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Impact of Palestine-Israel conflict on multinational stock prices use neural network and support vector machine comparison

Wresti Andriani[1], Gunawan Gunawan[2], Naella Nabila Putri Wahyuning Naja[3]
[1,2]STMIK YMI Tegal, Teknik Informatika, Teknik Informatika, Kota Tegal Indonesia
[3]Universitas Negeri Semarang, Ekonomi, Manajement, Semarang, Indonesia

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ABSTRACT

One form of prolonged geopolitical event is the conflict between Palestine and Israel, which has complex historical, political, and religious roots in the Middle East. This research aims to determine whether this conflict influences the share prices of the companies Unilever, McDonald's, and KFC. These three large companies are known as allies of one of the disputing countries. The method used by the Neural Network is compared with Support Vector Machine to find the best accuracy using RMSE and MAE. The greater the error value, the more affected the company is by this geopolitical factor. As a result, the accuracy of the SVM method is better than NN; the company most affected is KFC, with the RMSE value of 0.111, MAE of 0.020, followed by Unilever with RMSE 0.034, MAE 0.025 then McDonald's with RMSE 0.026 and MAE 0.116, is expected to help investors choose to invest in the company McDonald’s then Unilever.

Corresponding Author:

Gunawan,
Informatics Engineering
STMIK YMI Tegal
Pendidikan Street No. 1, Pesurungan Lor, Margadana, Kota Tegal, Jawa Tengah 52142, Indonesia
Email: gunawan@stmik-tegal.ac.id

1. INTRODUCTION

One form of prolonged geopolitical event is the conflict between Palestine and Israel, which has complex historical, political, and religious roots in the Middle East and influences stock price fluctuations (Yilmazkuday, 2024), causing uncertainty in market volatility (Smales, 2021b). This war was motivated by the UN decision in 1947, which divided the state of Palestine into two states, namely Palestinian Jews and Arabs. This formation was opposed by neighboring Arab countries, resulting in a protracted war, starting from the struggle over the status of Jerusalem. Against the blockade of Gaza from 1947-2007. Efforts for a peace agreement between Israel and Palestine continue, with the role of international mediators such as the United States, UN, and other countries tending to fail, thus having an impact on all sectors of world conflict (Divine, 2019).

The share price movements of Unilever and fast food companies such as McDonald's and KFC during conflict can provide insight into resilience and vulnerability to political tensions(Wood, Robinson et al., 2023). The Unilever company, founded in 1929-1930, was a joint company from England and the Netherlands that formed a new entity called Unilever, known as pro-Israel (Wood, Williams, et al., 2023). The fast food company from the United States operating in Indonesia, KFC (Obomwan, 2022), which was founded in the 1930s, is also on the boycott list against Israel. Likewise, the McDonald's company (Ashenfelter & Jurajda, 2022). This will, of course, affect the share price movements of these three companies and can raise concerns for investors who invest in them, as well as risk management and financial analysts, as to whether the shares they own are still safe or have the potential to experience losses.

Previous research predicted the Baltic using several machine learning methods such as KNN and Random Forest, producing results that using the KNN and Random Forest methods was better than the Autoregressive Moving Average method (Nõu et al., 2023). The advantage of the KNN method is that it is simple. Hence, it is easy to implement and understand and is effective on datasets that do not have too many features. Still, the weakness is that it is sensitive to data of different sizes; large datasets will take time and perform poorly on datasets with many features because the distance between points is less significant (L. Chen et al., 2021). While the Random Forest algorithm has the advantage of handling overfitting and being flexible, it also has the weakness of having long computational time complexity and being difficult to interpret (Hong & Lynn, 2020). Other research uses the Gaussians Naive Bayes algorithm (Ampomah et al., 2021), the results of which are the GNB LDA algorithm is better. However, this algorithm has the advantage of being simple and easy to understand, performing quickly and efficiently on large datasets. Still, it has weaknesses: naive assumptions on mutually independent datasets, low performance with numerical variables, and a lack of ability to understand complex relationships (Y. Chen & Zhu, 2023). Apart from that, the prediction of active COVID-19 cases uses a linear regression algorithm (Rath et al., 2020). As a result, there is a strong correlation between the dependent and independent variables. This algorithm also has advantages and disadvantages; the benefits are that it is simple and easy to understand, computationally efficient, and can manage independent and stable variables on small data sets, while the disadvantage is that if the linear regression model is too simple or complex, overfitting or underfitting can occur. Sensitive to outlier datasets and assumes independent residuals, which, if done, means the estimation results will be inaccurate (Ciulla & D'Amico, 2019).

