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Hyperparameter Tuning Deep Learning for Imbalanced Data

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Abstract—Imbalanced data is a challenge for the performance of classification algorithms. A situation where two classes consisting of the majority class dominate the minority class. As a result, algorithmic models tend to have high accuracy against the majority class. Imbalanced data can occur on any type of data, including data coming from Twitter. Twitter is one of the social media that is widely used to think about various things, including about the future Presidential candidate of the Republic of Indonesia in 2024. Tweet data was collected from October 8, 2022, to January 10, 2023. Anies Baswedan has a total of 34,962 tweets, Ganjar Pranowo 39,796 tweets, and Prabowo Subianto 12,398 tweets. These tweets can be identified to be categorized into positive sentiments and negative sentiments using several classification algorithm methods, namely Decision Tree, Naïve Bayes, and Deep Learning. The dataset comes from the tweets of Twitter netizens who are scraped and preprocessed using the RapidMiner tool. Prabowo Subianto's dataset achieved the best performance using the Deep Learning model with an accuracy rate of 85.42%, precision of 63.30%, recall of 91.77%, and AUC of 0.867.

Keywords—Hyperparameter Tuning, Deep Learning, Sentiment Analysis, Imbalanced Data

I. INTRODUCTION

Imbalanced data poses a challenge to the performance of classification algorithms. A state in which two classes consisting of the majority class predominate the minority class more. This causes the performance of classification algorithms to tend to have higher accuracy values in the majority class (Lin et al., 2022). Imbalanced data can occur in any type of data (Kurniabudi et al., 2022), including data derived from netizens' opinions on social media.(Septiana Rizky et al., 2022)(Hasib et al., 2022)

Netizen or commonly referred to as netizen is a combination of the word's internet and citizen (Putra et al., 2022) which means people who actively use the internet as a medium to issue opinions (I. Kurniawan & Susanto, 2019). One of the social media that is widely used by Indonesians is Twitter which is in the top 15 of the top ranks with 544 million active users under the QQ application with a slight difference of 25 million active users (Arianto, 2020).

Opinions have several components, and each application differs from one another, but most opinions consist of the username, the date of the opinion, and the context of the opinion (Saputra et al., 2022). Visitor opinions can be used to identify whether they belong to positive, neutral, or negative sentiment toward a content, application, product, or place (Mufidah et al., 2022). The opinions also play an important role not only as a reference for visitors to determine the place to be visited but also as material for evaluation of the party or institution concerned to make improvements so that visitors feel comfortable and satisfied (M.Abdelgwad et al., 2021). In order to identify these opinions, sentiment analysis is carried out.

Sentiment analysis is one of the branches of NLP (Natural Language Processing) which aims to form a system that can identify and extract an opinion or sentiment of a person in the form of text on something on social media (Pratama et al., 2019). It is hoped that this sentiment analysis will make it easier to find out public feedback based on opinions on Twitter (bani et al., 2022).

Based on the explanation above, this study will determine the best classification algorithm on imbalanced data that has accuracy, precision, recall, and AUC performance above 50%. Starting with the Preprocessing stage to the sentiment analysis stage with the Data Mining method, namely using Decision Tree, Naïve Bayes and Deep Learning and experiments carried out using Hyperparameter Tuning, Cross Validation, Data Split, SMOTE Upsampling, and Undersampling and assessing the quality of the analysis results of each classification algorithm.

II. LITERATURE REVIEWS

A. Study Literature

The first reference research was titled "Sentiment Analysis of 2024 Presidential Candidates with the Naïve Bayes Algorithm" (bani et al., 2022). This study used the Naïve Bayes model with k-fold cross validation. The Ganjar Pranowo dataset using the 7th fold produces an accuracy of 73.68% and AUC 0.74, the Anies Baswedan dataset with the 5th fold produces an accuracy of 71.43% and AUC 1.0, the Prabowo Subianto dataset produces an accuracy of 71.43% and AUC 1.0, the Prabowo Subianto dataset uses the 1st fold the resulting accuracy of 60.00% and AUC 0.92, and for the Ridwan Kamil dataset using the 3rd fold so that it produces an accuracy of 62.5% and an AUC of 0.65.

The second reference study is titled "Sentiment Analysis of Presidential Candidates Anies Baswedan and Ganjar Pranowo Using Naïve Bayes Method" (Saputra et al., 2022). This study used a dataset that came from Facebook and had 5 classes, namely very negative, negative, neutral, positive, and very positive. The model used is Naïve Bayes with 10-fold cross-validation as well as Quadgram Tokenization which results in 42.75% accuracy, 42.10% precision, and 42.70% recall.

