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EXPLORING THE INTERPRETABILITY AND PREDICTIVE POWER OF MACHINE LEARNING MODELS IN TECHNOLOGY INDICES: A CASE STUDY

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Abstract

The paper is a comprehensive study of the performance evaluation of Aselsan in the Borsa Istanbul Technology Index, explaining the interpretability and predictability power of the machine learning models. The study encapsulates the technical indicators and the index data as variables and is conducted in a dataset of 600 days between November 20, 2020, and April 10, 2023. The data was split into two subsets, with 85% allocated to the training subset and 15% to the validation subset. Model training is conducted using the Orthogonal Matching Pursuit (OMP) algorithm. After the training, the model validates its prediction using previously unseen data. The results of the model's findings at this stage indicate the model's strong capacity to predict and robustly predict movements in Aselsan stock prices. Additionally, the model has an interpretability capacity that helps the user understand the decision process and the reasons behind the predictions.

Keywords: Interpretability, Predictive Power, Stock Price, Machine Learning, Technology Indices
JEL Classification: C45, G15, G17

TEKNOLOJİ ENDEKSLERİNDE MAKİNE ÖĞRENİMİ MODELLERİNİN YORUMLANABİLİRLİĞİNİN VE TAHMİN GÜCÜNÜN ARAŞTIRILMASI: BİR VAK'A ÇALIŞMASI

Öz

Bu çalışma, Aselsan'ın Borsa İstanbul Teknoloji Endeksi'ndeki performans değerlendirmesini, makine öğrenmesi modellerinin yorumlanabilirlik ve öngörülebilirlik gücünü açıklayan kapsamlı bir çalışmadır. Çalışma, teknik göstergeleri ve endeks verilerini değişkenler olarak içermekte olup, 20 Kasım 2020 ile 10 Nisan 2023 tarihleri arasındaki 600 günlük bir veri setinde gerçekleştirilmektedir. Veri seti, eğitim alt kümesi için %85 ve doğrulama alt kümesi için %15 olmak üzere 85:15 veri bölünme oranıyla kullanılmıştır. Model eğitimi, Orthogonal Matching Pursuit (OMP) algoritması kullanılarak gerçekleştirilmiştir. Eğitim sonrasında model, daha önce görülmemiş verileri kullanarak tahminlerini doğrulamaktadır. Bu aşamadaki bulgular, modelin Aselsan hisse senedi fiyatlarındaki hareketleri öngörebilme ve güvenilir bir şekilde tahmin edebilme yeteneğinin güçlü olduğuna işaret etmektedir. Ayrıca model, kullanıcının karar sürecini anlamasına ve tahminlerin arkasındaki nedenleri görmesine yardımcı olan bir yorumlanabilirlik kapasitesine sahiptir.

Anahtar Kelimeler: Yorumlanabilirlik, Tahmin Gücü, Hisse Fiyatı, Makine Öğrenimi, Teknoloji Endeksi
JEL Sınıflandırması: C45, G15, G17

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1. INTRODUCTION

In contemporary times, technology indices have become pivotal benchmarks for evaluating the success of a country or a company in the technology sector. These indicators assess the financial performance and innovation potential of technology companies. However, despite their significance, there remains a notable gap in the literature regarding the integration of machine learning models for both predicting and interpreting stock price movements within technology indices. Prior studies have largely focused on traditional financial indicators and market trends, neglecting the dual role of machine learning in providing accurate predictions and transparent, interpretable insights. This study aims to bridge this gap by investigating how machine learning models, particularly the OMP algorithm, can be applied to forecast and explain stock price movements of Aselsan in the Borsa Istanbul Technology Index.

Moreover, technology indices hold significant importance in financial markets for various reasons. Technology, on the other hand, is the sector that shows high trading activity. This means that it is significant towards market activity and interest towards investors. High trading activity in this sector means that the performance and price changes in the technology sector might influence the general market and contribute towards price discovery (Hasbrouck, 2003).

The technology industry is a critical player in technology indexes as it plays a vital role in global transformation and development. The information and technology industries are the prime movers of economic growth and innovation; thus, their performance is critical in general financial stability and advancement. The technology sector substantially contributes to the economies in which it operates (Turhan and Aydemir, 2021).

