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STOCK MARKET TREND PREDICTION USING SUPPORT VECTOR MACHINES

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Abstract. *The aim of the paper was to outline a trend prediction model for the BELEX15 stock market index of the Belgrade stock exchange based on Support Vector Machines (SVMs). The feature selection was carried out through the analysis of technical and macroeconomics indicators. In addition, the SVM method was compared with a "similar" one, the least squares support vector machines - LS-SVMs to analyze their classification precisions and complexity. The test results indicate that the SVMs outperform benchmarking models and are suitable for short-term stock market trend predictions.*

Key words: *Stock market trend prediction, Support vector machines (SVMs), Classification*

1. INTRODUCTION

The key to generating a high return on the stock market lies in how well we are able to successfully predict the future movement of the market prices of financial assets [1, 2]. Consequently, a market trading strategy can be considered effective only if it relies on the precise prediction of the trend of change of the price index of that particular market [3].

In the field of economy, investors typically use fundamental and/or technical analysis to analyze prices of financial assets and make decisions. Fundamental analysis studies the forces driving the economy, industry groups and companies in order to define the intrinsic value of a financial asset. At the macroeconomic level it focuses on economic data such as inflation, unemployment and the level of the interest rate to assess the level of the current and future growth of the economy. At the company level, fundamental analysis is

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based on ratio analysis, but can also include the analysis of the competition, management and business concepts, while the factors that influence supply and demand for specific products are considered at the industry level. Unlike the fundamental analysis of capital markets, technical analysis is based on the assumption that the stock market events themselves offer sufficient data for predicting future values. The technical analysis relies on numerous qualitative and quantitative methods in order to produce reliable asset price trends. The simplest qualitative methods used within this analysis are based on the charting of asset prices and trading volume. These methods help us identify patterns of change that can be used to achieve profits in stock market trading. The related technical indicators belong to the quantitative methods and are a rather simple mathematical expression of the aforementioned price and volume changes. According to [4], technical indicators still have a key role in economic methods for the prediction of stock market index trends.

As a current state-of-the-art method, machine learning is gaining in significance in the field of predicting yield on the financial market. In many studies, the algorithms of machine learning have proven to be quite an effective method of prediction of the direction of movement of stock index values. Their effectiveness lies in their capability to accurately learn any detected patterns of change which are characteristic of stock market time series. Their degree of accuracy of an approximate 60% hit rate in predictions is often considered a satisfactory result for stock market trend prediction on capital markets [5], which means that the application of these methods could contribute to the increase in gain and decrease in the risk involved in trading.

The most frequently adopted algorithms of machine learning for trend prediction include Artificial Neural Networks (ANNs) [3], genetic algorithms (GAs) [6], fuzzy logic and chaos theory. According to [7], the methods most widely used for predicting stock market trends are the approaches based on Support Vector Machine (SVM) [1, 8, 9]. In [10] is pointed out that in most cases the Least Squares Support Vector Machines (LS-SVMs), and SVMs outperform other machine learning methods.

SVMs are based on the principle of Structural Risk Minimization (SRM), which has proven to be effective in comparison to the Empirical Risk Minimization (ERM) used for neural networks. The SRM minimizes the upper threshold of the expected risk, unlike the ERM which minimizes the error on the training data. This difference in particular gives the SVMs an advantage over neural networks in the data classification process. When compared to other methods, SVMs in theory do not require any previous assumptions regarding data properties and guarantee an efficient global optimal solution.

Despite their frequent use to predict trends on developed markets, according to our knowledge, there is an insufficient body of evidence on SVM application to the stock market trend prediction in frontier markets such as the market of the Republic of Serbia.

The main goal of the paper is to demonstrate the use of SVMs for the trend prediction of the Belex15 index from the Belgrade stock exchange. This index determines the price of the most liquid stocks which previously satisfied the criteria for participating in the index basket and are traded on the regulated market of the Belgrade Stock Exchange. Its role is to measure the changes in the price of the stock which is being traded.

In forming the SVM model, technical and macroeconomics indicators were used as input features while the trend of the stock market index was modeled as a problem of binary classification. This study represents a continuation of our prior work [11-13], which will now involve a newly proposed SVM-based prediction model and a more extended analysis.

The rest of the study is organized as follows: the second part of the paper presents the theoretical basis of the SVM method for binary classification. The third section describes the proposed prediction model, while the results of the testing are shown in section four. In section five, some of the conclusions and directions for further research are presented.