The third reference research is titled "Analysis of 2024 Election Sentiment with Naive Bayes Based on Particle Swarm Optimization (PSO)" (Putra et al., 2022). This study shows a comparison of the accuracy of Naïve Bayes using Particle Swarm Optimization (PSO) without using PSO. Naïve Bayes' performance using PSO is superior with an accuracy value of 78.33%, while without using PSO the accuracy result is 73.67%.

The fourth reference study is titled "Comparison of Naïve Bayes Method and Support Vector Machine on Twitter Sentiment Analysis" (Li et al., 2018). This study shows a comparison of the performance of the Naïve Bayes model with the Support Vector Machine. Naïve Bayes is superior with an accuracy value of 73.65%, precision of 0.75, recall of 0.75, and f1-score of 0.75 while SVM achieves accuracy values of 70.20%, precision of 0.73, recall of 0.71, and f1-score of 0.72.

The fifth reference research is titled "Sentiment Analysis of Public Perceptions Towards the 2019 Elections on Twitter Social Media Using Naive Bayes" (Juanita, 2020). This study used a dataset of tweets about the 2019 election to see the performance of the Naïve Bayes model in classifying 3 sentiment labels, namely negative, neutral, and positive. The results are accuracy for the training dataset of 81%, and for the testing dataset of 76%. The average precision sentiment is positive 86.65%, for negative sentiment 77.15%, and neutral sentiment is 80.95%. The average recall of positive sentiment is 36.68%, negative sentiment is 93.20%, and neutral sentiment is 86.80%.

The sixth reference study was titled "Sentiment Analysis on Twitter Social Media Against the Policy of Enforcing Restrictions on Community Activities Based on Deep Learning" (Farid et al., 2022). This study used deep learning-based sentiment analysis automation and determined the best model based on parameter trials using grid search. LSTM successfully classifies with an accuracy rate of 87.00%.

The seventh reference study was titled "Comparison of the Naïve Bayes and C4.5 Algorithms on 3-Period Presidential Sentiment Analysis on Twitter" (Albasithu & Wibowo, 2022). This study compared the accuracy results of the Naïve Bayes model with the C4.5 model in analyzing sentiment. Performance results showed that Naïve Bayes had a higher accuracy value with a value of 85.00% compared to C4.5 with an accuracy value of 78.00%.

The research reference was titled "Analysis of Twitter Sentiment towards PPKM Policy in the Midst of the Covid-19 Pandemic Using the LSTM Model" (Yahyadi et al., 2022). This study used the LSTM model with hyperparameter tuning to analyze 3 sentiment labels, namely positive, neutral, and negative sentiment. The tuning hyperparameters used are batch size 128, dropout rate 0.2, embed dim 32, epoch 10, hidden unit 16, and learning rate 0.0001. LSTM model performance results in 70.00% accuracy.

The ninth reference study was titled "Hybrid Methods Of Oversampling And Undersampling To Deal With Xyz University Academic Failure Data Imbalances" (Choirunnisa, 2019). This study combines two methods to overcome imbalanced data, namely oversampling with the Adaptive Semi-unsupervised Weighted Oversampling (A-SUWO) technique and undersampling using the Random Undersampling (RUS), Neighborhood Cleaning Rule (NCL), and Tomek-link techniques. The combined A-SUWO-Tomek-link method obtained the highest score, namely in the academic dataset, average accuracy 76.55%, precision 87.04%, recall 80.35% and on the Keel dataset, accuracy 85.41%, precision 93.18%, recall 90.545%.

B. Text Mining

Also called Text Data Mining (TDM) which refers to the process of extracting information from unstructured text documents (Riduan Achmad et al., 2021). Text Mining as the discovery of new and previously unknown information by computers, and automatically extracts information from different unstructured sources. Then, it combines the information successfully extracted from various sources (Fadillah, 2021). The Text Mining process consists of 4 stages, namely text processing, text transformation, feature selection, and pattern discovery (Yadav & Yadav, 2018).

C. Tokenizing

Process of splitting character sets based on spaces and at the same time removing certain characters contained in punctuation marks (McCann, 2020). Deleted characters are regarded as terms that do not affect how the text is processed, as well as delimiters or word separators. (Nugraha et al., 2022).

D. Stemming

Aims to homogenize words so that the list of words contained in the training data is reduced (Juanita, 2020). The stemming stage is found in the information retrieval system that can change the words contained in the document using predetermined rules (Joergensen Munthe et al., 2022). The system works by transforming every compound word contained in the document into a root word (Verawati & Audit, 2022)

E. TF-IDF

Derived from Term Frequency which is a technique for calculating the weight of words in documents starting from the beginning to the end sentence (Angeline et al., 2022). And Inverse Document Frequency is a factor that reduces the value of the previous Term Frequency. If a word in the document appears frequently, the weight value will decrease. TF-IDF is relatively popular in the process of weighting each word on a document. Focus on a term that often appears in a document by calculating the value of each word from how often it appears in a document (Ali et al., 2018).

