Proceedings of the 4th International Conference on Signal Processing and Machine Learning
DOI: 10.54254/2755-2721/45/20241486

Predicting the UK stock index after the outbreak of the Russia-Ukraine conflict

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Abstract. Accurate asset price forecasting is crucial for financial activities. With the continuous development of the Russia-Ukraine conflict, the global financial market has responded significantly and strongly to the geopolitical situation. As an international financial center, the UK market has also been impacted, with severe fluctuations in the UK stock index, potentially affecting investors. Therefore, this study selects the UK stock index as the research object, using three models to predict the UK market and evaluate model performance. The results indicate that SVM's fitting performance is inferior compared to that of the other two models during training. On test data, SVM exhibits poor predictive ability, while decision tree and random forest demonstrate high accuracy in their predictions. In particular, random forests provide a more precise simulation of price trends compared to decision trees, which closely aligns with actual value trends. This finding suggests that utilizing ensemble methods like random forest can enhance forecasting capabilities when analyzing stock market behavior.

Keywords: UK, Russia-Ukraine Conflict, SVM.

1. Research background

In the intricate tapestry of the global financial ecosystem, the interplay between international events and geopolitical dynamics crafts a narrative of volatility, uncertainty, and opportunity. The financial markets, often seen as the pulse of global economic health, are influenced by not just economic indicators but also the tumultuous winds of political events and international relations. Major geopolitical upheaval, including wars, diplomatic standoffs, and international conflicts, serve as catalysts, often igniting swift and intense reactions within the financial realm.

The recent Russo-Ukrainian War stands as a testament to this dynamic. Emerging from the shadows of international diplomacy, this conflict not only reshaped the geopolitical landscape but also sent ripples across global financial markets. While the immediate brunt was borne by Ukraine and Russia, the reverberations of this conflict have reached far and wide, touching the shores of nations both directly and indirectly involved.

The UK, with London as its financial heart, has always been at the crossroads of global finance. Its stock market, a reflection of both its domestic economic health and its position in the global economic order, becomes a focal point of study in such turbulent times. Understanding the nuanced impacts of the Russo-Ukrainian War on the UK stock market, especially the FTSE 100 Index, is not just an academic endeavor but also a necessity for investors, policymakers, and market strategists. After the onset of the conflict, there remains a dearth of research on predicting the British stock index. This study, therefore,

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embarks on a journey to unravel the intertwined threads of international conflict and financial market dynamics, aiming to provide a beacon for those navigating the murky waters of international political risks.

2. Literature review

The Footsie, also known as the FTSE 100 index, acts as a guardian for the interests of the leading 100 companies that are publicly traded on the London Stock Exchange (LSE). Beyond its numerical representation, it encapsulates the ebbs and flows of the UK's economic narrative. Historical analyses have consistently underscored the FTSE 100's susceptibility to a myriad of events, both domestic and international [1]. The Gulf War, the heart-wrenching 9/11 attacks, and the seismic shock of the Brexit referendum are but chapters in a long saga of global stock market reactions [2]. The 2014 Crimean conflict further solidified this narrative, and the tremors of this regional conflict were felt across the vast expanse of global markets. The European stock markets, with the FTSE 100 at the forefront, grappled with uncertainties stemming from potential energy supply disruptions, trade barriers, and the overarching shadow of geopolitical instability [3].

In the quest to decipher and predict stock market movements, a plethora of models have been brought to the fore. While traditional stalwarts like ARIMA and GARCH have held their ground, the advent of the digital era has introduced a fresh epoch characterized by the emergence of machine learning models, with neural networks and support vector machines leading the charge [4-7]. Recently, with the continuous development of the Russia-Ukraine conflict, UK asset prices have shown an irregular trend of change, which has caused immeasurable losses to investors. This triggered the thinking of this paper: In the context of the Russia-Ukraine conflict, can machine learning accurately predict British asset prices [8-10]?

3. Data source

The data for this study were obtained from Investing.com, a platform that provides historical data on the UK's FTSE 100 Index, encompassing details regarding the index's opening price, closing price, highest price, lowest price, and trading volume. This data was retrieved from the index's historical quotes and trend charts section on the website. We opted for this source because Investing.com is a widely trusted financial data provider, known for delivering high-quality market data suitable for various research and analytical tasks. In this study, we utilized the historical data of the UK's FTSE 100 Index, spanning from February 24, 2022, to September 21, 2023. The details of the selected time series are shown below in Table 1.

