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Comparative Analysis Between Naïve Bayes Algorithm and Decision Tree Loss Rate from Fire Disaster Data in DKI Jakarta Province

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Abstract

In urban locations like DKI Jakarta Province, fire poses a severe concern. Understanding the trends and variables that affect fire risk requires analysis of fire incidence data. To assess fire data in the DKI Jakarta Province, the method uses the Decision Tree and Nave Bayes algorithms. The Decision Tree identifies the primary causes of fires, whereas Naive Bayes forecasts fire risk using weather and historical data. These two algorithms' combined outputs offer a thorough understanding of the features and causes of a fire. By educating authorities and the public on how to manage this risk, this research helps to improve fire mitigation techniques. The safety and readiness for fire disasters in this area should increase. The accuracy of the two predictions made by the Naive Bayes algorithm is 75%. In contrast, the accuracy of the Decision Tree algorithm is 78%, leading to the conclusion that the Decision Tree approach is more helpful in categorizing the severity of fire disaster losses.

A. Introduction

The expansion of urban areas and the density of settlements in the DKI Jakarta Province are directly related to the significant increase in population. Indirectly, several events contributed to the fire calamity. Annual fire disasters in the DKI Jakarta region, especially during the dry season, have resulted in property loss or fatalities [1].

In many urban locations, like Jakarta, fire is one of the calamities that frequently occurs. Understanding the fire patterns in the DKI Jakarta Province in 2018 requires this study. This study's analysis of fire incidence data can help pinpoint regional patterns, primary causes, and distinctive features of local fires. Both economically and socially, fires can result in enormous losses. These losses include harm to property, loss of life, and emotional toll on the victims. With the aid of this study, it will be possible to assess the social and economic effects of the fires that occurred in the DKI Jakarta Province in 2018 [1].

This study can shed light on the typical fire causes by examining fire incidence data. This knowledge can be utilized to educate the public about fire safety precautions and assist government agencies in creating more potent fire prevention initiatives [2].

Studying fires helps us learn more about disasters in general. By analyzing fire incidence data, this study can shed light on the elements that affect the intensity and spread of fires. Future disaster prediction models may benefit from using this data to improve accuracy [3].

Information sharing regarding the possible risks of fire disasters is one of the measures taken to lower the risk of fire disasters in DKI Jakarta Province [4].
Prediction analysis of the potential hazard of fire catastrophes may be done using the 2018 Fire Occurrence dataset in the DKI Jakarta province. The Decision Tree and Naive Bayes algorithms provided conclusions and forecast fire disasters in the DKI Jakarta Province. This study has classified significant fire losses using the Nave Bayes approach and ranked large fire disaster losses using the decision tree method to determine whether the process is more suitable to utilize for categorizing significant fire disaster losses [5].

The purpose of this study's findings is to categorize the severity of fire disaster losses using the Naive Bayes and the Decision Tree methods and compare the Accuracy values of the Naive Bayes and Decision Tree methods. Overall, this research aims to categorize the severity of losses under the disaster object, the building, and its causes. The number of units, personnel, operation duration, and reaction time will also be categorized [6].

Data from fire incidents in the DKI Jakarta Province, which was utilized as a sample, was collected from data.Jakarta.go.id. After looking through other websites, I used this dataset because it contains all the variables [7].

B. Research Method

Two algorithmic techniques, the Decision Tree and Nave Bayes algorithms, can be employed to analyze fire incident data in the DKI Jakarta Province to come to conclusions and make predictions about fire disasters. Although these two algorithms analyze data differently, they can offer insightful information for comprehending and reducing fire risk [8].

A decision-making process known as the Decision Tree Algorithm creates a decision tree-like model. This technique can be used in the context of fire disaster analysis to pinpoint the variables that have the most impact on the likelihood of fires, such as location, season, building type, and human variables like irresponsibility. The association between these variables and fire events may be seen clearly in the Decision Tree. The Decision Tree analysis results can be used to conduct more precise and detailed preventive action and identify locations at a higher risk of fire [9],[10].

