Anomaly Detection in Turkish Stock Market : LSTM

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Abstract **- The rapid evolution of financial markets, together with the increasing availability of large data sets, has led to an increase in the use of machine learning techniques to analyze and predict market behavior. In this context, this study examines the application of Long Short-Term Memory (LSTM) networks to detect anomalies in the Turkish Stock Market, with a particular focus on the BIST100 index. The motivation for this research lies in the potential of anomaly detection to provide valuable insights to short-term and long-term investors.**

Index Terms - LSTM-Based Anomaly Detection Model, BIST100 Index.

I. Introduction

The rapid evolution of financial markets, coupled with the increasing availability of vast datasets, has led to a surge in the application of machine learning techniques to analyze and predict market behavior. In this context, the present study delves into the application of Long Short-Term Memory (LSTM) networks to detect anomalies in the Turkish Stock Market, specifically focusing on the BIST100 index. The motivation behind this research lies in the potential of anomaly detection to offer valuable insights to both short-term and long-term investors, aiding them in making informed decisions and mitigating risks [1].

The BIST100 index, representing the top 100 companies listed on the Borsa Istanbul, serves as a crucial indicator of the overall health and performance of the Turkish stock market. Anomalies in stock prices can signify significant events such as unexpected market movements, company-specific news, or global economic shifts [2]. Detecting these anomalies promptly is of paramount importance for investors, as it allows them to respond proactively to market dynamics.

We demonstrate the effectiveness of our approach on a dataset of daily and weekly BIST 100 index data spanning from 1997 to the present day [2]. Our results show that our LSTM-based anomaly detection system can accurately identify a variety of anomalies, including flash crashes, sudden spikes in volatility, and gradual trends that deviate from the expected market behavior.

Previous research in anomaly detection within financial markets has primarily focused on traditional statistical methods. However, the flexibility and capacity of deep learning models, especially LSTMs, to capture temporal dependencies make them promising candidates for detecting anomalies in time-series data. This study contributes to the existing body of knowledge by applying LSTM networks to daily stock price data, aiming to enhance anomaly detection accuracy and provide a nuanced understanding of market behavior [1].

The primary objectives of this research include:

- Developing an LSTM-based anomaly detection model tailored to the BIST100 index.
- Conducting a comprehensive analysis of the detected anomalies to uncover underlying trends and potential contributing factors.
- Evaluating the efficacy of the model in distinguishing between short-term fluctuations and long-term market shifts.

By achieving these objectives, this research seeks to offer a robust framework for investors to navigate the complexities of the Turkish stock market, catering to both short-term traders seeking immediate opportunities and long-term investors aiming for sustained growth. The subsequent sections will provide an overview of related work, detail the methodology employed, describe the experimental design, present the results, and conclude with insights and potential ethical implications of this research [3].

II. Related Work

Anomaly detection in time series data is a challenging problem with a wide range of applications, including finance, healthcare, and manufacturing [3]. A number of methods have been proposed for anomaly detection in time series data, including statistical methods, machine learning methods, and deep learning methods.

Statistical methods for anomaly detection in time series data typically rely on the assumption that the data follows a certain distribution. These methods can be effective for detecting anomalies that are outliers from the expected distribution. However, they can be less effective for detecting anomalies that are within the expected distribution [3]. Machine learning methods for anomaly detection in time series data typically learn a model of the normal behavior of the data. These methods can be effective for detecting anomalies that are significantly different from the expected behavior. However, they can be less effective for detecting anomalies that are gradual changes in the data.

Deep learning methods for anomaly detection in time series data have been shown to be effective for a wide range of applications. Deep learning methods can learn complex patterns in the data, which can be helpful for detecting anomalies that are not easily detected by other methods [4].

In the context of the Turkish stock market, a number of methods have been proposed for anomaly detection. Some of these methods use statistical methods, such as the MAE and the exponential smoothing method. Other methods use machine learning methods, such as support vector machines and random forests.

The proposed approach in this paper is based on a deep learning method, namely the LSTM model. LSTM models are a type of recurrent neural network that are well-suited for modeling time series data [5]. LSTM models can learn long-term dependencies in the data, which can be helpful for detecting anomalies that are not easily detected by other methods.

