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Enhancing the Performance of Machine Learning Algorithm for Intent Sentiment Analysis on Village Fund Topic

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Abstract

This study explores the implementation of Intent Sentiment Analysis on Twitter data related to the Village Fund program, leveraging Multinomial Naïve Bayes (MNB) and enhancing it with Synthetic Minority Over-sampling Technique (SMOTE) and XGBoost (XGB). The analysis categorizes tweets into six labels: Optimistic, Pessimistic, Advice, Satire, Appreciation, and No Intent. Initially, the MNB model achieved an accuracy of 67% on a 90:10 data split. By applying SMOTE, accuracy improved by 12%, reaching 89%. However, adding Chi-Square feature selection did not increase accuracy further. Incorporating XGB into the MNB+SMOTE model led to a 6% improvement, achieving a final accuracy of 95%. Comprehensive model evaluation revealed that the MNB+SMOTE+XGB model achieved 96% accuracy, 96% precision, 96% recall, and a 96% F1-score, with an AUC of 99%, categorizing it as excellent. These findings demonstrate that the combination of SMOTE for addressing class imbalance and XGBoost for boosting performance significantly enhances the MNB model's classification capabilities. The novelty lies in the integration of these techniques to improve intent sentiment classification for public opinion analysis on the Village Fund program. The results indicate that the majority of tweets labeled as "No Intent" reflect a lack of specific sentiment or actionable intent, providing valuable insights into public perception of the program.

Keywords: Multinomial Naïve Bayes, Intent Sentiment Analysis, SMOTE, XGBoost

1. Introduction

Village funds are funds sourced from the State Budget (APBN) intended for villages that are transferred through the Regency / City Regional Budget (APBD) and used to finance governance, development implementation, community development, and community empowerment [1], [2]. The implementation of village funds has experienced various obstacles in distribution, institutionalization, governance, and target use, as well as the readiness of implementers in the village [3]. With this phenomenon, netizens can voice their opinions to the wider public, for example, through opinions, criticisms, and promotions published on various social media, including Twitter [4].

Twitter is one of the social media that is familiar to the Indonesian people, which, of course, makes it easier to collect opinions compared to conducting surveys or distributing questionnaires [5]. The ease of using Twitter in data collection is a reason for researchers to use social media as a data source [6]. With the diverse perceptions of netizens on social media, researchers want to research Twitter netizen comments using Intent Sentiment Analysis [7]. Intent sentiment

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analysis is a computational task that analyzes people's intentions and attitudes from text created by users [8]. Almost similar to sentiment analysis. The difference is that Intent Sentiment Analysis focuses more on analyzing text based on intention or purpose [9]. Analyzing what people think and how they feel can provide the insights and advantages certain parties need to improve and enhance their products [10] continuously. Thus, by conducting an Intent Sentiment Analysis on the topic of village funds, the government can see the response or views of the community regarding the course of the village fund program.

Some researchers have conducted Intent Sentiment Analysis using the Multinomial Naïve Bayes algorithm, among others: [11] with 67.5% accuracy using the labels happy, worry, relief, and surprise; [12] with 78% accuracy using the labels Anger, Anticipation, Disgust, Fear, Joy, Sadness, Surprise, and Trust; [13] with 68% accuracy using Not Depressed, Maybe, and Depressed.

Based on previous research, because the accuracy of the Multinomial Naïve Bayes algorithm is less than 80% compared to other previous studies, such as those conducted by [14], [15], and [16], getting higher accuracy values using different algorithms, researchers want to add features to improve the performance of the model. Researchers use the Multinomial Naive Bayes algorithm, one of the popular machine-learning techniques for text classification, because it is simple, efficient, and performs well when combined with several other methods commonly called ensemble [17]. However, the resulting accuracy mostly uses 2 to 3 labels. Research [18] used ensemble machine learning (naive Bayes, decision trees, multilayer perceptron, and logistic regression) to classify positive, negative, and neutral. Another study [19] performed positive and negative classification using ensemble machine learning (Naïve Bayes, Boosting, and Bagging).

This researcher uses different labels or categories from previous studies. Labeling on Twitter netizen tweet data will use the Frame Analysis method. Frame analysis is used, and this data labeling method can categorize comments based on predetermined frames or labels [20]. Feature addition in the form of applying oversampling techniques using the SMOTE method to balance data [21], feature selection using the Chi-Square method to reduce data dimensions while maintaining important data [22], and using the XGB algorithm to strengthen the model [23].

