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Research Article

Impact of GIS and Naive Bayes on Ride-Hailing User Satisfaction

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ABSTRACT

In the digital age, consumer behavior has shifted towards online media, facilitated by the affordability, speed, and advancement of super apps like GOJEK. These apps offer multiple services in a single platform, transforming how people fulfill their daily needs. GOJEK, with its extensive services, has emerged as a dominant player in Indonesia, commanding a large user base. Despite competition from Grab, GOJEK's dominance underscores its efficient integration of the super app concept. A research study aims to assess and analyze the satisfaction levels of GOJEK users in Indonesia using the Naive Bayes method. The study seeks to understand user interactions with super apps and contribute to the evolving digital landscape of Indonesian society. The integration of GIS and data analysis techniques presents a promising avenue for improving user satisfaction and the overall success of ride-hailing services. As the industry continues to expand and evolve, the insights derived from this research could be crucial in shaping the future of the ride-hailing industry. The research employs the Naive Bayes classification method to gauge the probability of satisfaction among GOJEK users in Indonesia. The analysis of satisfaction probability is conducted to understand the extent to which users are content with the service. The study utilizes a dataset comprising 20,000 GOJEK user records from Indonesia. The dataset preparation involves the removal of missing values, duplicate entries, and data transformation to incorporate a label column that classifies user satisfaction based on the scores provided. The computations of prior, likelihood, and posterior probabilities using the Naive Bayes method reveal that the probability of GOJEK user satisfaction in the "Satisfied" category surpasses that in the "Dissatisfied" category. The model evaluation demonstrates a high level of accuracy, with accuracy and precision values reaching 0.645, a Recall value of 1.0, and an F1-score of 0.784. These outcomes indicate that the Naive Bayes model effectively predicts GOJEK user satisfaction based on the scores given.

Keywords: Naïve Bayes, Satisfaction, Gojeg, GIS, Ride Hailing

INTRODUCTION

The ride-hailing industry has experienced remarkable growth in recent years, with industry leaders like GOJEK dominating the Indonesian market [1]. However, the key to sustaining this growth lies in user satisfaction. It's not just a factor, but a pivotal element that directly shapes customer loyalty and retention [2]. Geographic Information Systems (GIS) offer a robust tool for analyzing and understanding the spatial aspects of user satisfaction. By integrating GIS with data analysis techniques like Naive Bayes, companies can gain crucial insights into the factors that influence user satisfaction and devise targeted interventions to enhance service quality [3], [4]. Previous studies have shown that GIS-based interventions can have a significant impact on user satisfaction. For example, by analysing spatial patterns of demand and supply, ride-hailing companies can optimize driver allocation, reduce wait times, and improve the efficiency of their services [5]. This, in turn, can lead to higher user satisfaction rates, thereby benefiting the companies in terms of customer loyalty and retention. Additionally, GIS can be used to identify areas where service improvements are most needed, allowing companies to target their resources effectively. However, it's important to note that GIS data can be complex and require significant processing power, which may pose challenges for some companies. Naive Bayes, a probabilistic machine learning algorithm [6], has been applied in various contexts to [4], [7]. By classifying user feedback based on given scores, Naive Bayes can help identify the features or attributes that most influence satisfaction. This information can tailor services to meet user expectations and preferences. Integrating GIS and Naive Bayes offers a unique opportunity to understand and improve user satisfaction in ride-hailing. By combining the spatial analysis capabilities of GIS with the predictive power of Naive Bayes, companies can develop interventions that are both geographically targeted and informed by a deep understanding of user preferences[8]. This approach can significantly enhance user satisfaction and, ultimately, the success of ride-hailing services [2], [9] like GOJEK.