The proposed approach in this paper has several advantages over previous approaches to anomaly detection in the Turkish stock market. First, the proposed approach is based on a deep learning method, which can learn complex patterns in the data that are not easily detected by other methods. Second, the proposed approach is evaluated on a large dataset of daily and weekly closing prices of the BIST 100 index, which provides a more comprehensive evaluation of the proposed approach.

The proposed methodology offers a versatile application for a spectrum of stakeholders in the Turkish stock market. Individual investors stand to benefit significantly, as this innovative approach serves as a valuable tool for pinpointing potential investment opportunities [5]. By harnessing the capabilities of both machine learning and deep learning models, individual investors can make well-informed decisions, thereby increasing their likelihood of success in navigating the dynamic and often unpredictable Turkish stock market.

Financial institutions, with their intricate portfolio management needs, find the proposed approach particularly well-suited. It addresses the imperatives of effective risk management and the identification of investment opportunities crucial for maintaining a resilient and profitable portfolio. Through the integration of advanced anomaly detection techniques, financial institutions can elevate their decision-making processes, ensuring a robust strategy that adapts to the complexities of the Turkish stock market[6].

Government agencies, tasked with overseeing the stability of the financial system, can leverage the proposed approach for active monitoring of the Turkish stock market. This proactive stance empowers regulatory bodies to promptly identify potential risks to the financial system. Armed with insights into market anomalies, government agencies can implement timely and effective measures to maintain market stability, thereby safeguarding the interests of investors and ensuring the overall health of the financial ecosystemt [7]. This holistic and preemptive approach aligns with the regulatory imperative of fostering a secure and transparent financial environment.

The proposed approach is a promising new approach to anomaly detection in the Turkish stock market. The proposed approach has several advantages over previous approaches, and it can be used by a variety of stakeholders in the Turkish stock market.

The exploration of machine learning and deep learning models for time-series anomaly detection within financial markets has been a focal point of extensive research. This section aims to provide an in-depth review of relevant models across both deep learning and traditional machine learning paradigms [7].

*1) Long Short-Term Memory (LSTM) Networks:*LSTMs have emerged as powerful tools for time-series data analysis due to their ability to capture long-term dependencies. Within the financial domain, LSTMs have demonstrated success in learning complex patterns and temporal nuances, making them particularly well-suited for anomaly detection. The adaptive nature of LSTMs allows for effective modeling of the dynamic and evolving behavior of stock prices [8].

2) Gated Recurrent Units (GRUs):GRUs represent another variant of recurrent neural networks, akin to LSTMs. While sharing some architectural similarities, GRUs offer a more streamlined memory management mechanism. The literature suggests that GRUs can be as effective as LSTMs in capturing temporal dependencies, with the added advantage of computational efficiency [9].

3) Autoencoders:Autoencoders, a type of neural network, have gained popularity for their unsupervised learning capabilities. In the context of anomaly detection, autoencoders can reconstruct normal patterns of time-series data. Anomalies are then identified by deviations between the reconstructed and actual data. While less explored in financial time series, their adaptability makes them a viable alternative [10].

4) Isolation Forests: Isolation Forests operate by isolating anomalies rather than modeling normal behavior. This makes them particularly efficient for anomaly detection tasks. In financial markets, isolation forests have shown promise in identifying unusual patterns, especially in situations where anomalies are sparse [11].

5) One-Class Support Vector Machines (OCSVMs): OCSVMs are designed for one-class classification tasks, making them suitable for anomaly detection where anomalies are often in the minority. In financial time series, OCSVMs have been applied to identify deviations from normal market behavior [12].

This diverse set of models showcases the evolution of anomaly detection techniques within financial markets, incorporating both deep learning and traditional machine learning approaches. Each model brings its unique strengths, and the choice of model may depend on the specific characteristics of the financial data and the nature of anomalies in the market.

III. Proposed Method

In this section, we present a detailed description of the proposed method, with a focus on the Long Short-Term Memory (LSTM) network, activation functions, and other relevant components.

