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Predicting Rupiah Sentiment Using Social Sentiment Analysis

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ABSTRACT

In recent years, the behavior of foreign currency exchange rates (FOREX) has attracted a lot of attention from policymakers, investors, academics and regulators because due to its rapidly changing prices. FOREX predicting based on sentiment analysis has attracted a wide variety of research in finance and natural language processing. The availability of news, social media networks, and the rapid development of natural language processing methods result in better predictive performance. However, new studies related on Rupiah (Rupiah is legal money circulating in Indonesia) sentiment and its correlation with other FOREX are still rare and interesting to study.The purpose of this study is to (1) assess the accuracy of predicting Rupiah sentiment using social sentiment analysis and (2) to investigate the correlation between Rupiah sentiment and IDR currency exchange rate. The methodological approach used for this study is based on social sentiment analysis on Twitter and Pearson correlation.The result of this study is (1) from the seven models that we compared, the Decision Tree (DT) and Random Forest (RF) algorithm models have the best accuracy to avoid misclassification based on AUC. The accuracy measured by F1-score has values of 92.13% for both DT and RF, and (2) Rupiah sentiment has a strong positive correlation with USD (P-value: 0.017, r-value: 0.421) and SAR (P-value: 0.016, r-value: 0.419) exchange rate. On the other hand, Rupiah sentiment has a low significant negative correlation with AUD (P-value: 0.051, r-value: -0.403) and EUR (P-value: 0.079, r-value: -0.479). Rupiah sentiment also has a low but positive correlation with MYR (P-value: 0.073, r-value: 0.180) and is not significant with SGD (P-value: 0.119, r-value: -0.348) although it has a positive correlation. The strong positive correlation represents that the more positive Rupiah sentiment on Twitter, the stronger IDR exchange rate against another foreign currency, and vice versa.

Keywords: *Rupiah sentiment, foreign currency exchange, sentiment analysis, social media*

Introduction

In recent years, the foreign currency exchange (FOREX) rate has attracted much attention from policy-makers, investors, academics, and regulators due to its rapid price appreciation. Surprising evidence is that unscheduled news releases related to FOREX can affect its returns, volume, and volatility. In contrast, negative news can decrease FOREX returns while positive news can increase FOREX returns [1].

This is inseparable from the rapid development of information release techniques. Social media like Twitter, LinkedIn, and Facebook are perfect platform to transfer news, opinions, thoughts, and views about any topic and issue to the public and significantly affects people's ideas and decisions [2]. It has become an essential tool to spread knowledge about finance [3].

Predicting FOREX based on sentiment analysis has attracted many kinds of research in finance and the natural language processing area to discuss the relationship between FOREX behavior and the sentiments of investors and news. Applying this approach steers many pieces of research to use such online sources. This research line takes advantage of already published data by applying data mining and information retrieval approaches, which provide improvements for the impact of social media to FOREX rate from another perspective [3].

The significance of this study is because in the last five years, most literature or research has focused exclusively on currency predictions in the crypto field. Meanwhile, currency exchange rate research is still very rare in the world, particularly in Indonesia. As a consequence, the gap in this research is that there are numerous studies on cryptocurrency price predictions, but predictions about the rupiah exchange rate are still uncommon, and no such research has been conducted. With the problem as a background, the research question [4] (RQ) is posed:

RQ_1: How accurate is predicting Rupiah sentiment using social sentiment analytics?
RQ_2: Is there any correlation between Rupiah sentiment and IDR currency exchange rate?

The purpose of this study is to (1) assess the accuracy of predicting Rupiah sentiment using social sentiment analysis and (2) to investigate the correlation between Rupiah sentiment and IDR currency exchange rate. The methodological approach used for this study is based on social sentiment analysis on Twitter and Pearson correlation.

This research consist of 7 sections. After this introduction, the rest of this study is structured as follows. Section 2 describes the background of the study. Section 3 explain the related work. Section 4 explain the methodology of the study. Section 5 details the results and discussion of this study, and section 6 summarizes the conclusion, and the section 7 states the future work and limitation [5].

