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Research Paper

Sentiment Analysis of Rising Fuel Prices on Social Media Twitter using the Naïve AlgorithmBayes Classifiers and AdaBoost

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Abstract

The government issued a policy of increasing the price of Indonesian fuel oil (BBM) in September 2022. This policy resulted from the war in Europe between Russia and Ukraine, which caused a surge in world oil prices because many respondents complained about the increase in fuel. This condition has caused much controversy or opinion among the public on social media, especially Twitter. With this phenomenon, sentiment analysis uses the Naïve Bayes classifiers algorithms to see how the public responds to government policies. The classification used in this sentiment analysisis Complaint or Not Complaint. Sentiment analysis of fuel rise on Twitter using Naïve Bayes classifier algorithm and AdaBoost Naïve Bayes classifier algorithm is applied to get the best classification by using hashtag tweets the increase in the price of fuel oil (BBM) which was taken 1000 tweets to be Used US a dataset. Data preprocessing consists of Text, Status, removal annotations, Remove hashtags, Remove urls, regexp, Indonesian stemming, and Indonesian stopword removal. The analysis results obtained an accuracy value of 70.69%, precision of 70.49%, recall of 71.45%, and AUC of 0.729 (good classification).

Keywords: Sentiments Analysis; Fuel Price hikes; Naïve Bayes Classifiers; Classification

Abstrak

Pemerintah mengeluarkan kebijakan menaikkan harga bahan bakar minyak (BBM) Indonesia pada September 2022. Kebijakan ini adalah hasil dari perang di Eropa antara Rusia dan Ukraina hal ini menyebabkan lonjakan harga minyak dunia karena banyak responden masyarakat yang mengeluhkan atas kenaikan BBM. Hal ini banyak menimbulkan kontroversi ataupun opini pada kalangan masyarakat di social media khususnya twitter. Dengan adanya fenomena tersebut, untuk melihat bagaimana tanggapan masyarakat terhadap kebijakan pemerintah maka dilakukan analisis sentimen menggunakan algoritma naïve bayes classifier. Klasifikasi yang digunakan pada analisis sentimen ini adalah Complaint atau Not complaint. Analisis sentimen kenaikan bahan bakar pada twitter menggunakan algoritma naïve bayes classifier dan adaboost, algoritma naïve bayes classifier ini diterapkan untuk mendapatkan klasifikasi terbaik. Dengan menggunakan hashtag tweets Kenaikan harga bahan bakar minyak (BBM) yang diambil 1000 tweet untuk di jadikan dataset. Preprocessing data terdiri dari Text, Status, Remove annotations, Remove hastag, Remove url, Regexp, Indonesian stemming, Indonesian stopword removal. Hasil analisis tersebut didapatkan nilai accuracy 70,69%, precision 70,49%, recall 71,45%, dan AUC yang didapat sebesar 0,729 (good classification).

Kata Kunci: Analisis Sentimen, Kenaikan Harga BBM, Naïve Bayes Classifier

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1. Introduction

BBM (material burn oil): isa type of material burn (fuel) generated from the refinery (refining) crude oil (crude oil). Oil raw from the earth is processed in refining (refinery), especially Formerly to produce products oil (oil products), which are included in it are BBM. In addition to producing fuel, refining Crude oil produces a variety of products, including gas, such as naphtha, light sulfur wax residue (LSWR), and asphalt (Juliani et al., 2022).

In early September 2022, the government decided to issue a policy to increase the price of fuel oil (BBM) in Indonesia. This policy resulted from the war in Europe between Russia and Ukraine, which caused a surge in world oil prices. The economic downturn has had a major impact on oil prices, including in Indonesia. The Russian oil trade embargo triggered a supply shock that made prices higher in global markets (Kurniasih & Suseno, 2022). Fuel is currently a very important commodity for society, especially for the economic industry. Fluctuations in fuel prices affect the operational costs of people's daily activities. The policy of increasing fuel prices sparked controversy on social media, including on social media Twitter (Kurniasih & Suseno, 2022).