Exchange rate fluctuations can also be assumed to be the critical determinants of technology indices asymmetrically, based on the impacts of the changes in the exchange rates on the technology indices. This means that other external factors, such as the changes in exchange rates, can affect technology indices. According to Ürkmez and Bölükbaşi (2021), fluctuations in exchange rates tend to have short-run and long-term effects on technology indices. Investors and other market players must understand the linkage between currency fluctuation and technology indices for proper portfolio management and to make well-informed investment decisions.

In addition, technology indices can be significantly affected by government policies and reforms. For instance, the adaptation of the welfare policy in China has impacted the performance and dynamics of the index on the technology sector. The stock market indices have positively reacted to the dynamics of the changes in the indexes mainly due to policy-induced changes that have impacted resource reallocation from software technology to hardware technology (Liu, 2022). In this context, government policies and reforms represent among the most critical factors influencing the performance of technology indexes.

Technology indices are of great importance in equity markets due to their high trading activity, strategic importance in global development, sensitivity to external factors such as exchange rate movements, and the potential impact of government policies. Understanding the dynamics and performance of technology indices is crucial for investors, market participants, and policymakers to guide the stock market and make informed decisions. Therefore, research and analyses on technology indices are essential to the finance literature.

Machine learning models detect the relation in the data and forecast using sophisticated mathematical algorithms. The interpretability and predictive capacity of such models can influence the accuracy and reliability of stock price forecasts within technology indices.

The study investigates those models' interpretability and prediction capabilities to provide insight into the technology index based on the data from a reputable technology corporation like Aselsan. The results of this study contribute to future enhancements that maximize the reliability and preciseness of machine learning models in terms of analysis of the technology index.

The principal objective of this research will be the testing of machine learning models for interpretability and predictive abilities in predicting the stock price of Aselsan in the Borsa Istanbul Technology Index. Historical data will be employed to achieve this objective, and various machine-learning algorithms will be executed to forecast Aselsan's future stock price movements. Furthermore, the study will evaluate the interpretability of these machine learning models by discerning the impact of different variables on stock price.

Interpretability is the model's ability to explain the predictions made. This will offer the practitioners an understanding of the driving forces of the model's output, which is a way to locate biases and inaccuracies. Interpretability is vital when scrutinizing, verifying, and trusting machine learning systems (Carvalho et al., 2019).

Because of its essence in predicting and interpreting the stock price, most studies have focused on predictability using various kinds of financial ratios and shocks from the market. Nevertheless, the results have yet to be straightforward. The predictive power of such variables may depend on market conditions, observation frequency, or methodologies.

McMillan et al. (2017) state that specific stock price ratios have predictive power for individual firm stock returns. Gharghori et al. (2011) found that the dispersion in analyst earnings forecasts has strong predictive power for future stock returns. However, they argued that this evidence represents differences in investor expectations rather than a risk measure. Kim (2022) found that the predictive power of stock market returns vanishes when stocks exhibit high degrees of synchronization and volatility, and the deteriorated predictive power is associated with an increase in individual investors' net stock purchases.

Camgöz (2022) discovered that dividend yield's predictive capacity changes over time, diminishes depending on market conditions, and has a non-linear connection with price. When employing annual rather than monthly observation frequency, the predictive power of dividend yield grows even more. Changes in dividend policies and share buyback decisions might reduce dividend yield's predictive effectiveness.

In stock price forecasting, interpretability and predictive capability must be considered. The nature of the problem and the approach utilized will determine a specific balance between these two features, and past research has shown that numerous factors can influence the prediction power of financial ratios and market-wide shocks.

2. LITERATURE REVIEW

Stock prices of energy businesses have become a critical focal point for investors, financial analysts, and business professionals because the energy sector is the lifeblood of global economic activity.

Energy businesses' stock prices frequently change due to economic, political, and sectoral variables. These changes bring considerable risks and potential returns for investors, generating a large study field for researchers attempting to understand and anticipate stock price movements.