Literature Review

Foreign Currency Exchange Rate

Foreign Currency Exchange (FOREX) deals with the exchange rates of different currencies. These rates provide important information for currency trading in global monetary market segments[6] said FOREX rates are influenced by several aspects, including political and economic events, as well as current business operations and shareholders' mental functioning. FOREX exchange is the synchronous sale of one exchange rate and purchase of someone else. It is required for forex trading on the global market [7]. FOREX is essential for currency trading in the financial sector. To organize large amounts of transactions in today's world, computer algorithms are required [8]. The foreign currency exchange market is one of the largest in the world's financial economy, with an average daily trading volume of more than 1.4 trillion US dollars [9].

Rupiah Currency

According of the statute on Bank Indonesia, Rupiah is legal money circulating in Indonesia [10]. So, the payment instrument agreed upon in Indonesia is the rupiah. Therefore may explain that currency only rupiah applies in Indonesia, while other currencies must be converted before being used in Indonesia with rupiahs [10], [11]. The rupiah exchange rate is a comparison of the value or price of the currency Rupiah currency with another country's currency Singapore dollars, Euros, US dollars, and other currencies are examples [10]–[12].

Sentiment Analysis

Sentiment analysis is used to examine a person's emotions, attitude, and expression and categorize them as positive, negative, or neutral. Sentiment analysis is divided into three major levels, which are as follows [13]–[18]:

- Analysis of Document Level: The task at this stage is to analyze the sentiment of the entire document. Depending on the text, the overall sentiment of the document is classified as positive, negative, or neutral. As a result, a comparative learning text cannot be considered at this level.
- Analysis of Sentence Level: The task at this stage is to analyze a specific sentence and determine whether it represents a negative, positive, or neutral opinion. A neutral sentence is one in which there is no opinion expressed.
- Analysis of Aspect Level: Both previously mentioned levels are incapable of evaluating one's likes and dislikes. As a result, the aspect level presents a comprehensive analysis. The entity level's primary function is identification. Previously, the aspect level was referred to as the feature level.

Social Media

Social media is the use of electronic and internet tools to share and discuss information and experiences with other humans more efficiently. Social media are forms of media that facilitate social interaction by utilizing easily available and flexible effective communication. It is the application of web-based and mobile technologies to transform interaction into an interactive dialogue [19].

Social media refers to a class of internet-based applications that are based on the ideological foundations of Web 2.0 technology and enable the creation and exchange of user-generated content. Social media is an abstract concept with elements such as social atoms (individuals), entities, and interactions [20].

Social media allows people to express their thoughts and opinions, sentiment analysis is at the heart of social media research and application. The benefit of social media is that it allows anyone from anywhere in the world to freely express his or her views and opinions without revealing his or her identity or fearing negative consequences [21].

Related Work

According to research conducted by Wołk [22] that investigates the impact of social media on financial prices in the context of cryptocurrencies. The data was obtained from Twitter and the psychological attitudes and behavior of the community, as revealed by social media analysis, have an impact on speculative cryptocurrency prices.

While the research conducted by Jain et al. [23], their study makes currency predictions. The data was obtained from Twitter as well. However, the method used in this study is Multiple Linear Regression. Furthermore, the results show that the multi-linear regression model can predict crypto prices in case studies of Bitcoin and Litecoin.

Research by Singh et al. [24] conducts sentiment analysis on social media using data from Twitter. According to the findings of this study, Twitter predictions have a power that is correlated with the object being correlated.

Twitter sentiment was found to have predictive power for Bitcoin results in a study conducted by Sattarov et al. [1], which used Twitter to filter public opinion and sentiment analysis from Twitter. This is supported by the correlation value, which has an accuracy rate of 62.48% when based on tweet sentiment related to historical prices.

In research by Pant et al. [25] to forecast prices, this study employs sentiment analysis. Twitter was used as the data source. The results show that the classification of positive and negative sentiments is accurate at 81.39%.

In study by Ranjit et al. [26] there are several similarities, including the use of the sentiment analysis method and the use of the same data source, namely Twitter. This studie's purpose is to predict the American dollar against the Nepalese rupee using fundamental and technical analysis. As a result, the sentiment analysis has an accuracy 90,63%.

