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A Comparative Study of Alternative Automatic Labeling Using AI Assistant

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Abstract: The development of AI assistants has become increasingly sophisticated, as evidenced by their growing adoption in assisting humans with various tasks. In particular, AI assistants have demonstrated potential in the field of sentiment analysis, where they can automate the labeling of text data. Traditionally, this labeling process has been performed manually by humans or using tools like the VADER Lexicon. This study is imperative to evaluate the performance of AI Assistants in sentiment labeling, as compared to traditional human-based labeling and the application of the VADER sentiment analysis algorithm. The methodology involves comparing the labeling results of Gemini and You AI with those of human labeling and VADER. Performance is evaluated using the Naive Bayes and K-Nearest Neighbour algorithms, and K-Fold Cross Validation is employed for evaluation. The results indicate that the performance of both AI assistants can closely approximate the performance of human labeling. Gemini's best accuracy is achieved with the k-NN algorithm at 53.71%, while You AI's best accuracy is achieved with the Naive Bayes algorithm at 48.30%. These results are close to the accuracy of human labeling (61.12%) using the k-NN algorithm and VADER (54.29%) using the Naive Bayes algorithm. This suggests that AI assistants can serve as an alternative for text data labeling, as the differences in performance are not statistically significant.

Keywords: AI;assistants; gemini; labeling; VADER; you ai

INTRODUCTION

Data labeling is the process of categorizing a dataset into specific groups, and it serves as an initial step in tasks related to machine learning (Telnoni et al., 2020). This process is crucial for various tasks such as data classification, entity recognition, and machine learning (Aditya Quantano Surbakti et al., 2021). Traditionally, data labeling has been performed manually by humans. However, this process can be time-consuming, costly, and prone to errors. Therefore, much research has focused on developing automatic data labeling methods (Ahmad & Gata, 2022).

Sentiment analysis aims to categorize text within a sentence or document, determining whether the expressed opinion falls into positive, negative, or neutral categories. This is achieved using artificial intelligence techniques to analyze the text and identify words and phrases that convey emotions (Asri et al., 2022). entiment analysis is also commonly referred to as Opinion Mining, and it can be used to analyze various types of texts, such as customer comments, product reviews, and social media posts (Gaja et al., 2023).

An AI assistant is a computer program that can interact with humans using natural language, akin to a regular conversation, to help complete various tasks and needs. This makes AI assistants an innovative solution for automating and simplifying social interactions across different fields, thereby improving communication efficiency and effectiveness (Sekarwati et al., 2021). One example of an AI assistant is Gemini, which is developed by Google and supported by LaMDA, a conversational language model that leverages the company's extensive knowledge base to provide a large-scale language model with remarkable power, intelligence, and creativity (Julianto, Kurniadi, & Jr, 2023). Another example is YOU AI, an innovative AI assistant developed by a dedicated team of researchers and entrepreneurs committed to user privacy and security. YOU AI offers a range of features that help users find information and complete tasks more easily, with a user interface and functionality similar to ChatGPT (YOU, 2022).

There have been several previous studies addressing text labeling for sentiment analysis. Generally, these studies employed various text labeling techniques but did not explore the use of AI assistants. The first study discusses sentiment analysis of the Vidio application, where text labeling was performed using VADER Lexicon and Inset (Gaja et al., 2023). The results showed that the accuracy achieved through the Inset process was 90%,

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while VADER Lexicon achieved an accuracy of 73%. The second study focused on sentiment analysis of the PeduliLindungi application, with data labeling using VADER Lexicon (Illia et al., 2021). This study found that the VADER library was more effective for sentiment analysis due to its lexicon-based approach tailored for social media. The third study analyzed public sentiment regarding the presence of electric vehicles, with labeling performed using VADER Lexicon (Anwar & Permana, 2023). The results indicated that 95% of the public expressed positive sentiment, while the remaining 5% expressed negative sentiment toward electric vehicles. The fourth study compared the accuracy of data labeling using VADER Lexicon with Naïve Bayes Classifier, using a dataset of public sentiment toward investment applications (Amaliah & Nuryana, 2022). The results showed that Naïve Bayes Classifier outperformed VADER Lexicon, with an accuracy of 78% compared to 67% for VADER Lexicon. The fifth study focused on analyzing customer reviews, with data labeling using VADER Lexicon (Barik & Misra, 2024). The results revealed that the VADER Lexicon model achieved an accuracy of 98.64%. To provide a concise summary of previous research, the research gaps are presented in a table, as shown in Table 1.

