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«Application of Machine Learning for KASE Market Index movement predictions»

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Abstract

Attempts to forecast stock market trends have been made by many researchers coming from different fields using different approaches and techniques. This research aims to investigate the application of machine learning models, specifically Support Vector Machine (SVM) and Long Short-Term Memory (LSTM), for predicting price movements in the Kazakhstan Stock Exchange (KASE) for KASE Index. The study utilizes historical stock price data for KASE Index from the period of 2007-2023 to train and test SVM and LSTM models. The research finds that SVM and LSTM models can produce satisfactory results in predicting the movements of KASE Index. The results suggest that both SVM and LSTM models have the potential to be effective tools for predicting price movements in KASE, and they can be utilized by investors and traders for making informed decisions in their trading strategies. This research contributes to the research on KASE as well as the literature on stock price prediction in the context of KASE by exploring the application of SVM and LSTM models.

Key words: KASE, Financial forecasting, Machine Learning, Technical Analysis, KASE Index

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Introduction

Artificial Intelligence (or AI) is one of the key elements of the Fourth Industrial Revolution (Industry 4.0) that is taking place globally. AI and particularly its component Machine Learning (or ML) has a lot to offer the financial world as finance as a field is rich with well-structured and well maintained, relatively easily accessible and comprehensive data available for use. Thus, it is not surprising that both Machine Learning researchers and finance researchers have shown interest in utilizing this data-rich financial environment and methods of Machine Learning for various purposes including financial risk management, analysis of stock markets, portfolio selection, asset price forecasting etc.

Attempts to forecast stock market trends have been made by many researchers coming from different fields using different approaches and techniques. Technical analysis and fundamental analysis are two classic approaches to forecasting the stock market. The technical analysis utilizes historical time-series data strictly from the stock market itself, the argument being that the stock prices include and reflect all the necessary parameters that affect the stock price, such as the financial environment, a company's activities, etc. Whereas the fundamental analysis is concerned with a specific company's overall performance, which is usually reflected in the financial statement and macroeconomics.

However, in recent years in addition to these classic approaches the interest in harnessing the power of artificial intelligence (AI) and particularly machine learning (ML) has been growing.

Using fundamental analysis approach in ML algorithms for stock price prediction may prove to be a challenging task as the financial statement data usually updates on quarterly or even annual basis and the factors to be considered may vary given different companies, industries, and countries. However, this is not the case for technical analysis.

Thanks to the capacity of ML algorithms to analyze any large datasets, which is usually the case for historical stock prices and other market indicators, and identify pattern and trends to potentially predict the market movement, which is the objective of technical analysis, ML and

technical analysis can go hand in hand. Hence the researchers have been studying application and effectiveness of various ML algorithms to the task of “seeing” the future of the market.

However, the current research heavily focuses on large stock markets. There is little research that considers smaller emerging stock markets not to mention frontier markets and there is no research that predicts the movement of stock prices listed on KASE or Indexes related to it using machine learning models. Given the 30-year anniversary of KASE it seems most appropriate for this research to fill the gap. This study will focus on building machine learning models using SVM and LSTM algorithms to forecast the movement of KASE Index based on historical time-series data and technical analysis.

The rest of this thesis is arranged as follows. The second section presents a review of the current literature regarding application of ML algorithms in finance in general and stock market forecasting specifically. The third section discusses KASE, the KASE Index and dataset as well as the theoretical framework of technical analysis and technical indicators. It also goes over SVM and LSTM algorithms to be implemented in the models and performance metrics for evaluation of results. The fourth section provides the discussion of modeling results and simulation of the best performing models in trading followed by concluding remarks.

Literature Review

Aziz et al. (2021), in their recent review of research on the application of ML in finance, published in the period from 1990 to 2018, mapped the literature on ML in finance using a topic modeling approach and identified three general categories of research:

- 1) Application of ML for Risk Management in Finance
- 2) Application of ML for Investment Analysis
- 3) Application of ML for Asset Modeling & Forecasting

The latter topic, according to Aziz et al. (2021), covers such sub-topics as forex forecasting, volatility modeling, portfolio optimization, energy forecasting, chaos and financial forecasting, as well as techniques for financial forecasting. The research topic of this thesis belongs to the third category, and specifically to stock market forecasting as part of techniques for financial forecasting.

Survey by Rundo et al. (2019) reviewed the application of ML to analyzing time-series data and its advantages compared to conventional approaches, such as AR, and showed that ML-based algorithms outperform them when it comes to accuracy. Although this survey is quite recent, researchers have started studying the application of ML algorithms for the stock market prediction task long before it.

Huang W. et al. (2005) used technical analysis for predicting the weekly movement direction of the Japanese Stock Market NIKKEI 225 Index with support vector machine (SVM) models. Moody and Saffell (2001) used the technical analysis approach but with a recurrent reinforcement learning algorithm allowing to successfully predict the monthly movement of S&P 500 index as well as intradaily U.S. Dollar / British Pound exchange rates in back tests.

In 2015 Patel et al. released two papers that research the topic of predicting stock index movement using Trend Deterministic Data Preparation for technical indicators and machine learning techniques (2015, January) as well as using fusion of various machine learning techniques including Support Vector Regression (SVR), Artificial Neural Network (ANN),

Random Forest (RF) and SVR (2015, March) for two Indian indices - CNX Nifty and S&P Bombay Stock Exchange (BSE) Sensex.

Jiao & Jakubowicz (2017) reviewed the effectiveness of four ML classification algorithms: Logistic Regression, Gradient Boosted Trees, Random Forest, and Artificial Neural Network (ANN) in predicting 463 stocks of the S&P 500 and found that recent information for closed European and Asian indexes can significantly improve the predictability for S&P 500.

More recently, Chen et al. (2019) built a hybrid EMD-LSTM (empirical mode decomposition - long short-term memory) model for financial time series prediction based on technical analysis. Another recent example also used LSTM to predict large-scale financial market movements by effectively finding meaningful relationships from noisy financial time series data (Fischer T., Krauss C., 2018).

In 2021 Rather M.A. proposed a new method for stock price prediction using a regression scheme implemented a long-short-term-memory-based (LSTM) deep neural network for National stock exchange of India and NIFTY-50 Index. He further used this method to build a portfolio optimization model that outperformed several conventional predictive models (Rather, 2021).

However not only the variety of ML algorithms applied in these studies is growing but their geography of studies is expanding as well and more researchers are turning their focus to emerging stock markets. As such Saetia & Yokrattanasak (2022) used ML algorithms to analyze technical indicators and Google Trends for the Thai stock market with an aim to develop portfolio selection models.

As the stock markets are driven not only by pure numbers but also by human behavior that quite often is led by emotions, the market sentiment becomes another useful factor for predicting the stock market dynamics. One of the first successful attempts to find the connection between the public opinion and the stock market changes was performed by Bollen et al (2011) where they found that Twitter posts can be helpful in predicting the closing values of Dow Jones

Industrial Index (DJIA). The success of Bollen et al. inspired researchers to integrate the market sentiment analysis into the conventional analysis to improve the market stock forecast (Li X. et al, 2011) and more recently to use it as an additional source for multi-source multiple instance learning models (Li J. et al., 2017).

In regard to the additional sources of data to enhance the predictive capacity of the ML model, it is important to mention the application of images, i.e. stock charts, which was shown to be successful in outperforming single-source models (Kim T., Kim H.Y., 2019).