Therefore, the author tries to do a sentiment analysis of the increase in fuel oil (BBM) on social media Twitter. This study aims to look at public opinion/response, especially to Twitter users in Indonesia, towards policies that the government has decided after the increase in fuel prices. In this study, the authors used the Naïve Bayes and Adaboost classification algorithms to analyze sentiment because this algorithm aims as a classification method for the classification of complaints and not complaints. Data collection in this study was carried out by obtaining a dataset. Data is Tweets from the Twitter user community grouped according to positive, negative, or neutral labels using the Naive Bayes approach. (Saputra, Rahmad, 2022).

Previous research that has been carried out relates to problems faced by other authors with the title "Application of the Naïve Bayes Algorithm in the Analysis of Increases in Fuel Oil on Twitter" by Rahmad Aldi Saputra and Sejati Waluyo in 2022. The results of comparative research between training data and test data are mutually exclusive. Related to the comparison, 80-20 gets a True Accuracy value of 81.00%, 70-30 gets a True Accuracy value of 83.00%, and 60-40 gets a True Accuracy value of 77.50%. (Saputra, RA, & Waluyo, S., 2022).

Another research is "Analysis of Sentiments in Online Ojek Services Using the Naïve Bayes Method" (Nugroho et al., 2016). The test results show that the system can classify sentiments using Naïve Bayes with an accuracy of 80% based on 800 tweet data consisting of 300 training data and 500 test data, in the title "Twitter Sentiment Analysis Using Text Mining With the Naïve Bayes Classifier Algorithm," (Sudiantoro, AV, & Zuliarso, E., 2018). The results of testing using Naïve Bayes get an accuracy of 84%, which means that the performance of the Naïve Bayes classifier algorithm can classify text data very well. (Sudiantoro, AV, & Zuliarso, E., 2018).

2. Methods

The research method used is Naïve Bayes. Naïve Bayes is a data mining/machine learning method that aims to group or classify data into several classes by exploiting the probabilities or opportunities of the data. (Hidayah, NF, & Budiman, SN, 2022).

The framework in this study can be described in Figure 1 with the following explanation:

1. Data Collection from Twitter

The data collected is taken from Twitter, tweets with hashtags according to the topic raised, namely about rising fuel prices. The data is obtained by connecting the Twitter API through the developer's Twitter account, and the search is carried out using the rapid miner.

2. Processing Gata Framework

Gata Framework is a website using the PHP programming language to process text data (Setiawan et al., 2020). It can be concluded that the Gata framework is a framework for Indonesian text mining preprocessing that provides Indonesian stopword removal. Indonesian stemming, regular expression (regexp).

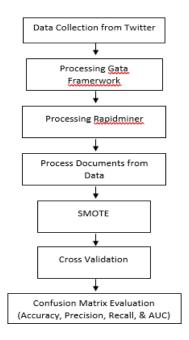


Figure 1. Framework sentiment analysis

Next, a separate sentence with two rds Which No needed with:

- a. Annotations removal process For removing text Which ownsannotation @ & # (Putra et al., 2022).
- b. Transformation Remove URLs: Fordelete URLs Which There is on say.
- c. Regexp: Regular Expressions are processed to remove sign read and number so that results appearonly in words.
- d. Indonesian Stemming: Words withthe same root word will be grouped.
- e. Stopwords removal: processomit common wordsusually seen in amount Lots And considered No relevantlike "uwwwuu," "wkwk," "re," etc. will be deleted.
- 3. Processing Rapidminer

RapidMiner is an open-source based data mining application. It contains stand-alone applications for data analysis and mining machines, such as data loading, transformation, modeling, and visualization. (Nofitri, R., & Irawati, N., 2019).

Rapid Miner is also the software used for science and developed by a company with the same name. The main function of this application is to run a business or commercial and is often used as a means of research, education, and training (Muhammad et al., 2018).