2. SUPPORT VECTOR MACHINES FOR CLASSIFICATION

One of the main characteristics of SVMs suggested by Vapnik [14] is that the problems of nonlinear classification can be solved using the method of convex quadratic programming - QP. In addition to the fact that SVMs always finds an optimal solution to the QP problem, within it we find only examples from the training group which make the greatest contribution, the so-called support vectors, which is why a sparse solution is formed.

Let us assume that there is a group of training data consisting of N elements x_i, $i = 1,...,N$, where each element is represented by a d-dimensional vector $x_i = (x_1,x_2,..., x_d)$ (the vector space with the dimension d). To each item of the data from the training group a value $y_i \in \{-1,1\}$ was added, that is, the class it belongs to.

In the vector space in which the data are presented, we need to find the optimal separating hyper-plane, so that all the data from the given class are from the same side of the plane - which is precisely the task of the training phase. The optimal hyper-plane is the one with the maximum margin, that is, the maximum distance from the training data.

Under the assumption of linear separable data, the separation condition for each point $\{x_i, y_i\}$ can be formulated using the following conditions:

$$\begin{aligned} w^T x_i + b &\geq 1, \;\; if \quad y_i = 1, \\ w^T x_i + b &\leq -1, \;\; if \quad y_i = -1. \end{aligned} \tag{1}$$

The hyper-plane is completely determined by the parameters w and b. Parameter w, the weight vector, determines the direction of the hyper-plane, while parameter b, the bias, determines the distance of the hyper-plane from the center of the coordinate system.

According to [15], in order to provide a solution for the optimal hyper-plane decision function, Lagarangian multipliers are used to reformulate the optimization problem. The solution is determined by identifying the saddle point for the following Lagrangian:

$$L(w,b;\alpha) = \frac{1}{2} w^t w - \sum_{k=1}^{N} \alpha_k (y_k[w^T x_k + b] - 1), \tag{2}$$

with Lagrangian multipliers $\alpha_k > 0$ for $k=1,\ldots,N$. We determine the differential of w and b:

$$\begin{cases} \dfrac{\partial L}{\partial w} = 0 \rightarrow w = \sum_{k=1}^{N} \alpha_k y_k x_k \\ \dfrac{\partial L}{\partial b} = 0 \rightarrow \sum_{k=1}^{N} \alpha_k y_k = 0. \end{cases} \tag{3}$$

Then L is transformed to the dual Lagrangian $L_D(\alpha)$:

$$\max_{\alpha} L_D(\alpha) = -\frac{1}{2}\sum_{k,l=1}^{N} y_k y_l x_k^T x_l \alpha_k \alpha_l + \sum_{k=1}^{N} \alpha_k \ , \tag{4}$$

with the conditions: $\sum_{k=1}^{N} \alpha_k y_k = 0$ for $\alpha_k \geq 0,\ k = 1,...,N$.

This is a quadric optimization (QP) problem with linear conditions, and the way to solve it is to maximize the dual Lagrangian in respect to α_k [14]. Thus, for an optimal decision function, we obtain:

$$f(x) = sign(\sum_{i=1}^{n_{sv}} \alpha_i y_i x_i^T x + b) \ , \tag{5}$$

where n_{sv} represents the training vectors with non-zero α_i , called support vectors.

In the case of linearly non-separable data, the slack variables ξ_i, $\xi_i \geq 0$ are introduced, which would tolerate "minor" errors during the learning phase of the classifiers and later during the classification. Now the conditions of the minimization are somewhat altered and it is necessary to determine the parameters w and b so as to minimize:

$$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N} \xi_i \ , \tag{6}$$

with the conditions:

$$y_i[(w \cdot x_i + b)] \geq 1 - \xi_i,\ i = 1,...,N \ \text{ and } \ \xi_i \geq 0 \ , \tag{7}$$

where C is the constant which makes a tradeoff by balancing between the margin and errors during learning.