The recent review by Jiang W. (2019) of the application of machine learning and deep learning models to stock prediction and forecasting showed that this area of research is still dynamically developing with a trend of using multiple sources and types of data.

As we can see this area of research is growing in many aspects including the variety of algorithms used, geography of stock markets analyzed, types of data utilized. However, the existing research still heavily focuses on large stock markets, e.g., US based NYSE, NASDAQ, Chinese Shanghai SE, or HKEX. And although this is changing there is still little research that considers smaller emerging stock markets where the data volume can affect forecast outcomes, not to mention frontier markets to which KASE belongs.

Moreover, the current literature related to KASE in general appears to be scarce. The existing research of KASE is mostly focused on the analysis of relationships between various macroeconomic indicators and the stock market and its index (Oskenbayev et. al, 2011) (Syzdykova, 2018) (Gnahe, 2020) or impact of oil price changes on the stock market (Yalcin, 2015) (Syzdykova, 2018). The exception to this would be an article by Kerimbek et al. (2019) outlining the history of KASE since 1993 and its development prospects.

However, the research that is dedicated to the application of any machine learning models in the context of KASE or using technical analysis for forecasting purposes of KASE listed stock or its Index is practically non-existent.

This research aims to fill the gap and will focus on building models utilizing machine learning algorithms to predict the movement of KASE Index based on historical time-series data and a set of technical indicators.

Dataset and Methodology

This section describes the dataset and the methodology used in the research. First it reviews Kazakhstan Stock Exchange (KASE), KASE Index and its behavior for the period from October, 2007 till March, 2023. Further it provides the description of the technical indicators built on the Index data and used as inputs for modelling. Following that the information on the models – SVM and LSTM - their application in different fields and appropriateness for the purpose of the study – is provided. Performance metrics to be used for evaluating the modeling results are described further.

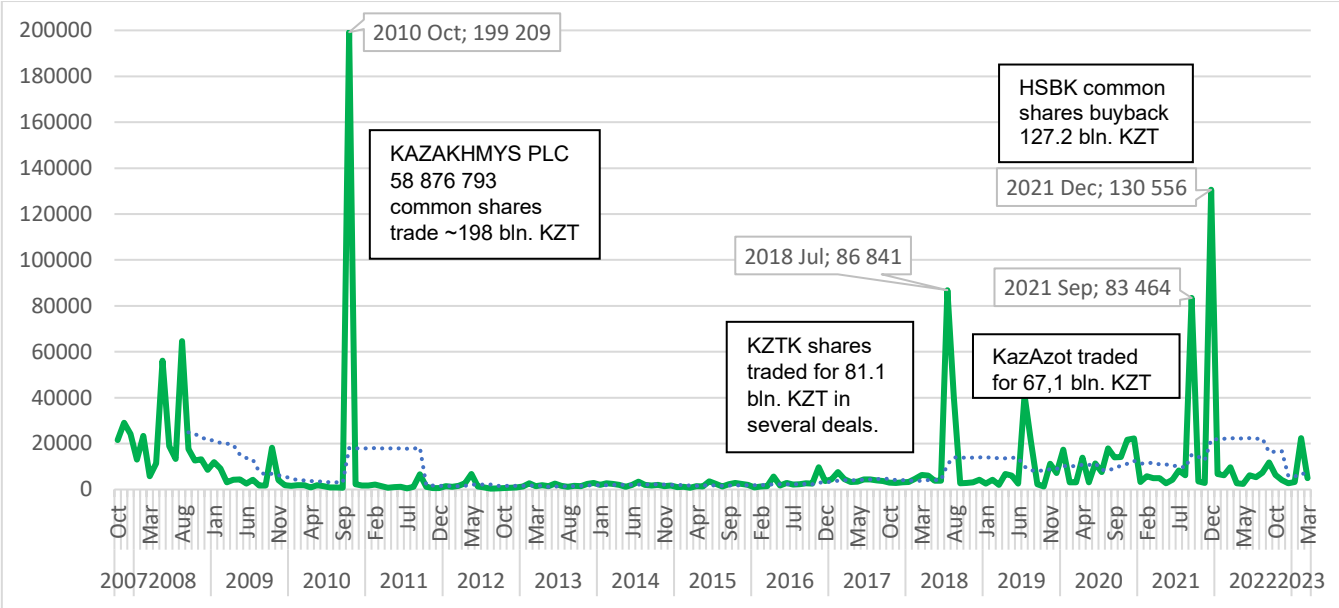
Kazakhstan Stock Exchange & KASE Index

For any prediction model to work as intended it is necessary to prepare a valid data set related to the specific phenomenon. In this paper I used stock market time-series data of KASE Index and technical indicators based on it. The data has been collected from official website of KASE (KASE Index - Kazakhstan Stock Exchange (KASE), 2023).

Before analyzing the data and Index it is important to understand KASE as a stock market and be aware of its characteristics. Established in 1993 in Almaty KASE is the main securities exchange in Kazakhstan for trading stocks, bonds, derivatives as well as other financial instruments. KASE is organized as a joint-stock company with a diverse ownership structure (57 shareholders) including several large financial institutions, including banks, insurance companies, and investment firms (94.52% of voting shares), as well as individual investors (5.48% of voting shares). KASE uses an order-driven trading mechanism, where buyers and sellers submit orders to the exchange's trading system, which matches the orders based on price and time priority. In terms of market capitalization KASE is considered a mid-cap stock exchange due to the relatively small number of large, well-established companies listed on it, compared to some of the larger exchanges. As for the trading volume again, compared to the

world's larger exchanges it is relatively small, however it has experienced growth in recent years and has been expanding its trading activity through partnerships with other exchanges.

Figure 1. KASE monthly trading volume in millions of KZT



KASE Index is a share market index reflecting the change in the total market value of the most liquid shares of the official list of KASE Exchange. It is a capitalization-weighted index, which means that the weight of each component stock is determined by its market capitalization. The index includes the largest and most liquid companies listed on KASE, representing a range of industries such as oil and gas, mining, telecommunications, and finance. The Index is calculated as follows:

$$\text{KASE Index} = \text{MC}_n / D_n$$

Where:

IndexKASE – KASE index in points;

MC_n – total market value of shares included in the representative list of the KASE Index, at the time of calculation of n, calculated in accordance with paragraph 11 of the KASE Index Methodology, in tenge.

D_n – the value of the total market value of all shares of the representative list of the KASE index on the first day of calculation of the KASE Index, adjusted taking into account the changes in the representative list of the KASE Index and the initial value of the KASE Index.

