

Sentiment Analysis of Public Service Performance in Jakarta Using the Naïve Bayes Algorithm and Support Vector Machine

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Abstract—An agency's service performance is crucial. Community feedback is one source of information that the government needs in order to enhance its performance. Nowadays, people frequently utilize social media to voice their dissatisfaction with the services they have received, offer recommendations for work programs, or just to get the most recent information. The outcomes of the public's opinions can be utilized as assessment material by business owners or associated agencies in order to make changes and raise the standard of future performance. The public can use a variety of social media platforms in Jakarta to voice any grievances, requests for information, and suggestions about the city's development process. Instagram is one of the social networking platforms that users frequently utilize. Monitoring every Instagram account on every Instagram account is a difficult task to complete by hand. Public opinion found on social media is automatically categorized in this study. Support Vector Machine (SVM) and the Naïve Bayes method are used for classification. Instagram user @dkijakarta provided the data that was used. After processing, the data will be divided into three sentiment classes: neutral, negative, and positive.

Keywords— Naïve Bayes, Support Vector Machine, sentiment analysis, public service.

I. INTRODUCTION

Nowadays, people's lives are experiencing many changes as a result of rapid advances in science and technology. Society has experienced a change in mindset towards becoming increasingly critical in responding to existing conditions, where with conditions like this the government's performance is required to be able to meet various community needs in all aspects. The government is a form of organization that works with the task of running a government system. One of the government's job functions is to disseminate information, communicate policies, work plans and performance achievements to the wider community, through traditional media, conventional media and new media. Communication using new media or internet technology can reach all parties directly and quickly, which is now widely enjoyed. Internet technology is one piece of evidence that we can see as the rapid development of technology in the fields of information and telecommunications. The development of the internet in Indonesia has shown significant development.

In this case, the government needs feedback from the community which is a source of information to improve performance. Open government is based on a collaborative and participatory process which will form a good government,

and therefore requires feedback from the community. The feedback needed from the community is not only positive, but also negative. The public often complains about the services that have been provided or make suggestions for work programs or simply want to know the information that currently exists. One way to get feedback from the public is to use social media.

This opinion given by the public can be used as evaluation material by company owners or related agencies to make improvements and also improve the quality of good performance in the future.

We can process public opinion data using data mining techniques. We can group opinions using data mining techniques, namely digging up information from a data source. Data mining usually uses 2 methods, namely classification and clustering. Classification is used to predict a class to map each data into a class target with the aim of accurately predicting the class target. The classification performed in this study is a multi-class classification where the system learns a map from an input to a set of classes with more than two classes. The classification that will be carried out in this research uses the Naïve Bayes method. The Naïve Bayes method is a method used to calculate the probability of an event occurring based on the influence obtained from observation results. This theory allows us to create a model of uncertainty from an event that occurs with facts from observations.

Based on the background of the problem, the problem formulation in this research is how to classify positive, negative and neutral comments from the people of Jakarta City?

1.1. Literature review

1.1.1. Understanding Naïve Bayes

Naïve Bayes is a method of classifying data with results of 62% being feasible and 38% not being feasible is assisted by the RFM method as data analysis for each customer based on segmentation using the "usage rate" attribute in the data so that the processed data can be a basic reference in making decisions [4]. Naïve Bayes Classifier is a simple, probability classifier based on Bayes' Theorem. Bayes' Theorem will be combined with "Naïve" which means that each attribute/variable is independent. Naïve Bayes Classifier can be trained efficiently in supervised learning [5].

$$P(H | X) = \frac{P(H/X) + P(X/H)}{P(X)}$$

X : Data with unknown class

H: Hypothesis data is a specific class

P(H/X): Probability of hypothesis H based on condition X (posteriori probability)

P(H): Probability of hypothesis H (prior probability)

P(X/H) : Probability of X based on the conditions in the hypothesis HP(X) : Probability of X

1.1.2. *Understanding Support Vector Machine*

Support Vector Machine (SVM) was first introduced by Vapnik in 1992 as a harmonious series of superior concepts in the field of pattern recognition [24]. SVM is an algorithm that works as follows and uses a non-linear algorithm to transform the original training data into higher order features. In this new form, it searches for the optimal partition of the linear plane (i.e, the "decision boundary" that separates tuples of one class from another). With appropriate nonlinear mapping for sufficiently high dimensions, data from two classes can always be separated by a hyperplane. SVM finds this plane using support vectors (the "big" training tuples) and edges (defined by the support vectors).