In the era of advances in digital technology, shifts in consumer behavior towards online media have become an unavoidable phenomenon. The increasing affordability, internet speed, and the development of super apps have revolutionized how people meet their daily needs, offering unparalleled convenience and efficiency. A super app, as proposed by Cobben et al. (2022), is a model that allows users to perform most smartphone functions in a single application or set of integrated applications [10]. This consolidation of services within a single app has significant implications for consumer behavior, as it simplifies and streamlines the user experience. One of the prominent examples of this super app concept can be found on the GOJEK platform in Indonesia. As a leading super application service provider, GOJEK has become the backbone of many Indonesians in meeting their transportation, food delivery, cargo delivery, and various other service needs.

Based on daily social.id data as of June 2023, GOJEK has around 170 million users worldwide and more than 90% of its users come from Indonesia. This phenomenon marks the expansion of GOJEK users in Indonesian society, thereby creating an environment where GOJEK becomes an important element in everyday life for smartphone users. GOJEK offers a wide range of services, including transportation, food delivery, cargo delivery, and various other services, catering to the diverse needs of its users. Meanwhile, GOJEK's main rival, Grab, recorded 187 million downloads of the Grab application in the same month. This means that Grab controls 66% of the market share in Indonesia. However, despite Grab's large user base, GOJEK's dominance in Indonesia is a testament to the significant influence of the services offered by the application on consumer behavior. GOJEK's success in providing these various services reflects the effective integration of the super application concept, meeting the needs of various users through one application.

Even though GOJEK has attracted many users, the question is user satisfaction with the services provided. Analyzing satisfaction levels is very important to identify potential improvements and service development. Therefore, this research will measure the probability and analyse the possibility of GOJEK user satisfaction in Indonesia. This research uses the Naive Bayes method to measure the likelihood of user satisfaction levels when using GOJEK. Through this study, we hope can better understand the dynamics of user interactions with super apps like GOJEK, especially in the context of the increasing digitalization of Indonesian society. In conclusion, the potential of GIS-based interventions and the application of data analysis techniques like Naive Bayes in improving user satisfaction in the ride-hailing industry is a topic of growing interest and importance [11]. As companies strive to enhance their services and gain a competitive edge, the integration of GIS and Naive Bayes presents a promising avenue for achieving these goals. The future of this research is bright, with the likelihood of yielding valuable insights and contributing to the ongoing evolution of the ride-hailing industry.

Geographic Information System:

Several previous studies discussed about on dynamic ride-hailing matching algorithms, focusing on fairness and efficiency. It introduces a new algorithm based on reinforcement learning, aiming to improve fairness, platform utility, and matching efficiency. The experiment was conducted on real data from three major cities in China, showing significant improvements in fairness and platform utility compared to baseline algorithms. The study also addresses challenges in the ride-hailing industry, such as order response rate and algorithm design. Overall, the research presents a comprehensive approach to algorithm fairness evaluation and matching efficiency, with a focus on real-time performance and practical application [12].

Naïve Bayes Method:

According to [4], the Naive Bayes classifier comes from Bayes' theorem, taken from the name of the British scientist Thomas Bayes, which is a classification method where this method is widely used in various fields. This method assumes that the predictor attributes are independent of each other and are the basis for classification decisions. Naive Bayes simplifies Bayesian algorithms using probabilistic and statistical methods and is very effective in text or document classification. In this classification technique, the document category value is determined based on the features or words that appear in the document. This method uses Bayes' probability theorem to predict future probabilities based on previous information or data. One of the main advantages of Naive Bayes is its ability to perform well on small training data sets used for parameter estimation. Its computational efficiency, simplicity of understanding and implementation, and ability to handle numerical and categorical data make it popular. However, Naive Bayes has limitations, especially the assumption of independence between predictors is only sometimes met and can affect accuracy. In addition, this method is sensitive to noise in the training data. Naive Bayes is used in text classification, spam detection, medical diagnosis, and data mining prediction. Naive Bayes is excellent at classifying and organizing information in text-related tasks, making it suitable for applications such as spam filtering. Moreover, its application in medical diagnosis shows its ability to handle complex data sets. Naive Bayes equation:

$$P(C|\mathrm{X}) = P(C)P(X|C)/P(X) \qquad (1)$$

Where:

P(C|X)	=	Posterior Probability
P(C)	=	Prior Probability
P(X|C)	=	Likelihood Probability
P(X)	=	Evidence Probability

The Naive Bayes equation, which expresses the posterior probability *(P(C|X))*, involves the prior probability *(P(C))*, the likelihood probability *(P(X|C))*, and the evidence *(P(X))*. This equation captures the essence of Naive Bayes by combining prior knowledge with observed data to make informed predictions. Naive Bayes incorporates Gaussian distributions to calculate probabilities when dealing with numerical data.