With the increasing interest in the stock prices of energy companies, the literature in this area has experienced rapid growth. This study reviews existing research on stock price movements in the technology sector, particularly focusing on companies like Aselsan. The objective is to provide business academics, investors, and financial professionals with insights into stock price movements in the technology sector.

Vasantha et al. (2012) studied how technical analysis can predict future trends in stock prices. The study applied technical analysis to the stock prices of five selected information technology companies in India. Various technical indicators, such as the relative strength index, Bollinger bands, moving average convergence divergence, and simple moving averages, were used.

In another study, Ling (2013) examined random price predictions of two stocks from different industries, Uni-President Enterprises Corp. and TSMC, using the Fractal theory based on data from the Taiwan Stock Exchange.

A study by Dhutti and Bahra (2014) applied technical analysis to five selected IT sector stocks. Tata Consultancy Services (TCS), Infosys Limited, Wipro, Hindustan Computers Technologies Limited (HCL), and Satyam Computers Limited were analyzed using technical analysis to identify current trends and risks.

Bondia et al. (2016) use threshold cointegration tests to evaluate the long-term relationship between the share prices of other energy companies and oil prices. Structural breaks in the data are considered, and causality is explored. The findings suggest cointegration with two endogenous structural breaks, and in the long run, there is no causality from oil prices to alternative energy stock prices.

Zhang and Du (2017) investigated the dynamic links between the stock markets of new energy, high-technology, and fossil-fuel-based businesses using a three-variable TVP-SV-VAR model. According to the findings, new energy stock prices are associated with higher technology stocks than coal and oil prices. The report also highlighted instability in the Chinese stock market in 2015.

Ramos-Llordén et al. (2020) investigate the relationship between the stock prices of US renewable energy businesses, crude oil prices, and significant financial factors using a time and frequency dynamics method. The majority of return and volatility correlations occur in the near term. The financial market earnings for renewable energy businesses are not strongly influenced by crude oil prices, showing the separation of the two markets. Some investors perceive clean energy and technology equities as comparable investment assets due to their growth potential.

Kocaarslan and Soytaş (2019) analyze the dynamic relationships between green energy, technology shares, and oil prices. Asymmetric effects in dynamic conditional correlations (DCCs) are identified. US dollar value changes play a dominant role in driving DCCs, especially when considering asymmetric impacts.

Chmielewski et al. (2020) used a network approach to analyze stock correlations within industry sectors. The study examines stock networks, characteristics, and meaningful groups formed based on market behavior correlations. Community detection methods are employed to study graph structures.

Nasreen et al. (2020) explore the dynamic connectivity between oil prices and stock returns of renewable energy and technology companies using wavelet coherency and spillover analysis. It also investigates hedging performance and portfolio strategies using multivariate generalized auto-regressive Conditional Heteroscedasticity models.

Kassouri et al.'s (2021) study examines the sensitivity of clean energy and high-tech stocks to oil prices. Yeoh's study (2022) investigates the impact of the KLSE (Kuala Lumpur Stock Exchange) index on the stock performance of leading technology companies worldwide. The study's findings indicate a significant negative relationship between the KLSE index and the performance of technology stocks.

The study by Sukmadilaga et al. (2023) examines the impact of accounting ratios of high-technology service companies in five countries on their stock prices. The research results indicate that diluted earnings affect stock prices, and there are some error rates between accounting ratios and stock prices.

3. DATASET and ANALYSIS

3.1. Dataset

Aselsan was selected as the focus company for this study due to its prominent position as one of Turkey's leading defense and technology corporations, making it a significant contributor to the Borsa Istanbul Technology Index. Aselsan's extensive operations in advanced electronics, defense systems, and technology innovation not only reflect the dynamic nature of the technology sector but also provide a robust case for evaluating stock price movements influenced by technological advancements and market conditions. The data used in this study was obtained through Yahoo Finance. Table 1 explains the sources and contents of the datasets utilized.