However, Nave Bayes is an algorithm that uses Bayes' theorem to create predictions based on the likelihood that an event will occur. Naive Bayes can be used to determine the possibility of a fire in predicting fire disasters based on various variables, including the weather, air temperature, wind patterns, and the history of previous fire incidents. These algorithms can help create early warning systems or models for predicting the risk of a fire, which can give authorities, firefighters, and the general public crucial information. The most important variables affecting the region's fire risk can also be found using Nave Bayes [10], [11], [12].

A more thorough assessment of the characteristics and variables influencing the occurrence of fires in DKI Jakarta Province can be made by merging the findings of the analysis of these two algorithms. The Nave Bayes algorithm's predictions can be a great source of inspiration for creating fire disaster prevention and mitigation plans that are more successful. These two methods offer insights that may help communities and authorities better plan for these risks, lessen the effects of fire disasters, and reduce their effects. [13],[14],[15].

C. Result and Discussion

Naturally , we need a omprehensive dataset with variables compatible with our technique to analyze data using these two algorithms and clearly define the problem and how to solve it. Download the necessary packages to run the algorithm after importing the data into the Rstudio program.

Table 1. Fire Risk Categories

Jenis Variabel	Variabel	Kategori
Dependent	Besar Kerugian	1 : 1 Juta - 250 juta 2 : 250 juta - 500 juta 3 : 500 juta - 750 juta 4: 750 juta - 1 M 5 : >1M
Independent	Objek Bencana	1 : B.Industri 2 : B.Perumahan 3 : B.Umum&Perdagangan 4: Kendaraan 5: B.Lainnya
	Bangunan	1 : Rendah 2: Menengah 3: Tinggi
	Penyebab	1: Kompor 2: Lainnya

		3: Lampu 4: Listrik 5: Rokok
	Lama responds	Numerik
	Jumlah Unit	Numerik
	Jumlah SDM	Numerik
	Lama Operasi	Numerik
	Luas Area Kejadian	Numerik

Data imported using broad categories from https://data.jakarta.go.id. Data that is pertinent to the analysis variables are chosen through the sorting procedure at year 2018. The data format cleaning and correction stage was completed (Pre-processing) before deploying Nave Bayes and Decision Tree. Random data selection was used to conduct the study. Refer to Figure 1 for the procedures that were followed.

```
#Input Data
library(readxl)
library(caTools)
library(readxl)
dataC7 <- read_excel("dataC7.xlsx")
View(dataC7)
used=as.data.frame.data.frame(dataC7[,2:10],dataC7$Kecamatan)
View(dataC7)

#Mengecek Nilai Data
head(dataC7)

#Mengecek Struktur Data
str(dataC7)

# Faktoring Data
lev.sebab = c("Kompor","Lain-lain","Lampu","Listrik","Rokok")
lev.idb = c("Rendah","Menengah","Tinggi")
lev.ob = c("B.Industri", "B.Perumahan","B.Umum&Perdagangan","Kendaraan","B.Lain")
lev.bk = c("1 Jt - 250 jt","250 jt - 500 jt","500 jt - 750 jt", "750 jt - 1 M", "> 1 M")

used$`Objek Bencana`=ordered(used$`Objek Bencana`,levels=lev.ob)
used$`Bangunan`=ordered(used$`Bangunan`,levels=lev.idb)
used$`Penyebab`=ordered(used$`Penyebab`, levels=lev.sebab)
used$`Besar Kerugian`=factor(used$`Besar Kerugian`,ordered=T,labels=lev.bk)
summary(used)

#Membagi Data Testing dan Training
split = sample.split(used, SplitRatio = 0.75)
train = subset(used, split == TRUE)
test = subset(used, split == FALSE)
```