Tabel 1. Research Gap

Research	**Labeling Technique**
(Gaja et al., 2023)	VADER & Inset
(Illia et al., 2021)	VADER
(Anwar & Permana, 2023)	VADER
(Amaliah & Nuryana, 2022)	VADER & Naïve Bayes Classifier
(Barik & Misra, 2024)	VADER
Present	**Asisten AI (Gemini & You AI)**

This study is essential because there is limited research on the use of AI assistants in the text labeling process. This research will employ the AI assistants Gemini and YOU AI for text labeling and compare these results with human or manual labeling and labeling using VADER. The modeling will use two algorithms: K-Nearest Neighbors (K-NN) and Naïve Bayes, with K-Fold Cross Validation for evaluation, to determine the performance of each text labeling process. The dataset used is a publicly available financial sentiment dataset downloaded from Kaggle.com, consisting of 500 data points.

K-Nearest Neighbors (KNN) has several advantages, including its ability to handle noisy training data, fast processing performance, ease of understanding, and capability to work with large datasets (Cholil et al., 2021; Julianto, Kurniadi, Septiana, et al., 2023). The effectiveness of K-NN has been demonstrated by research (Andriana et al., 2023), which achieved an "Excellent Classification" rating. Naïve Bayes is known for its good performance in classification tasks because it handles small datasets well, is efficient in selecting key parameters, and has fast execution times (Julianto, Kurniadi, & Jr, 2023; Pebdika et al., 2023). Research (Insan et al., 2023), indicates that Naïve Bayes received a "Good Classification" performance rating. Based on this, the chosen algorithms for the classification process are K-NN and Naïve Bayes.

METHOD

The research method utilizes four stages, illustrated through the research framework, as shown in Figure 1.

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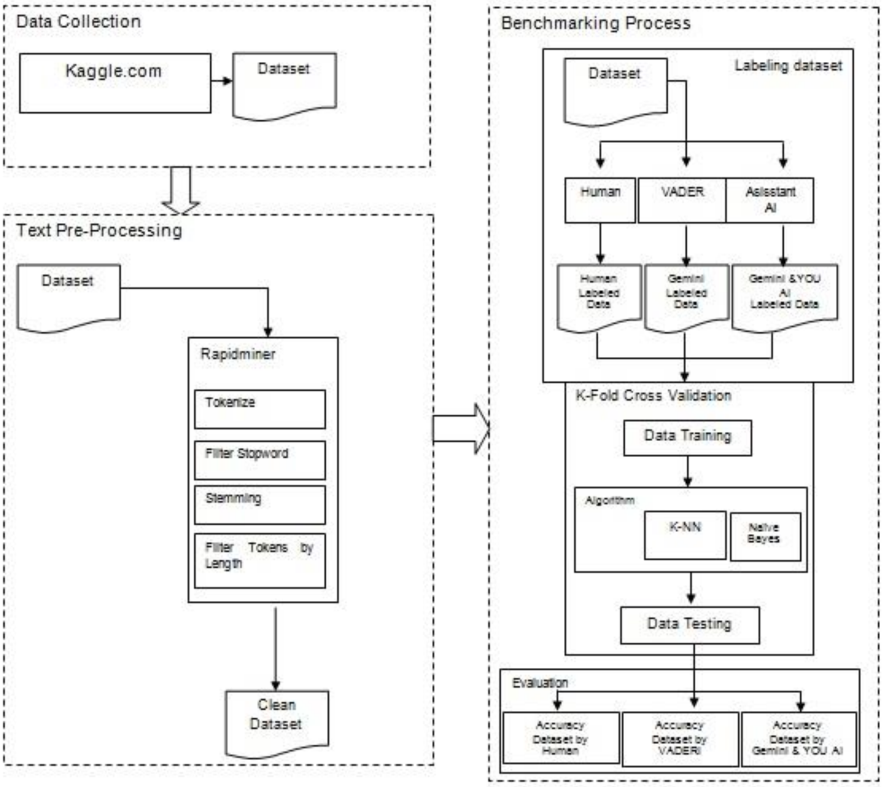

Fig 1. Research Framework

The first stage is Data Collection. The data is sourced from Kaggle.com and pertains to manually labeled financial sentiment, totaling 500 entries (Kaggle, 2022).