F. Twitter

Website that offers microblogging to be able to get in touch through tweets in real-time (Mahawardana et al., 2022). Social media helps netizens in messaging each other. In early 2013, Twitter netizens were able to tweet as many as 500 million more tweets per day which caused Twitter to become one of the popular social media (D. Putri et al., n.d.). Twitter is widely used to tell stories, discuss express outpourings of heart, and issue opinions on the specific subject matter (Nurhazizah et al., 2022). So many process Twitter data as learning for political purposes, product quality, service assessment, and much more (Samsir et al., n.d.).

G. Decision Tree

An algorithm commonly used for prediction and classification that has a construction like a decision tree and has a data structure formed from ribs (edge) and nodes (Tangkelayuk, A., Mailoa, E., 2022). There are three nodes (nodes) namely root node, internal node, and root terminal (Osman, 2019). Root nodes and internal nodes act as features or variables while terminal nodes act as labels or classes (Pattiiha et al., 2022). The determination of attribute as root is determined based on the highest gain value of the various attributes available (Nabila Batubara et al., 2022).

H. Naïve Bayes

Method of classification based on the Bayes Theorem using simple probabilities and having independent assumptions (Hasri et al., n.d.). The benefit of being a part of the supervised learning algorithm with the ability to select the estimated parameters required for the classification step despite having a small amount of training data (Rozaq et al., 2022). It can also qualify on each different domain and assume the existence of classes on other features (Azhar et al., n.d.; Indah Petiwi et al., 2022). Collect texts that are considered useful in analyzing sentiment. It plays a good role in classification in terms of data computation and precision (Fikri et al., 2020).

I. Deep Learning

Machine learning algorithm that uses a multilayer artificial neural network where the layers are formed in layers (Li et al., 2018). Neural networks function similarly to how the human brain works to automatically study data features (Hafifah et al., 1928). It is included in unsupervised learning and has many levels on data extraction and features (Hasibuan et al., 2022). Has a focus on data representation and can improve data representation from input data by adding successive learning layers (K. Dewi et al., n.d.).

J. RapidMiner

Software for processing data with the principle of data mining (Julianto et al., 2022). To perform classification, regression analysis, and grouping RapidMiner has 100 learning solutions (Ambon, 2022). Can extract patterns from datasets using a combination of various methods in databases, statistics, and artificial intelligence (S. Kurniawan et al., 2020). Easy to use for data calculations, simply drag and drop different types of operators into a panel to run them (Fanny Irnanda et al., n.d.). Compatible for a wide variety of operating systems as it is built with Javascript (Pascalina et al., 2023).

K. Gataframework

An application that works based on PHP (Hypertext Preprocessor) programming is used for preprocessing text Indonesian that can be combined with RapidMiner (Noviriandini et al., n.d.). The features provided for preprocessing are @anotation removal, Normalization: emoticons, Normalization: Indonesian slank, Normalization: acronym, Tokenization: regexp, Transformation: not (negative), words count, Indonesian stemming, and Indonesian stopwords (Aryanti, 2018). In addition, there is also an API (Application Program Interface) feature to send data coming from external applications (Anggraini, 2020). Gataframework has been proven to be able to overcome external constraints such as usability, capability, response, security, existence, and reliability and is also able to overcome internal constraints such as syntactic difficulties and has used a view controller model for its programming patterns (Rezki, 2020).