Previous research shows that geopolitical conflicts can influence stock prices in various sectors(Yilmazkuday, 2024) Investigating the influence of the geopolitical risk of the Ukraine-Russia war on stock prices of 29 countries using linear regression, the results show that Latvia and China are positively affected by 0.80 and 0.71. Other research (Smales, 2021) using GARCH, As a result, oil prices are not significantly affected by geopolitical factors.

Based on initial analysis of Unilever, McDonald's and KFC share price movements, it is clear that there are significant fluctuations and non-linear patterns. This is indicated by large daily variations and trends that are difficult to predict with simple linear models. Therefore, non-linear algorithms such as Neural Networks (NN) and Support Vector Machines (SVM) are considered more suitable to capture this complexity.

This research aims to determine whether the Palestine-Israel conflict has an effect on the share prices of multinational companies Unilever, McDonald's and KFC by comparing the accuracy of the NN and SVM methods. The evaluation results use RMSE and MAE, where a lower error value means the company is safer to invest in. This research aims to provide information to company owners and investors to make the right investment decisions while avoiding losses.

2. RESEARCH METHOD

2.1 Research Stage

The research design that will be carried out in this research is shown in diagram 1 below:

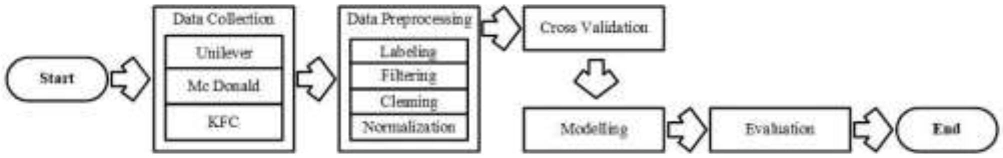

Figure 1. Flowchart of the Impact of the Palestine-Israel Conflict on Multinational Stock Prices: Comparison of ANN vs. SVM

From Figure 1 above, it can be explained that this research will begin with collecting stock price data owned by the three companies, namely Unilever, Mc Donald, and KFC, during the Palestine and Israel war, which was obtained online from the data linkhttps://finance.yahoo.com/quote/UL/historyandhttps://finance.yahoo.com/quote/MD/history also https://finance.yahoo.com/quote/KFC-USD/history then the data was carried out. Data preprocessing includes cleaning, missing, and normalization. After that, training data and testing data were separated using cross-validation. Then, testing was carried out using the Neural Network method compared to the SVM method and produced an evaluation using RMSE and MAE; after that, the most optimal accuracy was obtained and compared using data before the war heated up with steps the same thing to get what information. This war affected stock price movements.

2.2 Data Collection

The following is the Unilever Company Dataset taken from the link https://finance.yahoo.com/quote/UL/history from fast food companies Mc Donald https://finance.yahoo.com/quote/MCD/history and KFC https://finance.yahoo.com/quote/KFC-USD/history each of which was taken as daily time series data from May 2021 to 2024. At that time, Israel's attacks intensified, triggered by increasing tensions in Jerusalem and the city's holy sites—the length of the Al-Aqsa Mosque, as in Tables 1, 2, and 3.