The second stage is Text Pre-Processing. Although the dataset downloaded from Kaggle.com is already clean from noisy and redundant data, several Text Pre-Processing steps are still necessary to measure the performance of each labeling model. The tasks performed in this second stage include:

1. *Tokenize*, This is the process of breaking a sentence into smaller units called tokens (Prasetya et al., 2021);
2. *Filter Stopword*, This process aims to remove irrelevant or meaningless words in a sentence based on a stopword list (Rinandyaswara et al., 2022);
3. *Stemming*, This is a process used to find the root form of a word (Albab et al., 2023);
4. *Filter Token By Length*, This process limits each word that appears based on a minimum and maximum character threshold (Julianto et al., 2022).

The third stage is Dataset Labeling. In this stage, labeling will be performed using four methods:

1. Labeling by Human;
2. Labeling by VADER Lexicon;
3. Labeling by Gemini AI;
4. Labeling by YOU AI.

The two AI assistants function according to the following processes:

1. Natural Language Processing (NLP):
   Tokenization: The text was broken down into individual words or tokens.
   Vectorization: Each token was transformed into a numerical representation (vector) that captured its meaning and context.
   Syntactic Analysis: The sentence structure was analyzed to understand the relationships between words
2. Pattern Recognition:
   Language Model: Gemini was trained on a massive dataset of text, allowing it to learn patterns of words that frequently co-occurred and formed specific meanings.
   Sentiment Dictionary: Gemini possessed an internal dictionary containing words and phrases generally considered positive, negative, or neutral.
   Context: Gemini considered the context of the sentence and the overall text to determine a more accurate sentiment. For example, the word "very" could shift sentiment towards being more positive or negative depending on the subsequent word.
3. Sentiment Determination:

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Score Calculation: Gemini calculated a sentiment score for each part of the text, whether it was a word, phrase, or sentence.
Aggregation: These scores were then combined to produce an overall sentiment score for the text.
Classification: Based on the final score, Gemini would classify the text's sentiment as positive, negative, or neutral.

4. Influencing Factors:
Training Data Quality: The larger and more diverse the training data, the better Gemini's ability to understand nuances of language and context.
Text Complexity: Ambiguous text, sarcasm, or informal language could make it difficult for Gemini to determine sentiment.
Domain Specificity: Gemini might perform better in analyzing text from specific domains (e.g., product reviews, news) than others.

The fourth stage is Model Validation. In this stage, the performance of each labeling result will be measured using the K-NN and Naïve Bayes algorithms, and the model validation will be conducted using K-Fold cross-validation. The K-nearest neighbor algorithm is often used in classification. This algorithm works by grouping data into classes based on the nearest distance or similarity to the training data (Pratama et al., 2021). The stages of this algorithm are as follows :

1. Determine the value of k;
2. Calculate the distance between the data that will be classified against the label data;
3. Determine the smallest value of k;
4. Classify data based on a distance metric.

Calculation of proximity using a distance matrix can use the following formula:

$$dist\left(X_{1,}X_{2}\right) = \sqrt{\sum_{i=1}^{n}(x_{1i} - x_{21})} \quad (1)$$

Naïve Bayes Algorithm is a classification method derived from the Bayes theorem, which can predict future opportunities based on opportunities that existed in the past (Ayuningsih et al., 2019). The equation is as follows:
:

$$P(X|Y) = \frac{P(X|Y)P(X)}{P(Y)} \quad (2)$$

The fourth stage is Evaluation. In this stage, the accuracy of each model will be assessed to determine which model has the best performance.

RESULT

The first stage results in a dataset obtained from Kaggle.com, which contains manually labeled financial sentiment data, totaling 500 entries. This dataset is presented in the form of a table, as shown in Table 2
.