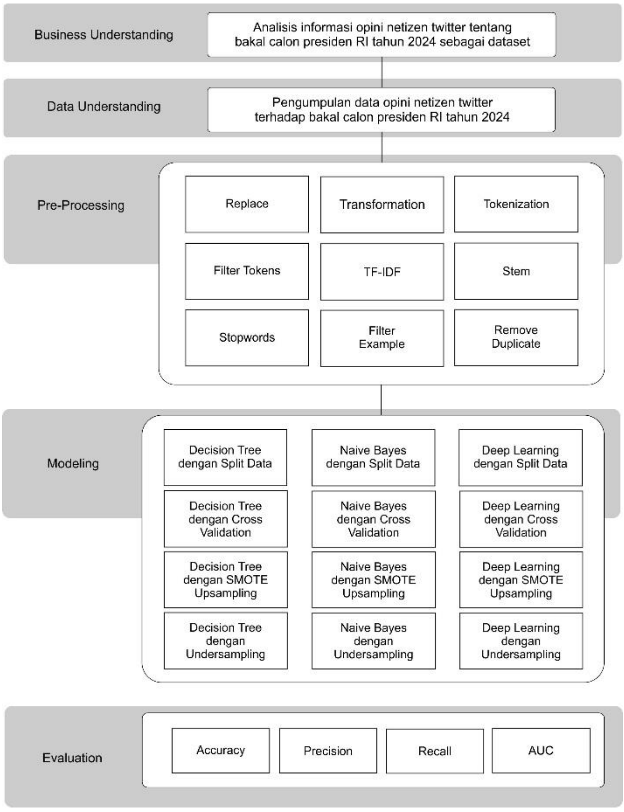
L. SMOTE

Synthetic Minority Over-sampling Technique is a technique that essentially improves the labels of minority classes by creating synthetic class labels and assigning classes based on the K-Nearest Neighbour (K-NN) class label, where the determining K value is the user (Balatti et al., 2022). In RapidMiner, the SMOTE Upsampling technique can be utilized by installing the SMOTE oversampling extension. Basically, one SMOTE Upsampling can only increase one class label only (Fernández et al., 2018).

Cases of imbalanced data need special treatment to obtain a good prediction accuracy model for all data labels (Yulian Pamuji F, 2022). In improving the performance of the sampling method, undersampling was added for the cleaning method (Choirunnisa, 2019). Upsampling resamples the dominant data while undersampling reduces the dominant data so that the dominant data and small data are equally large (Barus et al., n.d.; Pulungan et al., n.d.). Oversampling can create overfitting but excessive undersampling can also lead to loss of important information from the dataset (Tamara, 2022).

III. RESEARCH METHODS

Below is shown in picture 1. which displays research methods using the CRISP-DM method.



Picture 1. Research Methods

A. *Business Understanding*

The initial stage in CRISP-DM is to direct research toward goals. The definition and formulation of the problem are completed at this stage. Business understanding aims to be able to understand the topic of the problem and produce solutions and describe important factors that can affect the results of the research. This research uses a dataset of Twitter netizens' opinions on the future Presidential candidate of the Republic of Indonesia in 2024. In data mining, classification is needed to group based on the opinion data of Twitter netizens. It is hoped that the results of the study can be used as a reference for visitors to determine the place to be visited and also as evaluation material for the party or institution concerned to make improvements so that visitors feel comfortable and satisfied.

B. *Data Understanding*

The second stage of CRISP-DM is Data Understanding. The data to be classified needs to be understood before the study is conducted. At this stage, the research aims to collect, identify, and understand the data owned and used. The dataset used is data taken from the opinions of Twitter netizens on the future Presidential candidate of the Republic of Indonesia in 2024.

C. *Data Preparation*

The third stage of CRISP-DM is Data Preparation. After the data to be tested is understood, the next step is to prepare the data. The initial stage is carried out by preprocessing to prepare the dataset so that it can be more easily classified. At this stage, text or sentiment classification is carried out with the preprocessing stage so that text that has imperfect content such as missing data, invalid data, or also just a typo. In addition, there are also irrelevant data attributes. The data is better off discarded because its presence can reduce quality or accuracy. Therefore, in the initial data processing, text mining must go through several stages called preprocessing.

D. *Modeling*

At this stage, the dataset is tested using data mining techniques. Classification is carried out by applying several proposed data mining algorithms. In this study, testing was carried out using the Decision Tree, Naïve Bayes, and Deep Learning algorithms. After the test is carried out, subsequently the results obtained will be presented in the form of tables and graphs.

E. *Evaluation*

Evaluation is carried out based on accuracy, precision, recall, AUC, and Confusion Matrix values above 50%. The confusion matrix will describe the results of accuracy ranging from correct positive predictions, false positive predictions, correct negative predictions, and false negative predictions. Accuracy will be calculated from all correct prediction results (both positive and negative predictions) compared to all testing data. The higher the accuracy value, the better the resulting model will be. This stage will look in detail at the performance results of the algorithms tested on the dataset.

IV. RESULT AND DISCUSSION

Below is shown table 1 which shows a timeline of scraping data coming from tweets of Twitter netizens.