5. Process Documents from Data

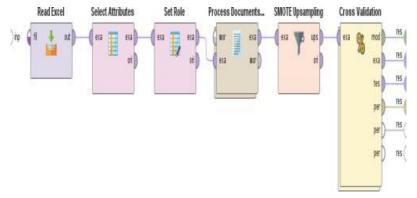


Figure 2. Processing Rapid Miner

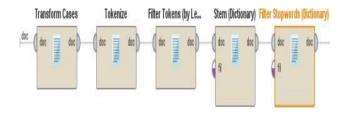


Figure 3. Process Documents From Data

In this process, several stages are applied to the dataset that has been imported, namely:

- a. Transform Cases: The stage of converting all capital letters to lowercase (Hardi et al., 2021).
- b. Tokenize: The stage of separating words in a sentence, such as words, phrases, symbols, or other meaningful elements (Ristyani Slamet et al., 2022).
- c. Filter Tokens (by Length): The process of taking important words from the token results; in this process, words with a certain length will be deleted.
- d. Stemming: The process of changing affixed words into root words.
- e. Stopword: The process of eliminating words that are not important or irrelevant to the object of research.

5. SMOTE

SMOTE is a popular method for dealing with class imbalance. This technique synthesizes new samples from the minority class to balance the dataset by re-sampling the minority class samples (Sulistiyowati & Jajuli, 2020).

6. Cross Validation

Cross-validation (CV) is a methodostatistics that can be used to evaluate performance models or algorithms. Where data is separated to become two subsets. That is the data learning process and data validation/evaluation. Cross-validation is sharing a dataset into two parts one part made data training And part Whichother made data testing. (Rilvani, Trisnawan & Santoso, 2019).

Cross Validation using the Naïve Bayes And AdaBoost algorithm can increase mark accuracy, precision, recall, and AUCs.

7. Confusion Matrix

This research results from the testing phasewill in evaluated using a table *Confusion Matrix* that is, *accuracy, precision, recall, and AUCs.*

Table 1. Confusion Matrix

Correct t		Classified as
Classification	+	-
+	true not complaint	False complaint
-	Falsecomplaint	true, not a complaint

The confusion matrix is a matrix that displays the results of a binary classification in a dataset. Several general formulas can be used in this matrix to calculate classification performance (Andika et al., 2019).

a. accuracy

Accuracy is the degree of closeness of the predicted value to the actual value (Prabowo & Fauzan, 2021).

b. Precision

Precision is the level of accuracy between the requested data and the predicted results provided by the model (Prabowo & Fauzan, 2021).

c. recall

A recall is the model's success in redefining information (Prabowo & Fauzan, 2021).

Adaboost

Adaboost used For classifydata on class respectively - respectively. Adaboostlook for category class based on the value of the weight owned by the class. This process is repeated so the class has an updated mark. On adaboost, the weight value will continue to increase on each iteration from the weight mark Which Wrong on every iteration. Adaboost is a typical ensemble learning algorithm, and the results have high accuracy. (Novianti et al., 2022).

3. Results and Discussion

Based on the results of the stages and research methods carried out, the results and discussion of the research are

3.1. Data Collection From Twitter

At this stage, the collection is carried outdata from social *media Twitter* based on, say, keys that become the background behind the problem taken. Process collection data: *Rapid Miner* is used as the tool by using *the search operator Twitter*. Data taken only speak Indonesia with amount record as much 1,000 data *tweets* Which use say keyincrease fuel price, on process This added *remove duplicate operator* for delete sentences or tweets that have a similarity. Here is the process of *crawling data on Twitter*.

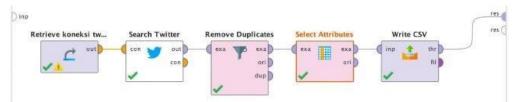


Figure 4. Process Crawling Twitter Data

The data generated in this process is saved in .csv format. On those files, the duplicate removal process will be carried out back to using the *remove duplicate feature* from *Microsoft Excel*, Which produces as many as 632 data *tweets*.

3.2. Data Labeling

After doing stage *crawl dataTwitter*, the next stage is *labeling* or labeling data in a manner manual by the writer. Labeling data on 632 data *tweets*, produce data with two classifications viz *complaint* and *not a complaint*. Following are the results from labeling data that has been done.