2. The Proposed Method/Algorithm

This study builds upon several previous research efforts. Research conducted by [24] utilized the Naïve Bayes Classifier (NBC) for predictive analysis, a model known for its simplicity and computational efficiency. However, NBC faces challenges in feature selection, which significantly impacts its accuracy. To address this issue, the Sparrow Search Algorithm (SSA) was employed to optimize feature selection by identifying the most relevant attributes, enabling the model to focus on significant data. The integration of SSA improved NBC's accuracy from 95.05% to 97.95%, along with increases in precision and recall. This optimization demonstrated SSA's effectiveness in refining feature relevance and reducing computational overhead. Nevertheless, this approach remains sensitive to SSA hyperparameter tuning and requires additional validation on more diverse datasets to ensure robustness and scalability.

Another study by [25] enhanced the Naïve Bayes algorithm by integrating Information Gain and Forward Selection techniques for feature selection. The proposed IG+FS+NB method showed significant accuracy improvements, achieving 84.15%, 74.79%, 86.50%, and 99.80%, respectively, across various datasets. These results surpassed the performance of conventional Naïve Bayes and IG+NB, underscoring the importance of effective feature selection in reducing computational complexity while maintaining high accuracy, especially in medical data classification.

Additionally, research by [26] improved the Naïve Bayes algorithm using Particle Swarm Optimization (PSO) for feature weighting in the South German Credit dataset. PSO increased accuracy by 0.46% and recall by 3.02% by identifying key attributes such as credit history and savings. However, precision decreased by 1.14% due to the limited number of weighted attributes. While PSO effectively refined classification, further research could explore additional optimization techniques to enhance precision and overall model performance. Another study [27] combined Naïve Bayes with Genetic Algorithms, achieving an accuracy of 80.95%.

Most previous studies focused on improving Naïve Bayes through feature selection techniques like Information Gain, Forward Selection, and SSA, which enhanced accuracy but often overlooked issues like class imbalance and contextual

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word representation. In contrast, this study integrates SMOTE to balance class distribution, word embedding for contextual feature representation, and Chi-Square for effective feature selection. Additionally, it combines Naïve Bayes with XGBoost to provide better handling of complex data structures, robust training on balanced datasets, and improved accuracy, addressing the limitations of previous methods.

3. Method

The research flow is an overview of the stages of the research process that will be carried out from beginning to end to achieve certain goals. The stages of the process carried out in this study are described in figure 1.

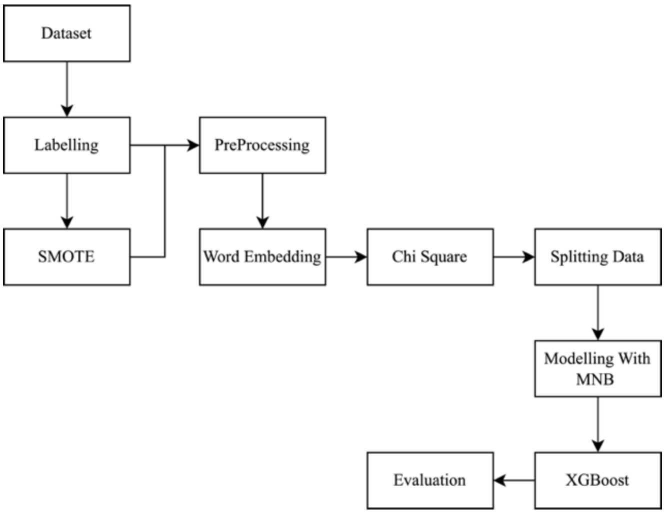

Figure 1. Research Flow

3.1. Data Collection

Data collection is the earliest stage of this research. Data can be obtained from many sources, one of which is by looking for it on the Internet, where the data can be public or private. In this study, researchers collected data from Twitter, which is a valuable platform for obtaining online data. The data collected consisted of tweets related to village funds, retrieved using the Snscrape library. Researchers utilized the keyword "village funds" during the data collection process in December 2022, resulting in 3078 Twitter comments. To ensure relevance, noise-reduction methods were applied to filter out irrelevant or off-topic tweets. This included removing tweets with unrelated hashtags, promotional content, links, or insufficient textual information, such as single-word replies or emojis. These steps ensured that only meaningful and relevant tweets were retained for further analysis, improving the quality and reliability of the dataset.

3.2. Data Labelling

The data labeling process in this study uses Frame Analysis to analyze netizen comments related to village funds. Frame Analysis is used because it categorizes comments into predetermined frames, making it easier for researchers to label each netizen comment. For instance, a comment such as "The village fund has really helped us build better roads" would be categorized under the Optimistic label, while a comment like "The funds are being misused by corrupt officials" would be labeled as Pessimistic. Researchers identified six frames or labels for netizen comments: Optimistic, Pessimistic, Advice, Satire, Appreciation, and No Intent. Manual data labeling was performed by determining specific characteristics, such as keywords, phrases, emotional expressions, or other indicators that signify a particular sentiment or intent in the text. For example, tweets containing expressions of gratitude or acknowledgment were labeled Appreciation, while sarcastic comments often included irony or humor and were categorized as Satire.

