# CHAPTER V
# CONCLUSIONS AND RECOMMENDATIONS

## 5.1 Conclusion

Based on the results of the research conducted, the following conclusions can be drawn :

1. The Swin Transformer method was effectively used for the categorization of chronic lymphocytic leukemia (CLL). The program successfully classified microscopic pictures of white blood cells into two categories: normal cells and cells suggestive of chronic lymphocytic leukemia (CLL). The shifting window attention method in the Swin Transformer facilitates the model's ability to efficiently extract both local and global data, hence enhancing its capacity to differentiate between the two classes successfully. The model was effectively integrated into a web-based application using Streamlit, enabling real-time picture predictions.
2. The Swin Transformer approach has outstanding performance according to assessment measures. Test results using the confusion matrix and evaluation metrics demonstrate that the model routinely attains accuracy, precision, recall, and F1-score values around 91%, with an F1-score of 0.9129. Furthermore, assessment outcomes using the ROC-AUC curve indicate the model's proficiency in differentiating between the two classes with a comparatively low error rate. The findings demonstrate that the model has precise, equitable, and dependable classification skills in identifying photos of chronic lymphocytic leukemia..
3. The architectural parameters and hyperparameters of the Swin Transformer affect the model's performance. The hyperparameter tuning technique, using Grid Search, effectively determined the ideal parameter combination using the F1-score as the principal metric. Factors like learning rate, batch size, and weight decay influence the model's accuracy, training stability, and generalization capacity. The use of class weighting mitigates data imbalance across classes, preventing the model from developing a bias towards the majority class and preserving its ability to reliably identify minority classes.

## 5.2 Recommendations

1. Dataset Development

   Future research is recommended to use larger and more diverse datasets, in terms of sources, image quality, and variations in conditions, to improve the model's ability to generalize to real-world data.
2. Hyperparameter Optimization
3. The use of other optimization methods, such as Bayesian Optimization or Random Search, could be considered to improve the efficiency of finding the optimal parameters compared to Grid Search.
4. More Robust Model Evaluation

   Future research could apply cross-validation techniques and testing on external datasets to ensure better model stability and generalization capabilities.
5. System Development and Real-World Implementation The system could be further developed into a cloud- or mobile-based application and integrated with other clinical data to serve as a more comprehensive diagnostic tool in medical settings.