CHAPTER V
CONCLUSION

5.1 Conclusion

Based on the entire process of design, algorithm implementation, through to the system functionality testing carried out in this research, several conclusions can be drawn as follows:

1. The integration of the SMOTE-NC technique on the acute fever medical record dataset provides a trade-off. The statistical significance test shows that the decrease in global Accuracy due to SMOTE-NC (a decrease of -1.50 points, from 0.7566 to 0.7416) is not statistically significant (p-value = 0.1920). This decrease is not large enough to be considered a meaningful performance degradation. Conversely, the increase in Macro Recall proved to be statistically significant (an increase of +3.97 points with a p-value = 0.0068), which shows that SMOTE-NC can improve the model's sensitivity toward the minority classes. Meanwhile, the Macro F1-Score did not show a statistically significant change (a slight increase of +0.62 points with a p-value = 0.5607).
2. Hyperparameter optimization using Optuna through the Bayesian Optimization approach succeeded in finding an optimal CatBoost configuration, with the resulting optimized classification model achieving a performance of an average Accuracy of 74.16%, Macro Recall of 64.74%, and Macro F1-Score of 64.08%. Based on the statistical significance test, CatBoost proved significantly superior to XGBoost on all evaluation metrics (Accuracy p=0.0029, Macro Recall p=0.0389, Macro F1-Score p=0.0229), while compared to Random Forest, no statistically significant performance difference was found (p>0.05 on all three metrics, although Accuracy approached the significance threshold at p=0.0522). Therefore, the final decision to use CatBoost at the implementation stage is based on architectural and operational superiority, in which CatBoost is able to natively manage nominal clinical features without requiring the mandatory Ordinal Encoding pre-processing computational load required by XGBoost

and Random Forest. Operationally, CatBoost recorded an inference time of only 0.024 ms, far faster than XGBoost (0.09 ms) and Random Forest (0.328 ms). This architectural superiority and response speed are what make CatBoost the choice for integration into the server-side environment (FastAPI) serving the mobile application.

3. The multiclass classification model was successfully implemented through a distributed Client-Server architecture based on REST API. This workload separation allows FastAPI to handle the heavy matrix inference execution, while the Flutter-based mobile application on the client side operates purely to render the diagnostic probability visualization. Black-Box Testing validated the robustness of this system; Pydantic protection on the server side succeeded in preventing data type anomalies, thereby protecting the user's mobile device from memory overload or a force-close incident.

5.2 Suggestions

Based on the research results, evaluation, and problem limitations that have been described, there are several suggestions that can be considered as a basis for development and refinement in future research, including:

1. Future research is advised to use a primary clinical dataset (real-world data) from healthcare facilities to represent more current demographic characteristics of the endemic patient population.
2. The application is advised to be integrated with the Application Programming Interface (API) of a Hospital Management Information System (SIMRS) or Electronic Medical Record (EMR). This integration will allow for the automated retrieval of a patient's laboratory data history, so that medical personnel do not need to manually input parameters.
3. Future research is advised to conduct testing on datasets from independent sources to assess the model's performance robustness across populations before the system is considered for implementation on a wider scope.