II. RESEARCH METHODOLOGY

In this research, the data collection method used is Primary Data and Secondary Data:

1. Primary data

Data obtained directly from the research object through the process of observation and literature study.

2. Secondary Data

The @dkijakarta Instagram data collection stage was carried out by crawling using a crawler application. By using this application we can retrieve all the tweet data we need and we can use it according to our analysis needs.

In this case, it explains the steps taken to obtain a research methodology, which is a stage that must be implemented so that research can be carried out more focused and makes it easier to analyze existing problems.

The research stages are explained as follows:

1. *Identification of problems*

Defining the problem is where the author deals with the research problem. The method used is the SWOT method for analyzing system requirements.

2. *Collecting data*

Collect data by collecting primary data and secondary data.

3. *Data Preprocessing*

At this stage, the raw data obtained is processed to convert it into data that is ready to be used. The processes carried out in this stage are cleaning the document from words that are not needed to reduce noise, making the letter forms uniform and deleting numbers and punctuation, changing sentences into words, carrying out the process of sorting words which are connecting words and taking the base word of a word that has an affix. For this data preprocessing stage, all steps are carried out manually. The following is the data preprocessing flow that will be carried out in this research:

a. *Cleansing*

Cleaning is the process of cleaning a document from unnecessary words to reduce noise. The words removed are HTML characters, keywords, emotion icons, hashtag(#), username(@username), url(http://site.com), and email(name@site.com).

b. *Case folding*

Case folding is the uniformity of letter shapes and the deletion of numbers and punctuation. In this case, only Latin letters between a and z are used.

c. *Tokenizing*

Tokenizing is the process of changing sentences into words.

d. *Stopword removal*

Stopword removal is the process of sorting out connecting words such as "and", "on", and so on.

4. *Data analysis*

Analyze and process data obtained from primary data and secondary data.

5. *Study of literature*

Study and collect sources in the form of books, magazines, e-books related to the concept in research.

III. RESULTS AND DISCUSSION

The data used in this research, both for the testing and training stages, is data collected from crawling results from the @dkijakarta Instagram account during a certain period from 1 October 2023 to 30 December 2023. The data obtained is in the form of raw data totaling 5836 data. The attribute that will be added is the classification attribute which is the classification class label of the existing dataset. The data used in training data and testing data each go through the same data preprocessing stages. The division of training data and test data in this research is 70:30.

In text classification, the goal that will be produced is to create a model that can classify document classes according to the data used. The classification carried out in this research uses the Naïve Bayes algorithm and Support Vector Machine (SVM). In order to get good classification results, various treatments are carried out in each model. There are 2 scenarios carried out in this research to obtain the optimal model.

1. *Scenario 1*

The implementation phase has been carried out and produced various values. Scenario 1 is run using the Naïve Bayes algorithm. There are 3 models that are worked on with different paths. Analysis of the results of model implementation will be presented below.

a. *Model 1*

Model 1 is carried out with a basic classification algorithm without additional configuration. The accuracy value obtained was 76.01%. With this accuracy value, it is not an optimal model, because only standard treatment is carried out.

b. *Model 2*

Model 2 is carried out using an algorithm developed from model 1. The algorithm that is run is trying to assign different weights. If model 1 is run using the Tf weighting method, in model 2 3 weighting methods will be given with the same frequent word value, namely 50. The results show that the use of the weighting method has an effect on the accuracy value.

TABLE 1. Accuracy results for each weighting method

Frequent words	Accuracy Value (percentage)		
	Tf	Tf-IDF	Binary
50	76.01	77.25	75.67

It was found that the Tf-Idf weighting had better accuracy results of 1.24%. Among the three weightings, the binary result has the lowest value. In model 2, the results obtained were also not optimal because the difference was only 1.24%, so it was necessary to try a third model.

c. Model 3

Model 3 is carried out using an algorithm developed from model 2. The algorithm that is run is trying to assign frequent word values. Giving different frequent word values will have an influence on the results. This is also used to see whether all weighting methods are able to meet all values and can produce the best accuracy. The frequent words values tested are 1 to 100 with a distance of 25.