Probability:

Probability is a mathematical and statistical concept used to quantify and explain uncertainty quantitatively. Probability is used to estimate the likelihood of an event occurring. The greater the possibility of an event occurring, the greater the probability of it occurring (Wahyono et al., 2020). Probability is expressed as a value between 0 and 1, where 0 means the event is unlikely to happen, and 1 means the event will happen. The closer to 1, the greater the probability of the event occurring. Probability is used as the basis of many statistical methods, especially in inferential statistics. For example, the concept of probability distribution is used in confidence intervals, hypothesis testing, regression analysis, and other statistical methods of an inferential nature.

Customer Satisfaction:

User satisfaction can be explained as the user's happiness or disappointment after comparing the performance or product results obtained with his expectations. This includes the level of user perception after comparing the product received with their expectations and post-purchase reviews indicating that the product at least met or even exceeded their expectations. Users describe products that meet standards and may even exceed their expectations. Factors that play an essential role in shaping user satisfaction include product quality, pricing, customer service, and the overall purchasing experience. Moreover, the recognition of the profound role of emotions, user perceptions, and preconceived expectations suggests that user satisfaction is not solely dependent on the physical attributes or service itself, but also on the complex interactions between these elements. Thus, user satisfaction becomes the organic result of interrelated dynamics, reinforcing that user engagement and their response to the product are rational, emotional, and psychological.

METHODS AND METHODOLOGY

Software development method with a waterfall approach, the waterfall model is a sequential software development approach where progress flows downwards in distinct phases: requirements, design, implementation, testing, and maintenance. Each phase must be completed before proceeding to the next, resembling a cascading waterfall. It offers clarity and structure but lacks flexibility for changes once a phase is completed. This method emphasizes thorough planning upfront, making it suitable for projects with well-defined requirements and stable environments. However, it may not be ideal for dynamic or evolving projects due to its rigid nature and limited adaptability.

To carry out this research, data collection procedures are needed, and data processing stages are carried out in data preprocessing and classification modeling using the Naive Bayes classifier algorithm. The stages for the research method can be seen in Figure 1 below:

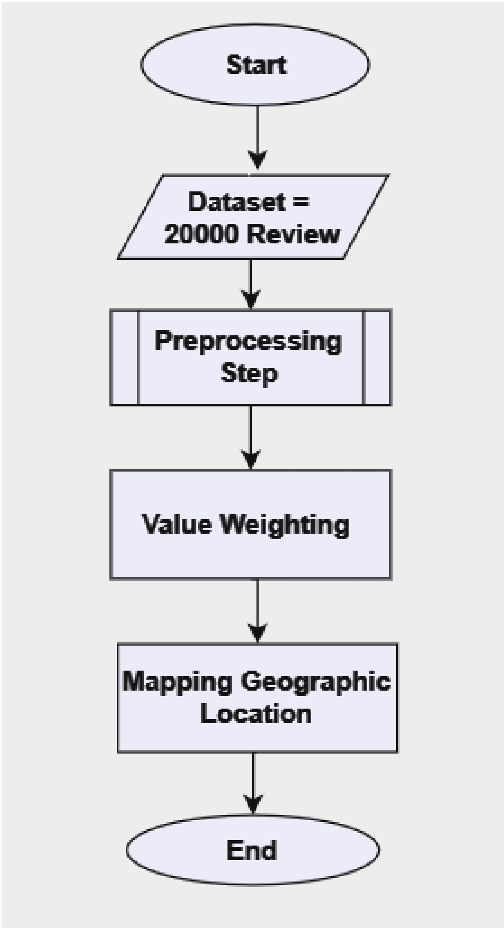

Figure 1. Flowchart of Open Research Steps

Figure 1 illustrates the stages followed by the researcher in conducting this study. The researcher utilizes the Naïve Bayes algorithm as the main algorithm in this research. The following is an explanation of each stage: 1) Data Collection: the researcher utilizes Google Colab as the primary tool for data extraction in this stage. The data extracted consists of reviews for the Gojek applications from Google Play. The review data is collected from April 26, 2024. 2) Pre-processing Data or pre-processing transforms data into a form that is easier, simpler, and more suitable for the user's needs. In this study, there are several processes involved in this data preparation stage, which are as follows: a)Tokenize, tokenization is a process aimed at grouping words that are present in each sentence; b)Transform Case is a process that functions to convert all letters in the data into lowercase. 3) Value Weighting: value weighting is a process used to assign weights to different attributes or features within a dataset based on their importance or relevance to the analysis or model being constructed. These weights are typically assigned to indicate the significance of each attribute in contributing to the desired outcome, such as classification accuracy or prediction performance. 4) Mapping Geographic Location is a mapping process of location points that are used as a visual of which areas have a busy level of GOJEK customer service.

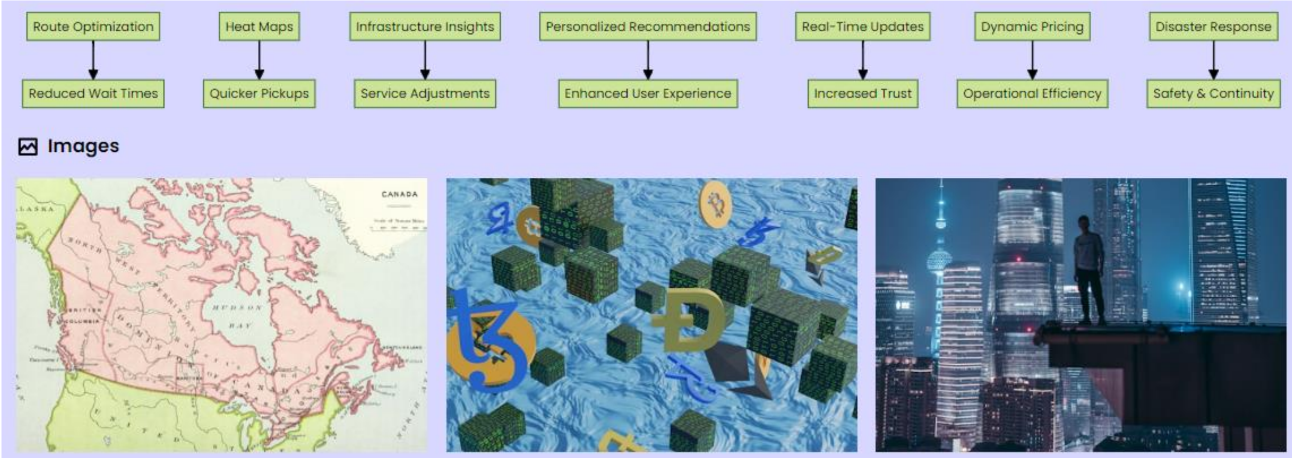

Figure 2. Proposed Model Developing Ride-Hailing User Satisfaction

RESULTS

Present the findings of the research paper in this section.

Dataset:

The dataset used in this research was taken from Kaggle, which contains 20.000 data on GOJEK users in Indonesia. This dataset consists of the username column which is the name of the user; the score, which is the user's assessment with a value in the range 1-5; the at field, the column which contains the date the user sent the evaluation, and the content field which contains comments given by the user to explain their assessment of their use. on the GOJEK application.