Table 1. PT UNILEVER Stock Price Movements

Date	Open	High	Low	Close	Adj Close	Volume
5/3/2021	6000	6000	5900	5900	5347.711	11454300
5/4/2021	5900	5950	5700	5750	5211.753	27736500
5/5/2021	5750	5900	5725	5775	5234.413	23481700
...	...	...	...	...	...	...
3/22/2024	2720	2750	2670	2720	2720	12568600

Table 1 describes the stock movement of PT Unilever from May 2021 to March 2024. The dataset obtained was 704 data and consisted of 7 variables: date, open, high, low, close, adj close, and volume.

Table 2. McDonald's Stock Price Movements

Date	Open	High	Low	Close	Adj Close	Volume
5/3/2021	237.990005	238.179993	235.380005	235.559998	220.35762	2458000
5/4/2021	234.630005	236.130005	233.240005	233.860001	218.767395	2529700
5/5/2021	234.119995	235.350006	231.559998	235.039993	219.871201	2070000
...	...	...	...	...	...	...
3/22/2024	283.880005	284.390015	282.119995	282.630005	282.630005	2556100

Table 2 shows a dataset of McDonald's share price movements; the number of datasets collected was 728, consisting of 7 variables: date, open, high, low, close, adj close, and volume.

Table 3. KFC Stock Price Movements

Date	Open	High	Low	Close	Adj Close	Volume
5/1/2021	6.645057	6.857709	6.327747	6.643198	6.643198	10763
5/2/2021	6.629734	6.645619	5.832972	6.114657	6.114657	17980
5/3/2021	6.114808	6.438286	5.675995	5.87886	5.87886	23570

...	...	...	...	...	...	...
3/23/2024	5.188221	5.19616	5.165246	5.16751	5.16751	19629

Table 3 shows a dataset of stock price movements from KFC. The dataset obtained was 1059 data with seven variables: date, open, high, low, close, adj close, and volume.

Figure 2. Fluctuation graph of Unilever, Mc Donald and KFC share price movements

Figure 2 shows daily stock price movements for Unilever, McDonald's, and KFC over a 30-day period. The increase in Palestinian and Israeli tensions in 2021 - 2024, including intensive attacks in May 2021, caused significant fluctuations in global stock markets. From the graph three companies show significant share price variations with several peaks and valleys, indicating volatility and trend changes that are difficult to predict using simple linear models.

2.3 Pre-processing Data

After the dataset collection is obtained, the next step is to preprocess the data, which includes (Alexandropoulos et al., 2019): (a) Labelling, this process involves assigning an appropriate label or category to each sample in the dataset according to the target or desired output. The feature label was selected for Close data in this research because it can be used to build statistical or machine-learning models that predict future stock price movements (Wu et al., 2020). This can help investors to plan trading or investment strategies. (b) Filtering, namely by filtering the date from old to new to become the latest date to the old one(Benhar et al., 2020). (c) Cleaning, namely by cleaning data from unnecessary data such as null, missing, and noisy (Felix & Lee, 2019). (d) Data normalization: The function of data normalization is to change the values of each feature in the dataset to a uniform or relative scale within a specific range. Normalization aims to ensure that all features have a balanced influence on the analysis and model being built, especially in machine learning and statistical analysis.

2.4 K- Fold Cross Validation

K-fold cross-validation is helpful for better model performance in various modeling cases. Model performance on machine learning involves dividing a data set into k equal subsets. Next, the model is tested k times; each subset is used as testing data, while the other k-1 subsets are used as training data. K-fold cross-validation is often used in research and model development to avoid bias that may occur due to random division of the dataset. It also helps maximize data use, as all samples are used for training and testing (Wong & Yeh, 2020).