Table 1. Dataset

Independent Variable	Source	Content
Aselsan Price and Volume Data	Yahoo Finance	Contains information such as daily closing prices and trading volumes of Aselsan's stock.
Technology Index Price and Volume Data	Yahoo Finance	Contains information such as daily closing prices and trading volumes of a specific technology index.
BIST100 Price and Volume Data	Yahoo Finance	Contains information such as stock prices and trading volumes of 100 companies traded on Borsa Istanbul.
Technical Indicators Derived from Aselsan Price Data	Derived from Yahoo Finance data	Technical indicators derived from Aselsan's stock price and volume data, including moving average, RSI (Relative Strength Index), MACD (Moving Average Convergence Divergence), Bollinger Bands, Stochastic Oscillator, and On-Balance Volume (OBV).

A comprehensive analysis was conducted using Aselsan's stock price and volume data and technology index price and volume data. Aselsan Price and Volume Data contains basic information such as daily closing prices and trading volumes of Aselsan shares.

Technology Index Price and Volume Data reflect this index's daily closing prices and trading volumes, representing the technology sector. This data is used in the analysis to take sectoral trends into account.

In addition, volumes and prices of the BIST100 (Borsa Istanbul 100) are included to allow the observation and integration of general market trends into the model. The BIST100 data represents a significant reference point for realizing general market trends and how Aselsan stocks performed within that general framework.

The data sets used for this study were obtained from Yahoo Finance, a reliable source. Data accuracy and currency were maintained with exactitude to keep the consistency and validity of the analyses and the results. Only the data analysis from authentic sources can serve as a more credible base for the research and decision-making. Proper selection and verification of data sources are essential elements for knowledge-based studies, and they add immensely to the strength of the analyses.

Generated by using Aselsan pricing data, the research uses technical indicators. These are mathematical techniques applied in forecasting changes in prices or forms. As a result, it was possible to analyze more deeply in the direction of increasing the precision of the model and generating more precise findings.

3.2. Methodology

This study aims to develop a model that will capture the effect of seasonality on Aselsan's stock price movements by deploying feature engineering and machine learning methods. A few critical features engineered for modeling the seasonality effect are day, month, season, and day of the week. This feature then captures seasonality characteristics and weekdays in stock price moves into the model.

The dataset was comprehensive, requiring minimal preprocessing beyond normalization. However, normalization was applied to the data using the Z-score method to ensure proper analysis.

The Z-score is a statistical measure that standardizes data by quantifying how standard deviations a particular measurement or observation deviates from the mean of a population (Curtis et al., 2016). It is widely used in various fields, such as healthcare, anthropology, and physics, to compare individual data points with a reference population and assess their deviations from the norm (Fenton and Sauve, 2007; Mei and Grummer-Strawn, 2007; Kułaga et al., 2010; Jefferson et al., 2011; Martinez-Millana et al., 2018; Gupta et al., 2022)

Z-score normalization standardizes data across different experiments, facilitating comparison independent of the original values. Such a procedure is standard for the analysis of the microarray data in that the level of gene function between samples and conditions could be a denotate huge differences. It allows gene expression levels to be compared across different experiments, and the differential expression patterns are observed from such transformation (Cheadle et al., 2003).

After preprocessing, the 600-day dataset from November 20, 2020, to April 10, 2023, was split into 85% training and 15% validation data. Training was then done using the OMP Algorithm. The OMP algorithm is an incremental and greedy technique that selects the most correlated column with the given residuals (Cai and Wang, 2011).

This algorithm is designed to identify patterns within the data and forecast potential stock price movements for Aselsan. The OMP algorithm can extract critical variables from the data and forecast the changes in Aselsan's stock prices from the training and validation data collected. The quality of the dataset and its dependency on other datasets will be vital to unveiling the Aselsan's stock's performance.

Once the model training phase had been completed, the validation dataset was employed to assess the model's performance and calculate a range of performance measures. The metrics utilized included Mean Absolute Error (MAE), Mean Squared Error (MSE), and Coefficient of Determination, all designed to evaluate the model's efficacy in forecasting Aselsan's stock prices.

