CHAPTER 5

DISCUSSION

5.1 Summary

Sentiment Analysis of the Free Meal Program voiced by Prabowo-Gibran tries to get public responses to the program. This analysis clarifies public perception of the policy through data taken from tweets on Twitter through the web scraping process. This project involves several phases, from data collection to final analysis. The data after being scraped will go through a cleaning stage which means that various preprocessing techniques can be carried out, including converting text to lowercase, removing URLs, usernames, punctuation, and irrelevant words. Then, stemming and foreign word translation are carried out to create uniform data.

The cleaned data is then converted into numeric form using the TF-IDF Vectorizer. This technique allows us to represent text in vector form so that it can be used by machine learning algorithms. The three algorithms used in this project are K-Nearest Neighbors (KNN), Naive Bayes, and Support Vector Machine. The results of the analysis show that KNN and Naive Bayes have the highest level of accuracy, which is 97.61%, while for SVM, the accuracy is slightly lower at 96.80%. This means that the results show that the machine learning model is reliable in analyzing public sentiment based on social media text. With a deeper analysis, it can be seen that the trend of public opinion tends to be positive, which means that the public is still accepted in the 'Free Meals' initiative. It cannot be ignored that there are a small number of people who express negative and neutral sentiments, reflecting concerns or misunderstandings about the program.

From the success of the project, we can draw the following conclusions:

a) Data quality is crucial: Good data cleaning will play a big role in achieving better results after analysis.

b) Appropriate model selection: KNN and Naive Bayes performed very well, so they are the primary choices for this case.

c) Dominantly positive sentiment: The Free Food Program has received strong positive support from the public.

Overall, the project successfully achieved its goal of measuring public response to a policy program in a structured and data-driven manner. The project also demonstrated that social media sentiment analysis can act as a powerful tool in evaluating public policies in real time.

5.2 Future Work

While this project has provided a lot of insights, there are several areas that can be further developed to improve the quality of analysis in future. Some suggestions for future work are as follows:

a) Larger Data Volume

In the current project, the dataset used consists of only a few tweets from Twitter. This data can also be taken from other social media platforms such as Facebook, Instagram, or TikTok for a broader analysis to provide a broader view of public sentiment.

b) Larger Demographic Analysis

This can be extended by integrating demographic information, such as age, location, and gender of users. This will help in providing insights into the variation in public responses across a group of people.

c) Using Deep Learning-Based Model

Traditional models were used in this work, but deep learning-based models using LSTM or Transformer—for example, BERT—will provide better accuracy by capturing complex contextual information from text in future approaches.

d) Clarity in Models

In data-driven decision making, interpretable models must be developed. Further research could be conducted to understand why the model makes certain predictions, making the results of the analysis more understandable to policy makers.

The above steps will allow further research to increase the scope of this project, improving the accuracy and relevance of the results. The current project has paved the way for the use of social media data as an effective public policy evaluation tool; thus, further development will have greater implications in the future for strategic decision making.