2.5 Data Modelling

After k-fold validation, the RMSE and MAE evaluation results are calculated using the Artificial Neural Network method and the Support Vector Machine method to find the most optimal accuracy. These results will provide information on whether the shares of these three companies impacted the Palestinian and Israeli wars and prove that geopolitical factors significantly influence share price movements. The calculation steps for the Artificial Neural Network method are (Liao et al., 2022):

a. Net Input Calculation:

The net input to neurons in a given layer is calculated as a linear combination of inputs and weights plus bias. For neurons at layer l, net input (Z_j) :

$$Z_j^l = \sum_{i=1}^{n}(w_{ij}^l \ x \ X_i) + b_j^l \tag{1}$$

Where w_{ij}^l Is the weight between neurons i at layer and neuron j at layer l, $X_i$is input to neuron i, b_j^l Is bias from neuron j at layer l.

b. Activation Function:

The output of each neuron is calculated by applying an activation function (σ) to the net input. For neurons j in layer l, output (σ) is calculated as:

$$a_j^l = \sigma(z_j^l) \tag{2}$$

This activation function allows the network to acquire non-linearity properties, enabling it to model complex relationships in the data.

c. Weight and Bias Update:

Weights and biases are updated based on changes calculated using learning algorithms, such as stochastic gradient descent. The change in weight (Δw_{ij}^l) is calculated as:

$$\Delta w_{ij}^l = \eta \ x \ \frac{\vartheta E}{\vartheta w_{ij}^l} \tag{3}$$

Where η is the learning rate and $\frac{\vartheta E}{\vartheta w_{ij}^l}$ It is the gradient of the cost function concerning those weights.

The Support Vector Machine (SVM) method uses a decision function formula to predict the class of a sample (Yan et al., 2020):

a. Decision Function:

SVM uses a decision function to determine the class of a sample. For the case of binary classification, the decision function is defined as:

$$f(x) = sign \ (\ w - x + b) \tag{4}$$

Where $f(x)$ It is the decision function, the sign is the sign function, w is the weight vector, x is the input vector, and b is bias.

b. Class Prediction:

To predict the class of a sample, the results of the decision function $(f(x))$ evaluated: if $f(x)$ > 0, then the sample is classified into the positive class, and if $f(x) < 0$, then the sample is classified into the negative class.

c. Margins:

The margin is the distance between the hyperplane and the closest samples of both classes. SVM attempts to maximize the margin when finding the best hyperplane that separates classes.

d. Kernel Functions:

SVM uses a kernel function to map the data into a higher feature space to predict classes from samples that are not linearly separable in the original space. The results of the kernel function are used to calculate the decision function.

e. C Parameters:

Parameter C in SVM controls the trade-off between the margin and the number of classification errors. A value greater than C tends to lead to smaller margins but lower classification errors, whereas smaller values of C tend to lead to larger margins but higher misclassification errors (Sun et al., 2019).

2.6 Evaluation

Evaluation results for predictions using Artificial Neural Network (ANN) and SVM(Ferreira et al., 2019) in this study used RMSE and MAE to measure how often the model correctly predicts the target class (Hajimirzaei & Navimipour, 2019).

RMSE (Root Mean Square Error) measures how well a regression model predicts continuous values. The Formula is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (5)$$

Where n is the total of samples, y_i Is the actual value of the i^{th}sample, and $\bar{y}_i$ Does the model predict the value? i^{th}sample. RMSE calculates the square root of the mean of the squares of the differences between the actual value and the value predicted by the model. This gives an idea of how big the average prediction error of the model is on the actual data. The lower the RMSE value, the better the model predicts the target value (Ćalasan et al., 2020).

MAE (Mean Absolute Error) is an evaluation metric used to measure prediction errors in regression models. The MAE formula is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \bar{y}_i| \quad (6)$$

Where n is the total sample, y_i Is the actual value of the ith sample, $\bar{y}_i$ Does the model for the ith sample predict the value. MAE measures the average of the absolute differences between the actual value and the value predicted by the model. This gives an idea of how big the average prediction error of the model is on the actual data. The lower the MAE value, the better the model predicts the target value (Tang et al., 2021).

3. RESULTS AND DISCUSSIONS

The data used in this research was collected online via the yahoo. Finance page, using historical data. Data taken since May 2021 from companies, namely Unilever, as many as 704, Mc. Donald 728 and KFC 1058 data.

Datasets from the three companies, after going through data preprocessing, obtained results as in Tables 4, 5, and 6.

