Research Article

Sentiment Analysis on the Quality of Public Services with User Satisfaction Prediction of YuhSinau Application Managed by BKPSDM Kabupaten Kebumen Using LSTM Method

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Abstract.

The quality of public services is critical in providing effective and responsive governance in an increasingly digital society. The development of the YuhSinau application by the Personnel and Human Resource Development Agency (BKPSDM) of Kebumen Regency offers an innovative response to the growing need for e-learning solutions for local government civil servants (Pegawai Negeri Sipil or PNS). However, determining the app's effectiveness and user satisfaction is critical. This demands a thorough sentiment analysis in order to acquire insights into users' thoughts and opinions about the quality of public services supplied by YuhSinau. The Long Short-Term Memory (LSTM) approach is used in this article to examine feelings and forecast customer pleasure. Data collection from multiple sources, initial data preprocessing, LSTM model construction, training, validation, and prediction are all part of the process. The results show that the model has some drawbacks, most notably its failure to appropriately explain variation in target data due to a negative R-squared value. Enhancements to the LSTM architecture, hyperparameter adjustment, and the use of more diverse and representative training data are proposed to improve the model. Continuous review and responsiveness to user comments are critical for improving the quality of public services via the YuhSinau application.

Keywords: sentiment analysis, public service quality, user satisfaction, YuhSinau application,LSTM method

1. Introduction

Quality public services are a necessary foundation for effective and responsive governance. In an increasingly digital world, public service maintenance innovation is becoming increasingly vital [1,2] The adoption of the YuhSinau application is one of the innovations put out by the Civil Service Development Agency (BKPSDM) in Kebumen district. This program offers e-learning options for Civil State Officers (PNS) in the Kebumen governance context.

The BKPSDM-operated YuhSinau application in Kebumen district is more than just an online learning tool. Furthermore, the program displays municipal governments' efforts to fulfill the demands of increasingly rapid technological changes [3, 4]. Civil government officers, as the backbone of bureaucracy, must always be equipped with current knowledge and abilities [5]. YuhSinau's application plays a strategic significance in this scenario.

However, the work of the application in a assisting PNS learning and development is still under covered, Through in-depth sentimental analysis, these inquiries promote a larger knowledge. Sentimental analysis is a technique that can provide a thorough understanding of people' sentiments and thoughts about a product or service [6,7]. Sentiment analysis will be utilized in this context to assess the quality of public service offered by the YuhSinau application. This comprehension will assist the BKPSDM of Kebumen district in making better judgments on the development and improvement of its services.

This article will go over how to perform a perceptual analysis of the quality of public services by predicting user satisfaction with the LSTM (Long Short-Term Memory) method, as well as the significance of the results of such an analysis in order to improve public service quality, public service, public services, services, and more efficient government.

2. Method

Data gathering is the initial step in sentimental analysis. The opinions and comments of YuhSinau app users will be examined as text data. This information can be collected from a variety of sources, including Google Play Store reviews, social media platforms, and user surveys. It is critical to collect representative data to get accurate sentimental analysis outcomes [8]. After gathering the text data, the data must be preprocessed. Text data is frequently cleaned and readied for use in analysis. This entails removing reading marks, turning all text to minuscule letters, and breaking words down into tokens. Proper initial data processing will enable the LSTM model to better comprehend sentence context [9].

When the text data is complete, the next step is to build an LSTM model. Long Short Term Memory (L STM) is a sort of neural network that can recognize temporal correlations in sequential input. This model is capable of detecting patterns and contexts in user review content. At this point, an LSTM architecture that suits the complexity of the data to be processed must be chosen. The LSTM model should be trained using data that has already been processed. The training data is a collection of user evaluations with a sentiment label (positive, negative, or neutral). The model learns to distinguish sentiment-related patterns in the review text during training. The model is validated and tested after it has been trained. Data that was not used during training will be used to evaluate the model's performance. Metrics like accuracy, precision, and acquisition are used to assess how successfully algorithms predict sentiment.

The final step in sentiment analysis is to forecast user satisfaction using a trained model. The model analyzes incoming reviews and evaluates whether they are good, negative, or neutral. The prediction findings can be utilized to assess user satisfaction with the YuhSinau application, providing useful information to Kebumen district BKPSDM in order to improve its service.

3. Result and Discussion

The data set used in this study is a fictitious data set derived from reviews on college websites. The data is a collection of reviews that have been labeled and cleansed of the user's personal information. The existing reviews have three labels: Positive, Neutral, and Negative.

One example of a Positive Review: "Online ratings are very neat and easily accessible, all the latest academic information is in handy." However, some users believe that this information is either limited or irrelevant. One example of a Negative Review is "Functions in campus information systems are often slow in responding to user actions, making the process slow."

The results of sentiment analysis were an important step in evaluating the quality of public services provided by the district of Kebumen's application YuhSinau BKPSDM. Certain limitations of the model used were discovered during the analysis process. Although the mean squared error value (MSE) is around 144.25, indicating a relatively low prediction error rate (10), it should be recognized that model evaluation requires more than just statistics [11].