TABLE 2. Accuracy results with frequent word experiments

Frequent words	Accuracy Value (percentage)		
	Tf	Tf-IDF	Binary
1	58.33333	66.89189	58.33333
5	71.95946	72.63514	71.73423
25	74.43694	76.57658	74.43694
50	76.01351	77.25225	75.67568
75	76.68919	78.04054	77.59009
100	77.36486	-	77.36486

It was found that the Tf-Idf weighting method got the best results but only stopped at a frequent word value of 75. For a frequent word value of 100, the Tf-Idf method could not fulfill this because there was no number of words that appeared during the weighting process. The following are the results of the number of words that appear in each frequent word.

TABLE 3. Number of words that appear

Frequent words	Accuracy Value (percentage)		
	Tf	Tf-IDF	Binary
1	7039	3826	7039
5	864	660	841
25	133	48	126
50	52	11	46
75	25	2	21
100	10	0	9

d. Model 4

The fourth model will be carried out in a flow manner, namely reviewing the preprocessing stages by trying to manually equate all the words in each data. The results obtained will be summarized in Table.

TABLE 4. Accuracy results after standardization

Frequent words	Accuracy Value (percentage)		
	Tf	Tf-IDF	Binary
1	62.51442	69.43483	62.51442
25	73.9331	76.35525	73.9331
50	75.08651	78.66205	74.74048
75	76.81661	78.77739	76.58593
100	78.54671	-	78.54671

In Figure 1 you can see the difference in accuracy results after standardization and before standardization. These accuracy results were taken at a frequent word value of 75.



Figure 1. Comparison of results between standard and non-standard

To achieve an optimal model, further analysis needs to be carried out, namely trying to review what words appear in the 100 frequent words in the Tf, Binary method, and in the 75 frequent words in the Tf-Idf method.

e. Model 5

Seeing that the words that appear in model 4 do not reflect the sentiment results per classification class and contain many conjunctions, in model 5 a word deletion process (stopword removal) was carried out. This word deletion process is carried out using the Rstudio application. For a list of stop words, see the attachment. The algorithm carried out is the same as model 4, namely experimenting with frequent word values with 3 weighting methods.

TABLE 5. Accuracy results for model 5

Frequent words	Accuracy Value (percentage)		
	Tf	Tf-IDF	Binary
1	65.39792	69.20415	65.39792
25	74.5098	76.58593	74.62514
50	76.81661	78.43137	76.81661
75	78.31603	79.00807	78.08535
100	78.89273	-	78.89273

There was a change in the accuracy value which increased in the accuracy results in the three weighting methods.

1. Naive Bayes algorithm conclusion

If we look at all the experimental models up to the last one, the accuracy results range from only 77 - 78%. Meanwhile, with the model of deleting and weighting the word dictionary itself, there was no significant effect. The final accuracy result obtained was 78.77739%, so we can conclude that the optimal accuracy value in classification using this algorithm is 78.77%. Next, this model will be analyzed for its classification performance. Overall the Naïve Bayes algorithm is less than optimal in the data used in this research. Naive Bayes assumes that each word in each category is independent of each other.

2. Scenario 2 Results

The implementation phase has been carried out and produced various values. Scenario 2 is run using the Support Vector Machine (SVM) algorithm. The data that will be used in the SVM model experiment consists of 2 data, namely before being standardized (2958 data) and 2888 data that have been standardized. There are 5 models that are worked on with different paths. Analysis of the results of model implementation will be presented below.

a. Model 1

The results obtained with standard treatment are for the C and γ values produced which are standard without any changes, namely $C=1$, $\gamma= 0.0001420656$. In Table the differences in accuracy results between the two will be presented.

TABLE 6. Initial accuracy results for model 1

Kernels	Accuracy Value
RBF	78.04054
Linear	73.76126

It was found that better accuracy results were achieved using the RBF kernel. The difference obtained between the two is 4.27%.

b. Model 2

With standard C and γ values, the dtm weighting method will be carried out using 3 methods. The kernel used will be RBF and Linear. In Table the differences in accuracy results between the two will be presented.