Research Methods

This section consist of three stages: (1) data collecting, (2) data pre-processing, and (3) data modelling.

Data Collecting

We used two different sources of data in this study: (1) we obtained daily IDR to another foreign exchange rates (USD, AUD, EUR, SGD, MYR, and SAR) from Google for 11 days (from October 25 to November 4, 2022), and (2) we used Python's Tweepy library version 3.10.0 to extract tweets for sentiment analysis from Twitter since the same period.

```
#Import library
import tweepy
import sys
import jsonpickle
import time
from datetime import datetime
from datetime import timedelta

#Insert consumer key and secret untuk akses API Twitter
consumer_key = "insert your consumer key"
consumer_secret = "insert your consumer secret"
auth = tweepy.AppAuthHandler(consumer_key,consumer_secret)

#Searching parameters
since =(datetime.now() + timedelta(days=-60)).strftime("%Y-%m-%d")
qry='rupiah meroket since:'+since +' lang:in -filter:url -filter:images' #Keywords and since date
maxTweets = 500 #Maximum tweet
tweetsPerQry = 500  # Tweet per query
```

Figure 1. Script for Collecting Public Tweets Sentiment

Tweet data was collected several times by combining different keywords to see the distribution of public sentiment towards the IDR exchange rates (Fig. 1). The keywords that used in this studies are “rupiah meroket”, “rupiah menguat”, “rupiah naik”, “rupiah melejit”, “rupiah turun”, “rupiah melemah”, and “rupiah terpuruk”. After entering each of the keywords, then each search result is stored in the csv file by taking the column of id, userid, name, date, location, and tweet with total of 1,239 rows. The tweets then will be manually labeled whether it is a positive or negative sentiment based on human judgment at the next step.

Data Pre-processing

The extracted tweets contain many slang words, emotions, misspellings, and so on. Due to the presence of these unwanted items in tweets, tweets must go through preprocessing stage before data modeling. The data pre-processing stages include the removal of usernames, the use of links, the removal of repeated letters, the detection of hashtags, removing punctuation marks in the tweets. The last process is manual labeling for sentiment based on human judgment. As a result of this stage, the number of the tweet was reduced from 1,239 to 1,000 tweets with total of 763 tweets identified as negative sentiment and 237 tweets identified as positive sentiment. The sample of the tweets with its label can be seen in Table. 2 on the right side.

Table 1. Tweet Labelling on IDR Social Sentiment

Username	Date	Tweet	Sentiment
Awaliah03_99222	2022/10/25	Rupiah **Menguat** ke Rp 15.585, Analis: Ekonomi Indonesia Solid.	Positive
BelomIngsinyur	2022/10/27	Gokil rakyat pada gotong royong di reksadana pasar uang, lanjutkan. Rupiah Ditutup Menguat Hingga Inflasi Australia Pecah Rekor	Positive
s_mulyatie	2022/11/2	Mantab. Ekonomi **meroket** bener Rupiah **Keok** Nyaris Sentuh Rp15.650 per Dolar AS	Negative
SalamDawwasJ	2022/11/4	Kurangi **Utang**. Kurangi Belanja Yang Gak Penting. Prioritaskan Pembangunan. Apa gak **khawatir** dgn kurs rupiah yg semakin **meroket** disaat banyak utang mata uang asing yg harus dibayarkan. Hanya si **dungu** yg menganggap baik-baik saja. Salam Jum'at Barokah.	Negative

Data Modelling

1. Feature Extraction: After removing the redundant words, the more frequently occurring words are kept in the feature vector as a feature list. The feature list is derived from training data and is then used in the testing phase to classify texts as positive or negative. After extracting the stopwords and dealing with negation words, the feature words may consist of unigrams or bigrams.

2. Training Stage: 80% of the training data are separated for training purposes during the training phase. Following the preprocessing and feature extraction steps, the probability of each feature in the training set is calculated.