NO	Text	Kelas Pembanding		
1	@sundingjalila Semoga sering2 di gelar ya pasar murah ini, karena sangat membantu warga dalam memenuhi kebutuhan pokoknya apalagi sekarang semuanya pada serba mahal seiring dengan kenaikan harga BBM	Not Complaint		
2	@ZeboLady Bubarkan Partai Politik yang setuju dan mendukung kenaikan harga BBM!!			
3	RT <u>@TheReal_Rizkhy</u> : <u>@detikcom</u> Pas <u>ada</u> demo <u>kenaikan</u> BBM, <u>dia malah</u> ngerayain ultah.			
4	RT @HeriMaspur: @niluhdjelantik @NasDem Mana ada pejuang rakyat termarjinalkan setuju dengan UU cilaka dan kenaikan BBM Pejuang palsu			
5	Alokasikan Rp 10,41 Miliar untuk Subsidi Masyarakat Terdampak Kenaikan%BBM https://t.co/Sn3zCBylZx	Not Complaint		
6	Dampak Kenaikan Harga BBM, Ojol dan Angkot Dapat Keringanan Pajak Nol Persen, Syaratnya Cukup%Mudah https://t.co/BZqs0sz0M3	Not Complaint		
7	Apakah sudah beradaptasi dg kenaikan BBM dan inflasi yg mengiringi ???. Kok rasa2nya bisa diatasi oleh Kepolisian yak ? ??? lanjutkan Ndan	Complaint		
8	@niluhdjelantik @NasDem Memeluk rakyat termarjinalkan tapi gak suka ada orang demo kenaikan BBM, itu sih ANJING https://t.co/heVGevfaOR	Complaint		
9	Pemkot Cimahi Lakukan Pendataan Pelaku UMKM Terdampak Inflasi atau Kenaikan Harga BBM https://t.co/OrZcdLMOFU	Not Complaint		

Figure 5. Results Labelling

Furthermore, the results of the data that has been labeled will be next to stage pre-*Processing with Gata Framework.*

3.3. Processing Gata Framework

Then results labeling, which has been collected, will *proceed with Gata Framework*. These files shared become files containing 25 to 50datasets. Share this file that has existing limitations to servers on the *website Gata framework*. Following is the view from *processing* using the website from *Gata Frameworks*.



Figure 6. Processing with Gata Frtamework

Several stages are done on the website Gata framework that is:

- a) *Annotations removal* on website Gata Frameworks, on stage This omitted the *mentioned mark* or @ on sentence so that later sentence in *tweets* No own sign @.
- b) # (Hashtags) removal, process This done to remove hashtags Which there is on calm tweets
- c) transformation Remove URLs on process This, URLs removed on sentence Which there are tweets inweb Gata Framework.
- d) *Tokenization Regular expressions (regexp)* On stage This, done disappearance symbol symbol Which there is in *tweets* so that Whichappear only just the sentence.
- e) *Indonesian Stemming* On process This sentence Which contains affix removed so that say Which contains affixe s thebe the appropriate base wordstructure Language Indonesia say Whichaffix beginning like *mem,mem, in* and so forth on the website Gata Frameworks.
- f) Indonesian Stop Word Removal stage This is the process of final processing with Gata Framework, i.e., deletion of words Which No relevant to analysis sentiment, likethe words but, for, with, which, on, and, say continue other on the website Gata Frameworks. Followingis the result of Processing with Gata Framework:

1 Test	Status	@Anotation Plemonal	# (Hash-Tag) removal	Transformation: Remove URL	Regesp	Indonesian Stemming	Indonesian Grop word
I Boundingjalla Semoga seringil di gelar ya pasar musah ini, karena sangat membantu waga dalam memeruhih bebuntua pokolinga apalagi sekarang semuanya pada serba mahali sering dengan kersakan karay ISBM.	Compliant	senoga sering? di gelar ya pasar murah ini, kasera sangat membantuwanga dalam memendii kebudakan pokologa apalagi sekarang semuanya pada serba mahal sering dengan kenaikan karya bitim	senoga seing? di gelar şapasa murak ni, kaena sangat membantu varga dalam memendi kebutahan pokolonya apalagi sek arang semuanya gada serbamahal selang dengan kenakan karya dan	senoga seingi digelar ya pasar murah ni, karena sangar membana waga dalam memenuhi kebutuhan pokolinya apalagi sek arang semuanya pada serba mahal sering dengan kenakan hanya Ibm	semaga sering di gelar ya pasar musahini kaseru sangat membantu varga dalam memendi kebutakan policilinga apalag sekarang semuanya pada serba mahal sering dengan kenalkan karya bitan	karna sangal barta waga dalampenah batah pokok apalag sekarang semaa pada serba mahal iting dengan naik harga bitin	maga gelar pasar mu penahbahah pokak s karga bilim
62-boludy Bubakan Parai Politik yang seraju dan mendakang keraikan karga 8894.1	Complaint	bdakanpatápoliti jagostáji da mendákopkesákanhagalóm. I	bubakan partaipolitik yang senjudan mendulungkenakan karyatibin J	bubukan persi politik yang sekuju dan mendukung kenaikan karga bian. I	bdakanpatépolik jangsirujada nendakanphesakan hagalitim	bidarpatsipolitik yang tuju dan dakang naik harga tibm	bubier perfiei politik tej
1 RT @TheFeal Flating @deskcom Pas ata demo keraikan BBVI, da malah soerayan atak	Not Complaint	it şəs ələ deno keralkarıldırı, də mələk ngerəşən ultak.	impas ada demo kenalkar bbm, dia malah mga ayamuhah.	it pac adademo keraikan bilm, da malah ngerapan ahak	n pes alla demo kenakan bon dia malah ngerapan ultah	irt pas ada demo naik tibm dia malak Ingerayah ultah	st pas demolitim nger
FT 6HeMaspe: Entitlidentili GNacOrn Maru adapripang salpat temaginakan setap dengan UU silata dan keraikan SBM, Pripang palsa	Conglaint	n mana ada pejsang rakyat termajinakan petiju dengan us olaka dan kenakan Itom, pejsang paksi	it mana ata pejuang-aligat termajinakan setuju dengan sucalaka dan kenaikan bitim, pejuang palau	filmana ada pejuang raligat termanjhali an penjis dengan su olah a dan kemakan titon, pejuang paksu	m mana ada pejuang rakyat termajirakan setaju dengan sa cilaka dan kenakan bitm pejuang palisa		fijuangsak paktemanj Mimijuang pakte
Massackat Tertampak KenaikanBBM MassaksorGe/aCBa/2s	Not Complaint	áckaskan p II, H milar untá sabsití muspará at terdangai kenakastitm letps et ucissílastejts	aldkasikan g 10.4 miliar antuk sebalid masgarakat terdangak kenaikantinn Intparit coriss Gerbajia	alokaskang 10,5 miliar anak sabsidi masyarakai terdampak kenakaritan	áokaskan pintilar unak sabsidi musyasakat sedampak kenakan libri	abkasig miliarantak sabsid masyarakat dampak saik tém	alokasi g milia sabsil dangak tibm
6 Dampak Kenalkan Harga BBM, Djol dan Angkot Dapat Keringanan Pajak Nol Persen, Syaratnya Oukip Modak Wran R co662 pollos/MD	Not Conglant	dampak hersakun harga töm, ojol dan angkot dapat keringaran pajak nol persen, syaratnya cukupmudah hittps ikt solbegolisolmü	dampái kimakan kagatám, njól dan angkot ápjal keinganat pajak noli perser, syaratnya cakupmaták Intocah cortocolocilmű	dampak kenalkan karpatén, ojol dan angkot dapat keringanan pajak nol persen, siyarahnya nukapmodak	dampak kesakan harjaktim ojol dan angkot dapat keingaran pajak nol persen syaranya cukup mudah	dampak sak harga bitmojol dan angkot dapat tingan pajak sol persen oyarat cakup matah	dampak kargadém oj pajak ndi persen syan