Figure 1. Preprocessing Data

The trial was conducted by randomly picking data. Following that step, special commands were utilized to process the data using the Nave Bayes and Decision Tree methodologies, yielding in-depth insights into the patterns and causes that affect fire incidences in DKI Jakarta Province. The command used to process data using the Naive Bayes approach is as follows; for more information, see Figure 2.

```
#model naive bayes
install.packages("e1071")
#model naive bayes
library(e1071)
hasil = naiveBayes(`Besar Kerugian`~.,data=used)
hasil

# Pelatihan model
NBmod = naiveBayes(`Kesejahteraan Kesehatan`~.,data=train)
NBmod

# Prediksi data testing
NBpred_test=predict(hasil,test)
summary(NBpred_test)

# Matriks Konfusi
(cm.nb=table(Predicted=NBpred_test,Actual=test$`Besar Kerugian`))

# Nilai Akurasi NB
cmm.nb=as.matrix(cm.nb)

n = sum(cmm.nb)
nc= nrow(cmm.nb)
diagm=diag(cmm.nb)
rowsumm = apply(cmm.nb,1,sum)
colsumm = apply(cmm.nb,2,sum)
p = rowsumm/n
q = colsumm/n

#Akurasi
(acc = sum(diagm)/n)
```

Figure 2. Using the Naïve Bayes method

The prior probability values, which express the likelihood of each class in the dataset, are provided with an emphasis in bold green. This clearly explains the data's class distribution (see image 3).

```
A-priori probabilities:
Y
 1 Jt - 250 jt 250 jt - 500 jt 500 jt - 750 jt   750 jt - 1 M          > 1 M
    0.69756098      0.10731707      0.06341463     0.05609756     0.07560976

Conditional probabilities:
                Objek Bencana
Y             B.Industri B.Perumahan B.Umum&Perdagangan  Kendaraan     B.Lain
1 Jt - 250 jt  0.031468531 0.667832168    0.269230769 0.003496503 0.027972028
250 jt - 500 jt 0.000000000 0.522727273    0.386363636 0.022727273 0.068181818
500 jt - 750 jt 0.115384615 0.500000000    0.384615385 0.000000000 0.000000000
750 jt - 1 M    0.000000000 0.782608696    0.217391304 0.000000000 0.000000000
> 1 M           0.096774194 0.548387097    0.354838710 0.000000000 0.000000000

                Bangunan
Y                    Rendah   Menengah     Tinggi
  1 Jt - 250 jt   0.91958042 0.06643357 0.01398601
  250 jt - 500 jt 0.88636364 0.11363636 0.00000000
  500 jt - 750 jt 0.84615385 0.11538462 0.03846154
  750 jt - 1 M    0.82608696 0.13043478 0.04347826
  > 1 M           0.77419355 0.19354839 0.03225806

                Penyebab
Y                     Kompor   Lain-lain       Lampu     Listrik       Rokok
  1 Jt - 250 jt   0.055944056 0.167832168 0.003496503 0.765734266 0.006993007
  250 jt - 500 jt 0.022727273 0.090909091 0.022727273 0.863636364 0.000000000
  500 jt - 750 jt 0.038461538 0.076923077 0.000000000 0.846153846 0.038461538
  750 jt - 1 M    0.000000000 0.086956522 0.000000000 0.913043478 0.000000000
  > 1 M           0.064516129 0.064516129 0.000000000 0.870967742 0.000000000

                Lama Respon
Y                      [,1]       [,2]
  1 Jt - 250 jt   0.1023893 0.07567192
  250 jt - 500 jt 0.1030303 0.07711469
  500 jt - 750 jt 0.1141026 0.08402279
  750 jt - 1 M    0.1057971 0.05426476
  > 1 M           0.1311828 0.15158068

                Jumlah Unit
Y                      [,1]      [,2]
  1 Jt - 250 jt    8.678322  6.630712
  250 jt - 500 jt 15.818182  6.949227
  500 jt - 750 jt 17.346154  7.288030
  750 jt - 1 M    20.217391  6.186176
  > 1 M           17.516129 10.308155

                Jumlah SDM
Y                     [,1]     [,2]
  1 Jt - 250 jt   42.23077 31.79930
  250 jt - 500 jt 78.02273 34.73386
  500 jt - 750 jt 85.96154 36.32022
  750 jt - 1 M    99.65217 28.62073
  > 1 M           87.09677 51.73287

                Lama Operasi
Y                      [,1]      [,2]
  1 Jt - 250 jt   0.4997086 0.2393561
  250 jt - 500 jt 0.5155303 0.2475826
  500 jt - 750 jt 0.5051282 0.2624148
  750 jt - 1 M    0.4557971 0.2828699
  > 1 M           0.5129032 0.2741556

                Luas Area Kejadian
Y                      [,1]      [,2]
  1 Jt - 250 jt    70.72378  97.63633
  250 jt - 500 jt 214.04545 167.51271
  500 jt - 750 jt 304.19231 256.72741
  750 jt - 1 M    376.78261 185.49441
  > 1 M           456.00000 255.04078
```