TABLE 7. Accuracy results with different methods

Method Weighting	Accuracy Values in the Kernel	
	RBF	Linear
Tf	78.04054	73.76126
Tf-Idf	78.04054	67.56757
Binary	78.04054	71.95946

The results show that performing the classification using the RBF kernel provides better accuracy results. The weighting method applies only to linear butter as it is the same for RBF butter.

c. Model 3

In model 3, the experiment was carried out with standardized data, namely 2888 data. The basic classification algorithm used is to use the RBF kernel without additional configuration. In the RBF kernel, accuracy results were obtained at 79.81% at values $C=20$ and $\gamma=2-1.25$.

d. Model 4

Model 2 is carried out with a basic classification algorithm using a Linear kernel without additional configuration. In the Linear kernel, accuracy results were obtained at 71.97% at values of $C=20$ and $\gamma=2-1.25$, where the value of γ will have no influence on accuracy. In the Linear kernel the results obtained were 7.84% lower.

e. Model 5

Model 3 is carried out with a basic classification algorithm using the RBF kernel with additional configuration, namely providing a weighting method. For the values of C and γ , the range will be equal, namely $C=2-0.4$ to $C=20.4$ with a distance of 0.1 and 0.001. The complete results of the gridsearch that has been run will be displayed in the attachment. By looking at the values of $C=20$ and $\gamma=2-1.25$, it is found that the results of the Tf method are 79.81%, the Tf-Idf method is 79%, and the Binary method is 79.7%. Figures 2, 3 and 4 show the differences in accuracy results obtained with the same weighting method and the same C and γ values. This figure does not show where the accuracy is in the middle, but only

shows that with the combination of C and γ , the results with Tf have a greater value.



Figure 2. Gridsearch with Kernel RBF method Tf

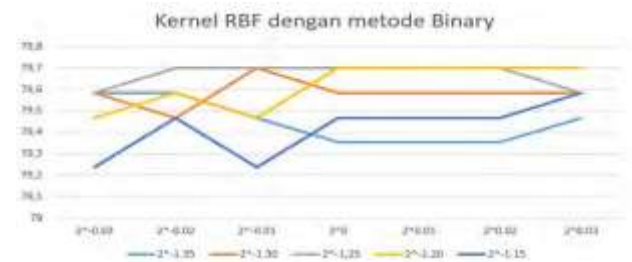


Figure 3. Gridsearch with Kernel RBF Binary method



Figure 4. Gridsearch with Kernel RBF Tf-Idf method

3. SVM algorithm conclusion

By using the SVM algorithm, good results are obtained using the RBF kernel without any stopwords. If we look at the same values of C and γ , the use of stop words and does not show the same results and tends not to change much. The best gridsearch optimization parameters carried out occurred in the range $C=2-0.06$ to 20.2 and $\gamma=2-1.35$ to $2-1.1$ with accuracy results of 79.7 to 79.81%.

The results of the Tf method show a better accuracy value because after reviewing the words there was 1 tweet that contained the same word and was repeated, namely "good good good". This word has an actual class, namely neutral, if in Tf this word is predicted as positive. Meanwhile, the Tf-Idf and Binary methods are predicted to be neutral. This is what makes the Tf method obtain good accuracy.

4. Data About Jakarta

To assess the performance of the classification results on the performance of public services in the City of Jakarta, implementation is carried out on data that is only related to the City of Jakarta.

4.1. Working with Naïve Bayes

The Naive Bayes algorithm is used to experiment with frequent words which are weighted using 3 methods, namely Tf, Tf-Idf, and Binary. The experimental results obtained are summarized in Table.

TABLE 8. Comparison of accuracy results with Naive Bayes

Use of stop words	Frequent words	Accuracy value		
		Tf	Tf-IDF	Binary
Without	1	57.95455	57.95455	57.95455
	5	61.36364	55.68182	60.22727
	50	53.40909	-	53.40909
With	1	60.22727	60.22727	60.22727
	5	52.27273	56.81818	52.27273
	50	56.81818	-	56.81818

The Tf-Idf method cannot display results because there are no words in the frequent words that are involved in the calculation process so they do not produce values and errors.

4.2. Working with Support Vector Machine

The SVM algorithm was used to work with 2 kernels, namely RBF and Linear, and the experimental treatment was the same as these kernels, namely with and without stopwords. The experimental results obtained are summarized in Table

TABLE 9. Comparison of accuracy results with SVM

Kernels	Method weighting	Without stop words	With stop words
RBF	Tf	59.09091	60.22727
	Tf-Idf	56.81818	56.81818
	Binary	57.95455	59.09091
Linear	Tf	67.04545	62.5
	Tf-Idf	61.36364	61.36364
	Binary	63.63636	63.63636

In Table, the results show that there are differences between Linear and RBF kernels. In the Linear kernel the accuracy value obtained is higher without stopwords, while in the RBF kernel the accuracy value obtained is higher using stopwords.