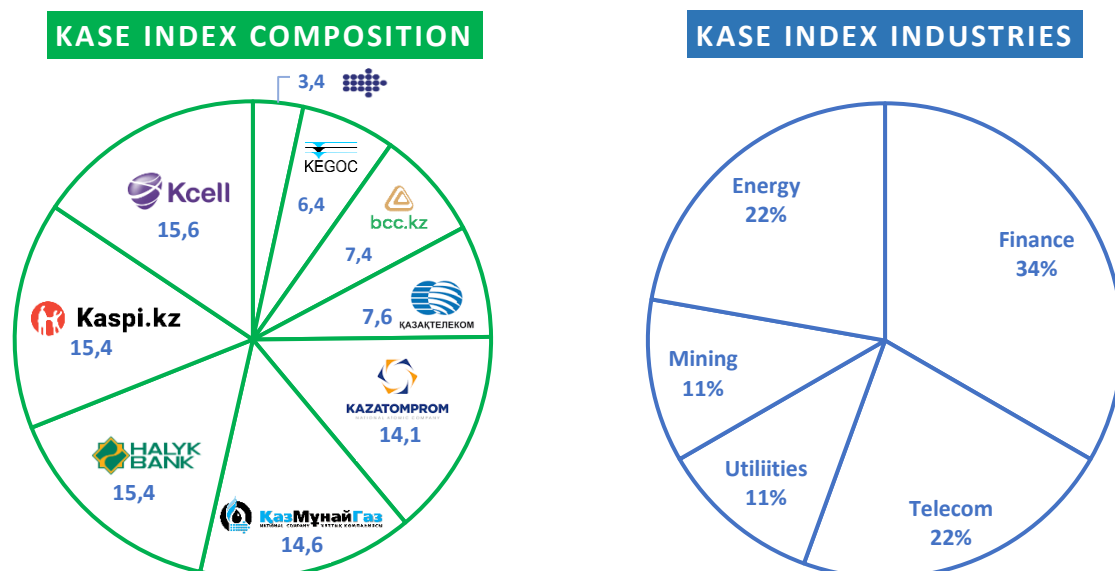
(KASE Index - Kazakhstan Stock Exchange (KASE), 2023)

Currently the Index includes the shares issued by the largest and financially stable resident companies of the Republic of Kazakhstan which are the following 9 companies (KASE Index - Kazakhstan Stock Exchange (KASE), 2023):

Table 1. Composition of KASE Index

	Code	Company	Weight	Shares, placed	Industry
1	KCEL	Kcell	15,6	199 999 975	Telecom
2	HSBK	Halyk Bank	15,4	10 908 249 222	Finance
3	KSPI	Kaspi.kz	15,4	191 176 929	Finance
4	KMGZ	NC KazMunaiGas	14,6	610 119 493	Energy
5	KZAP	NAC Kazatomprom	14,1	259 356 608	Mining
6	KZTK	Kazakhtelecom	7,6	10 338 514	Telecom
7	CCBN	Center Credit Bank	7,4	188 029 035	Finance
8	KEGC	KEGOC	6,4	259 998 191	Utilities
9	KZTO	KazTransOil	3,4	384 618 364	Energy

Figure 2. Composition of KASE Index



Dataset

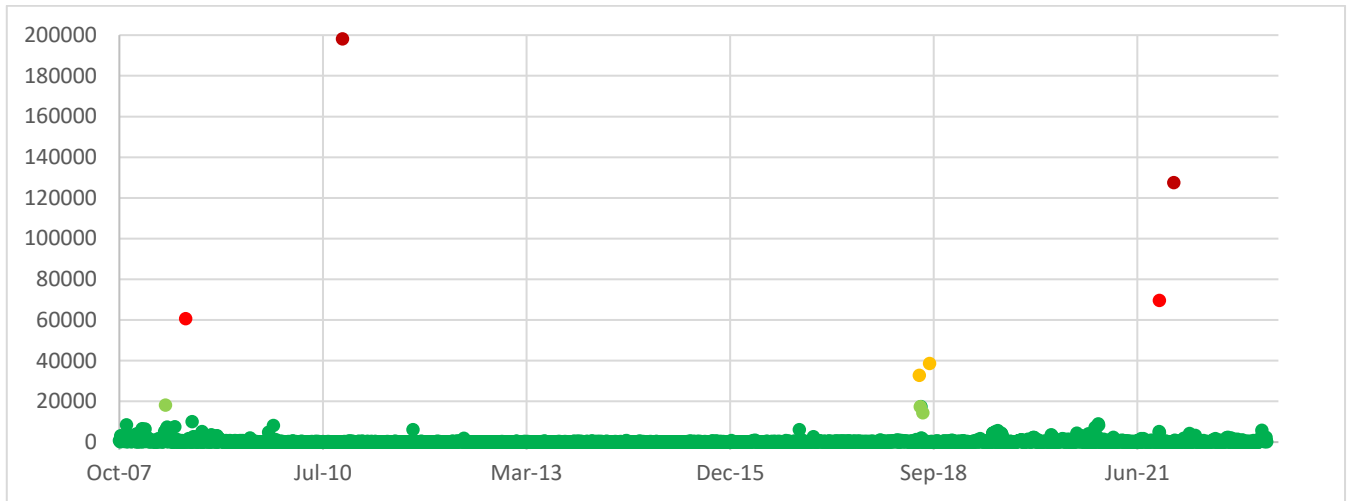
For the purpose of this research, a dataset for KASE Index daily prices (Open, Close, High, and Low) and trading volumes for the whole period of existence of the Index since inception in October 2007 till March 2023 (15 years) was used.

Figure 3. KASE Index daily close values, October 2007 – March 2023



The Index started on October 1, 2007, at the value of 2560,72 (Close). It dramatically dropped in 2008 due to the global financial crisis and due to the fact, that at the time the representative list of KASE Index included 5 banks who faced the most challenging consequences of the crisis. The effects of the 2011 European debt crisis and US Federal Debt crisis can also be seen on the chart as KASE Index went down from 2000 to 1000 in that year. Since 2015 the Index is on trending upwards in alignment with global financial markets represented here by S&P 500 Index.

Figure 4. KASE Index daily trading volume, mln. KZT



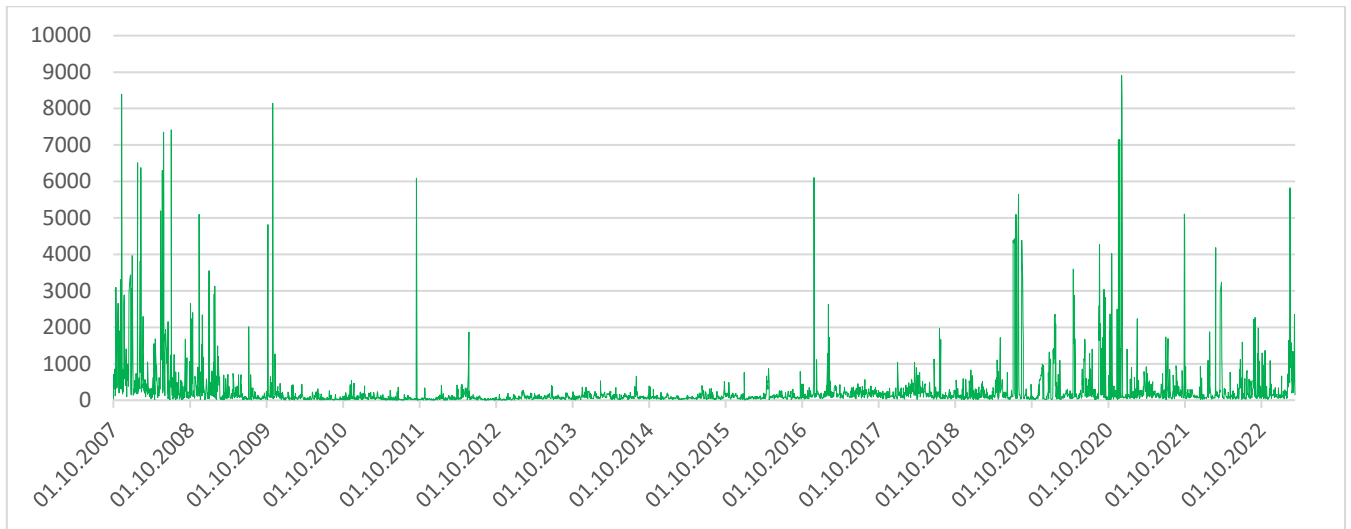
When examining daily trading volume data, we can see that the absolute majority of data points lie below the volume of 10 billion KZT. However, there are several extreme outliers caused by one-time non-regular events such as changes in the ownership of the companies (Kazakhmys PLC, KCell JSC) or share buy backs (Halyk Bank JSC).