Figure 3. Output Data Sorting

In addition, the stages of computing conditional class probabilities are completed to process data using the Naive Bayes approach. Calculating each attribute's probability about a particular class is a phase in these processes. This information is the foundation for creating fire risk estimates based on existing variables in fire analysis in the DKI Jakarta Province. So, to determine the prior probability, execute these steps (1.1):

$$P(Class = 1\ \text{Jt} - 250\ \text{jt}) = 0.69756098$$
$$P(Class = 250\ \text{jt} - 500\ \text{jt}) = 0.10731707$$
$$P(Class = 500\ \text{jt} - 750\ \text{jt}) = 0.06341463$$
$$P(Class = 750\ \text{jt} - 1\ \text{M}) = 0.05609756$$
$$P(Class => 1\ \text{M}) = 0.07560976 \quad (1.1)$$

While this happens, a bright blue highlight indicates the likelihood probability, which is the likelihood that the independent variable X will have the value it does if we know the class. This clearly shows how the independent variables and the current courses relate to one another. The probability likelihood value based on the "building" variable was as follows for a specific illustration. This procedure is a crucial component of the Naive Bayes approach used to process fire data in the DKI Jakarta Province, which will aid in creating predictions and a deeper comprehension of fire risk (see (1.2)).

$$P(Bangunan = Rendah|Class = 1\ \text{Jt} - 250\ \text{jt}) = 0.91958042$$
$$P(Bangunan = Rendah|Class = 250\ \text{jt} - 500\ \text{jt}) = 0.88636364$$
$$P(Bangunan = Rendah|Class = 500\ \text{jt} - 750\ \text{jt}) = 0.84615385$$
$$P(JBangunan = Rendah|Class = 750\ \text{jt} - 1\ \text{M}) = 0.82608696$$
$$P(Bangunan = Rendah|Class => 1\ \text{M}) = 0.77419355$$
$$P(Bangunan = MenengahClass = 1\ \text{Jt} - 250\ \text{jt}) = 0.06643357$$
$$P(JBangunan = Menengah|Class = 250\ \text{jt} - 500\ \text{jt}) = 0.11363636$$
$$P(Bangunan = Menengah|Class = 500\ \text{jt} - 750\ \text{jt}) = 0.11538462$$
$$P(Bangunan = Menengah|Class = 750\ \text{jt} - 1\ \text{M}) = 0.13043478$$
$$P(Bangunan = Menengah|Class => 1\ \text{M}) = 0.19354839$$
$$P(Bangunan = Tinggi|Class = 1\ \text{Jt} - 250\ \text{jt}) = 0.01398601$$
$$P(Bangunan = Tinggi|Class = 250\ \text{jt} - 500\ \text{jt}) = 0.00000000$$
$$P(Bangunan = Tinggi|Class = 500\ \text{jt} - 750\ \text{jt}) = 0.03846154 \quad (1.2)$$

The prediction stage of the testing data that was previously gathered is the following step, and it is based on the model created using the Nave Bayes approach. This testing data consists of a collection of data that was not used in the model training procedure so that it may be used as a reference for evaluating the model's performance and accuracy in identifying fire occurrences. How the model's prediction results are displayed emphasizes the expected outcomes for each sample of testing data. This makes it evident to what extent the model can classify fire data adequately based on the available variables. Refer to Figure 4 for further information on how this approach plays a crucial part in evaluating how well the model predicts fire events in the DKI Jakarta Province and helping to improve and develop future prediction models that are even more precise.

```
> # Prediksi data testing
> NBpred_test=predict(hasil,test)
> summary(NBpred_test)
 1 Jt - 250 jt 250 jt - 500 jt 500 jt - 750 jt    750 jt - 1 M        > 1 M
           101              14               2              14            5

> # Matriks Konfusi
> (cm.nb=table(Predicted=NBpred_test,Actual=test$`Besar Kerugian`))
                 Actual
Predicted         1 Jt - 250 jt 250 jt - 500 jt 500 jt - 750 jt 750 jt - 1 M > 1 M
  1 Jt - 250 jt              88               7               4            1     1
  250 jt - 500 jt             5               5               2            0     2
  500 jt - 750 jt             0               0               0            0     2
  750 jt - 1 M                1               3               0            7     3
  > 1 M                       1               0               2            0     2

> #Akurasi
> (acc = sum(diagn)/n)
[1] 0.75
```

