CHAPTER V
CONCLUSION

This chapter discusses the study's general findings and offers recommendations for more research.

5.1. Conclusions

Based on the findings of the study on the classification of stunting in toddlers using the Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) algorithms, the following conclusions can be made:

1. The K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) algorithms can effectively classify stunting in infants based on gender, age, weight, height, and Z-scores for height-for-age (HFA), weight-for-age (WFA), and weight-for-height (WFH). Both algorithms were reasonably successful in classifying the data into stunting and non-stunting groups.
2. With an optimum K value of 5, the KNN method achieved an accuracy of 96.72%, precision of 91.25%, recall of 67.73%, and F1 score of 77.52%. These results suggest that the KNN algorithm performs classification reasonably well, despite some prediction errors in the stunting data.
3. The SVM approach with a polynomial kernel performed better. The SVM model's accuracy, precision, recall, and F1 score were 97.47%, 90.82%, 78.96%, and 82.55%, respectively. These results suggest that the SVM strategy is more effective in detecting stunting than the KNN method with K = 5.
4. Testing and evaluation findings indicate that the best approach for categorizing stunting in the dataset is the SVM methodology with a polynomial kernel.
5. The SVM model with a polynomial kernel was developed as a web-based system using Flask.

5.2. Recommendations

Given the results of the study, a number of recommendations can be made.

1. Increase the quantity and variety of the dataset, particularly for data on toddlers in the stunting category. A larger dataset and a more balanced class distribution are expected to help the KNN and SVM models achieve better classification performance
2. Improve data quality by ensuring data completeness and validity. Comprehensive data can help in decision-making and enhance the effectiveness of categorization models to produce more accurate forecasts.
3. Conduct more diverse testing to ensure the model is more stable and the classification results obtained are optimized