Simple exploratory statistical analysis of the trading volume data renders the following results:

Table 2. Basic statistical measure of the dataset

Measure	Value
Number of data points	3801
Maximum (mln. KZT)	198 075
Minimum (mln. KZT)	0
Mean (mln. KZT)	420,89
Median (mln. KZT)	95,72
Mode (mln. KZT)	52,51
Below 10 bln	3790 (99,71%)
Below 5 bln	3771 (99,21%)

Figure 5. KASE Index daily trading volume - outliers removed, mln. KZT



By removing outliers from this dataset, we can observe that more accurate picture where trading with KASE Index shares was relatively active before 2008 as the global economy was booming, collapsed with the global financial crisis and recovered only 10 years after.

The above-described dataset was used as the input data for the models together with technical indicators built based on them (see example in Table 3).

Table 3. Original dataset for KASE Index

No	Date	Volume, KZT m	Open	High	Low	Close
1	01.10.2007	32,07	2550,32	2571,26	2525,93	2560,72
2	02.10.2007	705,08	2540,33	2694,51	2518,86	2681,17
3	03.10.2007	306,81	2685,97	2691,65	2612,81	2612,81
...
3799	07.03.2023	2353,21	3322,11	3328,51	3301,96	3311,38
3800	09.03.2023	479,80	3316,88	3316,88	3291,42	3291,42
3801	10.03.2023	149,25	3291,40	3319,19	3282,83	3298,53

Technical Analysis and Indicators

According to John J. Murphy, one of the key figures in the field of technical analysis, technical analysis is the study of market action for the purpose of forecasting future market movements (Murphy, 1999). Market action here, also referred to as price action by technicians,

consists of price and trading volume data for a specific stock, an Index or derivative traded on the market. The theory that allows for technical analysis to work is that the price of an asset already reflects all available information regarding the asset, including fundamental factors such as economic data, news events, and company financials, and therefore price action can be used to predict market movements.

Here it is important to point out that technicians do not accept Efficient Market Hypothesis (EMH) even in the weak form (also known as random walk theory) which states that past prices, trading volume, and earnings data do not affect an asset's price and it moves randomly. For the users of technical analysis, the markets have weak non-efficient form. Whether EMH is true or not is a subject of long-lasting debate since its introduction by Fama in 1970. Since then, several recognized empirical studies have shown that financial markets can be predicted to certain degrees especially given differing psychology and behavioral patterns of market participants (Abu-Mostafa & Atiya, 1996), (Naseer and Tariq, 2015), (Zhong and Enke, 2017).

Having established that technical analysis is capable of providing a desired outcome i.e. predicting price movements, it is necessary to go over the tools it uses to do exactly that. In the context of this research the main tools of technical analysis to be used for machine learning modelling are technical indicators built on the price and volume data and applied by traders and investors to identify trends and patterns in financial markets. Technical indicators use mathematical calculations to plot lines, curves, or other visual representations of market data, and are typically displayed alongside price charts. These visual representations of course are useful for humans to identify patterns and trends in the market visually and in fact it is how the technical analysis started in the early 20th century. (Murphy, 1998) However, the machine learning model have no use for visual plots of these indicators and rather needs the technical indicator values as input.

There is a plethora of different technical indicators used in the technical analysis, however for the purpose of this research a set of common trend-following, momentum and trend-strength

indicators was used. The indicators potentially may produce good predictions without creating issues with multicollinearity. The latter issue might arise since when constructing these indicators, the same price and volume data are used as inputs (Fliess & Join, 2009). Therefore, when it comes to using technical indicators for modelling the more the better is not the case. The indicators used are described below.

Moving averages (herein after MA) are averages of past prices that help smooth out short-term and sometimes random fluctuations and identify longer-term trends. Simple MAs for 5 and 20 days were used since five trading days constitute a week and twenty trading days constitute a month. (Murphy, 1998)

Moving Average Convergence Divergence (herein after - MACD) is a trend-following indicator that shows the relationship between two moving averages of prices. The MACD indicator is calculated by 26 and 12 day exponentially weighted moving averages (EMA), specifically subtracting 12-day EMA from 26-day EMA. In practice MACD is plotted on the price chart together with the signal line (9-day EMA) and whenever they cross traders interpret a bullish or a bearish signal depending on how the MACD line crossed the signal line from below to above (upward trend) or from above to below (downward trend). (Murphy, 1998)

Relative Strength Index (herein after - RSI) is a momentum indicator developed by J. Wells Wilder Jr. in 1978 that measures the magnitude of recent price changes (or strength of price movement) to determine overbought or oversold conditions. It oscillates between 0 and 100 and is calculated using the average gains and losses over a given period of time by the following formula:

$$\text{RSI} = 100 - [100 / (1 + \text{RS})]$$

Where:

RS (relative strength) = average gain during the up period for the specified period / average loss during the down period for the specified period.

RSI is usually calculated on a 14-period time frame, but this time frame can be customized to suit different needs. An RSI value above 70 is typically considered overbought, while a value below 30 is considered oversold. (Murphy, 1998)

Similar to RSI **Williams %R** is also a momentum indicator that measures the level of a security's closing price relative to its high-low range over a given time period. It oscillates between -100 and 0, with values below -80 considered oversold and values above -20 considered overbought (Murphy, 1998). Like the RSI, traders may use Williams %R to identify potential trend reversals and confirm the strength of existing trends, however Williams %R is more sensitive to short-term price movements than RSI. This means that Williams %R can generate signals more quickly, but can also produce more false signals. On the other hand, RSI is less sensitive to short-term price movements, which means that it can take longer to generate signals, but may be more reliable. Given this difference in sensitivity both indicators have been used as inputs for the models. (Fliess & Join, 2009)

Parabolic Stop and Reverse (herein after - SAR) is a trend-following indicator that is used to determine the direction of the trend and timing to enter and exit positions in a market. It plots points above or below price to signal when a trend is reversing and can be used to set stop-loss orders or identify potential entry or exit points. The formula for parabolic SAR is based on acceleration factor (AF) and extreme points (EP) and uses current price and the indicator's previous values (Murphy, 1998):

$$PSAR(n) = PSAR(n-1) + AF \times (EP - PSAR(n-1))$$

Where:

- PSAR(n) is the PSAR value for the current period;
- PSAR(n-1) is the PSAR value for the previous period;
- AF is the acceleration factor (starts at 0.02, increases by 0.02 with new EP, maximum value 0.20);
- EP is the extreme point for the current trend.

SAR is represented by a series of dots on a price chart positioned below or above the price that signal possible reversals in the trend. Dots above price signal a downtrend whereas dots below the price indicate an uptrend. It is often used in conjunction with other technical indicators, such as RSI and Williams %R, to confirm signals and help traders make more informed decisions (Fliess & Join, 2009).