Figure 4. Prediction Model

According to the projection results, there is a chance that 88 disasters might result in losses between $1 million and $250 million, five disasters could result in losses between $250 million and $500 million, and so on. The output above displays the confusion matrix results based on the anticipated findings. The accuracy of the calculation is 0.75, or 75%, as a result of the matrix confusion. To process the Decision Tree approach, use the command below and look at Figure 5.

```
library(party)
library(rpart)
#Membagi Data Testing dan Training
split = sample.split(used, SplitRatio = 0.75)
train = subset(used, split == TRUE)
test = subset(used, split == FALSE)

fit <- rpart(`Besar Kerugian`~.,data=test, method = 'class')
summary(fit)
fit$variable.importance
barplot(fit$variable.importance)


library(rattle)
fancyRpartPlot(fit)
# prediksi testing
prediksi = predict(fit, newdata =test, type = "class")
# Confusion matrix
table(prediksi, test$`Besar Kerugian`)

library(caret)
confusionMatrix(data=prediksi,reference=test$`Besar Kerugian`)
```

Figure 5. Confusion Matrix

Estimates of the likelihood of an accident involving fire with losses falling within a specific nominal range can be made using the prediction findings. As an illustration, the prediction results indicate roughly 88 occurrences with possible losses between 1 million and 250 million, five events ; fiveedicted to have losses between 250 million and 500 million, and so on. Refer to Figure 6 for more information on how this data can be used to determine how fire risk is distributed based on the variety of potential losses.

```
> fit <- rpart(`Besar Kerugian`~., data=test, method = 'class')
> summary(fit)
Call:
rpart(formula = `Besar Kerugian` ~ ., data = test, method = "class")
  n= 137

          CP nsplit rel error    xerror      xstd
1 0.04761905      0 1.0000000 1.0000000 0.1284922
2 0.01000000      5 0.7142857 0.9761905 0.1276198

Variable importance
Luas Area Kejadian         Jumlah SDM        Jumlah Unit       Lama Operasi            Penyebab
                48                 19                 17                 14                   1
       Lama Respon
                 1
```

Figure 6. The Output of Processing the Decision Tree Method

The confusion matrix, which shows a comparison between the model's projected results and reality, also records the correctness of the model's results. The model's accuracy is estimated to be 75% based on the confusion matrix, which represents how well the model can categorize fire incidents. This data summarizes how well the model performed in predicting fire disasters based on data processed using the Decision Tree approach. Understanding and improving the fire risk prediction process in DKI Jakarta Province depends on the data processing procedure and applying special commands in the Decision Tree approach.

The location of the incident, the number of personnel handling the disaster, the number of fire fighting units, the response time of the extinguisher, the length of operation, and the causes of the fire, as mentioned in (1.3) are the factors that have the most significant impact on the magnitude of the disaster loss.

$$P(Bangunan = Tinggi|Class = 750 \text{ jt} - 1 \text{ M}) = 0.04347826$$
$$P(Bangunan = Tinggi|Class => 1 \text{ M}) = 0.03225806 \quad (1.3)$$