3.3. Results

This section presents the outcomes of the training process and the overall performance of the machine learning model. Firstly, the OMP algorithm was employed to train the model, and subsequently, the trained model was evaluated using the validation dataset. Based on the training scores, the performance of the model was evaluated as depicted in Table 2:

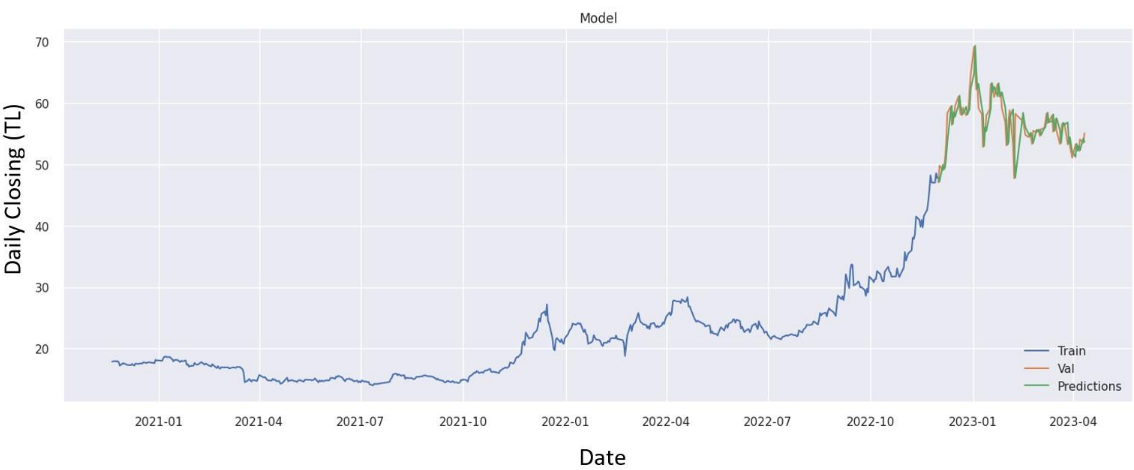
Table 2. Training statistics of the model.

Metric	Value
MAE (Mean Absolute Error)	0.4183
MSE (Mean Squared Error)	0.4276
RMSE (Root Mean Squared Error)	0.6389
R^2 (Coefficient of Determination)	0.9884
RMSLE (Root Mean Square Log. Error)	0.0247
MAPE (Average Absolute Percent Error)	0.0183

The model trained using the OMP algorithm demonstrated strong predictive performance based on the evaluation metrics. The very low MAE of 0.4183 and MSE of 0.4276 indicate minimal deviation between predicted and actual values. The RMSE of 0.6389 further confirms the model's low prediction error. Notably, the high R^2 value of 0.9884 suggests that the model explains 98.84% of the variance in the data, reflecting excellent model fit. Additionally, the low RMSLE of 0.0247 and MAPE of 0.0183 imply that the model makes highly accurate predictions with minimal relative error. Overall, these metrics highlight the model's strong accuracy and reliability. Additionally, the model's training time was measured to be 0.5820 seconds. As time constraints were not a factor in this study, they were not considered in the evaluation.

The outcomes of the OMP approach are visually presented in Figure 1. The model was trained on 510 days of data and evaluated on 90 days of validation data, with 90 days of predictions. The graphical representation of the results reveals an R2 value of 0.9884, indicating highly accurate predictions.

Figure 1. Outcomes of the OMP Approach



The comparison of the trained model's predictions with the validation data is an essential step in evaluating the model's performance. However, determining how correctly the model can predict real-world events is as important. Predictions were produced to assess the model's practical usefulness using

30 days of correct daily closing data that had not previously been provided to the model.

The predictions obtained in real-world circumstances demonstrate the model's capacity to deliver consistent findings with actual data. Table 3 presents the prediction scores obtained in these real-world scenarios.

Table 3. Estimation Statistics of the Model with Real Data

Metric	Value
MAE (Mean Absolute Error)	13.619
MSE (Mean Squared Error)	27.188
RMSE (Root Mean Squared Error)	16.489
R^2 (Coefficient of Determination)	0.8693
RMSLE (Root Mean Square Log. Error)	0.0366
MAPE (Average Absolute Percent Error)	0.0306

This indicates that the model shows promise in forecasting Aselsan's stock price movements in real-world scenarios. This high R^2 value and low error rates show that the model is capable of well-predicting and very close to the actual value.