The Average Directional Index (herein after ADX) is a technical indicator that measures the strength of a security's trend regardless of its direction developed by J. Welles Wilder in 1978 in the framework of his technical analysis system called the Directional Movement System. ADX is non-directional indicator as it indicates only the strength of the trend but not its direction. It ranges from 0 to 100, with values above 25 typically indicating a strong trend. The ADX is calculated using the difference between the +DI (positive directional indicator) and -DI (negative directional indicator), which are based on the security's price movements. Traders may use the ADX to help identify the strength of a trend and to make decisions about entering or exiting positions. ADX is often used in combination with moving averages or oscillators since it cannot indicate the direction of the price movement (Fliess & Join, 2009).

Using the original dataset for KASE Index containing price action data and Technical Analysis library for Python programming language the final dataset to be fed to the models was created. The final dataset had a total of 3782 samples.

Table 4. The final dataset with technical indicators used for modelling.

Date	Volume, KZT m	Close	ma5	ma20	26ema	12ema	MACD	RSI	Williams %R	SAR	ADX
29.10.2007	1903	2613	2568	2567	2576	2582	6,14	53,79	-40,73	2532	10,14
30.10.2007	1348	2617	2583	2570	2579	2587	7,88	54,03	-38,41	2532	9,61
31.10.2007	1501	2641	2598	2568	2585	2596	10,76	55,87	-9,71	2555	9,35
01.11.2007	1845	2590	2609	2567	2585	2595	9,43	51,26	-68,07	2574	10,63
02.11.2007	436	2556	2603	2574	2583	2589	5,94	48,35	-75,99	2714	9,67
07.03.2023	2353	3311	3318	3345	3328	3330	1,53	44,08	-74,46	3340	24,78
09.03.2023	480	3291	3310	3341	3325	3324	-1,63	38,37	-82,89	3329	23,99
10.03.2023	149	3299	3307	3339	3323	3320	-3,52	41,29	-69,12	3329	23,88

Models

In this study two models using Support Vector Machine (herein after – SVM) and Long short-term memory (herein after - LSTM) machine learning algorithms were built to predict the directional movement of KASE Index.

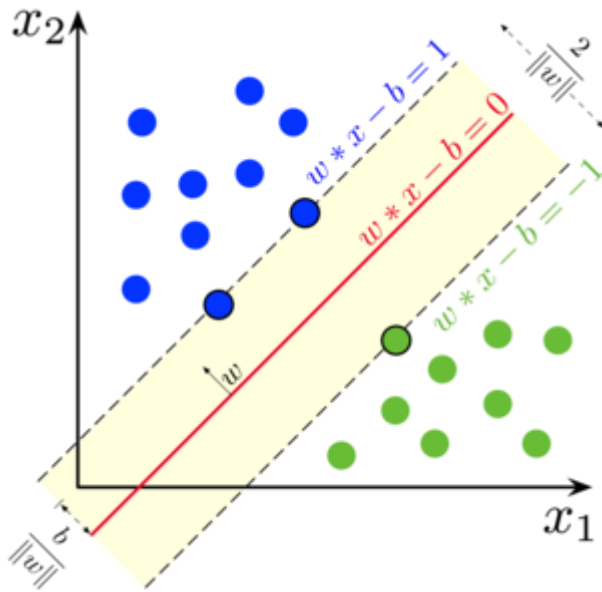
Support Vector Machine

Support Vector Machine (SVM) is a supervised machine learning algorithm used to solve regression, classification, and outlier detection problems. It was first introduced to the world by Corinna Cortes and Vladimir Vapnik in 1995 in their work titled "Support-Vector Networks," where they described a novel way to implement linear classifiers using the theory of statistical learning. (Cortes & Vapnik, 1995). Since then, SVM has only grown more popular and been used as a tool for a wide array of applications such as image classification and object recognition (Thai et al., 2012), natural language processing and sentiment analysis (Rezwanul et al., 2017), bioinformatics and medical diagnosis (Lin et al., 2008), financial prediction (Lin et al., 2013) (Strader et al., 2020) and more (Cervantes et al., 2020).

At its core SVM is an extension of the maximal margin classifier, a straightforward and intuitive classifier. However, the maximal margin classifier is limited in its applicability, as it only works with data sets where classes can be separated by a linear boundary. Hence the support vector classifier and further SVM were developed as an expansion of the maximal margin classifier, allowing for a wider range of applications. Moreover, the latter was designed to be able to handle non-linear class boundaries (James et al., 2017).

SVM works by finding the best possible decision boundary (or hyperplane) that can separate different classes in a given dataset. In case of binary classification problems, where the objective is to classify data into one of two possible classes, SVM aims to find a hyperplane that maximizes the margin between the two classes where the margin is the distance between the hyperplane and the closest data points from each class thus separating the two classes, as shown in the following figure:

Figure 6. Maximum-margin hyperplane and margins for an SVM



In figure 6, the red line represents the hyperplane that separates the two classes. The two closest data points (one from each class) that lie on the margin are called support vectors. These support vectors essentially determine the hyperplane, since their position and orientation affect the margin.

In the case of a linearly separable dataset, as mentioned above SVM finds the hyperplane that maximizes the margin between the two classes. The hyperplane is defined by the equation:

$$w * x + b = 0$$

where w is the weight vector perpendicular to the hyperplane, x is the feature vector of a data point, and b is the bias term (Hastie et al., 2017).

In cases when the dataset cannot be separated linearly, SVM uses a kernel function i.e. a function that maps the original data into a higher-dimensional feature space by computing the dot product of the transformed feature vectors in the higher-dimensional space without actually computing the transformation explicitly where the classes may be linearly separable. This allows SVM models to handle complex datasets as it is computationally quite efficient. SVM employs several kernel functions including as linear, polynomial, radial basis function (RBF), and sigmoid. The choice of kernel depends on the nature of the dataset and the problem at hand (Scholkopf & Smola, 2018).

As mentioned previously SVM has been used for financial forecasting and specifically to classify the movement of stock prices in the stock market. In these cases, the SVM model is fed a set of features that are indicative of stock price movements and a corresponding set of labels that indicate whether the stock price went up or down. Then the model learns to classify future price movements based on the patterns it observes in the training data.

Since the features to be used as input to SVM can vary depending on the problem at hand, it is worth outlining some common features applicable for stock price movement forecasting using machine learning models. These commonly used features include the technical indicators described above as well as news sentiment and economic indicators (Strader et al., 2020). Using the news sentiment implies application of sentiment analysis to determine the tone and sentiment of news articles and social media posts about a particular stock or market index. Positive or negative sentiment can affect investor sentiment and behavior, which in turn can move stock prices. As for the economic indicators such as inflation rates, interest rates, and GDP growth rates, they might prove useful for modeling as providers of insights into the overall health of the economy and the potential direction of the stock market.

Once the features have been identified, they are normalized i.e., preprocessed to rescale the input into similar ranges, and then fed into the SVM algorithm. Further, as previously described the SVM algorithm finds the hyperplane that separates the two classes (i.e., stock price went up or down) with the largest margin. After the training, the SVM algorithm takes in a new set of features and uses the learned weights and biases to predict the movement of the stock price – up or down.

Long short-term memory - LSTM

LSTM represents an artificial recurrent neural network (RNN) architecture widely used in Deep learning and Artificial intelligence. It was developed by Sepp Hochreiter and Jurgen Schmidhuber in the 1990-s as an RNN method that can successfully deal with vanishing or

exploding gradients which quite often affected the effectiveness of other RNN models (Hochreiter & Schmidhuber, 1997). It is worth discussing here how basic RNN algorithms work in order to understand the advantages of LSTM.