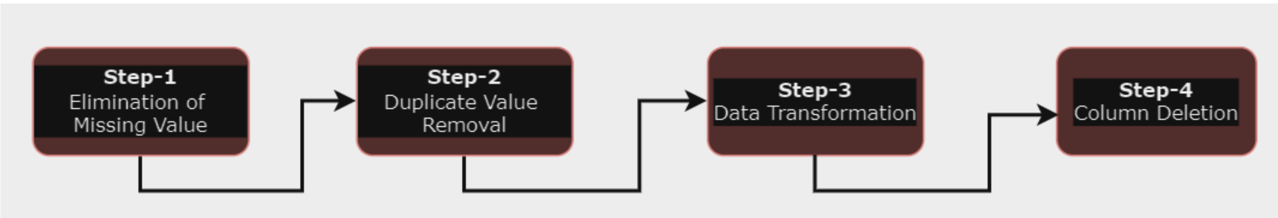

Figure 3. Step by step Preprocessing Data

Pre Processing Data:

After the dataset is obtained, the following data-cleaning preprocessing step is carried out. This process is carried out so that the data is clean, consistent, and ready to be applied to the desired model or analysis. The `df.isnull().sum()` code counts the number of null (*NaN*) values in each column in the `df` frame. In the first step, `.isnull()` produces a boolean data frame where each cell indicates whether the corresponding value in the original data frame is null or not; then, `.sum()` is used to sum these boolean values in each column, gives the total number of null values in each column of the data frame. The result is a Pandas Series, as shown in Figure 3, with a hint of the number of null values for each column. These results will provide insight into how much value is lost and can help in the decision-making process regarding appropriate data-handling strategies:

```
[6]  # check if there are any Null values
     df.isnull().sum()

     userName    0
     score       0
     at          0
     content     0
     label       0
     dtype: int64
```

Figure 4. Check Data with Null Values

The following process is duplicate value removal. This is done to delete values that are considered to be duplicates or have the same value. The `*df.isnull().sum()*` code is used to check for null (NaN) values in each column in the `df` data frame. This process begins with using the `.isnull()` method, which produces a new data frame with a boolean value (`*true*` or `*false*`) for each cell in the original data frame. In this context, a `**true**` value indicates that a cell contains a null value, while a `*false*` value indicates that the value in that cell is not null. The next step involves using the `*.sum()*` method after using `*.isnull()*`. The `*.sum()*` method adds the boolean values in each data frame column. Thus, the final result of `*df.isnull().sum()*` is a pandas series containing the total number of null values in each data frame column, sorted according to the column order in the data frame. The results of this process provide an understanding of how many values are missing in each attribute, which is essential for deciding on appropriate data handling strategies, such as removing null values, filling in null values with proper values, or other methods relevant to the context of data analysis or modelling what will be done.

	userName	content	score	at	appVersion
0	Yuga Edit	akun gopay saya di blok	1	2022-01-21 10:52:12	4.9.3
1	ff burik	Lambat sekali sekarang ini bosssku apk gojek g...	3	2021-11-30 15:40:38	4.9.3
2	Anisa Suci Rahmayuliani	Kenapa sih dari kemarin sy buka aplikasi gojek...	4	2021-11-29 22:58:12	4.9.3
3	naoki yakuza	Baru download gojek dan hape baru trus ditop u...	1	2022-09-03 15:21:17	4.9.3
4	Trio Sugianto	Mantap	5	2022-01-15 10:05:27	4.9.3

Figure 5. Duplicate Value Removal

The third step is data transformation; this process is carried out to obtain more structured information and can facilitate analysis or modeling, which involves classifying satisfaction based on the scores given. Figure 3 shows the data transformation process in the `*df*` data frame. The process begins by adding a new column named 'label'. This column is generated from the 'score' column, where each value is changed based on conditions determined by the lambda function. Specifically, the lambda function evaluates each value in the 'score' column and determines whether the value is greater than 3. If the value is greater than 3, the 'label' column will be filled with the value 'Satisfied,' whereas if not, it will be filled with the value 'Not satisfied.' Next, the results of the transformation are displayed using the command `***print(df[['userName,' 'score,' 'label']]),***` which selects a specific subset of the data frame to be displayed. The final result of this process is shown in Figure 3, namely in the form of a transformed data frame. Then, this dataset has a new column in the form of a 'label,' which provides satisfaction classification based on the value in the 'score' column.

```
[18] columns_to_drop = ['at','content']

     df.drop(columns=columns_to_drop, inplace=True)
     df.head()
```