7 Apakah sadak beradaptasi da keraik an BBM dar inikati gomengiring 777. Kali, tasabnya bisa diatad oleh Kegolisian yak 1777 lanuh an Nobe.	Complaint	quit di sudal beralightet digli eraili er tion dia inflati gymenging 777 kok rasidhya bisa diatasi deh kepolistanyak ? 777 lanjahan ndar.	apik ah subah beradaptasi digikerakan bilan dan rifusi igi menging 777 koh rasa biga bisa datasi oleh kepolisian yak? 777 lanjah anndan.	apakah sedak beradaptasi diji kenak at bitin dan infladi gi mengingi 777 kok rasalnya bisa dakasi oleh kepdisian yak ? 777 kelokan ndan.	10m dat inflating menging kol rasanya	apakah sobah abaptasi opnah bom ban inflasing meplicik sasa nya bisa atas dak polisiyak lanjandan	adapt as from infles in
 Belichtigkanti: ENacClen Meneick salgat temaginakan tagi gak saka ada orang deno kenakan BBM, itu sih ANJA Girtts Mischer Gesta DR 	Complaint	memelik salgat temarjitah as tapi gak suku ada orang demok esaik arbitm, itu sih anjing kitps://k.co/kevgevkaor	memeluk salgar temagisakan tapi gak saka ada orang deno kenakan birn, itu sih anjing kitps di sohengesisor	memelak rakyar termanjirahkan tapi gali suka ada orang demo kenalkan bbm, itu sik anjing	memeldi salgat tempajisah an tapi gali saka ada orang demo kenaikan bilan itu sih anjing	peldi rahgat termarjinah an tapi gak odia ada orang demonah bitmitu sih anjing	peluk rakyat temajika demo birm anjing
Pendiot Cimali Lakakan Pendasan Pelaku UMIM Terbangak bifaci atau Kimali un Haga BBM	Not Complaint	perskot simalni akskut pendatuat pelaku unikni tendampak inflesi aksi kenakat kaspa bilan inteps ilit pokozodimolis	perikot omáli lakultan pendatuan pelaku umkm redangak tiflaci atas kenakan karga bon hitpositusultarsidinoku	penkot cimaki lakukan pendasan pelaksi umkin terdanpak tiriladi atau keraikan kargabbin	pertikor cimalni takakar pendatuan pelaku umlim terdampak milaci atau kemalkan karga tam	penkor omaki laku data aku unkm dangak inflesi aku nak kargatdan	penkot cimali laku da inifasi karga bilm
6 Étoim Bacipeari Crems Harapamya begin, lisastorre bisa de elola or positif dit mengarakat, socialya demo benakan bism mangarakat, socialya demo benakan bism iyap yak bergening merekat, saantya sepak bola jadi penyambung kida rakgat. Sapoter saladaka mangarakat.	Not Complaint	scrposkił utk menyuarakan icz isu sociał	hai spannya begitu, karakisme bisa dikéda sor positirudi mengupankian bousipa sodaki mespasika, sodalnya demokrakian bism juga gak bergeming mereka, saatinya sepak bolaj adi penyambang kidah rakyat sepak bolaj adi penyambang kidah rakyat seporter sakabat manyarakat.	haripannyabegita, isarakme bisa dikelola ori positir di menjuarak ari isa sa, sosiali masijarak ar, soalnya demo kenak ari bism japa gali bengeming-merika, saannya sepak bola jadi penyambang labah rakyar. seporter sahabat masjarakat.	scrposité uté menguarakan isu isu sosial	har sp begitu farafisme bisak aloka sor posifir afi saara kuusa sossal magyarak ar soal dano naki blan jaga gaki genting mereka saat sepak bola jadi penyambang lidak nakyat suporter sakabat masyarak at	harap Faradisme kelok tra isu social masyara gening sepak bolape sakgat suponer sakab