Table 2. Dataset

No	Tweet	Label
1	ChatGPT: Optimizing Language Models for Dialogue https://t.co/K9rKRygYyn @OpenAI	Neutral
2	Try talking with ChatGPT, our new AI system which is optimized for dialogue. Your feedback will help us improve it. https://t.co/sHDm57g3Kr	Positive
3	ChatGPT: Optimizing Language Models for Dialogue https://t.co/GLEbMoKN6w #AI #MachineLearning #DataScience #ArtificialIntelligence\n\nTrending AI/ML Article Identified & Digested via Granola; a Machine-Driven RSS Bot by Ramsey Elbasheer https://t.co/RprmAXUp34	Neutral
4	THRILLED to share that ChatGPT, our new model optimized for dialog, is now public, free, and accessible to everyone. https://t.co/dyvtHecYbd https://t.co/DdhzhqhCBX https://t.co/l8qTLure71	Positive
5	As of 2 minutes ago, @OpenAI released their new ChatGPT. \n\nAnd you can use it right now ðŸ'‡ https://t.co/VyPGPNw988 https://t.co/cSn5h6h1M1	Negative
6	Just launched ChatGPT, our new AI system which is optimized for dialogue: https://t.co/ArX6m0FfLE.\n\nTry it out here:	Positive

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	https://t.co/YM1gp5bA64	
…	…	
499	I've seen enough. ChatGPT + Beanie Babies = Profit. DM me to invest\n\nhttps://t.co/wVEanJHhUZ	Negative
500	I need someone to tell me whether providing feedback on ChatGPT is bringing the apocalypse closer or pushing it further away.	Negative

The dataset has two attributes: Tweet and Label. It is free from noisy data and missing values, as verified when the dataset was imported into RapidMiner. The statistical analysis from RapidMiner shows that there are 0 missing values, with 143 positive labels, 79 negative labels, and 277 neutral labels. The statistical results from RapidMiner are presented as shown in Figure 2.

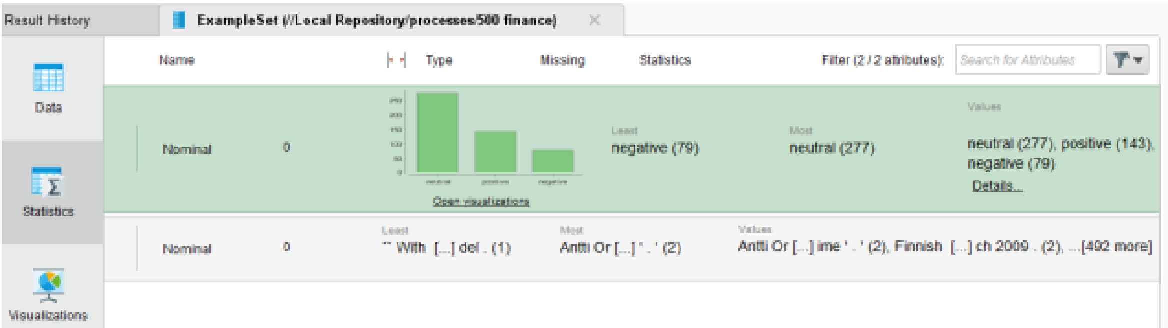

Fig 2. Statistics Data

Next, since the dataset does not contain any missing values or noisy data, the work can proceed to the subsequent stages.

The second stage results in a dataset that is ready for performance evaluation, having undergone Text Pre-Processing steps including Tokenization, Stemming, Stopword Filtering, and Filtering Tokens by Length. The Text Pre-Processing was performed using RapidMiner. The modeling process is presented as shown in Figure 3
.