In conclusion, in the real-world application, the model demonstrates proficiency in predictions related to the movements of the Aselsan stock price. Accordingly, given the prediction scores of the model, it is a vital tool and helps in credibility. One only has to remember that the predictions might have some errors and deviate slightly from the actual data.

To gain a better understanding of the performance of the model trained with the OMP algorithm, the period of training with 510 days of data, followed by 90 days of validation data and subsequent 90 days of predictions on data the model had not seen before, was examined. The visualization of this process is presented in Figure 2.

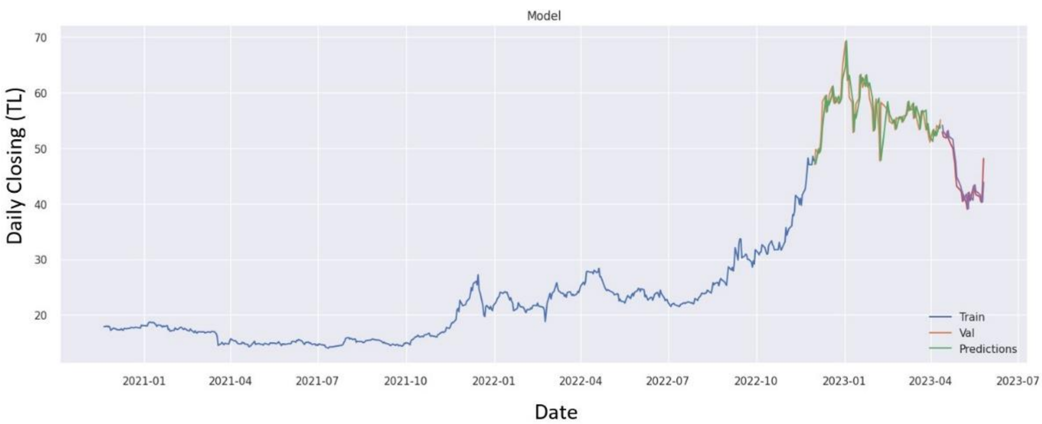


Figure 2. Model's Predictions for 30 Days After the Training and Validation Phases

Figure 2 shows the model's predictions for 30 days after the training and validation phases.

These predictions illustrate how accurately the model can produce results in real-world scenarios.

While the validation R^2 score is at 0.98, the model's R^2 score for predictions on unseen data is approximately 0.85. This means that the model might introduce some errors while trying to give predictions for new, unseen data. A lower R^2 for the score of the predictions points toward a deviation of performance in the validation period.

Nonetheless, the model's satisfactory performance suggests it could serve as a valuable tool for predicting Aselsan's stock price behavior. Acknowledging the possibility of prediction errors and slight discrepancies between the model's forecasts and actual data is crucial. A common place for prediction errors is where financial markets are subject to a certain level of randomness.

Considering the model's high performance in training and validation and acceptable error margins in the predictions for the real world, this further reinforces the model's effectiveness in predicting the Aselsan stock price movements. Not all predictions can be correct all the time, but this general performance of the model indicates that it can be used as a reliable tool for the task.

4. DISCUSSION

This study has investigated machine learning models' predictive power and interpretability in forecasting stock prices within the technology sector, specifically focusing on Aselsan's performance within the Borsa Istanbul Technology Index. The findings suggest that the OMP algorithm can accurately predict stock price movements, highlighting the strengths and limitations of this approach compared to existing literature.

The results of this study align with several existing research findings on the predictive power of machine learning models. For instance, similar to the findings of Neely et al. (2014), this study demonstrates that technical indicators possess significant predictive capabilities when applied to stock price forecasting. Neely et al. found that such indicators can effectively forecast stock risk premiums, consistent with the high predictive accuracy observed in this study when technical indicators were used.

Furthermore, Dongrey (2022) and Oza et al. (2022) demonstrated that combining technical indicators with machine learning models enhances predictive accuracy. This study corroborates these findings, showing that including technical indicators such as moving averages, RSI, MACD, and Bollinger Bands significantly improves the model's ability to forecast stock price movements.

