equalization (CLAHE) method was able to sharpen local anatomical boundary details without producing noise as bright as that of HE. However, the drawback of this method is that it can trigger the appearance of patchy textures in normal lung tissue that can visually resemble the pattern of cancer cell nodules.

The gamma correction method itself differs from the two previous methods, as it provides a non-linear pixel intensity transformation that specifically widens the range of dark areas, particularly in the lung parenchyma region. The application of this method has proven capable of significantly sharpening the boundary between cancer cell nodules and healthy tissue, while preserving the natural characteristics of the CT-Scan image itself without introducing excessive distortion. On the other hand, the application of contrast stretching provided the most subtle visual characteristic changes through the linear stretching of pixel values. Through this method, the lung CT-Scan images appear clearer compared to the original images, however this less aggressive change causes the texture of cancer cell nodules to appear faint in the images.

The changes in visual characteristics of the results will naturally affect the performance of the MobileNetV2 model in the medical image classification case study, where the application of contrast enhancement techniques itself has proven to be necessary as the majority of methods succeeded in improving the accuracy performance compared to the original images (baseline). Judging from the comparison of accuracy and loss values, the HE method consistently demonstrated the ability to improve model performance when compared to the use of original images as well as several other contrast enhancement techniques. Based on the results obtained, the application of HE has proven to be highly effective and resistant to the influence of changes in training stage strategies as well as hyperparameter configurations in the architecture used. This can be evidenced by the achievement of the highest accuracy value reaching 0.99 or 99% in scenarios 1 and 3, with the lowest loss value of 1.20, and the application of HE has also proven to still deliver the highest accuracy value in scenario 2 of 0.95, where in this scenario 2 the other enhancement methods as well as the baseline data experienced very drastic performance declines. This achievement proves that a very sharp contrast enhancement can make the edge features of cancer cell nodules become so clear and easy for the model to extract without being obstructed by background texture.

On the other hand, the application of gamma correction managed to achieve fairly good performance in scenario 4 at 0.97, but proved to be less stable under changes in the training strategy applied in scenario 2, obtaining only an accuracy value of 0.80. Meanwhile, the application of the CLAHE method, which provides an excessive local contrast enhancement effect, actually experienced a performance decline in scenario 2, causing the accuracy value to drop to 0.88. These results indicate that the application of CLAHE is prone to triggering an over-sensitivity phenomenon that can lead to classification errors. And with the contrast stretching method, despite having delivered good performance in scenarios 1 and 4, this method also experienced the same outcome as the other methods, dropping in scenario 2 with an accuracy value of 0.86, indicating a less aggressive approach in bringing out the features of cancer cell nodules.

Sebagai kesimpulan akhir, metode Histogram Equalization (HE) merupakan metode contrast enhancement yang paling direkomendasikan berdasarkan hasil penelitian ini. HE merupakan satu-satunya metode yang memberikan performa yang konsisten untuk keseluruhan skenario pelatihan. Hal ini disebabkan oleh ketegasan fitur yang dihasilkan tidak hanya memudahkan ekstraksi fitur pada awal pelatihan, namun juga memberikan kestabilan model hingga akhir, sehingga terbukti paling baik dalam membantu arsitektur MobileNetV2 dalam melakukan klasifikasi kanker paru-paru secara akurat dan juga konsisten.

5.2 Suggestions

Based on the limitations and research results that have been achieved, there are several suggestions for the development of research in the next stage. The first suggestion is that future research could employ more complex Convolutional Neural Network (CNN) model architectures such as VGG, ResNet, or EfficientNet, with the aim of evaluating whether these architectures are capable of extracting lung cancer cell nodule features with greater precision and higher sensitivity compared to the MobileNetV2 model architecture. The second suggestion is that the enhancement process could utilize other enhancement techniques such as sharpening, which is a technique for edge sharpening with the purpose of clarifying the shape of cancer cell nodules, noise reduction techniques to eliminate irrelevant patches that may be incorrectly recognized by the CNN model, as well as segmentation stages that isolate the lung organ area from other organs. By exploring these techniques, it is hoped that the loss of vital medical information can be minimized while simultaneously presenting more optimal visual features before being inputted into the classification model.