5. Classification Model Performance Analysis

Analysis of the performance of the classification model is carried out by looking at the precision, recall and f-measure values of each class. In this section, 2 classification performance analyzes will be carried out.

5.1. Scenario 1

The results of the classification model analysis showed that the best classification model was obtained, namely with an accuracy of 78.77%. Optimal accuracy does not mean that it has good performance. When looking at the confusion matrix, the data could not be classified correctly so many 0 values appeared, so another model was used, namely with an accuracy of 78.66%. This accuracy value is obtained using the Tf method for frequent words with a value of 75. The following is the confusion matrix table obtained.

TABLE 10. Best confusion matrix for scenario 1

		Actual		
		negative	neutral	positive
Predicted	Negative	0	157	1
	Neutral	1	682	0
	positive	0	26	0

After getting the confusion matrix results, we try to calculate the precision, recall and f-measure values for each class and will be presented in table.

TABLE 11. Precision, recall and f-measure values for scenario 1

Mark	Classification class		
	negative	neutral	positive
Precision	0.000000	0.788439	0.000000
Recall	0.000000	0.998536	0.000000
F-Measure	-	0.881137	-

5.2. Scenario 2

The results of the analysis of the classification model, obtained the best classification model with the best combination of C and γ , namely at C=20 and $\gamma=2-1.25$ of 79.81%. This accuracy value is not necessarily optimal and shows that it has good performance. Table will show the appropriate calcification class carried out by looking at the confusion matrix.

TABLE 12. Best confusion matrix for scenario 2

		Actual		
		negative	neutral	positive
Predicted	Negative	8	0	0
	Neutral	150	682	24
	positive	0	1	2

Next, to see the performance of the classification results, the precision, recall and f-measure values are calculated in Table.

TABLE 13. Precision, recall and f-measure values for scenario 2

Mark	Classification class		
	Negative	neutral	positive
Precision	0.050633	0.99854	0.076923
Recall	1.000000	0.79673	0.666667
F-Measure	0.096386	0.886292	0.137931

Based on the results shown in the table above, the neutral class is the one that dominates the most in the classification process. The accuracy of the classification obtained is influenced by several factors, including the amount of text or terms identified, the amount of training data used, classification features, the algorithm used, and the similarity of words that exist during the classification process.

5.3. Performance of Public Services in the City of Jakarta in looking at the performance of classification results regarding the performance of public services in the City of Jakarta, it is necessary to carry out an assessment using data related to public services in the City of Jakarta. The data contains sentiments per class, namely positive, negative and neutral. The data that will be used to view public service performance is 293 data which have been explained in chapter 5, namely the implementation chapter. A total of 293 data were processed and worked on with scenarios 1 and 2. The best scenario result configuration is in scenario 2 model 2, namely using a Linear kernel in the calculations and carried out without removing stop words. The results obtained are depicted in the following confusion matrix.

TABLE 14. Confusion matrix data for Jakarta

		Actual		
		negative	neutral	positive
Predicted	Negative	33	16	1
	Neutral	9	24	0
	positive	1	2	2

Next, to see the performance of the classification results, the precision, recall and f-measure values are calculated.

TABLE 15. Precision, recall and f-measure values for Jakarta data

Mark	Classification class		
	negative	neutral	positive
Precision	0.6600	0.7273	0.40000
Recall	0.7674	0.5714	0.66667
F-measure	0.70966	0.639993	0.500001

To see what topics are discussed in this 293 data, you can search for words that often appear using the Rstudio wordcloud library. In table we will discuss words that frequently appear in each category:

Table 16. Contents of the top 15 words for each class

positive		negative		neutral	
word	freq	word	freq	word	freq
Already	14	There is	60	Which	46
There is	13	No	55	Jakarta	45
police	8	Which	49	There is	35
And	7	tap	35	road	35
road	6	Already	35	Help	33
fire	4	day	28	day	30
car	4	water	26	And	29
wheel	4	dead	25	No	28
congested	3	Jakarta	25	market	26
Which	3	And	23	please	25
Behind	2	congested	23	Already	24
Blessing	2	road	22	every	22
Can	2	officer	22	without	22
From	2	This	21	manukan	21
Darmo	2	until	20	tama	21

Because there are conjunctions that are still taken, try to carry out a deletion process for the same words so that they better reflect the class category.