Table 1. Timeline scraping dataset

Name	Scraping Date	Dataset
Anies	14 Oct - 19 Nov 2022	34.962
Ganjar	8 Oct 2022 - 10 Jan 2023	39.796
Prabowo	8 Oct - 18 Nov 2022	12.398

A data cleaning process is used to remove duplicate data and information unrelated to the subject of the Republic of Indonesia's potential presidential candidate in 2024 from the raw data that has been acquired. After the data cleaning process, data were obtained for the future Presidential candidate of the Republic of Indonesia in 2024 Anies Baswedan totaling 709 data, Ganjar Pranowo 3,348 data, and Prabowo Subianto 844 data. Then, the data is created into a dataset consisting of text and label attributes. The text attribute contains the opinions of Twitter netizens regarding the candidates for the 2024 Indonesian President, namely Anies Baswedan, Panjar Pranowo, and Prabowo Subianto, while the label contains sentiments that are classified as positive and negative. The dataset of each prospective Presidential candidate of the Republic of Indonesia in 2024 is stored in the form of a .xlxs format file so that three datasets are formed, namely Anies Baswedan, Ganjar Pranowo, and Prabowo Subianto.

Data categorization and labeling were carried out by a lecturer at Indonesian Sultan Aji Muhammad Idris Samarinda State Islamic University. This is done so that the data status becomes normal in text mining research. The results of the data labeling process are as follows Table 2 to 3.

Table 2. Anies Baswedan dataset labeling results.

Labels	Total
Positive	513
Negative	196

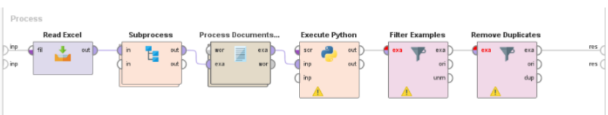
Table 3. Ganjar Pranowo dataset labeling result

Labels	Total
Positive	7866
Negative	180

Table 4. Prabowo Subianto dataset labeling result

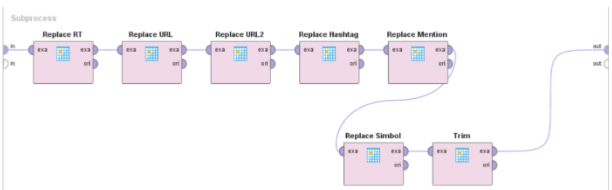
Labels	Total
Positive	656
Negative	188

Using RapidMiner, text preprocessing is the first step in the research procedure. To prevent errors brought on by lengthy data processing, the text preprocessing step is split into two stages. Preprocessing phase can be seen in Picture 2.



Picture 2. Preprocessing Phase

The first phase of preprocessing consists of Read Excel, Subprocess, Process Documents from Data, and Execute Python, Filter Examples, and Remove Duplicates. Subprocess phase can be seen in Picture 3.



Picture 3. Subprocess Phase

Phases in the Subprocess operator in which there are Replace RT, Replace URL, Replace URL2, Replace Hashtag, Replace Mention, Replace Symbol, and Trim. Process documents from data phase can be seen in Picture 4.

Picture. 4 Process Documents from Data Phase

The processes contained in the Process Documents From Data operator are Transform Cases, Tokenize, Filter Tokens (by Length). Researchers use the Web Service (URL) from Gataframework on the Execute Python operator to carry out Stopwords and Stem with the Python computer language since RapidMiner does not offer dictionaries for Stopwords and Stem in Indonesian. Throughout the entire preparation phase, RapidMiner 9.10.011 was used.

Replace RT, Replace URL, Replace URL2, Replace Hashtag, Replace Mention, Replace Symbol, and Trim to remove unnecessary components such as Symbol @, #, emoticons, and excessive letter writing that can damage the meaning of the word.

Transform cases is an operator that has a function to convert tweets from twitter netizens into lowercase letters.

The tokenize operator in RadipMiner is useful for removing all numbers contained in the text.

Filter tokens (by length) to select text by deleting tweets whose characters are less than four and more than twenty-five characters long. If a tweet is found whose character is less than four or more than twenty-five characters, it will automatically be deleted.

Stem forms a word into a base word. The stem process uses the Web Service (URL) of Gataframework with the Python programming language on the Execute Python operator.

Stopwords filters tweet text through the Web Service (URL) provided by the Gataframework website.

Table 5 shows, wordlist stores important words contained in the text Here are the important words against Anies Baswedan.

Table 5. A collection of important words

Word	In Documents	Total
presiden	335	355
capres	131	136
nasdem	83	95
calon	80	87
partai	67	83
indonesia	69	76
deklarasi	73	74
pilpres	62	64
dukung	51	55
jokowi	48	54
forum	43	51
jakarta	31	39
membangun	27	36

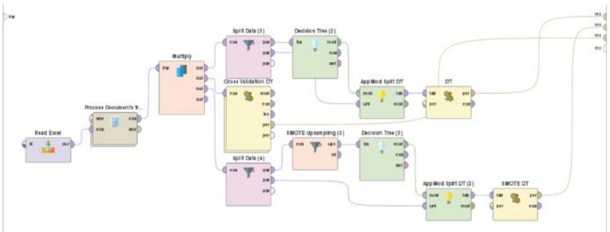
TF-IDF is a weighting of terms that have been formed. Here are the weight values of some of Prabowo Subianto's terms in Table 6.