To ensure the accuracy of the labeling process, validation was conducted with the assistance of a psychologist. The validation process involved reviewing a sample of the labeled data to ensure that the assigned labels accurately reflected the intended sentiment or intent of the comments. Any discrepancies identified during this validation process were discussed and resolved collaboratively, ensuring consistency and credibility in the labeling methodology. This thorough approach ensures that the labels assigned to the data are both reliable and meaningful for subsequent analysis. The "No

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Intent" label is used for comments that do not align with the other five labels (Optimistic, Pessimistic, Advice, Satire, and Appreciation) and do not exhibit relevance to the core topic of village funds. While this label plays a supportive role in the data labeling process, it is not the primary focus of this study.

3.3. Oversampling

This research uses oversampling using the SMOTE (Synthetic Minority Over-sampling Technique) method to overcome the dataset's class imbalance. This method has been proven effective in improving model performance in the case of class imbalance [28]. SMOTE is one of the popular and widely used oversampling methods to address data imbalance [29]. This approach works by creating new synthetic samples based on a linear combination of existing minority samples [30]. The main goal of SMOTE is to achieve a more balanced proportion between the majority class and minority class in the dataset without losing information while maintaining the representation of the minority class [31]. After the application of SMOTE, the dataset will have a more balanced class distribution, which will help improve the model's ability to learn patterns from minority classes. However, it is important to note that oversampling using SMOTE also has potential downsides, such as the risk of overfitting the model or generating synthetic data that may not accurately represent real-world distributions. By applying to oversample using the SMOTE method, it is hoped that this research can improve the model's performance in classifying minority classes and overcome the problem of data imbalance in the dataset used.

To evaluate the effectiveness of SMOTE, the distribution and performance of the model across different label categories were analyzed. It was observed that oversampling had a stronger impact on certain minority labels, such as Pessimistic and Satire, which initially had very few samples. These categories showed significant improvement in classification metrics, including recall and precision, after applying SMOTE. On the other hand, labels with relatively higher initial representation, such as Optimistic, were less affected by the oversampling process. This indicates that while SMOTE effectively balanced the dataset, its impact varied depending on the initial distribution of each label, highlighting the nuanced effects of this method.

3.4. Text Preprocessing

Text preprocessing in this study includes several stages: Cleaning, Case Folding, Text Normalization, Tokenization, Filtering, Stemming, and Data Transformation stage [32]. Cleaning removes noise such as URLs, hashtags, and special characters, ensuring that only meaningful text is retained. Case Folding standardizes the text by converting all characters to lowercase, avoiding inconsistencies caused by capitalization. Text Normalization replaces informal language and abbreviations commonly found in tweets, like "u" becoming "you," to improve semantic clarity. Tokenization divides the text into individual words, creating a structured dataset for further analysis. Filtering eliminates irrelevant words, such as stop words, to focus on the most significant content. Stemming reduces words to their root forms, such as converting "running" to "run," reducing variations and dimensionality. Finally, Data Transformation prepares the cleaned text for subsequent stages, ensuring consistency and compatibility with the modeling process. These steps collectively enhance the quality and structure of the data, supporting accurate and efficient analysis.

3.5. Word Weighting

After preprocessing, the data is weighted using the TF-IDF (Term Frequency-Inverse Document Frequency) technique. TF-IDF determines the importance of a word in a document based on two components: Term Frequency (TF) and Inverse Document Frequency (IDF). TF measures how often a word appears in a document, while IDF assigns higher weights to words that are rare across multiple documents, making them more informative. The TF-IDF value is calculated by multiplying TF and IDF, giving the highest weight to words that frequently appear in a specific document but are uncommon in others. This process transforms text into numerical representations, enabling machine learning algorithms to better understand patterns and relationships within the data [33].

3.6. Feature Selection

In addition to addressing the class imbalance problem with SMOTE, feature selection methods are also applied in this study to identify features that are most relevant to the target class. One of the commonly used feature selection methods is Chi-Square. Chi-Square is used to test the relationship between each feature and the target class. Features that have a strong relationship with the target class will be considered more informative and selected for use in the formation of the classification model [34]. By applying feature selection using the Chi-Square method, this research can reduce the dimension of irrelevant features and improve the performance of the classification model by focusing on the features that are most informative in predicting the target class.