TABLE 17. Contents of the top 15 words after stopwords

positive		negative		neutral	
word	freq	word	freq	word	freq
police	8	tap	35	Help	33
fire	4	water	26	market	26
car	4	dead	25	please	25
wheel	4	officer	22	manukan	21
behind	2	Help	20	tama	21
blessing	2	please	15	open	20
Darmo	2	police	15	gold	20
dharmahasada	2	manukan	13	holiday	20
green	2	goes out	13	shops	20
love	2	number	11	order	20
left	2	pln	11	water	19
kpp	2	light	10	dead	19
light	2	holiday	10	tap	19
fluent	2	order	10	officer	13
light	2	new	9	number	10

It can be concluded that the words that represent each sentiment are:

TABLE 18. Contents of words from each class

Class	Say
Positive	Fire, car, wheel, rear, blessing, darmo, dharmahasada, green, love, left, kpp, lamp, smoothly, light
Negative	Off, pln, lights, new
Neutral	Market, tama, open, gold, shops

If you look at the words that appear, there are several interesting ones in each class:

a. Positive class

Fire and dharmahasada were identified as positive words because after looking at the data these words. It turns out that the use of fire and dharmahasada lie in one sentence. Public sentiment tends to be praise because the fire has been contained by the PMK car arriving at the location. Here is the sentence:

There was a fire in Dharmahasada, a workshop and there were already 2 fire trucks trying to put it out. The fire in a kind of warehouse on Jalan Dharmahasada caused traffic jams. There were PMK cars and the fire started to be extinguished.

b. Negative class

Blackout, pln, and lights were identified as negative words because after looking at the data these words. It turned out that these words indicated that complaints to PLN had long been extinguished. The places where the PLN has blackouts are spread across the areas of Karah Agung, Tenggilis, West Gayungsari, Wonocolo, Kartini, Semampir, Bringin, and Tarik. The other words for extinguished are lights that have gone out, traffic lights that have gone out and there is information about a fire where PMK has just started, giving rise to negative sentiment from the public.

c. Neutral class

Market, shops, gold, were first identified as neutral words because after looking at the data these words. It turned out that these words were contained in one sentence which indicated information to related parties to regulate gold shops in the Manukan Tama market. Apart from that, there are also things about the flower market and rungkut market.

IV. CONCLUSION

Classification is carried out using the Naïve Bayes algorithm and Support Vector Machine (SVM). The data used is taken from Instagram @dkijakarta. This data will be processed and grouped into 3 sentiment classes, namely positive, negative and neutral.

REFERENCES

- [1] S. Apriliyani, P. Piksi, and G. Bandung, "Use Of Electronic Medical Records For Purpose * Correspondent Author: Sinta Apriliyani," vol. 1, no. 10, pp. 1399–1410, 2021.
- [2] Fitriani Astika, "Implementation of Electronic Medical Records (EMR) at 'X' Hospital Pekanbaru in 2019," J. Hosp. Manag. Heal.Sci., vol. 1, no. 1, pp. 43–53, 2020, [Online]. Available: <http://journal.almatani.com/index.php/jhmhs/article/view/26>.
- [3] R. Ordila, R. Wahyuni, Y. Irawan, and M. Yulia Sari, "Application Of Data Mining For Grouping Patient Medical Record Data Based On Type Of Disease Using A Clustering Algorithm (Case Study: PT.Inecda Poly Clinic)," J. Computer Science ., vol. 9, no. 2, pp. 148–153, 2020, doi: 10.33060/jik/2020/vol9.iss2.181.
- [4] I. Ranggadara, G. Wang, and ER Kaburuan, "Applying Customer Loyalty Classification with RFM and Naïve Bayes for Better Decision Making," Proc. - 2019 Int. Semin. Appl. Technol. Inf. Commun.Ind. 4.0