Table 1. Descriptive Statistical Analysis

Indicator	Sample Size	Minimum	Maximum	Average	Standard Deviation	Median	Kurtosis	Skewness
FTSE 100 Index	395	6826.150	8014.310	7477.696	255.361	7488.110	-0.275	-0.219

In this study, encompassing 395 data points, the relatively large sample size aids in enhancing the credibility and reliability of the statistical analysis. The FTSE 100 Index exhibits an average value of 7477.696, accompanied by a standard deviation of 255.361. The average value reflects the overall market trend during the study period, while the standard deviation measures the extent of market volatility. Additionally, the median stands at 7488.110, assessing the market's median level. After calculation, the data set shows a negative kurtosis value of -0.275, indicating a platykurtic distribution. The negative skewness value of -0.219 indicates a slight left-skewed distribution, potentially implying that the market's downside risk was marginally higher than the upside risk during the study period. The price trend is shown below in Figure 1.

Figure 1. Price trend of UK stock index

To facilitate model training and testing, we partitioned the dataset into training and test sets based on chronological order. The data split ratio was set at 8:2, indicating that 80% of the dataset was allocated for training purposes, while the remaining 20% was exclusively reserved for testing. The specific divisions are as follows:

Training Set Timeframe: Spanning from February 24, 2022, to May 25, 2023, this encompasses approximately one year of data.

Test Set Timeframe: Covering the period from May 26, 2023, to September 21, 2023, this includes data from roughly four months.

Partitioning the data chronologically aided in preserving the temporal continuity of the data, reflecting the real-world dynamics of financial markets more accurately. The training dataset was used to train the model and optimize its parameters, while the test dataset was utilized for evaluating the model's performance and ability to generalize.

4. Methodology

The UK stock market, specifically the FTSE 100 Index, was forecasted in this study using three distinct regression models. These variants encompass support vector regression (SVR), decision tree regression, and random forest regression tree.

4.1. Support Vector Regression (SVR)

SVR is a machine learning algorithm tailored for regression problems. Its primary objective is to establish a regression model by minimizing prediction errors. The essence of SVR is to identify a hyperplane such that the distance (referred to as the margin) between the training data points and this hyperplane is minimized. All data points within this margin fall within a tolerance range controlled by a specific parameter.

4.2. Decision Tree Regression

The Decision Tree Regression model is specifically designed for regression tasks in the domain of artificial intelligence, specifically machine learning. This project aims to develop a decision tree model for the prediction of continuous numerical outputs, rather than performing decision tree classification. It segments the feature space into multiple rectangular regions, where each region's data points share the same predicted value, typically the average of the data points within that region. The tree construction involves selecting a feature and its corresponding threshold to bifurcate the dataset into two subsets. This process is recursively repeated on each subset until certain stopping criteria are met. The ultimate value predicted on the leaf node is determined as the mean of the data points contained within that specific node.

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4.3. Random Forest Regression Tree

The random forest regression tree is a component of the random forest model tailored for regression tasks. It amalgamates multiple decision trees for regression analysis. The working principle of the random forest regression tree encompasses the following: First, constructing random sample sets from the original training dataset; second, building a regression tree for each random sample set; and third, generating predictions using these trees for new input data. The final prediction is the average (or weighted average) of these regression tree predictions. This model boasts robustness, interpretability, and high performance. It can also estimate feature importance, aiding in identifying influential features for the regression problem.

5. Results

Three distinct regression models were utilized to predict the trajectory of the UK stock market (FTSE 100 Index) in this paper. Initially, the Support Vector Regression (SVR) model was employed, with its kernel type set to Radial Basis Function (rbf). The regularization parameter, C, was set to 1.0, playing a pivotal role in modulating the model's complexity. Subsequently, the decision tree regression model was constructed, with the tree's maximum depth unrestricted (None), allowing the tree to grow optimally. The minimum number of samples needed to perform a split was established as 2, while the leaf node's minimum sample requirement was established as 1. Lastly, the random forest regression tree model was employed, comprising 100 decision trees. The ensemble nature of the random forest model endows it with high performance and robustness, making it apt for various regression challenges. Figure 2 below displays the anticipated outcomes of the three models.