3.7. Data Splitting

After passing the feature selection stage, the next step is the data splitting stage. Splitting data is the process of dividing data into two parts, namely training data and test data. The purpose of splitting data is to ensure that the model built can be generalized well to data that has not been seen before. This research will be conducted four times, splitting data, namely 60:40, 70:30, 80:20, and 90:10. Data that has been split four times will be tested using the Multinomial Naive Bayes-XGBoost algorithm.

3.8. Modelling

After splitting the data, the next step in this research methodology is to build a classification model. In this research, the classification model will be formed using a combination of Multinomial Naïve Bayes and XGBoost. First, the Multinomial Naïve Bayes model will be built. Multinomial Naïve Bayes is a commonly used classification algorithm in text processing. This algorithm is suitable for classification with features with a multinomial distribution, such as using TF-IDF in the previously conducted dataset.

3.9. Model Evaluation

Model evaluation is a crucial stage in assessing the performance of an algorithm. This stage involves analyzing metrics such as accuracy, precision, recall, F1-score, and Area Under the Curve (AUC) to comprehensively understand the algorithm’s ability to predict the target class [35]. The Confusion Matrix is employed as the foundation for these evaluations, detailing the relationships between predictions and actual outcomes. True Positive (TP) represents the number of correctly predicted positive samples, while True Negative (TN) accounts for correctly predicted negative samples. False Positive (FP) refers to samples that were incorrectly predicted as positive, and False Negative (FN) indicates samples that were incorrectly predicted as negative. From this matrix, various metrics are derived. Accuracy, for instance, measures the proportion of correctly classified samples against the total samples, providing a holistic view of the model's performance. Precision focuses on the accuracy of positive predictions, while recall, also referred to as sensitivity, evaluates the ability of the model to correctly identify positive samples. The F1-score balances precision and recall, offering a harmonic mean of the two metrics.

The Receiver Operating Characteristic (ROC) curve is another essential tool for evaluating the model's performance. It illustrates the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR) at varying thresholds. TPR, synonymous with recall or sensitivity, is calculated by dividing the number of true positives by the sum of true positives and false negatives. Conversely, FPR is determined by dividing the number of false positives by the sum of false positives and true negatives. The ROC curve plots TPR on the y-axis and FPR on the x-axis, where a curve closer to the upper left corner signifies superior model performance. The AUC is a numerical representation of the ROC curve, quantifying the model’s ability to distinguish between positive and negative classes. An AUC value of 1 indicates a perfect model, whereas a value of 0.5 implies the model performs no better than random guessing. Higher AUC values demonstrate the model’s enhanced capability in differentiating between classes effectively.

4. Results and Discussion

4.1. Result

Oversampling is used to overcome the problem of class imbalance in the dataset. Class imbalance occurs when the number of samples in one class is much less or more than in other classes [36]. Figure 2 is a data visualization of the number of each label in the dataset.

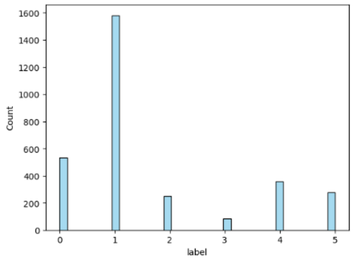


Figure 2. Data Visualization Before Oversampling

In figure 2, it can be seen that label 1 (no_intent) has more data than the other labels, so there is a data imbalance in the dataset used. Therefore, researchers applied oversampling using the SMOTE method to overcome this problem. SMOTE can help increase the number of samples in the minority class to balance it with the majority class. Figure 3 is a visualization of the number of each label in the dataset that has gone through the oversampling stage.

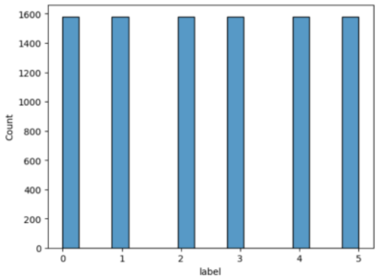


Figure 3. Data Visualization After Oversampling

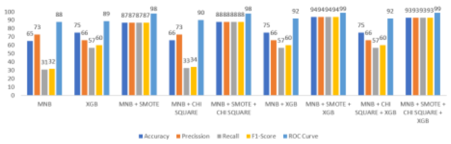
The next stage is feature selection using the Chi-Square method. Feature selection aims to reduce data dimensions, increase computational efficiency, and improve model performance by retaining the most relevant features that significantly impact the target variable or analysis objective. Figure 4 displays data that has passed the feature selection stage.

	aat	abadi	abai	abang	abdi	abdul	abed	abpd	absori	abung	...	yuni	yunus	yusron	yusuf	yusup	yuuk	ywiwit	zakat	zaman	zona
0	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.0	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	0.000000	0.000000	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9481	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9482	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9483	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.000000	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9484	0.0	0.0	0.0	0.0	0.0	0.0	0.000000	0.314816	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9485	0.0	0.0	0.0	0.0	0.0	0.0	0.067299	0.000000	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