- Retrospect. Challenges, *iSemantic* 2019, no. September, pp. 564–568, 2019, doi: 10.1109/ISEMANTIC.2019.8884262.
- [5] ASR Sinaga and D. Simanjuntak, "Expert System for Detecting Toddler Malnutrition Using the Naïve Bayes Classifier Method," *J. Inkofar*, vol. 1, no. 2, pp. 54–60, 2020, doi: 10.46846/jurnalinkofar.v1i2.110.
- [6] A. Febrianto, S. Achmadi, and AP Sasmito, "Application of the K-Means Method for Clustering Visitors to the Itn Malang Library," *J. Mhs. Tech.Inform.*, vol. 5, no. 1, pp. 61–70, 2021.
- [7] R. Rusliani, "Cash Receipts and Disbursements Application Program Using PHP at the Noor Hidayatullah Mosque in Banjarmasin. This study discusses the application of the accounting information system for cash receipts and disbursements at the Noor Hidayatullah Mosque in," no. 36, pp. 1–10, 2020.
- [8] F. Technology, AND Informatics, and U. Dinamika, "Designing Website User Interfaces onCV. Alpha Raya Technic," 2021.
- [9] MI Puspita, I. Ranggadara, and I. Prihandi, "Zachman framework for designing information system logistics management," *Int. J. Recent Technol. Eng.*, vol. 8, no. 3, pp. 4030–4034, 2019, doi: 10.35940/ijrte.C5377.098319.
- [10] AF Sallaby and I. Kanedi, "Designing a Doctor's Schedule Information System Using the CodeIgniter Framework," *J. Media Infotama*, vol. 16, no. 1, pp. 48–53, 2020, doi: 10.37676/jmi.v16i1.1121.
- [11] RT Waruwu and A. Sindar, "Expert System Determines Types of Child Developmental Disorders Using the Certainty Factor Method," *Sci. Comput. Sci. Informatics J.*, vol. 1, no. 2, pp. 1–4, 2020.
- [12] M. Sari, S. Defit, and GW Nurcahyo, "Expert System for Detecting Diseases in Children Using the Forward Chaining Method," *J. Sistem Inf. and Technol.*, vol. 2, pp. 5–9, 2020, doi: 10.37034/jsisfotek.v2i4.114.
- [13] A. Apriliani et al., "Forecasting Sales Trends of Restaurant Menus Using Sales Trend Forecast of a Restaurant Menus Using Single Moving," *J. Teknol. Inf. and Computer Science.*, vol. 7, no. 6, pp. 1161–1168, 2020, doi: 10.25126/jtiik.202072732.
- [14] RR Rizky and ZH Hakim, "Expert System for Determining Hypertension in Pregnant Women at Adjidarmo Rangkasbitung Regional Hospital, Banten Province," *J. Sisfokom (Inf. and Computer Systems)*, vol. 9, no. 1, pp. 30–34, 2020, doi: 10.32736/sisfokom.v9i1.781.
- [15] Priyono and N. Nuris, "TOPSIS Method Decision Support System for Diagnosing Dengue Fever," *Inti Nusa Mandiri Journal*, vol. 15, no. 1, pp. 51–58, 2020.
- [16] EA Saputra and S. Nurmiati, "Web-Based Decision Support System for Determining Symptoms of Major Diseases at Salak Bogor Hospital," *J. Ilmu Komput.*, pp. 1–4, 2019, [Online]. Available: <https://jurnal.pranataindonesia.ac.id/index.php/jik/article/view/58>.
- [17] Y. Yuvidarmayunata, "Web-Based Expert System Using Backward Chaining Method to Determine Appropriate Nutrition for Pregnant Women," *INTECOMS J. Inf. Technol. Comput. Sci.*, vol. 1, no. 2, pp. 231–239, 2018, doi: 10.31539/intecom.v1i2.302.
- [18] AW Ganda Anggara, Gede Pramayu, "Building an expert system using Bayes' theorem to diagnose lung disease," *Semin.Nas. Technol. Inf. and Multimed.* 2016, pp. 79–84, 2016.
- [19] TF Ramadhani, I. Fitri, and ETE Handayani, "Web-Based ISPA Disease Diagnosis Expert System Using Forward Chaining Method," *JOINTECS (Journal Inf. Technol. Comput. Sci.)*, vol. 5, no. 2, p. 81, 2020, doi: 10.31328/jointecs.v5i2.1243.
- [20] A. Gunawan, S. Defit, and S. Sumijan, "Expert System for Identifying Gynecological Diseases Using the Android-Based Forward Chaining Method," *J. Sistem Inf. and Technol.*, vol. 2, no. 1, pp. 15–23, 2020, doi: 10.37034/jsisfotek.v2i1.30.