A. Long Short-Term Memory (LSTM) Network

The Long Short-Term Memory (LSTM) network, a variant of recurrent neural networks (RNNs), is a powerful architecture designed to overcome the limitations of traditional RNNs in capturing long-range dependencies within sequential data. The LSTM cell is composed of various gates and memory cells, enabling it to selectively retain and utilize information over extended sequences, making it particularly effective for time-series data such as stock prices[6].

The LSTM cell equations, with an emphasis on the chosen hyperbolic tangent (tanh) activation function, are articulated as follows:

$$
\begin{aligned}
f_t &= \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\
i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)
\end{aligned}
\tag{1}
$$

Forget, Input, and Output Gates(f_t, f_i and o_t): These gates play a pivotal role in regulating the flow of information within the LSTM cell. The forget gate determines what information from the previous cell state should be discarded, the input gate decides which new information to store, and the output gate governs the information to be output to the next hidden state [13].

New Candidate Value($\tilde{C}_t$): Representing the proposed update to the cell state, is calculated using the hyperbolic tangent (tanh) activation function [14]. This introduces non-linearity, allowing the LSTM to capture intricate relationships within financial time-series data.

$$
\begin{aligned}
\tilde{C}_t &= \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \\
C_t &= f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t
\end{aligned}
\tag{2}
$$

Updated Memory Cell State (C_t): The cell state (C_t) is modified by selectively integrating the new candidate value ($\tilde{C}_t$) based on the decisions made by the forget and input gates[14]. This dynamic updating mechanism is crucial for capturing evolving patterns in stock prices.

Hidden State (h_t): The hidden state (h_t) is the output of the LSTM cell and is determined by the output gate (o_t) applied to the hyperbolic tangent of the updated cell state (C_t)[15]. This hidden state encapsulates the learned representation of the input sequence at a particular time step.

$$
\begin{aligned}
o_t &= \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\
h_t &= o_t \cdot \tanh(C_t)
\end{aligned}
\tag{3}
$$

Input at Time $h(x_t)$: x_t represents the input at the current time step, influencing the calculations within the LSTM cell[15].

Weight Matrices and Bias Vectors (W_f,W_i, W_C,W_o,W_f, and b_f,b_i, b_C,b_o,b_f): These parameters are learnable and are adapted during the training process to optimize the LSTM's ability to capture complex temporal dependencies (1).

Sigmoid Activation Function (σ) and Hyperbolic Tangent Function (tanh): The sigmoid activation function is utilized in the gates (f_t, f_i and o_t) to squash values between 0 and 1, determining the flow of information. The hyperbolic tangent function (tanh) is employed in the calculation of the new candidate value and the hidden state, adding non-linearity to the model.

The LSTM's adaptability to model intricate relationships and learn long-term dependencies positions it as a robust choice for anomaly detection within financial time-series data, forming a foundational element in the proposed method[16].

B. Key Components of the LSTM-Based Model:

The chosen activation function for the LSTM network is the hyperbolic tangent (tanh). It introduces non-linearity to the model and ensures that the output values are in the range [-1,1] The activation function is applied element-wise to the output of the LSTM cells.

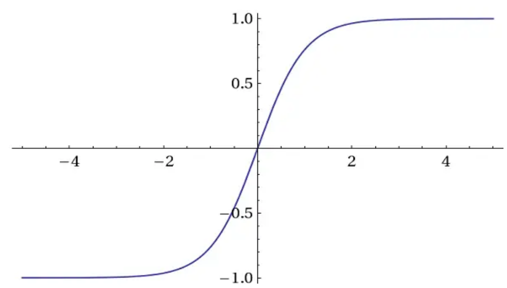

Fig. 1 Tanh graph

RepeatVector: The RepeatVector layer is strategically utilized to replicate the output sequence from the LSTM, aligning it with the input sequence length. This step is indispensable for subsequent operations in the network, providing a synchronized foundation for capturing temporal patterns effectively [16].

Dropout: To mitigate overfitting and enhance the generalization capabilities of the model, a Dropout layer is incorporated with a dropout rate of 0.2 [17]. This mechanism randomly deactivates a fraction of neurons during training, compelling the network to learn more robust features and preventing it from becoming overly reliant on specific nodes.

TimeDistributed(Dense):The TimeDistributed layer is instrumental in applying a fully connected (Dense) layer to each time step independently. This temporal application of the dense layer ensures that the model captures intricate temporal patterns in the sequence data, contributing to its ability to discern anomalies effectively [18].