	userName	score	label
0	Robbi Eko	5	Puas
1	mimi cedar	5	Puas
2	Elisabeth Kiswati Ladiyo	5	Puas

	userName	content	score
133	Abu karim aljabbar Mkatiksaidi	Ramah banget	5
134	Fathan Mubina	Setelah update kok nggak bisa dibuka	4
135	Nyauw Jin Fie	Good	5
136	Tanaka Kun	Good	5
137	Anton S.	Sangat membantu	5

Figure 6. Column Process Deletion

After the previous data transformation, the fourth step is deleting specific columns from the data frame. In the code above, this step is carried out using the variable `***columns_to_drop***,` which contains the names of the columns to be deleted, namely '**at**' and '**content**.' The `drop` method on the `df` data frame allows us to delete these columns. By setting the `***columns***` parameter in the `drop` method with the value `***columns_to_drop***`, we tell pandas to remove the mentioned columns from the data frame. Setting the parameter `***inplace=True***` indicates that these changes will be applied directly to the data frame `***df***', without creating a new data frame. This process of deleting columns can be helpful in situations where they are irrelevant to the analysis or modelling to be performed or if they contain no longer needed information. The result is as in Figure 4, namely a data frame that has been changed with the previously specified columns ('***at***' and '***content***') having been deleted. This transformation can simplify the data structure according to the desired analysis needs.

Probability Calculation Using Naïve Bayes Method:

The Naive Bayes method is applied to calculate the probability of satisfaction. At this stage, the researcher uses the label column that was added previously. The Naive Bayes method is used to estimate the likelihood of user satisfaction with the score inputted by each user using the basic formula from Bayes' theorem; this method combines prior probabilities with feature distribution probabilities to produce posterior probabilities. This posterior probability is then used to predict user satisfaction based on the given feature values. Probability calculations are carried out by following the following equation:

$$P(C|\mathrm{X}) = P(C)P(X|C)/P(X) \quad (1)$$

Calculating the posterior probability of each category "Satisfied" and "Not Satisfied". This can be explained by applying the following formula (1):

Known:

P(C="Satisfied") = 0.6457

P(C="Not Satisfied") = 0.3543

Calculate:

P(X/"Satisfied") = 0.9148 + 0.0851

= 1.0

P(X/"Not Satisfied") = 0.7555 + 0.1251 + 0.1192

= 0.9999

*P(X) = (P(C="Satisfied") * P(X/"Satisfied")) + (P(C="Not Satisfied")*

** P(X/"Not Satisfied"))*

= (0.6457 * 1.0) + (0.3543 * 0.9999)

= 0.9999

P(C="Satisfied"/X) = P(C=" Satisfied ") × P(X/" Satisfied ") / P(X)

= 0.6457 * 1.0 / 0.9999

= 0.6457

P(C="Not Satisfied"/X) = P(C="Not Satisfied") × P(X/"Not Satisfied") / P(X)

= 0.3543 * 0.9999 / 0.9999

= 0.3543

In this calculation, the most significant probability value is the Posterior Probability of "Satisfied" (0.6457 > 0.3543), so the Naive Bayes model tends to predict that the satisfaction level of GOJEK users is included in the "Satisfied" category.