RNNs are a type of neural networks which in turn are machine learning algorithms that imitate the structure and function of the human brain. Neural networks are built with interconnected nodes – neurons - working in unison to process and analyze data. NNs are usually organized in layers where the first layer receives the input data, and each further layer performs different operations with this data to arrive at a desired outcome. One of the specialties of recurring neural networks is their effectiveness in working with time-series data thanks to their ability to learn and remember long-term dependencies in the data sequence and use them to produce output. These dependencies are learnt during the training through the process of backpropagation by computing the loss function and the gradient (i.e. rate of change) of the loss. One of the biggest challenges of RNNs are vanishing/exploding gradient problems, where the gradients become too small/big thus making it difficult for the model to learn the long-term dependencies. (Goodfellow et al., 2016)

LSTM overcomes this problem by introducing a special memory cell that can store and retrieve information over long periods of time. The cell is controlled by three gates – the input gate, the output gate, and the forget gate – that regulate the flow of information in and out of the cell. The input gate determines how much new information is added to the cell from a layer of the network, the output gate controls how much information is output from the cell, and the forget gate decides how much information should be discarded from the cell. (Greff, K., et al, 2016)

Given the above-described features of the LSTM algorithm it has proven its effectiveness dealing with sequential data in such areas as natural language processing (Melamud et al., 2016), image and video processing (Donahue et al., 2017), healthcare (Wang et al., 2018), robotics (Park et al., 2018), and time-series analysis (Gamboa, 2017). LSTM models have also

been applied successfully in finance for stock market prediction (Vargas et al., 2017), anomaly detection (Ergen & Kozat, 2020) and risk management (Wang et al., 2019).

As for the modeling process itself, much like for SVM, it starts with identifying unput features which could be original market stock data, technical indicators, economic indicators, news sentiment or all combined. Since LSTM is a neural network, its architecture will be different from SVM and will consist of an input layer that takes in the features, one or more LSTM layers that are designed to help the model capture and learn patterns in the data, and an output layer that produces an output – up or down – when framed as binary classification problem (Greff, K., et al, 2016).

Performance metrics

After collecting and processing data, building and running models the next step is to evaluate the models i.e. how correctly models can predict the movement of a stock price or index. The problem at hand being a binary classification problem the most common and appropriate methods to evaluate the performance of such models are accuracy, precision, recall, F1 score and ROC AUC score (Guido & Müller, 2016).

These metrics can be derived from a confusion matrix which shows the number of true positives (TP) - correctly classified positive outcomes, false positives (FP) – incorrectly predicted positive outcomes, true negatives (TN) – correctly predicted negative outcomes, and false negatives (FN) - incorrectly predicted negatives outcomes. These are the four possible outcomes of a binary classification problem (Guido & Müller, 2016).

Figure 7. Confusion matrix

	Actually Positive (1)	Actually Negative (0)
Predicted Positive (1)	True Positives (TPs)	False Positives (FPs)
Predicted Negative (0)	False Negatives (FNs)	True Negatives (TNs)

Using the confusion matrix data one can measure the accuracy of the model which is a measure of the model's overall performance. It is defined as the number of correct predictions divided by the total number of predictions:

$$Accuracy = \frac{TP}{TP + FP + TN + FN}$$

Accuracy measures the proportion of true positive and true negative predictions made by the model. However, accuracy can be misleading in cases where the dataset is imbalanced, meaning that there are many more instances of one class than another.

In such cases precision and recall would be more appropriate since they measure the model's ability to correctly identify positive instances. Precision is defined as the number of true positive predictions divided by the total number of positive predictions (true positive + false positive):

$$Precision = \frac{TP}{TP + FP}$$

In other words, precision measures the proportion of instances classified as positive by the classifier that are actually positive.

On the other hand, recall, also known as true positive rate or sensitivity, is a measure of the model's ability to correctly identify all positive instances. It is defined as the number of true

positive predictions divided by the total number of positive instances in the dataset (true positive + false negative):

$$Recall = \frac{TP}{TP + FN}$$

Recall measures the model's ability to avoid false negatives, which are instances that are predicted as negative but are positive. In other words, it measures the proportion of actual positive instances that the classifier correctly identified as positive.

It is clear here that recall and precision have an inverse relationship. That is, as recall increases, precision tends to decrease, and vice versa. This is because a classifier that identifies more positive instances (higher recall) is likely to also identify more false positives, which reduces the precision. For example, consider a binary classifier that is designed to detect fraudulent credit card transactions. A high precision would mean the classifier correctly identifies only the fraudulent transactions and minimizes the number of false alarms, whereas a high recall would mean the classifier can correctly identify a large proportion of the fraudulent transactions in the dataset. If the classifier is tuned to have high recall, it may identify many transactions as fraudulent (including some that are legitimate), resulting in a lower precision. Conversely, if the classifier is tuned to have high precision, it may identify only the transactions that are highly likely to be fraudulent, resulting in a lower recall. The balance between recall and precision depends on the specific application and the desired trade-offs. In some applications, such as detecting fraud or identifying disease, high recall may be more important than high precision to ensure that all cases are detected, even if there are some false positives. In other applications, such as filtering spam or detecting objects in images, high precision may be more important than high recall to minimize false positives and ensure that only relevant instances are identified (Guido & Müller, 2016)

In cases when both recall and precision are important, the F1 score can be a useful metric to evaluate the performance of a classifier, as it takes into account both precision and recall, and provides a balanced view of the classifier's effectiveness, especially when the dataset is

imbalanced (Géron, 2019). It is defined as the harmonic mean of precision and recall, which gives equal weight to both metrics:

$$F1\ score = \frac{2 * (precision * recall)}{precision + recall}$$

Another useful metric is ROC AUC Score (Receiver Operating Characteristic Area Under the Curve) which is a performance metric that measures the ability of a binary classifier to distinguish between positive and negative classes. It is a curve that plots the true positive rate (TPR) against the false positive rate (FPR) at various classification thresholds. The area under the ROC curve (AUC) is a measure of the overall performance of the classifier. A classifier with an ROC AUC score of 1 is considered to be perfect, while a score of 0.5 indicates that the classifier is no better than random guessing (Géron, 2019).

Since the end goal of predicting the stock market movement is to gain insight into the market, trade using this new knowledge and make profit, it would be interesting to see the performance of the best models in a trading simulation. The trading simulator would be built in the same environment as the models and would use a data for the period outside of training and testing dataset, preprocess it using the same technical indicators and apply the built model to generate trading signals. If the model predicts an upward movement and no shares are held, the code would buy shares, and if the model predicts a downward movement and shares are held, the code would sell them. If it is the last day of trading and shares are still held, they are sold, and the final portfolio value is calculated.

Modeling & Results

In the experimental phase of the study two ML models – SVM and LSTM – have been built and sixteen simulations were run using four different sets of technical indicators as features for two time periods – 2013-2022 and 2007-2023.

Based on the similar research for S&P 500 Index (Kamalov et al., 2020) and S&P Bombay Stock Exchange (BSE) Sensex (Patel et al., 2015) as well as considerations related for a trade-off in accuracy for longer period due to the possibility of more noise in the data, initially 10-year period from January 2013 to December 2022 for KASE Index was used for modeling. However, SVM model performed no better than 50/50 chance for some set of technical indicators based on this 10-year period and it's been decided to use the whole period of existence of the KASE Index from October 2007 till March 2023. This decision allowed to improve the performance for SVM.