3. Testing Stage: 20% of the data is used for testing purposes because the texts have yet to be classified by our model utilizing acquired knowledge from the training dataset. If the contraction words "not" appear, they are handled appropriately. The attributes from the procured testing dataset are then fetched in turn, and the prediction from each feature or attribute in the testing dataset is determined using the equation (1).

$$P\ (wi\ |c) = \frac{(Count\ (wi,\ c)+1)}{(\sum w \in V\ Count\ (w,\ c)+|V|)} \quad (1)$$

The probability of one line of text is calculated by multiplying the probability of each feature in one line by the following equation (2).

$$P(s) = P(s) * P\ (wi\ |c) \quad (2)$$

Where P(s) is the prediction of the entire sentence Following that, the completed prediction of a text is calculated by multiplying it by the probability of the class in question. The following equation will be used.

$$\text{Probability} = P(s) * Class\ Probability \quad (3)$$

If the testing line contains no words from either of the training set's classes, then a lexicon-based approach was used in this case. As a result, the following test metrics will be utilized in this study:

1) Accuracy: This test, all observations of our system are correctly labeled, this test will apply if the data is balanced.

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (4)$$

2) Precision: Precision is calculated by dividing the number of correct results by the total number of returned results.

$$\text{Precision} = \frac{(TP)}{(TP+FP)} \quad (5)$$

3) Recall: Recall is defined as the proportion of accurate data divided by the number of test result that should have been returned.

$$\text{Recall} = \frac{(TP)}{(TP+FN} \quad (6)$$

4) F1-score: F1-score is a metric that combines precision and recall into a single metric.

$$\text{F1} - \text{score} = \frac{(2^* P^* R\ )}{(P+R)} \quad (7)$$

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5) AUC: Area of Under Curve represent the ability of classifier to avoid false of classification

$$\text{AUC} = \frac{1}{2} x (\frac{(TP)}{(TP+FN)})(\frac{(TN)}{(NP+FP}) \tag{8}$$

6) Min-max Normalization: This normalization used to sequeeze the data into range [0-1].

$$\text{Normalization} = \frac{Xi-Xmin}{Xmax-Xmin} \tag{9}$$

7) Pearson correlation (r): Pearson's correlation coefficient returns a value between -1 and 1. The interpretation of the correlation coefficient are:

- -1 : strong negative relationship,
- 0 : no relationship, and
- 1 : strong positive relationship

8) P-value: P-value is the probability of obtaining a test statistic result at least as extreme as the one that was actually observed, assuming that the null hypothesis (H0) is true. An interpretation of a *P-value* based on significane level of 10% are:

- $p \leq 0.01$: very significant,
- $0.01 < p \leq 0.05$: strong significant,
- $0.05 < p \leq 0.1$: low significant, and
- $P > 0.1$: no significant

Notes: *(TP=True Positive, TN=True Negative, FP=False Positive, FN=False Negative, Xi=Data at (i), Xmin=Data Minimum, Xmax=Data Maximum).*

Results and Discussion

Rupiah Sentiment Analysis

The findings of this study demonstrate the accuracy of Rupiah sentiment using accuracy, precision, recall, and the F-measure. We divided our 1,000-tweet dataset into 20% test data and 80% train data.

We used Sklearn and Vectorization in this analysis to assess the F1-score of a single classification, yielding the following results: K Nearest Neighbor (91,11%), Decision Tree (92,13%), Logistic Regression (89,13%), Naïve Bayes (63,81% based on accuracy) and Random Forest (92,13%). In addition, we examine the accuracy of the ensemble algorithm classification model. LGBMBoost (89,95%), XGBoost (89,88%), AdaBoost (87,50%), and Stacking-Voting Classifier (91,11%) are some of the results.

Based on the model evaluation of the eight algorithms used, we can show that only Naive Bayes did not pass the model evaluation. Table 2 shows seven models that passed accuracy, precision, recall, F1-score, and AUC score evaluations. The Decision Tree and Random Forest algorithms have the highest scores for each measurement of the seven algorithms that were successfully evaluated.