Table 4. Results Of Normalization of PT Unilever Share Prices

Row	Close	Open	High	Low	Adj Close	Volume	Data
1	-2.374	-2.386	-2.386	-2.426	-2.376	-0.432	Mar 22, 2024
2	-2.374	-2.324	-2.340	-2.347	-2.376	-0.540	Mar 21, 2024
3	-2.313	-2.324	-2.279	-2.315	-2.305	-0.070	Mar 20, 2024
...	...	...	...	...	...	...	...
704	2.532	2.678	2.572	2.674	2.295	-0.483	May 1, 2021

Table 4 shows the results of data normalization using a dataset from PT Unilever by selecting the close feature as the target/label.

Table 5. Results Of Normalization of Mc.Donald

Row	Close	Open	High	Low	Adj Close	Volume	Date
1	0.974	1.037	0.976	1.041	1.186	-0.234	Mar 22, 2024

2	1.081	1.067	1.035	1.066	1.224	0.921	Mar 21, 2024
3	1.063	1.018	0.987	1.004	1.263	0.093	Mar 20, 2024
...	...	...	...	...	...	...	...
728	-1.330	-1.212	-1.298	-1.245	-1.426	-0.337	May 1, 2021

Table 5 shows the results of data normalization using a dataset from McDonald's by selecting the close feature as the target/label.

Table 6. Results Of Normalization of KFC

Row	Close	Open	High	Low	Adj Close	Volume	Date
1	-0.885	-0.881	-0.901	-0.844	-0.885	-0.052	Mar 23, 2024
2	-0.881	-0.897	-0.886	-0.857	-0.881	-0.031	Mar 22, 2024
3	-0.897	-0.874	-0.890	-0.869	-0.897	-0.031	Mar 21, 2024
...	...	...	...	...	...	...	...
1058	-0.554	-0.554	-0.569	-0.571	-0.554	-0.095	May 1, 2021

Table 6 shows the results of data normalization using a dataset from McDonald's by selecting the close feature as the target/label. From the results of data normalization, graphs of share price movements for the three companies are obtained as in Figures 2, 3, and 4, where each image explains an image of stock price movements that have been normalized and given targeting/labeling close data.

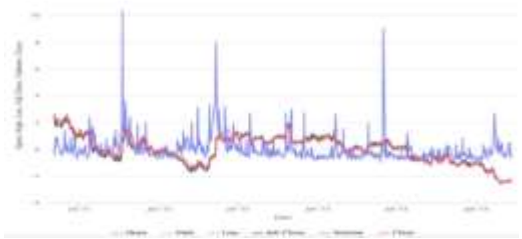

Figure 3. PT Unilever Stock Price Movements with the Close Feature as the label

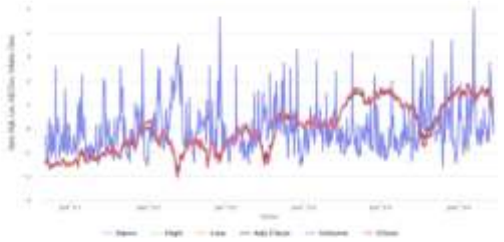

Figure 4. McDonald's Stock Price Movements with the Close Feature as the label

Figure 5. KFC Stock Price Movements with the Close Feature as the label

Figures 3, 4, and 5 show stock price movements after the data preprocessing process using the Close feature selection as the data label. In this image, it is shown in red. The results of research comparing the Artificial Intelligence and Support Vector Machine methods on share price movements from PT Unilever, McDonald's, and KFC are shown in Table 7.

Table 7. Comparison of ANN and SVM Methods

Algoritma	UNILEVER		McDonald's		KFC	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
ANN	0.243	0.129	0.151	0.151	0.124	0.084
SVM	0.234	0.125	0.145	0.116	0.111	0.027

Table 7 shows that by using the Support Vector Machine algorithm, the company Mc. Donald and KFC are better than Unilever companies with RMSE of 0.145 and 0.111, respectively. MAE is 0.116 and 0.027. Meanwhile, using the Artificial Neural Network algorithm is also better for McDonald's and Koo. Mc. Donald with RMSE of 0.151 and 0.124, respectively, and MAE of 0.151 and 0.084. They use a Support Vector Machine better than an Artificial Neural Network algorithm.