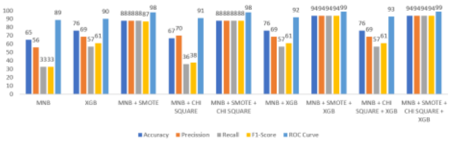
9486 rows × 4000 columns

Figure 4. Data Display After Feature Selection

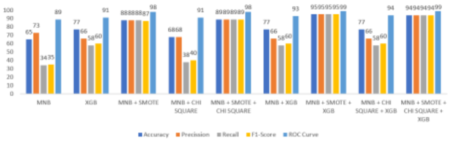
In figure 4, the initial 6119 features were reduced to 4000 best features. This helps reduce the data's dimensionality and retain the most significant features. Then, data was modeled by splitting the data 60:40, 70:30, 80:20, and 90:10. Figure 5 is the result of model evaluation.



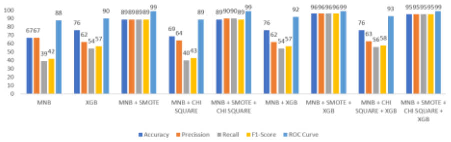
Splitting Data 60:40



Splitting Data 70:30



Splitting Data 80:20



Splitting Data 90:10

Figure 5. Model Evaluation Graph with Data Splitting Ratio

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Based on figure 5, it can be seen that the Multinomial Naïve Bayes (MNB) model with a data splitting ratio of 90:10 without adding features has an accuracy of 67%, which is higher than other data ratios. The MNB model for the SMOTE technique to balance the data experienced a significant increase in accuracy, namely 12%, so that the accuracy of the MNB+SMOTE model became 89%. Adding feature selection does not improve accuracy. So, the accuracy of the MNB+SMOTE+CHI SQUARE model remains at 89%. The addition of the XGBoost (XGB) algorithm to the model also increased by 6%, so the accuracy of the MNB+SMOTE+CHI SQUARE+XGB model increased by 95%.

The Multinomial Naïve Bayes (MNB) model using the SMOTE technique on minority data and strengthening the model using the XGBoost (XGB) algorithm, obtained the best accuracy value at a data splitting ratio of 90:10, namely 96%. To achieve optimal performance, the hyperparameters of the XGBoost algorithm were carefully tuned during the training process. The grid search method was used to test various combinations of hyperparameters, including the learning rate, maximum depth, number of estimators, and subsample ratio.

Specifically, the learning rate was tested within the range of 0.01 to 0.3, the maximum depth was varied between 3 and 10, and the number of estimators ranged from 50 to 200. Subsampling ratios were adjusted between 0.6 and 1.0 to control the randomness of the boosting process. The best combination of hyperparameters, which included a learning rate of 0.1, a maximum depth of 6, 150 estimators, and a subsample ratio of 0.8, was selected based on cross-validation performance. This tuning process ensured that the XGBoost model was effectively optimized for the dataset, contributing to the overall improvement in accuracy and robustness of the classification results.

The confusion matrix results on the MNB+SMOTE+XGB model with 90:10 data splitting is presented in figure 6.

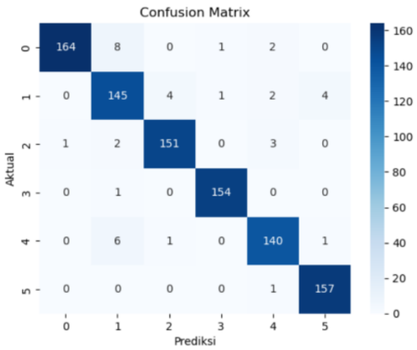

Figure 6. Confusion Matrix in Splitting Data 90:10

Based on figure 6, the calculations for accuracy, precision, recall, and f1-score are as follows.

Accuracy

$$Accuracy = \frac{164+145+151+154+140+157}{164+145+151+154+140+157+8+1+2+4+1+2+4+1+2+3+1+6+1+1+1} = \frac{911}{949} = 0{,}9599 \approx 96\%$$

Precision

$$Average\ Precision = \frac{0{,}99+0{,}90+0{,}97+0{,}99+0{,}95+0{,}97}{6} = \frac{5{,}77}{6} = 96\%$$

Recall

$$Average\ Recall = \frac{0{,}94+0{,}93+0{,}96+0{,}99+0{,}95+0{,}99}{6} = \frac{5{,}76}{6} = 0{,}96 \approx 96\%$$

F1-score

$$F1 - Score = 2\ \times \frac{0{,}96 \times 0{,}96}{0{,}96+0{,}96} = 2 \times \frac{0{,}9216}{1{,}92} = 0{,}96 \approx 96\%$$