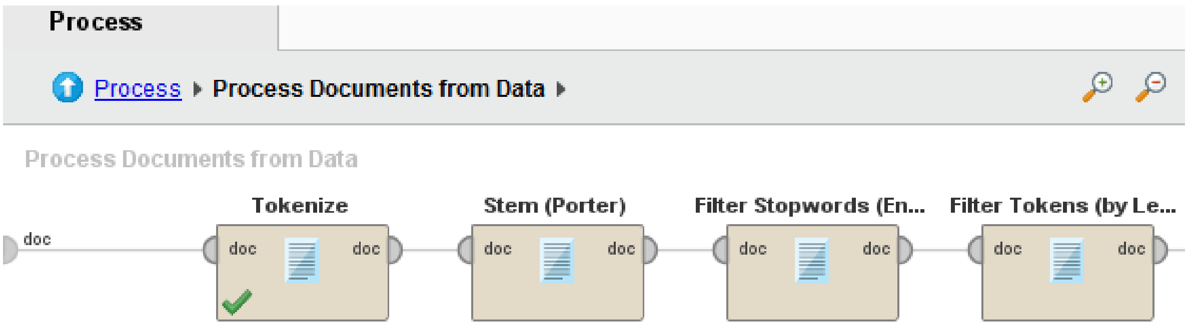

Fig 3. Text Pre-Processing

After the modeling process shown in Figure 3, the results of the Text Pre-Processing are presented as shown in Figure 4..

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Row No.	Sentiment	text	aapl	aberdeen	able	abloy	acanb	acando	accessorie
1	positive	geosolutions ...	0	0	0	0	0	0	0
2	negative	lows possibil...	0	0	0	0	0	0	0
3	positive	quarter comp...	0	0	0	0	0	0	0
4	neutral	according fin...	0	0	0	0	0	0	0
5	neutral	swedish buy...	0	0	0	0	0	0	0
6	positive	surprised gre...	0	0	0	0	0	0	0
7	negative	billion deal m...	0	0	0	0	0	0	0
8	negative	communicati...	0	0	0	0	0	0	0
9	positive	kone sales ro...	0	0	0	0	0	0	0
10	neutral	stockmann d...	0	0	0	0	0	0	0
11	positive	circulation rev...	0	0	0	0	0	0	0
12	negative	disappoints s...	0	0	0	0	0	0	0
13	positive	subdivision ...	0	0	0	0	0	0	0
14	neutral	viking line ca...	0	0	0	0	0	0	0

Fig 4. Hasil Text Pre-Processing

Figure 4 shows that each sentence in the dataset is broken down into words, or tokens. These tokens are transformed into attributes, so the initial dataset with 2 attributes now has 2,153 attributes. With this result, the dataset is now ready to proceed to the next stage.

The third stage produces a dataset that has been labeled by humans, VADER, Gemini AI, and YOU AI. Human labeling has already been completed, as the dataset obtained from Kaggle was manually labeled. The labeling using VADER was performed using RapidMiner, which includes the VADER operator. The modeling process is displayed as shown in Figure 5..

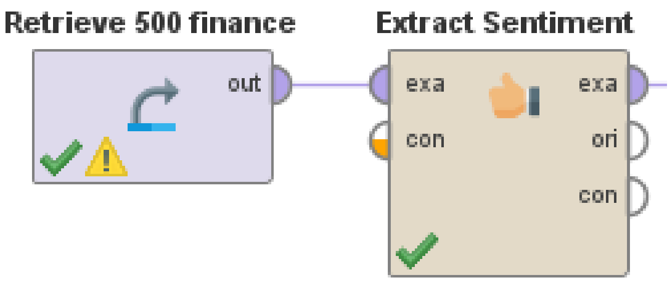

Fig 5. VADER Labeling Model

Extract Sentiment is an operator provided by RapidMiner, which includes an option to use VADER. The results of this modeling process are presented as shown in Figure 6.

Score	Scoring Stri...	Negativity	Positivity	Uncovered T...	Total Tokens	Sentence
0.667	positive (0.67)	0	0.667	0	1	The GeoSolutions techno...
-0.692	negative (-0.6...	0.692	0	0	1	$ESI on lows, down $1.5...
0.667	positive (0.67)	0	0.667	0	1	For the last quarter of 20...
0		0	0	1	1	According to the Finnish-...
0		0	0	1	1	The Swedish buyout firm ...
0.667	positive (0.67)	0	0.667	0	1	$SPY wouldn't be surpris...
-0.692	negative (-0.6...	0.692	0	0	1	Shell's $70 Billion BG De...
-0.692	negative (-0.6...	0.692	0	0	1	SSH COMMUNICATIONS...
0.667	positive (0.67)	0	0.667	0	1	Kone 's net sales rose by...
0		0	0	1	1	The Stockmann departm...
0.667	positive (0.67)	0	0.667	0	1	Circulation revenue has i...
-0.692	negative (-0.6...	0.692	0	0	1	$SAP Q1 disappoints as ...
0.667	positive (0.67)	0	0.667	0	1	The subdivision made sa...
0		0	0	1	1	Viking Line has canceled...
0		0	0	1	1	Ahlstrom Corporation ST...