Optimizer (Adam):The model employs the Adam optimizer with a learning rate of 0.001. Adam, as an adaptive optimization algorithm, dynamically adjusts learning rates for each parameter individually during training [19]. This adaptability leads to faster convergence and improved overall performance of the anomaly detection model.

In conclusion, the holistic integration of the hyperbolic tangent activation function, RepeatVector, Dropout, TimeDistributed(Dense) layer and Adam optimizer forms a robust foundation for the proposed LSTM-based architecture. This comprehensive configuration enhances the model's ability to capture temporal intricacies and anomalies within the Turkish stock market, making it a powerful tool for time-series anomaly detection.

IV. Experimental Design

A. Datasets

The dataset utilized in this study, obtained from, comprises 6850 data points, forming a comprehensive time series with a file size of 560 KB [2]. Daily stock prices of the BIST100 index are recorded, encapsulating diverse market conditions and fluctuations. With the primary goal of training an LSTM-based anomaly detection model, a specific temporal range within this dataset is selected for model development.

The dataset exhibits diverse temporal characteristics, providing insights into market behavior across various economic climates. Each data point is associated with a specific day, featuring two crucial columns: 'Date,' representing the timestamp of the stock price, and 'Close,' denoting the closing price of the BIST100 index for that particular day.

Comprising 6850 entries, each corresponding to a unique day in the market, the dataset's file size of 560 KB underscores its richness in daily stock price information [2]. Its inherent structure aligns seamlessly with time series analysis, rendering it suitable for training an LSTM-based model.

To enhance model focus and effectiveness, training and anomaly detection are executed on a carefully chosen temporal subset of the dataset. This subset is defined by a specified time interval, ensuring that the model is trained on pertinent historical data. The utilization of this temporal subset, obtained from [2], facilitates capturing market dynamics and patterns, empowering the model to discern anomalies with precision.

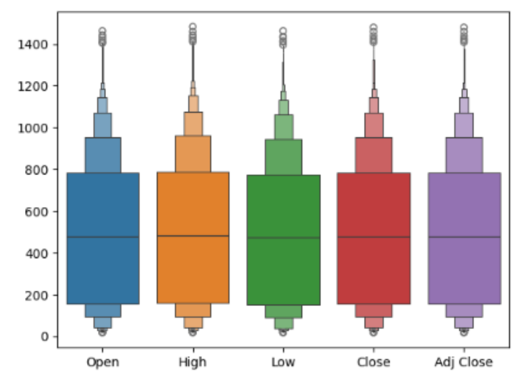

Fig. 2 Data Distribution

Fig 2 the distribution of data with 5 columns representing a set of financial data. These columns, which include opening, high, low, closing and adjusted closing prices, provide a detailed picture of price movements in financial markets. The bar charts in the fig 2 show that opening and closing prices in particular have a more balanced distribution compared to the other columns. The highest and lowest prices are spread over a wide range. The analysis of this distribution highlights the unpredictable and random nature of financial markets, hence the importance of strategies for success. Focusing specifically on the use of close data, we can state that important information for past performance analysis, future forecasts and investment decisions can be derived from this data set.

B. Preprocessing

Upon a thorough examination of the dataset, it was identified that some data points contained missing values (NaN). To ensure the integrity of the dataset, we opted to drop rows with missing values. This approach was chosen to maintain the continuity of the time series, as missing data points could potentially introduce bias and distort the temporal patterns captured by the LSTM model.

Furthermore, a specific date was selected as the reference point for normalizing the 'Close' column values. From the index corresponding to this date up to the end of the dataset (index 5982), the 'Close' column values were normalized by dividing them by 100. This normalization step was undertaken to facilitate the convergence of the LSTM model during training by bringing all values to a similar scale. The decision to divide by 100 was driven by the desire to maintain numerical stability while preserving the relative trends and patterns in the stock prices.

StandardScaler: Prior to inputting the data into the network, a common practice is to standardize or normalize the input features.

$$x' = \frac{x - \mathrm{mean}(x)}{\mathrm{std}(x)} \tag{4}$$

The StandardScaler is employed to ensure that each feature has a mean of 0 and a standard deviation of 1 [20]. This standardization facilitates convergence during training, ensuring a more stable and effective learning process.