The results of manual calculations are displayed in the classification report in figure 7.

	precision	recall	f1-score	support
0	0.99	0.94	0.96	175
1	0.90	0.93	0.91	156
2	0.97	0.96	0.96	157
3	0.99	0.99	0.99	155
4	0.95	0.95	0.95	148
5	0.97	0.99	0.98	158
accuracy			0.96	949
macro avg	0.96	0.96	0.96	949
weighted avg	0.96	0.96	0.96	949

Figure 7. Classification Report on Splitting Data 90:10

Based on figure 7, the model obtained an accuracy score of 96%, a precision score of 96%, a recall score of 96%, and an f1-score score of 96%. Next, the model evaluation was repeated using the Receiver Operating Characteristic Curve (ROC Curve). The Receiver Operating Characteristic (ROC) Curve is a graphical tool used to evaluate the performance of binary classification models by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at different threshold levels. The area under the ROC Curve (AUC) indicates the model's ability to distinguish between classes, with a higher AUC reflecting better performance. An AUC of 1 indicates perfect classification, while 0.5 suggests no better performance than random chance [37]. The application of the ROC Curve is presented in figure 8.

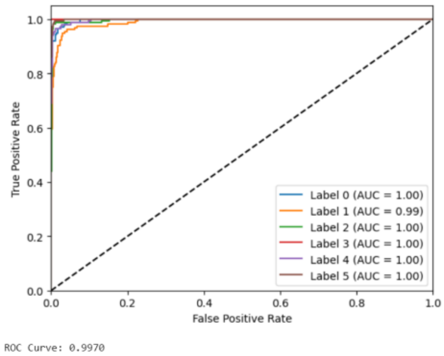

Figure 8. ROC Curve in Splitting Data 90:10

Based on figure 8, the ROC Curve value of the MNB-XGB+SMOTE model with a data splitting ratio of 90:10 is 99%, which means the model is in the Excellent category. Naturally, model evaluation results using a confusion matrix are different from the ROC curve because both are different evaluation methods with different goals and interpretations. The confusion matrix provides detailed information about the model's performance in predicting individual classes. In contrast, the ROC curve provides an overall view of the modelling ability to differentiate classes in general.

Several models have an ROC Curve with the same score of 99%, but only the MNB+SMOTE+XGB model with a data splitting ratio of 90:10 has the highest accuracy, precision, recall, and f1-score level. So, based on the experiments carried out, the addition of SMOTE and XGB is the best solution for improving the performance of the Multinomial Naïve Bayes algorithm. The results of the model comparison and the data splitting are presented in table 1.

Table 1. Model Comparison

Model	Splitting	Accuracy	Precision	Recall	F1-Score	ROC Curve
MNB	60:40	65%	73%	31%	32%	88%
	70:30	65%	56%	33%	33%	89%
	80:20	65%	73%	34%	35%	89%
	90:10	67%	67%	39%	42%	88%
XGB	60:40	75%	66%	57%	60%	89%
	70:30	76%	69%	57%	61%	90%
	80:20	77%	66%	58%	60%	91%
	90:10	76%	62%	54%	57%	90%
MNB + SMOTE	60:40	87%	87%	87%	87%	98%

 ISSN 2723-6471

	70:30	88%	88%	88%	87%	98%
	80:20	88%	88%	88%	87%	98%
	90:10	89%	89%	89%	89%	99%
MNB + CHI SQUARE	60:40	66%	73%	33%	34%	90%
	70:30	67%	70%	36%	38%	91%
	80:20	68%	68%	38%	40%	91%
	90:10	69%	64%	40%	43%	89%
MNB + SMOTE + CHI SQUARE	60:40	88%	88%	88%	88%	98%
	70:30	88%	88%	88%	88%	98%
	80:20	89%	89%	89%	89%	98%
	90:10	89%	90%	90%	89%	99%
MNB + XGB	60:40	75%	66%	57%	60%	92%
	70:30	76%	69%	57%	61%	92%
	80:20	77%	66%	58%	60%	93%
	90:10	76%	62%	54%	57%	92%
MNB + SMOTE + XGB	60:40	94%	94%	94%	94%	99%
	70:30	94%	94%	94%	94%	99%
	80:20	95%	95%	95%	95%	99%
	90:10	96%	96%	96%	96%	99%
MNB + CHI SQUARE + XGB	60:40	75%	66%	57%	60%	92%
	70:30	76%	69%	57%	61%	93%
	80:20	77%	66%	58%	60%	94%
	90:10	76%	63%	56%	58%	93%
MNB + SMOTE + CHI SQUARE + XGB	60:40	93%	93%	93%	93%	99%
	70:30	94%	94%	94%	94%	99%
	80:20	94%	94%	94%	94%	99%
	90:10	95%	95%	95%	95%	99%