Table 2. Accuracy of Rupiah Sentiment Prediction

	Classifier	Accuracy	Precision	Recall	F1-Score	AUC Score
1	Decision Tree	0.964824	0.911111	0.931818	0.921348	0.953006
3	Random Forest	0.964824	0.911111	0.931818	0.921348	0.953006
0	KNN	0.959799	0.891304	0.931818	0.911111	0.949780
7	Voting Classifier	0.959799	0.891304	0.931818	0.911111	0.949780
5	XGBoost	0.954774	0.888889	0.909091	0.898876	0.938416
2	Logistic Regression	0.949749	0.854167	0.931818	0.891304	0.943328
6	AdaBoost	0.939698	0.807692	0.954545	0.875000	0.945015
4	LGBM	0.939698	0.833333	0.909091	0.869565	0.928739

Based on the AUC value (see Table 2), the Decision Tree and Random Forest algorithm models are the best to avoid misclassification. This is due to the dataset in this study is not balanced, so we should not get too caught up in the accuracy results (because the total negative tweets are 763, and the positives are only 237, this does not balance). Therefore, in this study the measurement value that we take as a determinant of accuracy is to use the F1-score.

So, based on the study, we can discussion that random forest and decision tree are the models with the best level of accuracy as measured by the F1-Score. This is in accordance with other research which also claim that Random Forest analysis has the greatest accuracy analysis [27] and [28]. Then, according to studies by Rathan et al [29], it is also true that the Decision Tree algorithm has the highest accuracy score.

Correlation Between Rupiah Sentiment and IDR Exchange Rate

The last goals of this study is to investigate the correlation between Rupiah sentiment and IDR currency exchange rate. Correlation is used to discover a linear relationship between Rupiah on Twitter and IDR currency exchange rate to another foreign currencies and P-value is used to analyze the significany ot the correlation between the sentiment and IDR exchange rates.

From the results of our analysis by applying the correlation and P-value analysis approach, we can see Rupiah sentiment has both positive and negative correlation with IDR exchange rate. To test the correlation, we do comparisons in several foreign currencies, including USD (United Stated Dollar), MYR (Malaysian Ringgit), SAR (Saudi ArabiA Riyal), AUD (Australia Dollar), EUR (Euro), and SGD (Singapore Dollar).