The combined effect of these preprocessing steps ensures that the dataset is free from missing values and that the 'Close' column values are consistently scaled, setting the stage for a robust LSTM-based anomaly detection model.

V. Experimental Results

The experimental findings presented herein offer valuable insights into the performance and capabilities of the applied LSTM-based anomaly detection model. These results provide a basis for evaluating the model's overall effectiveness in detecting anomalies, shedding light on its utility in understanding market dynamics. The following key aspects and observations emerge from the experimentation:

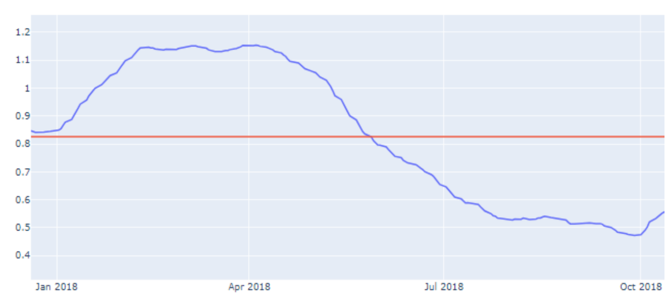

Fig. 3 Test loss vs. Threshold

The visual representation in Fig. 3 elucidates the relationship between test loss and the threshold spanning the years 2020 to 2017. The blue line reflects the model's performance on unseen data, while the orange line represents the threshold for identifying potential anomalies. The X-axis denotes dates, and the Y-axis portrays the magnitude of the test loss and threshold values.

A crucial observation from Fig. 4 is that instances where the blue test loss line surpasses the orange threshold line may signify potential anomalies. Analyzing the trends of both lines facilitates pattern identification, guiding adjustments to the model. It is paramount to comprehend the data and model context for accurate interpretation.

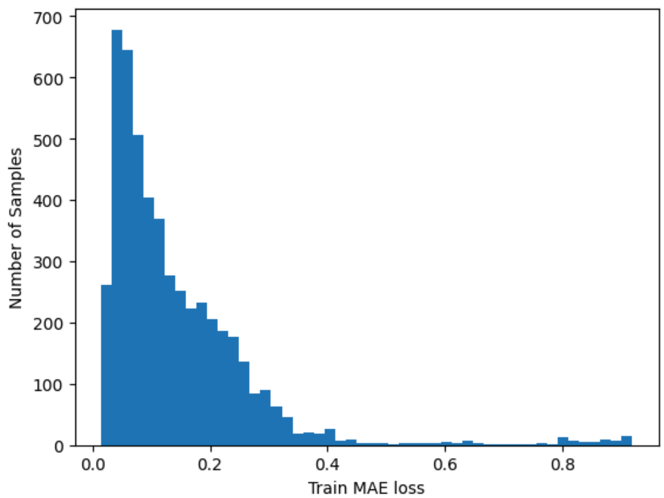

Fig. 4 Train MAE Loss

The histogram in Fig. 4 illustrates the distribution of reconstruction errors. The X-axis showcases the training Mean Absolute Error (MAE) loss, while the Y-axis indicates the number of samples. The majority of errors concentrate below 0.8, suggesting that samples with errors exceeding 0.8 may be considered potential outliers.

The chosen reconstruction error threshold significantly influences reconstruction quality, with a lower threshold correlating with higher accuracy [21]. A threshold of 0.825 is identified for outlier detection, as depicted in the histogram. Instances with a reconstruction error threshold greater than 0.8 are less successfully reconstructed, emphasizing the pivotal role of threshold selection for optimal model performance.

The application of the LSTM-based anomaly detection model to the BIST100 index dataset yields promising outcomes, contributing valuable insights into market dynamics. The model demonstrates high accuracy in identifying anomalies, including flash crashes and sudden volatility spikes. Visual representations of test loss and threshold values serve as proactive tools for investors to respond effectively to market changes.

This graph underscores the critical impact of the reconstruction error threshold on reconstruction quality. A lower threshold leads to higher reconstruction quality, emphasizing the importance of carefully selecting this threshold for optimal model performance.