In order to see how different technical indicators would affect the performance of the models both SVM and LSTM model used four sets of technical indicators:

1. Moving Average
2. MACD
3. Set of RSI, Williams %R, Parabolic SAR and ADX
4. Combined set of MA, MACD, RSI, Williams %R, Parabolic SAR and ADX

The closing values of the KASE Index data was preprocessed to create these features and a target column, where 1 represents an upward movement and 0 represents a downward movement in the next period. The goal of each model was to classify the outcome for the next day as 1 (i.e. Index went up) or 0 (i.e. went down). The data was split into training and testing sets using the ratio of 80/20. (03.01.2013 – 29.12.2020) / (30.12.2020 – 30.12.2022)

The SVM model used the data normalized with StandardScaler and an SVM classifier with linear kernel. The parameters of the LSTM model are described in the table below (Table 5).

Table 5. Parameters of the LSTM model

Parameter	Description
LSTM layer	Specifies the number of memory cells in the LSTM layer. In this case, there are 50 LSTM neurons.
Input shape	(X_train.shape[1], 1) The first element specifies the number of time steps in the input sequence, and the second element specifies the number of features in each time step.
Dense layer	A single output neuron with a sigmoid activation function, which predicts the probability of an upward price movement.
Loss function	Binary cross-entropy, commonly used for binary classification problems.
Optimizer	Adam, an adaptive learning rate optimization algorithm.

After training the models were run to make predictions on the testing data. Further, the predictions were compared to the actual labels to calculate evaluation metrics, including accuracy, precision, recall, f1 score, confusion matrix, and area under the ROC curve (AUC). Here upward movement of the Index is classified as 1 and assigned as the positive, while downward movement is classified as 0 and assigned as the negative.

Table 6. Performance metrics for SVM model given different sets of input data, 2013-2022.

SVM Model				
Indicators	MA 5 & 20	MACD	RSI, Williamson%, SAR & AXD	All
Metric				
January 2013 – December 2022				
Accuracy	0.5524	0.5540	0.5996	0.5524
Precision	0.5524	0.5540	0.5920	0.5524
Recall	1	1	0.88	1
F1	0.7116	0.7130	0.7094	0.7116
Confusion matrix	tp-fp [269 218] fn-tn [0 0]	[272 219] [0 0]	[238 164] [31 54]	[269 218] [0 0]
AUC	0.5000	0.5000	0.5662	0.5000

Table 6 first shows the results of the model using the data for the period from 2013 to 2022. From the table, we can see that the highest accuracy and precision were achieved using the RSI, Williams%, SAR & ADX technical indicators, with an accuracy of 0.5996 and a precision of 0.5920. However, the recall was lower for this set of indicators at 0.88, compared to the other

sets of indicators where the recall was 1. The F1 score was relatively similar for all sets of indicators, ranging from 0.7094 to 0.7130. Finally, the AUC score, which measures the model's ability to distinguish between positive and negative samples, for this set of indicators was 0.56, indicating that the model's performance is better than random chance.

However, the performance of the model when using other sets of indicators containing MA and/or MACD is basically a random chance with AUC Score of 0.5. As mentioned before, the confusion matrix shows the number of true positives, false positives, true negatives, and false negatives for each set of indicators. With true negatives and false negatives being 0 it clearly shows that for these three sets of indicators containing MA and/or MACD the model predicts only upward movement in the market. This might be explained by the fact that during 2013-2022 the KASE Index had a clear upward trend while MA and MACD are trend indicators using average values for given sub-periods.

Figure 8. KASE Index in the period from 2013 to 2022



This led to the decision to expand the timeframe of the dataset and include the KASE Index values from its inception in October, 2007 till March, 2023. The performance results for this period are shown in the second part of Table 7.

Table 7. Performance metrics for SVM model given different sets of input data, 2007-2023.

SVM Model				
Indicators Metric	MA 5 & 20	MACD	RSI, Williamson%, SAR & AXD	All
October 2007 – March 2023				
Accuracy	0.5773	0.5808	0.5350	0.5416
Precision	0.5736	0.5777	0.5669	0.5723
Recall	0.92	0.90	0.68	0.68
F1	0.7070	0.7038	0.6174	0.6216
Confusion matrix	[386 287] [33 51]	[379 277] [42 63]	[284 217] [135 121]	[285 213] [134 125]
AUC	0.5361	0.5428	0.5179	0.5250

Looking at the accuracy metric, the MA 5 & 20 and MACD indicators have the highest accuracy, with 0.5773 and 0.5808, respectively. However, in contrast with the first timeframe the set of RSI, Williamson%, SAR & AXD indicators has a lower accuracy of 0.5350 compared to 0.5996.

For the precision metric, which measures the proportion of instances classified as positive by the classifier that are positive, all indicators have similar performance with values ranging from 0.5669 to 0.5736.

The recall metric indicates the proportion of positive instances that are correctly identified by the model. In this case, the MA 5 & 20 and MACD indicators have the highest recall, with values of 0.92 and 0.90, respectively. The RSI, Williamson%, SAR & AXD indicator has a lower recall of 0.68.

The F1 score, a weighted average of precision and recall, for the MA 5 & 20 and MACD indicators have the highest F1 score, with values of 0.7070 and 0.7038, respectively, while the RSI, Williamson%, SAR & AXD indicator has a lower F1 score of 0.6174.

As for the AUC, the MACD indicator has the highest AUC value of 0.5428, while the RSI, Williamson%, SAR & AXD indicator has the lowest AUC value of 0.5179 which is quite close to random guessing.

From this it becomes clear that extending the timeframe led to a better performance using the sets of indicators containing Moving Averages. The period from 2007 till 2023 saw not only an upward trend but also the falling of the KASE Index together with global financial markets crash during the 2008 crisis. This most likely allowed the model to better learn dependencies in the data compared to the period of mostly upward movement of the Index.

Overall, with the data for the period from 2007 to 2023 the SVM model performed best when using MACD as primary input feature across all performance metrics except for recall.

Like SVM models before, the LSTM models also were run for two timeframes.

Table 8. Performance metrics for LSTM model given different sets of input data, 2013-2022

LSTM Model				
Indicators Metric	MA 5 & 20	MACD	RSI, Williamson%, SAR & AXD	All
January 2013 – December 2022				
Accuracy	0.5646	0.5437	0.5708	0.5728
Precision	0.5643	0.5563	0.6048	0.5776
Recall	0.9293	0.87132	0.6431	0.8438
F1	0.7022	0.6790	0.6234	0.6858
Confusion matrix	tp-fp [250 193] fn-tn [19 25]	[237 189] [35 30]	[173 113] [96 105]	[227 166] [42 52]
AUC	0.5220	0.5041	0.5623	0.5411

In case of the first period (2013-2022) the LSTM model's accuracy was highest when the set of technical indicators including everything MAs 5 & 20, MACD, RSI, Williamson%, SAR & AXD amounting to 0.5728. Although the set of indicators with only RSI, Williamson%, SAR & AXD is not too far behind it with 0.5708.

The precision scores range from 0.5563 for MACD to 0.6048 for the set of RSI, Williamson%, SAR & AXD. However, the range for recall scores not only wider but they are inversed with the lowest of 0.6431 for the set of RSI, Williamson%, SAR & AXD to the highest for 0.9293 MA. This indicates that the LSTM for this timeframe has the same issue as SVM, although in a weaker form, and tends to predict upward movement in the market, as the number of false positives is higher than the number of false negatives for the sets of indicators containing MAs. The confusion matrix confirms this with a high number of true and false positives for this set of technical indicators.