Implementation of Naive Bayes Classifier:

This method is applied by combining the prior probability with the feature distribution probability to produce a posterior probability. This posterior probability is then used to predict user satisfaction based on the given feature values.

```
Probabilitas Prior Puas: 0.6457
Probabilitas Prior Tidak Puas: 0.3543

Likelihood Puas:
5    0.914899
4    0.085101
Name: score, dtype: float64

Likelihood Tidak Puas:
1    0.755574
2    0.125176
3    0.119249
Name: score, dtype: float64
```

Figure 7. Calculation Prior Probability

The results of implementing the Naive Bayes method in calculating prior probabilities and likelihood are presented below. The prior probability is the probability of the appearance of the satisfaction category ('Satisfied' or 'Not Satisfied'). In this study, the prior probability of 'Satisfied' is calculated by dividing the number of entries with the label 'Satisfied' by the total number of entries and the prior probability of 'Not Satisfied.' After that, the likelihood calculation is carried out, where for the 'Satisfied' category, the likelihood is calculated by dividing the number of entries with the label 'Satisfied' that have a specific score by the total number of 'Satisfied' entries. A similar process was carried out for the 'Dissatisfied' category. The result of this step is a probability distribution for each score value in each satisfaction category. Furthermore, the results of calculating the prior probability and likelihood can be used in the Naive Bayes formula to calculate the posterior probability. This process underlies the Naive Bayes model's ability to predict user satisfaction based on the scores input by each user.

CONCLUSION

Summarize the main outcomes and their significance**.**

The results of posterior probability calculations using the Naive Bayes method show that the probability of GOJEK users being in the "Satisfied" category is 0.6457, higher than the "Not Satisfied" probability of 0.3543. Calculations using the Naive Bayes method show a high level of accuracy, with a value of accuracy and precision reaching 0.6457. The Recall value was 1.0, and the F1 score was 0.784. Conclusion based on the research results, researchers can draw conclusions that a consumer satisfaction prediction system can help an admin determine the classification of customer satisfaction with GOJEK's web-based services by applying the Naive Bayes method. The Naive Bayes method, by utilizing training data, obtains the result of classifying the probability value of the "satisfied" class as more significant than the probability value of the "not satisfied" class. Integrating GIS (Geographic Information Systems) and Naive Bayes analysis significantly impacts ride-hailing user satisfaction. GIS provides spatial insights, allowing companies to optimize routes, enhance service coverage, and improve response times, leading to higher user satisfaction. Naive Bayes analysis complements this by accurately predicting user satisfaction based on various factors, enabling personalized services and targeted improvements. Together, they enhance the overall user experience, increase customer loyalty, and drive the success of ride-hailing services by efficiently addressing user preferences and optimizing service delivery.

To advance the understanding and application of user satisfaction within super apps like GOJEK, several avenues for future research and development are proposed. Model Enhancement and Comparison involve refining the Naive Bayes Model to enhance its predictive capabilities and conducting comparative analyses with alternative algorithms to benchmark performance. Feature Analysis aims to identify critical factors influencing user satisfaction, including temporal dynamics, to uncover trends and influential events. User Segmentation and Personalization strategies involve categorizing users based on satisfaction levels for targeted strategies and tailoring services to individual satisfaction levels. Service Expansion and New Markets focus on strategizing service growth into new regions and comparing user satisfaction across different locales. Integration with GIS involves spatial analysis to map satisfaction geographically and route optimization using GIS data for efficient service delivery. Policy and Regulation Impact Assessment entails evaluating the effects of policy changes on satisfaction and formulating compliance strategies. Economic and Societal Impact Study examines super app usage's macroeconomic effects and societal implications. Cross-industry applications explore extending research to other super app services and customizing satisfaction models for diverse sectors. Technology and Innovation Influence study the impact of emerging technologies on satisfaction and the correlation between innovation rates and user satisfaction. User Experience (UX) and Interface Design involve informing app design improvements and researching the effects of enhanced accessibility on user satisfaction. Rigorous data analysis techniques, cross-validation, and ethical considerations regarding user privacy and data security should underpin these future works. Thank you to Universitas Negeri Yogyakarta for providing funding to hold research presentations at international conferences.

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Conflict of Interest:

Declare potential conflicts of interest; otherwise declare **"None**" or "The authors declare that there is **no conflict of interest".**

The authors declare that there is **no conflict of interest".**

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