Table 6. TF-IDF weighting

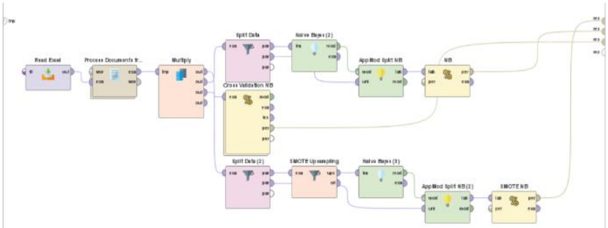
aamiin	abdul	abud	acara	adakan	adalah	adem
1.0	0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	1.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0	0.0
0.0	0.0	0.0	0.0	0.0	0.0	0.0

The outcomes of a model test that involved categorizing tweets containing views from internet users using decision trees, naive bayes, and deep learning algorithms. The Decision Tree employs the criterion parameter gini index and a maximum depth of 20, while Naive Bayes uses the Laplace correction parameter and no other special settings. In hidden layer sizes, epochs, and activation functions, deep learning employs hyperparameter tuning.

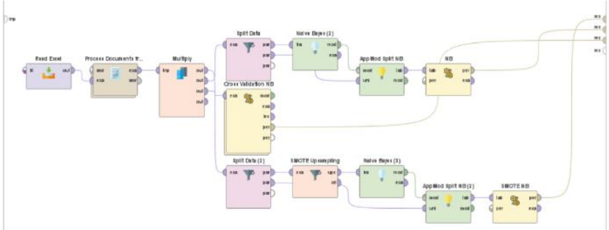
Split Data uses a ratio of 70% for training data and 30% for test data so that negative sentiment data is more likely to be evenly distributed on both training data and test data. Cross Validation with 10 folds for the selection of the best algorithm because it tends to provide less biased accuracy compared to leave-one-out Cross Validation and bootstrapping. The candidates for the President of the Republic of Indonesia in 2024 who are the object of research are Anies Baswedan, Ganjar Pranowo, and Prabowo Subianto. Decision tree, naïve bayes and deep learning algorithm models can be seen in Picture 5 to 7.



Picture 5. Decision Tree algorithm model



Picture 6. Naïve Bayes algorithm model



Picture 7. Deep Learning algorithm model

Research model design using Read Excel, Process Document From Data, Multiply, Split Data, Cross Validation, Decision Tree, Naïve Bayes, Deep Learning, and Performance. Read Excel serves to read the dataset in the form of an Excel file. Process Document From Data serves to process word text before entering the modeling stage. Multiply is used so that the dataset can be used branched and shared by existing operators. Split Data is in charge of dividing test data and training data, Cross Validation is a statistical method that evaluates the performance of algorithms where the data is separated into learning process data and validation data in order to get the best algorithm. SMOTE Upsampling and Undersampling function to balance imbalanced data. Performance is used to determine the results of accuracy, precision, recall, and AUC obtained from the algorithm used.

RapidMiner only has a laplace correction as a Naive Bayes parameter that is useful for adding a value 1 to each attribute to prevent classification results that produce a value 0 because the test data is not present in the training data, but the estimated probability value remains unchanged. (Listiowarni, 2019; Rizky Noer Alif, 2022). Comparing the precision of the laplace correction to the estimated probability, there is little difference. (Indrajaya, 2018; Yudhana et al., 2022).

Criterion gini index RapidMiner provides 5 criteria on the Decision Tree including gain_ratio, information_gain, gini_index, accuracy, and least_square. Gini index is a probability obtained by selecting two data that have different classes (Zarkasyi et al., 2022). The Gini index was chosen because it is able to increase the accuracy and precision values for classification (Haditira et al., 2022; Muningsih, 2022).

Maximal depth to set the depth of the tree to be created and limit its size to the Decision Tree, the parameters used are maximal depth (Afdhal et al., 2022; Husein & Brutu, 2022). The maximum depth value of 20 is able to produce good performance (S. Dewi, n.d.; Handayani, 2022).

The parameters used in Hyperparameter Tuning Deep Learning are the activation function, hidden layer sizes, and epoch. Hyperparameter Tuning aims to improve classification performance and determine the appropriate parameter values for datasets (Andini et al., 2022; T. A. E. Putri et al., 2023).