4.2. Discussion

In this research, data collection was carried out with the help of the Snscrape library with the keyword "village funds" from the beginning to the end of December 2022. The data that has been collected will be labeled manually using the frame analysis method, and the data that has been labeled will be validated by a psychologist to ensure that the data to be used is of good quality. Next, text preprocessing is carried out on the data to ensure the data is ready for further processing. There are several stages in text preprocessing used in this research, namely data cleaning, case folding, text normalization, tokenization, filtering, stemming, and data transformation. Data that has passed the text preprocessing stage will be given weight to each word using the TF-IDF method to give more emphasis or attention to words considered more relevant.

There is an imbalance in the data used, so the data will be balanced through the oversampling stage using the SMOTE method. This method will increase the number of samples in the minority class to balance it with the majority class. Next, data dimensions are reduced while retaining features significantly impacting the target variable or analysis objectives using feature selection with the Chi-Square method. After the data has gone through the feature selection stage, it will go through the data splitting stage to separate the data into two parts, namely training data and test data, with different ratios, namely 60:40, 70:30, 80:20, and 90:10. This research developed a model using the MNB algorithm

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and strengthened it using the XGB algorithm. The MNB model without adding features has a low accuracy of 67% compared to previous research, which had an accuracy of 67.5% [11], 78% [12], and 68% [13]. The low accuracy of the MNB model makes researchers want to improve its performance.

In the experiments, the MNB model with a data splitting ratio of 90:10 without adding features has an accuracy of 67%, which is higher than other data ratios. The MNB model, using the SMOTE technique to balance the data, experienced a significant increase in accuracy, namely 12%, so that the accuracy of the MNB+SMOTE model became 89%. The addition of feature selection with the Chi-Square method does not increase accuracy. So, the accuracy of the MNB+SMOTE+CHI SQUARE model remains at 89%. The addition of the XGBoost algorithm to the model also increased by 6%, so the accuracy of the MNB+SMOTE+CHI SQUARE+XGB model increased by 95%.

In the experiments conducted, the MNB model with a 90:10 data splitting ratio without additional features achieved an accuracy of 67%, which was higher than other data ratios. The MNB model, using the SMOTE technique to balance the data, showed a significant improvement in accuracy, increasing by 12% to achieve 89% accuracy for the MNB+SMOTE model. However, the addition of feature selection using the Chi-Square method did not improve accuracy, as the MNB+SMOTE+CHI SQUARE model maintained an accuracy of 89%. This may be due to the characteristics of the dataset, where most features are already highly informative and relevant, leaving little room for improvement through feature selection. The Chi-Square method, which measures the statistical relationship between features and the target class, might have limited impact when the dataset already contains high-quality features. Additionally, potential feature redundancy could reduce the effectiveness of the Chi-Square method.

The addition of the XGBoost (XGB) algorithm to the model further increased accuracy by 6%, resulting in the MNB+SMOTE+CHI SQUARE+XGB model achieving 95% accuracy. XGBoost was chosen for its ability to handle imbalanced data, its effectiveness in capturing complex patterns through boosting, and its efficiency in processing large datasets. Compared to other boosting algorithms, such as AdaBoost or Gradient Boosting Machines, XGBoost offers additional optimizations, including regularization to reduce overfitting and parallel processing for faster computation. These features make XGBoost a suitable choice for improving the model's performance in this study. Based on the experiments, the evaluation shows that the MNB+SMOTE+XGB model with a 90:10 data splitting ratio achieved the best performance, with 96% accuracy, 96% precision, 96% recall, 96% f1-score, and a 99% ROC Curve. The MNB model, enhanced with the SMOTE technique and supported by the XGBoost algorithm, proved to be an effective solution for improving the model's performance on the dataset used in this study. This is also evident in table 2, which presents a comparison with previous studies.

Table 2. Comparison with Previous Research

Researcher	Model	Labels	Accuracy
[38]	SVM (TF-IDF + Chi-Square)	Sadness, Anger, Happy, Fear, and Love	75.28%
[39]	KNN (Bag of Word)	Joy, Love, Surprise, Anger, Fear, and sadness.	59%
[40]	LSTM (Fast text)	Happiness, Sadness, Fear, Disgust, Anger, and Surprise	73.14%
[41]	SVM	Anger, Fear, Joy, Love, sadness, and Surprise	90%
This Research	MNB + SMOTE + XGB	Optimistic, Pessimistic, Suggestion, Satire, Appreciation, No Intent	96%

Table 2 compares the results of the current study with several previous studies that used different models and techniques to classify emotions or intentions in texts. The first study by [38] used the SVM model with TF-IDF and Chi-Square to classify emotions such as sadness, anger, happiness, fear, and love, achieving an accuracy of 75.28%. The second study by [39] used the KNN model with the Bag of Words approach to classify joy, love, surprise, anger, fear, and sadness, with a lower accuracy of 59%. The third study by [40] employed the LSTM model with FastText to classify happiness, sadness, fear, disgust, anger, and surprise, achieving an accuracy of 73.14%. The fourth study by [41] utilized the SVM model to classify anger, fear, joy, love, sadness, and surprise, with a fairly high accuracy of 90%.