In the same steps, this research also compared the share price movements of the three companies with the dataset before the war started to heat up, namely around 2005 to 2007. This activity was carried out to determine whether geopolitical factors would influence the share price movements of the three companies' shares. Data is obtained on the same page, and results are obtained as in Table 8.

Table 8 Comparison of Stock Price Movements Before the War

Algoritma	Unilever		Mc.Donald		KFC	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
ANN	0.037	0.029	0.028	0.151	0.028	0.019
SVM	0.034	0.025	0.026	0.116	0.111	0.020

Table 8 compares the artificial Neural Network algorithm with the Support Vector Machine for three companies: Unilever, McDonald's, and KFC. Support Vector Machine also turns out to be superior to ANN in both Unilever and Mc companies. McDonald's is 0.034 and 0.026 for RMSE, 0.025, but MAE is still better for the KFC company, namely 0.020. The comparison is shown in the figure 5.

Figure 6. Comparison of RMSE and MAE for ANN and SVM Algorithm

Figure 6 compares the share price movements of the multinational company Unilever, company Mc. Donald and KFC. Data taken from the period before the Palestinian and Israeli war of aggression heated up, which was taken online from 2005 to 2007, and compared with share price data for the three companies when they were more aggressive, namely the period from May 2021 to the present. The blue color represents the ANN algorithm, and the red color represents the SVM algorithm. RMSE and MAE are used to measure the error level, and the smaller or closer to 0, the more accurate it is; in the graph above, stock prices before the war escalated were better than during the war. This means that geopolitical factors can influence stock price movements.

Previous research has shown that geopolitical conflicts can affect stock prices across various sectors. Yilmazkuday (2024) used linear regression to study the impact of geopolitical risk from the Russia-Ukraine war on stock prices in 29 countries. The results showed that Latvia and China were positively affected, with values of 0.80 and 0.71, respectively. Another study by Smales (2021) used GARCH to analyze oil price volatility and found that oil prices were not significantly affected by geopolitical factors and used only one evaluation result is error level. This study differs by using non-linear algorithms, Neural Networks (NN) and Support Vector Machines (SVM), to analyze the impact of the Palestine-Israel conflict on the stock prices of multinational companies like Unilever, McDonald's, and KFC. Using daily stock data from May 2021 to March 2024, the evaluation results show that the SVM algorithm has better accuracy than NN based on RMSE and MAE, as shown in Table 8.

The novelty of this research lies in the use of non-linear algorithms (NN and SVM) that can capture complex and non-linear patterns in stock data influenced by geopolitical events, which cannot be well accommodated by linear models like linear regression used in previous research. By using these methods, the research provides more accurate and in-depth insights into how geopolitical conflicts affect the stock prices of multinational companies, offering better guidance for investors and company owners in making investment decisions.

4. CONCLUSION

This study concludes that in the stock price movements of multinational companies Unilever, McDonald's, and KFC during the Palestine and Israel war, the Support Vector Machine method is more accurate than the Artificial Neural Network method. The RMSE and MAE for Unilever are 0.234 and 0.125, respectively. McDonald's is 0.145 and 0.116, and KFC is 0.111 and 0.027. It is concluded that Unilever is most affected by geopolitical factors, followed by Mc. Donald's and then KFC. Thus, it is hoped that the results of this study can provide practical recommendations for investors or companies on the importance of paying attention to external factors such as economic conditions and political news in making decisions and supporting investors in investing more informally to avoid significant losses, such as external factors. This study has limitations in sample size, historical data coverage, and external factor analysis that may affect the generalizability of the findings. For future research, it is recommended to use more complete data, various more sophisticated machine learning models.

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