Determine whether neurons in the hidden layer are engaged using the activation function. (Wijaya & Wahyuningsih, 2022). There are 4 activation functions used, including Tanh, ReLu, ELu, and Maxout.

Tanh's activation function converts the input value x into a value with a range of -1 to 1 (Wijaya & Wahyuningsih, 2022). Tanh's advantage is that it produces good performance for the classification of two classes, and is easier to train. Tanh is a widely used activation function for hidden layers (Tjahyanto & Atletiko, 2022).

The ReLu (Rectifier Linear Unit) activation function converts the input value x into a value with a range of 0 to infinity. ReLu has the advantage of solving the problem of missing gradients and is computationally efficient. ReLu's performance is able to get good accuracy and precision performance (Firmansyah & Herawan Hayadi, 2022).

The ELu (Exponential Rectifier Linear Unit) activation function is a modification of ReLu to overcome dead neurons and has a negative value and an average activation value close to 0. ELu has a clear saturation region in the negative region so that the representation is more stable, the learning process is faster and more accurate, and is suitable for classification (Trisiawan & Yuliza, Valentina et al., 2022).

The Maxout activation function can return maximum input and can also be used alongside dropouts by doubling the number of parameters for each neuron and the number of its parameters trained is also higher (Panneerselvam, 2021). In terms of processing efficiency, Maxout outperforms ReLu and is more motivating while also being less likely to result in dead neurons. (Hsieh, 2020).

Hidden layer size is the number of hidden layers and the number of neurons in each hidden layer that have weighting inputs and procedures to produce neuron output through the activation function. The number of hidden layers and neurons has the effect of preventing overfitting, preventing long data training, and improving performance for classification and prediction (Harumy et al., 2022).

One cycle of machine learning to learn the training data to be processed is called an epoch. The number of epochs determines the performance results of the model used (Wasil et al., 2022). Among epochs 3, 5, 10, 12, 15, the highest accuracy performance uses epoch 15 (Isa & Junedi, 2022). The training of the data ends at period 30 because the loss outcomes do not change. (Ivan & Purnomo, 2022). Therefore, this study uses epochs 5, 10, 15, and 20.

Following preprocessing, 709 data from Twitter users' opinions on Anies Baswedan were included in the dataset. Following that, RapidMiner is used to process the data with a modeling design, and the results are as Table 7.

Table 7. Best model of Anies Baswedan's dataset

Model	Metode	Acc	Pre	Rec	AUC	Avg
NB	SMOTE Upsampling	68.54%	44.29%	52.54%	0.568	55.54%
DT	SMOTE Upsampling	74.18%	52.44%	72.88%	0.733	68.20%
DL	SMOTE Upsampling	82.63%	73.91%	57.63%	0.806	73.69%

Table 7 compares the performance of Naive Bayes, Decision Tree, and Deep Learning models using hidden layer 50 neurons, 10 epochs, and Maxout activation functions. The Deep Learning model with the SMOTE Upsampling method has the best performance for the Anies Baswedan dataset, with an average value of 73.69%. 3348 data were included in the dataset of Twitter users' opinions on Ganjar Pranowo after preprocessing. Following that, RapidMiner is used to process the data with a modeling design, and the results are as Table 8.

Table 8. Best model of Ganjar Pranowo's dataset

Model	Metode	Acc	Pre	Rec	AUC	Avg
NB	Undersampling	82.17%	6.38%	60.87%	0.707	55.03%
DT	SMOTE Upsampling	92.33%	17.07%	60.87%	0.673	59.39%
DL	SMOTE Upsampling	97.34%	33.33%	39.13%	0.887	64.63%

With Tanh activation functions, 20 epochs, and hidden layer 50 neurons, Table 8 compares the performance of Naive Bayes, Decision Tree, and Deep Learning models. The Deep Learning model with the SMOTE Upsampling method has the best performance for the Ganjar Pranowo dataset, with an average value of 64.63%.

844 data were included in the dataset of Twitter users' opinions of Prabowo Subianto after preprocessing. Following that, RapidMiner is used to process the data with a modeling design, and the results are as Table 9.

Table 9. Best model of Prabowo Subianto's dataset

Model	Metode	Acc	Pre	Rec	AUC	Avg
NB	Split Data	80.24%	54.05%	71.43%	0.708	69.13%
DT	Cross Validation	80.68%	60.00%	39.89%	0.691	62.42%
DL	Cross Validation	85.42%	63.30%	91.77%	0.867	81.80%

With Tanh activation function, 20 epochs, hidden layer 50, and 50 neurons, Table 9 compares the performance of Naive Bayes, Decision Trees, and Deep Learning. Deep Learning with Cross Validation has the best performance on Prabowo Subianto's dataset, with an average score of 81.80%.