The current research employs a combination of MNB with SMOTE and XGB to classify text into categories such as optimistic, pessimistic, suggestion, satire, appreciation, and no intent. This study achieved the highest accuracy of 96%, indicating a significant improvement in classification performance compared to previous research. One of the main advantages of the method used in this research is the combination of SMOTE, which addresses class imbalance, and XGB, which enhances model performance through boosting techniques. Compared to previous studies, the use of hybrid methods in this research proved to be more effective in achieving high classification accuracy.

While this study demonstrates a notable improvement, further comparative analysis with deep learning or hybrid approaches could provide additional insights. For instance, models like BERT or BiLSTM with attention mechanisms are widely known for their superior performance in text classification tasks and could be benchmarked against the methods used in this research. Including such comparisons would help assess whether the proposed method remains robust when evaluated against state-of-the-art deep learning models on similar tasks. This could also highlight the practical benefits and trade-offs of using MNB, SMOTE, and XGB compared to more complex architectures.

Finally, it is important to note the computational resources required for training the model. The addition of SMOTE, which generates synthetic samples, and XGBoost, which employs boosting techniques, increases computational complexity compared to simpler models. For this research, training was conducted on a standard machine with an Intel Core i7 processor and 16GB of RAM, which was sufficient to complete the process efficiently. However, as the dataset size increases or more complex methods are applied, higher computational resources may be needed. Addressing these resource requirements is essential for ensuring the replicability and scalability of the proposed method.

5. Conclusion

Based on the experiments carried out in this research, the MNB model with a data splitting ratio of 90:10 without adding features has an accuracy of 67%, higher than other data ratios. The MNB model, using the SMOTE technique to balance the data, experienced a significant increase in accuracy, namely 12%, so that the accuracy of the MNB+SMOTE model became 89%. Adding feature selection with the Chi-Square method does not increase accuracy. So, the accuracy of the MNB+SMOTE+CHI SQUARE model remains at 89%. The addition of the XGBoost (XGB) algorithm to the model also increased by 6%, so the accuracy of the MNB+SMOTE+CHI SQUARE+XGB model increased by 95%. So, it can be concluded that using the SMOTE technique and strengthening the model using the XGB algorithm can significantly improve the performance of the MNB model in data classification.

The evaluation results show that the MNB model, which is strengthened with the SMOTE technique and the XGB algorithm (MNB+SMOTE+XGB) at 90:10 data splitting, has the best performance with accuracy, precision, recall, and f1-score of 96%. Thus, using the SMOTE technique and strengthening the model with the XGB algorithm is an effective solution for improving the performance of the classification model. In this research, people's views on the topic "Village Funds" from the beginning to the end of December on Twitter social media tended not to contain specific intentions or goals or were unrelated to certain sentiments.

The accuracy metrics reported in this study are derived from internal testing on a dataset collected from Twitter, which provides valuable insights into the model's performance within the context of this specific platform. However, to enhance the robustness and generalizability of the model, future work could incorporate validation using external datasets from other social media platforms, such as Facebook, Instagram, or Reddit. These platforms often have diverse user bases and communication styles, which could help evaluate the model’s ability to adapt to different linguistic and contextual variations. This approach would not only validate the model's effectiveness in broader contexts but also highlight its versatility in analyzing sentiment and intent across various domains. Including results from external datasets could strengthen the claim of the model's applicability beyond the current dataset, showcasing its practical utility in real-world scenarios [42], [43].

6. Declarations

6.1. Author Contributions

Conceptualization: M.K.A., P.P.P., R.A.M., K., T.A.P., Y.E., R.A.M., M.B.F., I., and C.R.G.; Methodology: Y.E.; Software: M.K.A.; Validation: M.K.A., Y.E., and C.R.G.; Formal Analysis: M.K.A., Y.E., and C.R.G.; Investigation: M.K.A.; Resources: Y.E.; Data Curation: Y.E.; Writing Original Draft Preparation: M.K.A., Y.E., and C.R.G.; Writing

Review and Editing: Y.E., M.K.A., and C.R.G.; Visualization: M.K.A. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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