The F1-scores, which are the harmonic mean of precision and recall, range from 0.6234 to 0.7022, indicating that the model has a moderate level of performance. However, due to the issue with the upward bias prediction caused by MA indicators, the F1-score becomes invalid.

Finally, the only acceptable AUC score of 0.5623 belongs to the RSI, Williamson%, SAR & AXD set of technical indicators, for other sets the model's ability to predict the movement of the Index is just slightly better than random guessing.

Overall, much like for SVM the RSI, Williamson%, SAR & AXD set provides the best results for LSTM model given a 10year period between 2013 and 2022.

Table 9. Performance metrics for LSTM model given different sets of input data

LSTM Model				
Indicators Metric	MA 5 & 20	MACD	RSI, Williamson%, SAR & AXD	All
October 2007 – March 2023				
Accuracy	0.5614	0.5624	0.5521	0.5574
Precision	0.5617	0.5901	0.6020	0.5750
Recall	0.9451	0.6840	0.5632	0.7684
F1	0.7046	0.6336	0.5819	0.6578
Confusion matrix	[396 309] [23 29]	[288 200] [133 140]	[236 156] [183 182]	[322 238] [97 100]
AUC	0.5154	0.5479	0.5508	0.5321

When the data timeframe has been expanded from October 2007 to March 2023 again the performance for all sets of indicators that included moving averages improved. Much like for SVM the performance of the LSTM model with the MACD as input features yielded better overall results.

Based on these simulations it seems that the RSI, Williamson%, SAR & AXD has the potential to produce more robust results for different timeframe and cycles in the market and across different performance metrics compared to other technical indicators containing moving averages. However, MACD may improve the performance of the models if the market data contains examples of both downtrend and uptrend for the models to learn as it did in the simulations of this research.

As for the comparison between SVM and LSTM performance it is necessary first to identify metrics that would be most appropriate for the given dataset. The dataset is relatively balanced between “Price rise” classes with upward movement (1) being 53% and downward movement (0) of 47%. Moreover, the costs of false positives and false negatives are not significantly different. And although precision and recall helped in identifying the flaws of the models when using the 10-year period, there is no need to use such metrics for comparison between the and LSTM models. Therefore, accuracy can serve as a good measure of performance. SVM Additionally, the ability of the AUC score to indicate the performance of the model compared to a 50/50 random might also be useful for comparison reasons.

As can be seen in Tables 10 & 11 given the same set of indicators and timeframe with very similar AUC scores SVM models outperform LSTM models in accuracy albeit slightly.

Table 10. Comparison of SVM and LSTM using RSI, Williamson%, SAR & AXD for 2013-2022

Metric	SVM	LSTM
Accuracy	0.5996	0.5708
AUC	0.5662	0.5623

Table 11. Comparison of SVM and LSTM using MACD for 2007-2022

Metric	SVM	LSTM
Accuracy	0.5808	0.5624
AUC	0.5428	0.5479

Having identified the best performing models for both SVM and LSTM with specific sets of indicators, the next step was to place the model in a setting that is closer to real-life application i.e. run a trading simulation for a new data. In this case the trading simulation was run using the KASE Index values for 19 trading from March 10 to April 10 of 2023 which is outside of the dataset used for training and testing the models. The simulator was given 10000 US dollars and traded in accordance with the rules describe in the methodology section.

Interestingly, both SVM models despite being trained using different sets of technical indicators and timeframes and difference in accuracy produced the same return.

Table 12. Performance of both SVM models in the trading simulation

Metric	SVM Value
Initial portfolio value	\$10000.00
Final portfolio value	\$10455.14
Trading period (days)	19
Trading period return	4.55%
Annualized return	80.46%

The LSTM models, on the other hand, differed in their trading performance. Here in Table 13 LSTM 1 is the LSTM model that was trained using the RSI, Williamson%, SAR & AXD set and timeframe of 2013-2022, whereas LSTM 2 is the model that used MACD and the 2007-2023 timeframe.

Table 13. Performance of LSTM models in the trading simulation

Metric	LSTM 1	LSTM 2
Initial portfolio value	\$10000.00	\$10000.00
Final portfolio value	\$10205.67	\$10387.79
Trading period (days)	19	19
Trading period return	2.06%	3.88%
Annualized return	31.00%	65.63%

The trading simulator has further proven the findings of the accuracy evaluation of the models i.e. the SVM models in this context outperform the LSTM models. Moreover, the positive returns provided by the application of the models indicate their potential usefulness for traders. However, it is necessary to point out that much like technical analysis itself these models, when used in real life trading or investing should be used in combination with other tools available.

Conclusion

This study sought to explore the application and effectiveness of machine learning models, specifically Long Short-Term Memory (LSTM) and Support Vector Machine (SVM), in predicting the movements of KASE Index on the Kazakhstan Stock Exchange (KASE) utilizing the methods of technical analysis. It was built based on the existing literature on the application of machine learning algorithms for stock market forecasting but represents the first of its kind in terms of applying the said algorithms in the context of KASE. To train and test the models, historical data on KASE Index values from 2007 to 2023 as well as the set of technical indicators were utilized.

The study found that both LSTM and SVM models can produce satisfactory outcomes in forecasting the movements of KASE Index with SVM models having a slight edge over LSTM models. As a result, these models could be valuable tools for investors and traders seeking to make informed decisions about their trading strategies on KASE.

While the findings of this study demonstrate the potential effectiveness of Long Short-Term Memory (LSTM) and Support Vector Machine (SVM) models in predicting the movements of KASE Index, there are some limitations to be considered. One of the main limitations is the relatively small dataset utilized in this study, covering only the period from 2007 to 2023. The study showed that expansion of the timeframe can yield better performance from the models. However, for the KASE Index one would have to wait for new data to accumulate. Therefore, future studies might also consider application of these models to specific stocks listed on KASE which have longer history.

Additionally, the study utilized a limited set of technical indicators to train and test the models to avoid issues with multicollinearity, which may have restricted their accuracy. Therefore, incorporating different technical indicators may prove useful. Moreover, it would be interesting to see in future research application of not only different technical indicators but also

economic indicators and news sentiment as features to train and test the models and investigate their effect on the accuracy of the predictions.

Given the always developing breakthrough nature of AI and machine learning, future research can investigate the performance of other ML algorithms such as Transformer-XL, Prophet, WaveNet in predicting the movements of KASE Index or stocks listed on KASE.

This research expands the literature on stock price forecasting in the context of KASE by demonstrating that SVM and LSTM models have the potential to enhance investment decision-making by predicting price movements with satisfactory level of accuracy.

As such the findings will hopefully contribute to the research of KASE as a frontier stock market and will ignite the interest in the topic among Kazakhstani researchers.

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Appendix A. Software and Dataset.

The models in this study were built and run in Jupyter Notebook using Python programming language. The libraries used include libraries for scientific computing, data analysis, data visualization, technical analysis and implementation of machine learning models: numpy, pandas, matplotlib, talib, tensorflow, sklearn and keras.

The original dataset and Jupyter Notebooks containing the Python code and modeling results can be accessed on KazGUU Ondrive through the following link:

[MD Application of ML for KASE backup](#)