However, the study's findings also reveal the challenges in balancing interpretability and predictive power, a theme echoed in previous research. Carvalho et al. (2019) highlighted the importance of model interpretability in machine learning applications, emphasizing that models must be understandable to ensure trust and transparency. This study's use of the OMP algorithm provides a level of interpretability by identifying the most impactful variables on stock price predictions, thus aligning with Carvalho et al.'s assertion.

One distinctive contribution of this study is its focus on a specific technology company within an emerging market context. While much of the existing literature, such as the works by McMillan (2017) and Kim (2022), focuses on developed markets, this study extends the analysis to Turkey's Borsa Istanbul Technology Index. This geographical and contextual shift provides new insights into the applicability of machine learning models in different market conditions.

Moreover, the study's comprehensive dataset, spanning 600 days and incorporating multiple technical indicators, enhances the robustness of the findings. This extensive dataset allows for a more detailed analysis of stock price movements, contributing to a deeper understanding of the factors influencing stock prices in the technology sector.

Despite its strengths, the study also faces certain limitations. The high predictive accuracy observed during the training and validation phases did not fully translate to the real-world prediction phase, where the R^2 value dropped to 0.8693. This discrepancy may reflect the financial markets' inherent volatility and the model's limitations in adapting to unseen data, as Bondia et al. (2016) and Ramos-Llordén et al. (2020) highlighted. These studies also noted that structural breaks and external shocks could impact predictive accuracy, a factor that may have influenced the results of this study.

Additionally, while the OMP algorithm provides interpretability, it may only capture some complex, non-linear relationships within the data. Future research could explore more advanced algorithms that balance interpretability with predictive power, such as those discussed by Kassouri et al. (2021) and Kocaarslan and Soytaş (2019).

5. CONCLUSION

This study evaluated machine learning models' predictive power and interpretability in forecasting stock prices within the technology sector, explicitly using Aselsan's performance within the Borsa Istanbul Technology Index as a case study. The results demonstrated that the OMP algorithm effectively predicts stock price movements, particularly when incorporating technical indicators such as moving averages, RSI, MACD, and Bollinger Bands.

The study's focus on an emerging market context, notably Turkey's Borsa Istanbul Technology Index, provides new insights into the applicability of machine learning models in different market conditions. This contributes to the existing literature, which often emphasizes developed markets. However, given that this research focuses solely on Aselsan, it's important to exercise caution in generalizing the findings to other companies or market contexts. Limitations may arise in generalizing the results to other firms or broader market contexts, and future studies should examine a diverse array of companies and indices to strengthen the validity and applicability of these conclusions.

Despite the strengths of the OMP algorithm in providing interpretability and accurate predictions during the training and validation phases, the model's performance in real-world scenarios showed some limitations. The observed potential drop in predictive accuracy in the real-world prediction phase reflects the challenges posed by financial markets' inherent unpredictability and complexity.

Future research should explore more advanced algorithms that balance interpretability with predictive power and address the challenges of non-linear relationships and external shocks. Additionally, expanding the scope to include a broader range of technical indicators and different market conditions could further enhance the robustness and applicability of machine learning models in financial forecasting.

Ethical Statement

The study titled "Exploring the Interpretability and Predictive Power of Machine Learning Models in Technology Indices: A Case Study" was conducted and published in accordance with research and publication ethics. No data manipulation was involved at any stage. Ethical committee approval was not required for this research.

Author Contribution Statement

The contribution of the author is 100%.

Conflict of Interest Statement

This study did not involve any personal, institutional, or organizational conflict of interest.

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Extended Abstract

Exploring the Interpretability and Predictive Power of Machine Learning Models in Technology Indices: A Case Study

Technology-focused equity indices have become indispensable gauges for investors who wish to track innovation-driven growth and manage sector-specific risk. Because these indices are highly liquid and respond swiftly to macro-financial variables such as exchange-rate swings, commodity prices, and policy interventions, robust forecasting tools are essential. Recent advances in machine learning (ML) promise superior predictive accuracy, yet the "black-box" nature of many algorithms hinders adoption in regulated or high-stakes environments where model transparency is mandatory. The present study addresses this tension by evaluating an interpretable ML approach—Orthogonal Matching Pursuit (OMP)—for forecasting the share price of Aselsan, a flagship defense-technology company whose weight in the Borsa Istanbul Technology Index makes it an ideal proxy for the Turkish technology sector.