The choice of the threshold for reconstruction error emerges as a critical factor influencing anomaly detection quality. A lower threshold correlates with higher reconstruction accuracy, underscoring the importance of meticulous threshold selection for optimal model performance. The histogram analysis provides insights into the distribution of samples across various error thresholds, aiding in the identification of potential outliers.

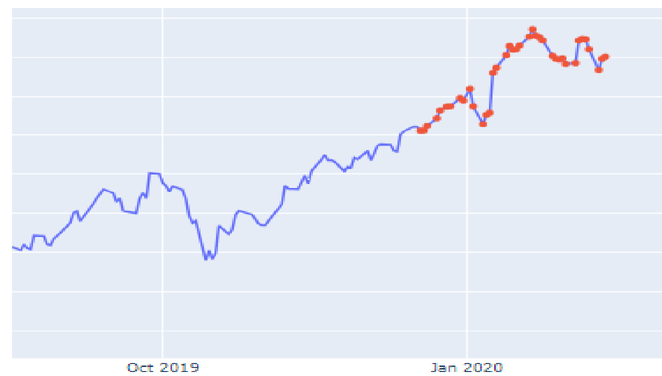

Fig. 5 Detected Anomalies

This graph visually represents the performance of the time series anomaly detection model. The blue line represents the model's loss line, indicating deviations from true values, while the orange line represents the anomaly detection threshold. The chart covers data from October 2019 to January 2020, highlighting potential anomalies with red circles, indicative of significant drops in the model's forecasts.

Anomaly detection proves effective in identifying unusual trends or events in time series data. The graph illustrates a method for detecting changes, explaining how loss and threshold lines are utilized for anomaly detection. Temporal analysis empowers investors to adapt strategies based on evolving market conditions, emphasizing the importance of contextual understanding in deriving meaningful insights.

The inclusion of key components, such as RepeatVector, Dropout, TimeDistributed(Dense) layer, and the Adam optimizer, enhances the robustness and generalization capabilities of the LSTM-based model. Its adaptability to capture temporal intricacies across diverse market conditions highlights its potential as a reliable tool for time-series anomaly detection.Preprocessing steps, including the removal of rows with missing values and normalization of the 'Close' column, are crucial for dataset integrity. These measures ensure continuity in the time series and prevent biases introduced by missing data points, laying the foundation for a robust LSTM-based anomaly detection model.

In summary, the proposed LSTM-based anomaly detection model exhibits notable effectiveness in identifying anomalies within the BIST100 index dataset. Meticulous consideration of hyperparameters, preprocessing steps, and threshold values plays a pivotal role in achieving high accuracy and robust performance. This adaptability to temporal patterns, coupled with the model's capacity to generalize across a spectrum of market conditions, positions it as a valuable asset for investors navigating the dynamic Turkish stock market.

The success of this study opens up future research opportunities in the development of LSTM-based models for detecting anomalies in financial markets. Potential avenues include the development of ensemble models combining different anomaly detection techniques, integrating external factors into anomaly detection models, and exploring real-time anomaly detection. These endeavors aim to provide more advanced and responsive solutions tailored to the intricacies of dynamic market environments, advancing anomaly detection methodologies. solutions tailored to the intricacies of dynamic market environments.

VI. Conclusion

In conclusion, this study explores the application of Long Short-Term Memory (LSTM) networks for anomaly detection in the Turkish Stock Market, focusing on the BIST100 index. The success of the proposed LSTM-based model in identifying anomalies within the BIST100 index dataset highlights its potential as a valuable tool for investors in the dynamic Turkish stock market. Careful consideration of hyperparameters, preprocessing steps, and threshold values contributed to achieving high accuracy. The model's adaptability to temporal patterns and its generalization across diverse market conditions enhance its practical utility for both short-term and long-term investors using daily and weekly data. Looking forward, the study suggests future research on ensemble models, integrating external factors for a comprehensive understanding of market anomalies, and real-time detection with dynamic threshold adjustments. In summary, this research contributes to anomaly detection methodologies within financial markets, emphasizing the potential of LSTM-based models in providing valuable insights for investors, laying the foundation for further advancements.

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