Fig 6. VADER Labeling Model Result

The labeling results can be seen in the Score attribute. If the value is >= 0.05, it is classified as positive; if <= -0.05, it is classified as negative; and if = 0, it is classified as neutral (Asri et al., 2022). Based on the modeling

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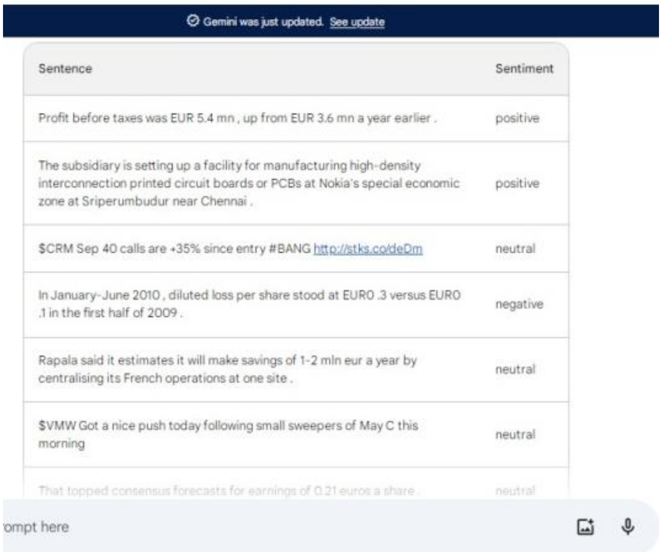
results, there are 239 positive labels, 86 negative labels, and 174 neutral labels. The next labeling process uses Gemini AI, which was performed directly on the Gemini AI website. The labeling process is presented as shown in Figure 7.



Sentence	Sentiment
Profit before taxes was EUR 5.4 mn , up from EUR 3.6 mn a year earlier .	positive
The subsidiary is setting up a facility for manufacturing high-density interconnection printed circuit boards or PCBs at Nokia's special economic zone at Sriperumbudur near Chennai .	positive
$CRM Sep 40 calls are +35% since entry #BANG http://stks.co/deDm	neutral
In January-June 2010 , diluted loss per share stood at EURO .3 versus EURO .1 in the first half of 2009 .	negative
Rapala said it estimates it will make savings of 1-2 mln eur a year by centralising its French operations at one site .	neutral
$VMW Got a nice push today following small sweepers of May C this morning	neutral
That topped consensus forecasts for earnings of 0.21 euros a share .	neutral

Fig 7. Labeling by Gemini AI

This labeling process results in 151 positive labels, 125 negative labels, and 223 neutral labels. The command used during labeling was "Please provide a Positive, Negative, or Neutral label for each of the following sentences." The final labeling process uses YOU AI. Similarly to Gemini AI, labeling was conducted on the YOU AI website. The labeling process is presented as shown in Figure 8..