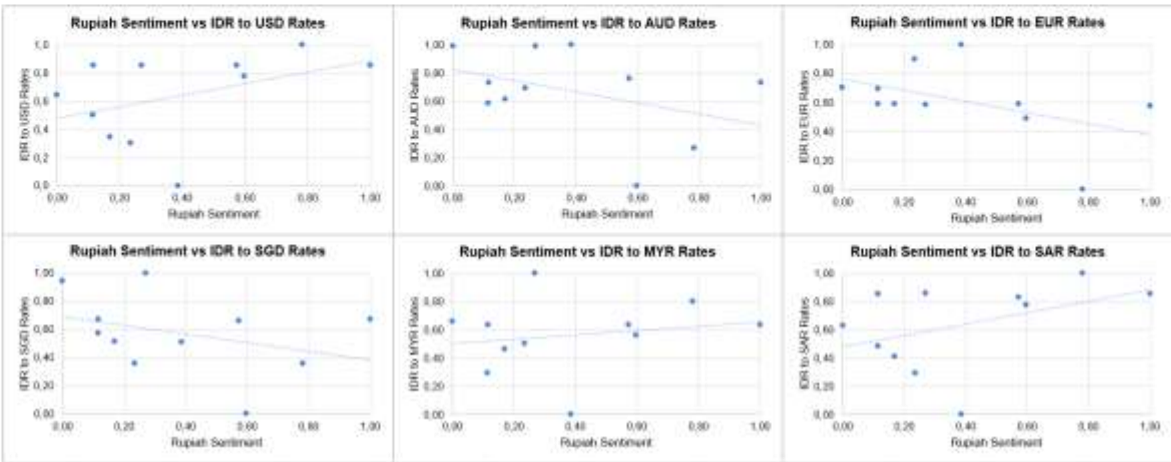

Figure 2. Correlation Between Rupiah Sentiment and Idr Exchange Rate

Fig 2. shows the correlation between Rupiah sentiment against IDR exchange rates to other countries currencies. Based on the figure above we can see that Rupiah sentiment has a positive correlation with USD (United States Dollar), MYR (Malaysian Ringgit), and SAR (Saudi Arabia Riyal) exchange rates. The greatest positive correlation is in IDR to USD with a correlation coefficient is 0.421 followed by IDR to SAR (r-value: 0.419) and IDR to MYR (r-value: 0.180) (See Table 3). On the other hand, Rupiah sentiment has a negative correlation against AUD (Australia Dollar), EUR (Euro), and SGD (Singapore Dollar) exchange rates. Based on Table 3 below we can see that the largest negative correlation is in EUR (r-value:-0.479), AUD (r-value: -0.403), and SGD (r-value: -0.348) currency.

Table 3. Evaluation of Significancy Between Rupiah Sentiment and IDR Exchange Rates

Rupiah sentiment - vs -	r- value	P-value	Corr.	Significancy
IDR to USD Rate	0.421	0.017	Positive	Strong significant
IDR to AUD Rate	-0.403	0.051	Negative	Low significant
IDR to EUR Rate	-0.479	0.079	Negative	Low significant
IDR to SGD Rate	-0.348	0.119	Negative	No signicant
IDR to MYR Rate	0.180	0.073	Positive	Low significant
IDR to SAR Rate	0.419	0.016	Positive	Strong significant

Table 3 represents the evaluation of the significance between Rupiah sentiment against IDR exchange rates to another country's currency. From the sixth foreign currency above we can see that Rupiah sentiment in Twitter has a strong positive correlation with USD (P-value: 0.017) and SAR (P-value: 0.016) exchange rate. It means that the more positive Rupiah sentiment on Twitter, the stronger IDR exchange rate against USD and SAR.

On the other hand, Rupiah sentiment has low significant negative correlation with AUD (P-value: 0.051) and EUR (P-value: 0.079) that means the more positive Rupiah sentiment in Twitter, the IDR exchange rate against AUD and EUR has not getting waker significantly. Rupiah sentiment also has low but positive correlation with MYR (P-value: 0.073) that means the more positive Rupiah sentiment in Twitter, the IDR exchange rate against MYR has not getting stronger significantly. Rupiah sentiment has not significancy with SGD (P-value: 0.119) although it has positive correlation that means the more positive or negative Rupiah sentiment in Twitter, the IDR exchange rate against SGD has no impact.

On the other hand, Rupiah sentiment has a low significant negative correlation with AUD (P-value: 0.051) and EUR (P-value: 0.079) that means the more positive Rupiah sentiment in Twitter, the IDR exchange rate against AUD and EUR has not getting waker significantly. Rupiah sentiment also has a low but positive correlation with MYR (P-value: 0.073) which means the more positive Rupiah sentiment in Twitter, the IDR exchange rate against MYR has not getting stronger significantly. Rupiah sentiment is not significant with SGD (P-value: 0.119) although it has a positive correlation that means the more positive or negative Rupiah sentiment in Twitter, the IDR exchange rate against SGD has no impact.

Conclusion

In this study, (1) we examine the accuracy of predicting Rupiah sentiment using social sentiment analysis, and (2) we investigate the correlation between Rupiah sentiment and IDR currency exchange rate. The result of the first aim is that from the seven models that we compared, the Decision Tree (DT) and Random Forest (RF) algorithm models have the best accuracy to avoid misclassification based on AUC. The accuracy measured by F1-score has values of 92.13% for both DT and RF.The answer of the second goal is that Rupiah sentiment has a strong positive correlation with USD (P-value: 0.017, r-value: 0.421) and SAR (P-value: 0.016, r-value: 0.419) exchange rate. On the other hand, Rupiah sentiment has low significant negative correlation with AUD (P-value: 0.051, r-value: -0.403) and EUR (P-value: 0.079, r-value: -0.479). Rupiah sentiment also has a low but positive correlation with MYR (P-value: 0.073, r-value: 0.180) and it is not significant with SGD (P-value: 0.119, r-value: -0.348) although it has a positive correlation. The strong positive correlation represents that the more positive Rupiah sentiment in Twitter, the stronger IDR exchange rate against another foreign currency, and vice versa.

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