Figure 7. Processing with Gata Framework

3.4. Processing with Rapid Miner

At this stage, testing is carried out using the *tools Rapidminer*. Stages This is done with some process tests tried on the dataset to produce more accurate data for implementation *machine learn n ing*.

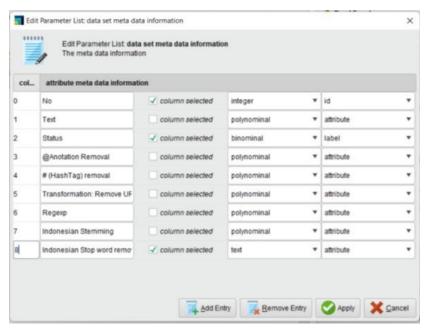


Figure 8. Imported Data

In stages, this is done by *importing* data already in *processing with the Gata Framework website* application to the application RapidMiner using operator read excel.

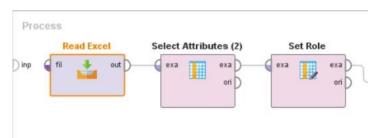


Figure 9. Operator attributes and Set Roles

This stage is done to throw away attributes Which No needed. Then do change on parameter roles become a state. This will make it possible. We choose sub gathering column for saved data.

3.5. Process Documents From Data

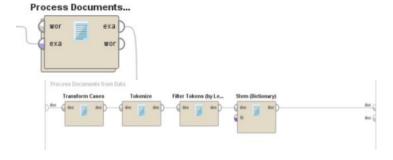


Figure 10. Processing Documents From Data

Stage furthermore Which covers stages Process Documents from Data as follows:

- a) Tokenize, the tokenizing process is the process of cutting the input string based on each word of its composition. This stage is carried out to separate word for word from a sentence text.
- b) Transform Cases; this stage makes tweet data into all lowercase letters, from capital letters to ordinary lowercase letters.
- c) Filter Token by Length (4.25), this stage aims to get words that are
- d) between 4 and 25 characters long.
- e) Steaming Additions, this stage aims to compare distributor data generated by removing data affixes such as "di," "me," "meng," "ter," "ber," "kan," "nya," and others.
- f) Stopword the process of eliminating words that are not important or irrelevant to the object of research.

3.6. Cross Validation (CV)



Figure 11. NB+AdaBoost cross-validation

The cross-validation operator is added. This operator functions as a testing tool with Adaboost and Naïve Bayes operators. Then the applied model and performance operators are added to the process to determine the level of accuracy, precisions, recall, and AUC (Area Under Curve) in the dataset.

3.7. Confusion Matrix

From the overall classification results obtained, this process is carried out for test results classification using the *confusion matrix method* with a number of data that have been tested. At this stage, the author looks for *accuracy, precision, recall, And AUC*.

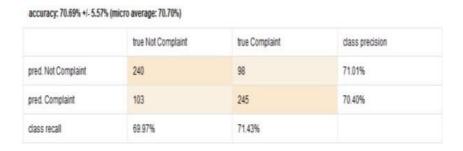


Figure 12. Results accuracy Algorithm NB

Figure 12 shows that mark *accuracy* is big, 70.69%, with an error tolerance of 5.57%, with a *true complaint value* of 245 *records* and *true not complaint* of 240 *records*.

	D 19902 - 000	American Section	
	true Not Complaint	true Complaint	dass precision
pred. Not Complaint	240	98	71.01%
pred. Complaint	103	245	70.40%
class recall	69.97%	71.43%	

Figure 13. Precision NB Algorithm Result

Figure 13 shows that mark precision is big 70,49 % with an error tolerance of 4.61%, with *true complaint* value 245 *records* and *true notcomplaint* 240 *records*.



Figure 14. Results recall Algorithm NB

Figure 14 shows that mark *recall* as big 71.45% with a toleranceerror of 9.47%, with a *true valueof complaint* 245 *records* And *true not complaint* 240 *records*.



Figure 15. Chart ROC Algorithm Naïve Bayes

Based on the results, testing *performance* produces *curve* ROC like in Figure 15 And *mark* AUC, which obtained as big0.729 (*good classification*).

4. Conclusion

Testing the data crawl resultsfrom social media Twitter with queries #Rise in fuel prices with algorithmNaïve Bayes has succeeded. The approach uses the method text proven mining and Naïve Bayes algorithm effectively to classify perspectives tweet *Not Complaint* and *Complaint*; this thing supported with it generates markaccuracy of 70.69%, precision of 70.49%, recall of 71.45%, And AUC Which got a big 0.729 which was evaluated with a confusion matrix.

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