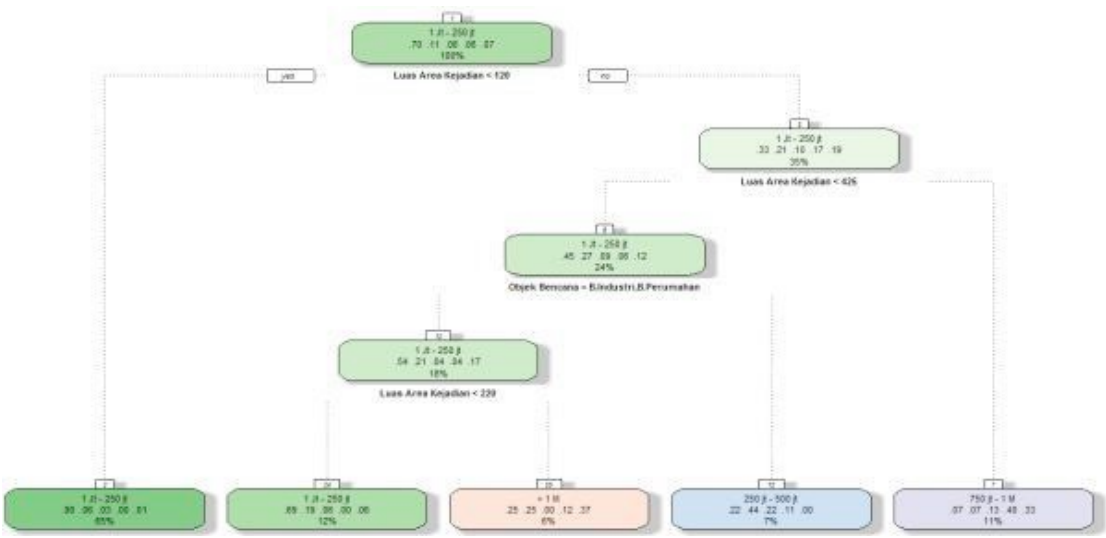

Figure 7. Decision Tree Plot

According to the decision tree plot, the anticipated loss is between 1 million and 250 million dollars if the building area is less than 120. Suppose the building area is greater than 120 but at most 425. In that case, the loss for industrial and residential structures is anticipated to remain between 1 and 250 million dollars. In comparison, it is predicted to be between 250 and 500 million dollars for other objects. Refer to Figure 7 for further information.

```
> confusionMatrix(data=prediksi,reference=test$`Besar Kerugian`)
Confusion Matrix and Statistics

                 Reference
Prediction        1 Jt - 250 jt 250 jt - 500 jt 500 jt - 750 jt 750 jt - 1 M > 1 M
  1 Jt - 250 jt              88               5               1            0     3
  250 jt - 500 jt             1               5               1            1     0
  500 jt - 750 jt             4               3               5            2     1
  750 jt - 1 M                0               0               2            4     2
  > 1 M                       2               2               0            0     5

Overall Statistics

               Accuracy : 0.781
                 95% CI : (0.7024, 0.8471)
    No Information Rate : 0.6934
    P-Value [Acc > NIR] : 0.01455

                  Kappa : 0.5505
```

Figure 8. The Results of the Confusion Matrix Construction

The Decision Tree method provided an accuracy rate of 78.1% from the confusion matrix building findings, demonstrating how well the model can categorize fire incidents based on the processed data. The number of true positives, true negatives, false positives, and false negatives is shown in the confusion matrix, which compares the results of the model's predictions with the actual data. The Decision Tree method can predict and classify fire events fairly accurately by studying this confusion matrix. The information in this report provides an in-depth analysis of the Decision Tree algorithm's performance in processing and interpreting fire data in the DKI Jakarta Province. Figure 8 shows how this study also lays a crucial foundation for the future creation of a more precise and trustworthy fire risk prediction model.

D. Conclusion

According to the accuracy level, the Decision Tree method is more accurate than the Naive Bayes method. With a 75% accuracy rate for the Naive Bayes algorithm and a 78% accuracy rate for the Decision Tree algorithm, it can beion Tree technique performs better than the Naive Bayes algorithm at classifying the severity of fire disaster losses.

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F. References

[1] Suparyanto dan Rosad (2015, "Pemetaan Kerawanan Kebakaran Menggunakan Pendekatan Integrasi Penginderaan Jauh Dan Persepsi Masyarakat Di Kecamatan," *Suparyanto dan Rosad (2015*, vol. 5, no. 3, pp. 248–253, 2020.

[2] M. V. Tampubolon, "Studi Literatur Pencegahan Bahaya Kebakaran pada Pemukiman Masyarakat Suku Baduy dan Penerapannya," *Arsitektura*, vol. 18, no. 2, p. 351, 2020, doi: 10.20961/arst.v18i2.44957.