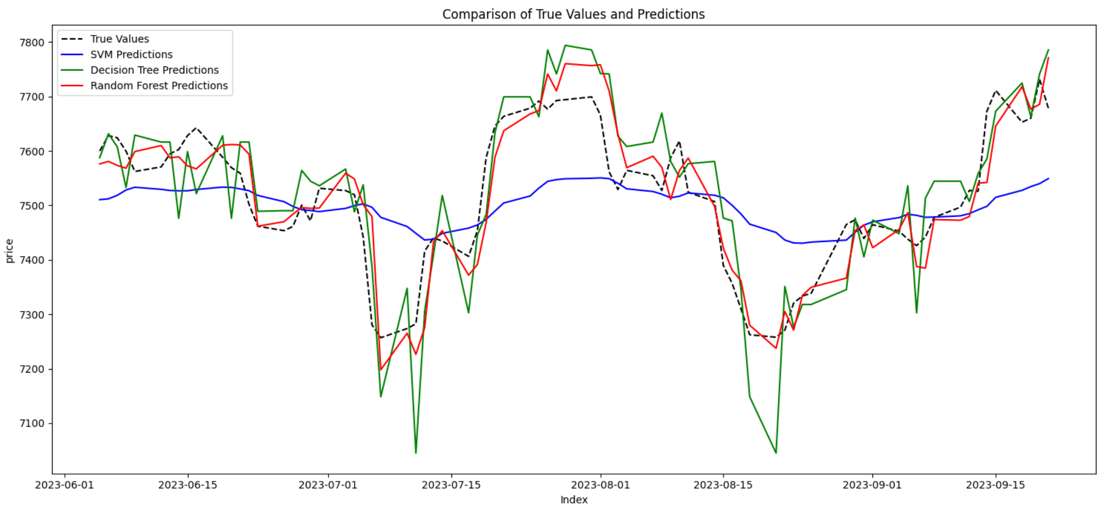

Figure 2. Test set results comparison for SVM, decision tree, and random forest models

To assess the performance of each model, this report introduces two statistical measures, namely mean square error (MSE) and R-squared (R^2), to demonstrate the efficacy of the models. MSE serves as a quantitative indicator for predictor quality, derived from the squared Euclidean distance and always yielding positive values that decrease as errors approach zero. R-squared (R^2) considers the count of predictors within a regression model. It adjusts for overfitting by penalizing models with too many predictors, enhancing the precision of evaluating the model's conformity with the data.

In this experiment, three major predictive models were evaluated: support vector machine (SVM), decision tree, and random forest. On the training set, the SVM's fitting performance was inferior to that of the other two models. On the test set, the SVM's predictive capability remained subpar, whereas both the decision tree and random forest exhibited outstanding predictive results. Notably, the random forest, in simulating price trend changes, demonstrated higher accuracy compared to the decision tree, more closely mirroring the actual value trends.

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In this study, a detailed evaluation and comparison were conducted on three machine learning predictive models: SVM, decision tree, and random forest. To comprehensively assess the performance of the models, we considered not only the common metric mean squared error (MSE) but also introduced the R-squared value, which indicates the level of association between variables, to measure the model's explanatory power over variability. The SVM model achieved an MSE of 10,937, with an R^2 value of 0.3162, indicating that the SVM model could only explain 31.62% of the variability in the data. While SVM performs well on smaller datasets and can simulate nonlinear relationships, its application on larger datasets is limited, and the choice of kernel function can potentially impact its performance. Concurrently, the decision tree model had an MSE of 6,221 and an R^2 value of 0.6111. This suggests that the decision tree model can explain 61.11% of the variability in the data. The primary advantage of the decision tree lies in its exceptional interpretability and capability to model nonlinear relationships. However, it might overfit and is relatively sensitive to outliers. Lastly, the random forest model showcased the best predictive capability in this experiment, with an MSE of 3,230 and an impressive R^2 value of 0.7981, signifying its ability to explain 79.81% of the variability in these data. This strongly indicates the random forest's significant advantage when dealing with complex datasets (See Table 2).

Table 2. Model comparison table

Model	Mean Squared Error (MSE)	R^2
SVM	10,937	0.3162
Decision Tree	6,221	0.6111
Random Forest	3,230	0.7981

6. Conclusion

Three prediction models, namely support vector machine (SVM), decision tree and random forest, were evaluated in this experiment. On the training set, SVM's fitting performance is inferior to that of the other two models. On the test set, the prediction ability of SVM is still poor, but the prediction effect of decision tree and random forest is excellent. Compared with decision tree, random forest is more accurate in simulating price trends and closer to the real value trend. In the forecast results of this experiment, the decision tree model for the future 30-day forecast of the FTSE 100 index reveals significant volatility, which may lead to some uncertainty in the prediction of the future movement of the market. In contrast, the predictions of the random forest model show a more stable trend, providing market participants with relatively stable expectations. The SVM model predicts the FTSE 100 to remain stable at a relatively low level, which may suggest that the market may experience slow or sideways growth for some time in the future. In addition to the above three algorithms, other methods commonly used to deal with complex data sets, such as neural networks, deep learning, etc., are also attracting attention. As a mathematical calculation model based on the design idea of an artificial neuron system, the neural network approach has made many breakthrough achievements in image recognition, natural language processing and other fields, and is being gradually applied in all walks of life. As an important branch in the field of neural networks, deep learning extracts more abstract and high-level information from input samples through multi-level abstract representation and automatic feature learning, and is widely used in image classification, speech recognition, natural language understanding and other tasks. Although neural networks have the advantages of powerful nonlinear modeling ability and rapid training and inference of massive samples, they also have some disadvantages, such as difficulty in parameter adjustment, large consumption of computing resources and black box attributes, which is not conducive to the interpretation of results. Therefore, factors such as the type of problem, the number of samples, the limitation of computing resources and the requirement of the explainability of the results should be considered when selecting the appropriate algorithm, and the selection should be made according to the actual situation.

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