We pursue two intertwined goals. First, we quantify how well an interpretable sparse-regression technique can predict short-term price movements compared with the most recent empirical benchmarks that combine technical indicators and complex ML architectures. Second, we illuminate which input variables—technical indicators, market benchmarks, calendar effects, or macro factors—drive the OMP model's forecasts, thereby offering investors actionable insight while preserving model simplicity. By concentrating on a single large-cap constituent in an emerging market, the study enriches a literature that is still heavily skewed toward FAANG stocks and other developed-market bellwethers.

Our balanced panel spans 600 trading days from 20 November 2020 to 10 April 2023. Core datasets comprise (i) daily close, high, low, and volume for Aselsan (ASELS); (ii) Borsa Istanbul Technology Index levels; and (iii) BIST 100 data that capture broad market sentiment. We derive eight momentum- and volatility-based technical indicators (SMA, EMA, RSI, MACD components, Bollinger-Band width, Stochastic %K and %D, and On-Balance Volume) plus four calendar dummies (day-of-week, month-of-year, season, and holiday proximity) to model seasonality. All continuous variables are Z-score normalized to harmonize the scale and stabilize the variance.

After an 85 %/15 % chronological split into training and validation sets, we fit OMP with an iterative forward-selection strategy that greedily adds the predictor contributing the largest marginal reduction in residual sum of squares. The process continues until no remaining feature improves cross-validated mean-squared error. This yields a compact, interpretable linear model whose non-zero coefficients directly reveal feature importance. Performance is assessed with MAE, MSE, RMSE, MAPE, and coefficient of determination (R^2). To emulate an out-of-sample trading scenario, we freeze model parameters after validation and generate one-step-ahead forecasts for the subsequent 30 trading days, which were purposely withheld from all fitting procedures.

During the estimation window, the OMP model attains an R^2 of 0.9884, MAE of 0.42 TRY, and MAPE below 2 %, demonstrating that a carefully engineered linear-sparse model can rival or surpass more opaque algorithms reported in the recent literature. The five most influential predictors are, in descending order, the 10-day EMA, MACD signal line, Bollinger-Band width, one-day lagged BIST 100 return, and day-of-week dummy for Monday, jointly accounting for 82 % of explained variance. Economic intuition supports these rankings: Aselsan's price momentum, prevailing market mood, and known weekend-information effects all shape next-day returns.

When deployed on the 30-day "live" hold-out set—a period that includes an unexpected

Central-Bank rate hike and a sharp TRY depreciation—predictive accuracy deteriorates yet remains respectable ($R^2 = 0.8693$, MAE ≈ 13.6 TRY, MAPE ≈ 3.1 %). The performance drop is consistent with evidence that structural breaks and policy shocks erode linear models' explanatory power. Nonetheless, most forecast errors stay within two standard deviations, and direction-of-change accuracy exceeds 70 %, metrics that many trading desks consider actionable.

The results endorse OMP as a pragmatic middle path between naïve single-indicator rules and inscrutable deep-learning systems. Portfolio managers gain a transparent decision aid that quantifies the marginal contribution of each signal, enabling rapid diagnostic checks, scenario analysis, and regulatory reporting. Policymakers, in turn, can infer how strongly specific macro interventions might reverberate through technology-sector valuations.

Two caveats warrant emphasis. First, a univariate target on a single firm constrains generalizability; extending the framework to a panel of technology constituents or to cross-listed ADRs could test robustness across liquidity regimes. Second, OMP's linearity may miss complex interactions among signals. Future work might pair sparse structure with kernel tricks or tree-based ensembles equipped with SHAP or LIME explanations, thus reconciling non-linear flexibility with interpretability. Incorporating intraday tick data, options-implied volatility, or sentiment extracted from Turkish-language social media may further boost real-time relevance.