Table 10. Performance of the entire algorithm model

Dataset	Model	Split Data				Cross Validation				SMOTE Upsampling				Undersampling			
		Acc	Pre	Rec	AUC	Acc	Pre	Rec	AUC	Acc	Pre	Rec	AUC	Acc	Pre	Rec	AUC
Anies	DT	72.77%	51.85%	23.73%	0.669	71.78%	48.72%	38.78%	0.677	74.18%	52.44%	72.88%	0.733	68.08%	44.30%	59.32%	0.660
	NB	67.61%	40.38%	35.59%	0.539	66.99%	41.74%	48.98%	0.518	68.54%	44.29%	52.54%	0.568	65.73%	41.67%	59.32%	0.545
	DL	78.87%	73.33%	37.29%	0.758	76.30%	57.78%	53.06%	0.786	82.63%	73.91%	57.63%	0.806	73.24%	51.06%	81.36%	0.829
Ganjar	DT	97.01%	18.18%	8.70%	0.803	96.86%	9.09%	3.85%	0.829	92.33%	17.07%	60.87%	0.673	80.88%	6.14%	63.04%	0.766
	NB	90.94%	7.50%	26.09%	0.583	87.69%	5.59%	26.92%	0.507	92.33%	6.45%	17.39%	0.552	82.17%	6.38%	60.87%	0.707
	DL	98.17%	56.25%	19.57%	0.737	97.18%	27.22%	27.92%	0.807	97.34%	33.33%	39.13%	0.887	78.18%	6.38%	76.09%	0.856
Prabowo	DT	78.26%	50.98%	46.43%	0.681	80.68%	60.00%	39.89%	0.691	78.26%	51.16%	39.29%	0.656	67.98%	37.86%	69.64%	0.693
	NB	80.24%	54.05%	71.43%	0.708	76.77%	48.35%	26.92%	0.500	77.47%	49.15%	51.79%	0.500	65.61%	37.19%	80.36%	0.552
	DL	86.17%	64.79%	82.14%	0.892	85.42%	63.30%	91.77%	0.867	87.35%	77.27%	60.71%	0.832	84.19%	63.79%	66.07%	0.837

A summary of the performance data for each algorithm model is shown in Table 10. Based on the best outcomes for the Split Data, Cross Validation, SMOTE Upsampling, and Undersampling methods, Deep Learning has different parameters and architectures for each dataset.

Tanh's Deep Learning activation function, 50 hidden layers, 50 neurons, and 5 epochs are used in Split Data and Cross Validation on the Anies Baswedan dataset. Maxout activation function, 50 hidden layer neurons, and 10 epochs are used in SMOTE Upsampling. undersampling with 50 hidden layer neurons, 15 epochs, and ReLu activation function.

Split Data employs the Deep Learning activation function Maxout, hidden layer 50, 50 neurons, and 5 epochs for the Ganjar Pranowo dataset. Maxout activation function, hidden layer 50, 100, 50 neurons, and 10 epochs are used in cross-validation. Tanh's activation function, 50 hidden layer neurons, and 20 epochs are used in SMOTE Upsampling. undersampling using 50 hidden layer neurons, 5 epochs, and the Tanh activation function.

ELu's Deep Learning activation function, hidden layer of 50 neurons, and 10 epochs are used in Prabowo Subianto's dataset, Split Data. Tanh's activation function, 50 hidden layers, 50 neurons, and 20 epochs are used in cross-validation. ReLu activation function, 50 hidden layers, 50 neurons, and 15 epochs are used in SMOTE Upsampling. Tanh activation function, hidden layer 50, 100, 50 neurons, and 15 epochs with undersampling.

The best model performance is then determined by averaging datasets and algorithmic models with accuracy, precision, recall, and AUC results above 50%. With accuracy values of 85.42%, precision 63.30%, recall 91.77%, AUC 0.867, and an average of 81.80%, Prabowo Subianto's dataset, using the Deep Learning algorithm model and the Cross Validation method, had the best performance.

V. CONCLUSION

Best classification algorithm model for sentiment analysis with a value above 50% is the Deep Learning model using the Cross Validation method on the Prabowo Subianto dataset with an accuracy value of 85.42%, precision 63.30%, recall 91.77%, and AUC 0.867.

It is hoped that the following study will make use of additional classification algorithm models, such as Random Forest, Neural Network, and others, to enable classification using a variety of models. Other oversampling and undersampling techniques can also be used to improve the precision of the results.

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