The main source of worry is a square R value (determination coefficient) of roughly -0,0095, indicating that the model does not match the data and cannot effectively explain the target data variance. It denotes a discrepancy between model predictions and changes in user behavior or emotions [11]. This discovery raises concerns about what might occur throughout the analysis.

A negative R-square value can be created by a variety of circumstances [12]. The complexity of user review data is one possible factor. Text data frequently contains

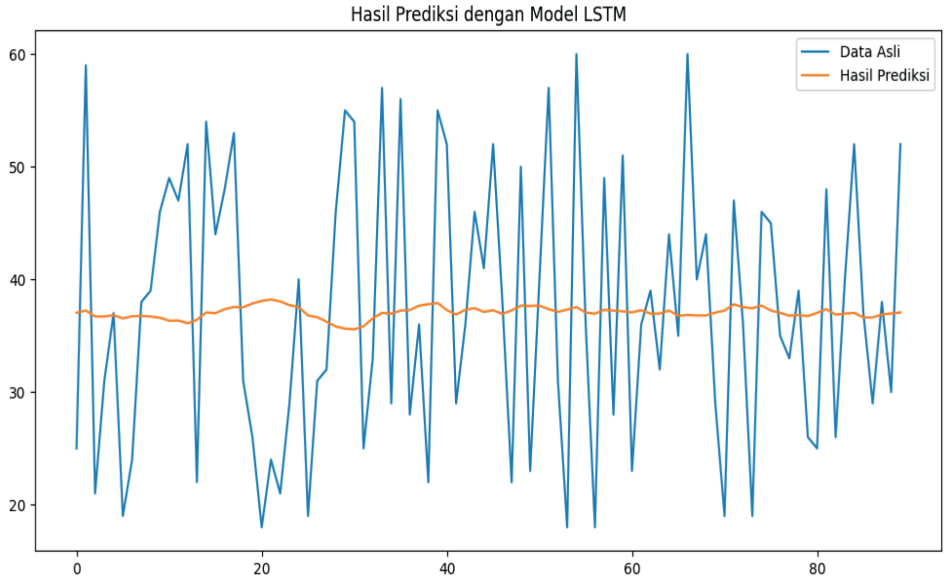

Figure 1: Predicting Results with LSTM Method.

several nuances, linguistic variants, and subtexts. The LSTM model utilized in this investigation may not fully accommodate the amount of complexity. But we must not give up hope. Several actions can be performed to construct models and improve the findings of sentimental analysis. First, enhancing the architecture of the LSTM model could be the solution. We can improve the model's understanding of the context and patterns of the more complicated review text by adding a layer or neuron [13].

Furthermore, hyperparameter settings must be considered. Experimenting with different hyperparameter combinations, such as learning speed or the number of training periods, can assist improve the model's performance [14]. It is also critical to examine the quality of the data utilized in training. More diverse and representative data can aid in the training of a better model, improving its ability to interpret human emotions.

Model performance can be affected by optimizing algorithms during sentiment analysis. More complicated algorithms or better text processing techniques may be required. Beyond the technical considerations, it is critical to note that the outcomes of sentimental analysis are not the end objective, but rather a means to an end goal. The main goal of the application YuhSinau is to improve the quality of public services offered by the BKPSDM district of Kebumen. As a result, in addition to model perfection, it is critical to assess the efficiency of the improvement methods put in place.

In this context, long-term evaluation is required. By observing changes in UMK, R-squared values, and user satisfaction, the BKPSDM district of Kebumen can continue to assess the impact of previous improvements and make additional modifications as needed. Keep in mind that in sentiment analysis, dealing with complexity in user review data is common. The YuhSinau app may receive reviews with a variety of writing styles, situations, and points of view. To address this difficulty, a more complex and responsive approach is required. In addition to relying on sentiment analysis results, the BKPSDM district of Kebumen should be open to direct input from YuhSinau program users. This entry may provide useful insights that are not reflected in sentimental analysis data.

Despite the challenges, this endeavor demonstrates Kebumen district BKPSDM's dedication to long-term progress in providing quality public services. It is hoped that through continuous improvement and development efforts, the sentiment analysis model will be able to provide more accurate and reliable results, assisting Kebumen district BKPSDM in making the YuhSinau application a more effective tool in supporting PNS learning and development while also increasing user satisfaction.

4. Conclusion

The sentiment analysis of the application YuhSinau BKPSDM district of Kebumen yielded some significant data values. A mean square error (MSE) of roughly 144.25 implies a low rate of model prediction error. The square R value (determination coefficient) is, however, around -0,0095, suggesting that the model does not match the data and cannot properly explain the target data variance.

Inconsistency between model prediction and variation in user behavior or emotions shows a model shortcoming [15]. As a result, more effort is required to increase model performance. Improvement attempts may involve refining the LSTM model architecture, adjusting hyperparameters, or making better use of data to train models. With sufficient refinement, the model is projected to offer more accurate prediction results with lower MSE values and higher R-squared values, allowing it to better explain data fluctuations.

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