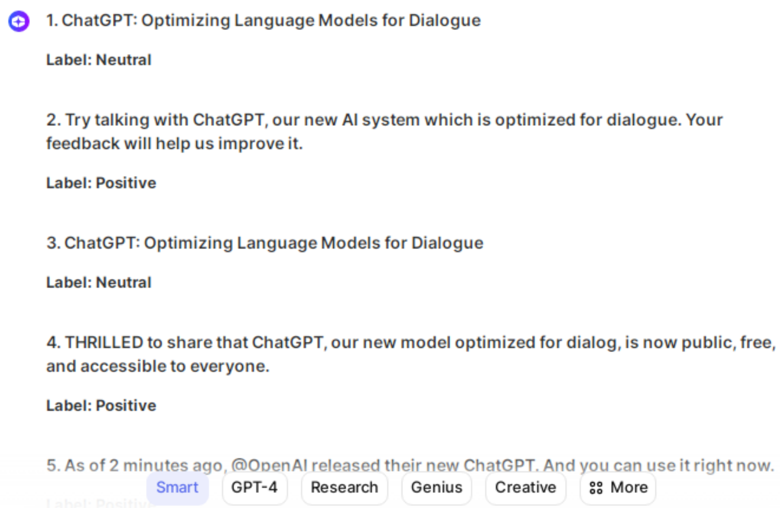


Fig 8. Labeling by YOU AI

The YOU AI used is the standard version, which has a limit of 50 data points per labeling session. Therefore, the labeling process was divided into 10 sessions to cover the full 500 data points. The command given for labeling was the same as that used with Gemini AI. Labeling with YOU AI resulted in 211 positive labels, 135 negative labels, and 153 neutral labels.

The fourth stage produces performance metrics for each dataset. Modeling was conducted using RapidMiner with the Naïve Bayes and K-NN algorithms, and validation was performed using K-Fold Cross Validation. The modeling process is presented as shown in Figure 9.

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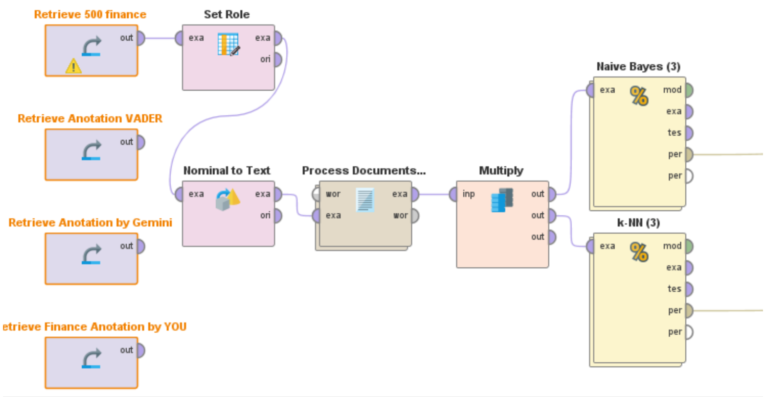

Fig 9. Performance Testing Modeling

Performance testing for each dataset uses the same modeling and operators, with only the dataset being swapped out. The results of the model performance testing are presented as shown in Table 3..

Table 3. Result Performance Test

No	Dataset	K-NN		Naïve Bayes	
		Accuracy	Kappa	Accuracy	Kappa
1	Labeling (Human)	61.12%	0.219	55.11%	0.210
2	Labeling (VADER)	48.51%	0.207	54.29%	0.245
3	Labeling (Gemini AI)	53.71%	0.240	48.30%	0.203
4	Labeling (YOU AI)	44.30%	0.163	48.91%	0.219

Both AI Assistants employ natural language processing techniques to convert text into machine-readable data. With this data, the AI Assistants can compare the text to previously learned patterns. The results of this comparison are then used to determine whether the text contains positive, negative, or neutral sentiment. Pattern recognition is the differentiating factor between the two AI Assistants. The pattern recognition referred to here includes language models, sentiment dictionaries, and context. Each AI Assistant has a different pattern recognition approach, which will affect the accuracy of sentiment assignment. Ultimately, the AI Assistant that provides sentiment closest to or identical to human labeling will be the best choice. Gemini AI exhibited a superior accuracy performance of 53.71% compared to YOU AI using the K-NN algorithm, likely due to Gemini's more advanced pattern recognition capabilities.

CONCLUSION

The research results indicate that alternative labeling methods using AI assistants like Gemini and YOU AI for sentiment analysis are feasible, as the performance test results do not show significant differences compared to human labeling. The best performance was achieved with human labeling using the K-Nearest Neighbour algorithm, yielding an Accuracy of 61.12% and a Kappa value of 0.219. This study primarily focuses on comparing the performance of each labeling method, suggesting that future research could aim to enhance the achieved performance and explore the use of additional AI assistants..

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