[3] D. Oktafia and D. D. L. C. Pardede, "Perbandingan Kinerja Algoritma Decission Tree Dan Naive Bayes Dalam Memprediksi Kebangkrutan," vol.

2008, p. 2008, 2008.

[4] N. Sudiana, O. Rovara, and A. Astisiasari, “Analisis Potensi Bahaya Bencana Kebakaran Perkotaan Di Provinsi Dki Jakarta,” *J. Sains dan Teknol. Mitigasi Bencana*, vol. 13, no. 2, p. 110, 2019, doi: 10.29122/jstmb.v13i2.2904.

[5] D. Sartika and D. I. Sensuse, “Perbandingan Algoritma Klasifikasi Naive Bayes, Nearest Neighbour, dan Decision Tree pada Studi Kasus Pengambilan Keputusan Pemilihan Pola Pakaian,” *Jatisi*, vol. 1, no. 2, pp. 151–161, 2017.

[6] M. Karim and R. M. Rahman, “Decision Tree and Naï ve Bayes Algorithm for Classification and Generation of Actionable Knowledge for Direct Marketing,” *J. Softw. Eng. Appl.*, vol. 06, no. 04, pp. 196–206, 2013, doi: 10.4236/jsea.2013.64025.

[7] “Data Kejadian Kebakaran di Provinsi DKI Jakarta.” https://data.jakarta.go.id/dataset/kejadiankebakaran

[8] B. F. Z. Al-Bayaty and S. Joshi, “Comparative Analysis between Naïve Bayes Algorithm and Decision Tree to Solve WSD Using Empirical Approach,” *Lect. Notes Softw. Eng.*, vol. 4, no. 1, pp. 82–86, 2016, doi: 10.7763/lnse.2016.v4.228.

[9] R. Amini, I. Saragih, and F. Lestari, “KERENTANAN KEBAKARAN DAERAH PERKOTAAN : ANALISIS RISIKO DAN PEMETAAN DI JAKARTA TIMUR , INDONESIA,” vol. 4, pp. 1974–1981, 2023.

[10] T. Rosandy, “Naive Bayes Vs C4.5 Ke Kelancaran Biaya Tetek Bengek,” *2016*, vol. 2, no. 01, pp. 52–62, 2016.

[11] A. P. Wibowo and F. S. Papilaya, “Analisis Pola Kebakaran Lahan di Kalimantan Timur dengan MODIS dan VIIRS,” *Media Komun. Geogr.*, vol. 21, no. 1, p. 84, 2020, doi: 10.23887/kg.v21i1.23253.

[12] F. Septian, T. Sukwika, and M. D. D. Maharani, “Identifikasi Hambatan Pada Penanganan Penanggulangan Kebakaran Di Wilayah Jakarta Timur menggunakan metode bowtie analysis dan A’WOT analysis,” *J. Migasian*, vol. 5, no. 2, pp. 52–64, 2021, doi: 10.36601/jurnal-migasian.v5i2.180.

[13] A. Rizki, “Pemanfaatan Sistem Informasi Geografis (Sig) Untuk Pemetaan Tingkat Kerawanan Kebakaran Permukiman (Studi Kasus Di Kecamatan Tambora Kota Jakarta Barat),” 2022.

[14] W. W. Osman *et al.*, “Sosialisasi Kesiapsiagaan Masyarakat dan Arahan Pencegahan Bahaya Kebakaran di Kawasan Permukiman Padat Penduduk (Studi Kasus: Kelurahan Pannampu Kecamatan Tallo Kota Makassar),” *J. TEPAT Teknol. Terap. Untuk Pengabdi. Masy.*, vol. 5, no. 2, pp. 124–137, 2022.

[15] R. Pawiranata *et al.*, “Analisis Tingkat Kesiapsiagaan Siswa Dalam Menghadapi Bencana Kebakaran di SMAN 50 Jakarta “ Analisis Bahaya Kebakaran Perkotaan Kecamatan Jatinegara merupakan Badan Pusat Statistik (BPS) sebanyak 195,” pp. 30–42, 2023.