The Lagrangian with a second set of Lagrange multipliers due to the slack variables ξ_k, is used to solve this optimization problem:

$$L(w,b;\alpha) = \frac{1}{2} w^t w + C\sum_{k=1}^{N} \xi_k - \sum_{k=1}^{N} \alpha_k (y_k [w^T x_k + b] - 1) + \xi_k) - \sum_{k=1}^{N} \nu_k \xi_k \ , \tag{8}$$

with Lagrange multipliers $\alpha_k > 0$, $\nu_k > 0$ for $C = 1,..., N$. After replacing the differentials of w, b, and ξ_i in (8) the following dual QP problem can be obtained:

$$\max_{\alpha} L_D(\alpha) = \sum_{k=1}^{N} \alpha_k - \frac{1}{2}\sum_{k,l=1}^{N} y_k y_l x_k^T x_l \alpha_k \alpha_l \ , \tag{9}$$

with the conditions: $\sum_{k=1}^{N} \alpha_k y_k = 0$ for $0 \leq \alpha_k \leq C,\ k = 1,...,N$.

The obtained optimal hyper-plane decision function is the same as for the linear separable case.

For nonlinear classification, input samples from the input space are mapped onto a high dimensional feature space using a kernel function $K(x_i,x)$, which is defined by the inner product between x and x_i and satisfies Mercer's condition.

The solution for this optimization model follows the same abovementioned procedure [15], the problem as a constrained optimization problem is formulated in the primal weight space, followed by the formulation of the Lagrangian. Then the conditions for optimality are taken, and the final step is to solve the problem in the dual space of Lagrange multipliers. In the dual Lagrangian for linearly non-separable cases, the kernel function replaces the inner products and gives the following Lagrangian:

$$\max_{\alpha} L_D(\alpha) = \sum_{k=1}^{N} \alpha_k - \frac{1}{2} \sum_{k,l=1}^{N} y_k y_l K(x_k, x_l) \alpha_k \alpha_l \, , \tag{10}$$

with the conditions: $\sum_{k=1}^{N} \alpha_k y_k = 0$ for $0 \le \alpha_k \le C,\ k = 1,...,N$.

Finally, the non-linear decision function is the following:

$$f(x) = sign(\sum_{i=1}^{n_{sv}} \alpha_i y_i K(x_i, x) + b) \, . \tag{11}$$

To be able to compute the bias b, the Karush Kuhn–Tucker (KKT) condition for the optimum constrained function is introduced, where:

$$x_i [y_i ((x_i \cdot w) + b) - 1] = 0 \text{ for any } i \text{ for which } \alpha_i \ne 0 \, . \tag{12}$$

A more detailed and more complete description of the derivation given above can be found in [14, 15].

3. Data Analysis and Model Formation

To evaluate the prediction model, the study relied on data for the Belex15 index, taken from the website of the Belgrade Stock Exchange. Six variables make up the series, and are determined on a daily basis: the closing price, the change in the value of the index from the previous trading day (given in percentages), the opening price, highest price, lowest price and the trading volume.

In forming the SVM model, technical and macroeconomics indicators were used as input features.

As mention before, technical indicators have a key role in the prediction of stock market trends. They can be divided into the following groups: trending indicators, volume indicators and oscillators. For the Belex 15 index trend prediction, volume indicators could not be used since the index cannot be purchased directly.

In accordance with the reviews of experts in the field of prediction and machine learning methods, as well as the results from our previous studies [11,12], nine technical indicators from the other two groups of indicators were considered for use by the prediction model. They included the following: MA (Moving Average - the average of the closing price of a security over a specified number of periods), EMA (Exponential Moving Average - the moving average of the closing price calculated using a smoothing factor to place a higher weight on recent closing prices), DM (Directional Movement System – the index that measures the strength of a market trend, whether that trend is positive or negative), Momentum (MoM – the indicator that shows the absolute change in closing prices), RSI (Relative Strength Index – the index that measures the speed and change of price movements), the Stochastic Oscillator %K (an indicator that predicts the price turning points by comparing a security's closing price to its price range over a given time period), Stochastic Oscillator %D (the average of the last three %K values calculated daily), MACD (Moving Average Convergence-Divergence, the indicator that measures the strength and direction of the trend and momentum) and the Rate of Change (RoC, the indicator that shows the percentile change in the closing prices).

In [11, 12], we established the basis for the formation of a standard LS-SVM model for predicting the trend of the Belex15 index. The selected features in this paper were used to create the proposed SVM model, which enables us to later compare the prediction results of various models. What follows is a short description of the used methodology and the selection process of the applied indicators, as presented in [11,12]

Time series characteristics. The characteristics of time series were studied in more details in [11], and two lagged values of the logarithmic return were selected as input features. The lags were determined according to the obtained values of the auto-correlational coefficients. Fig. 1 shows the autocorrelogram for the available time series data.

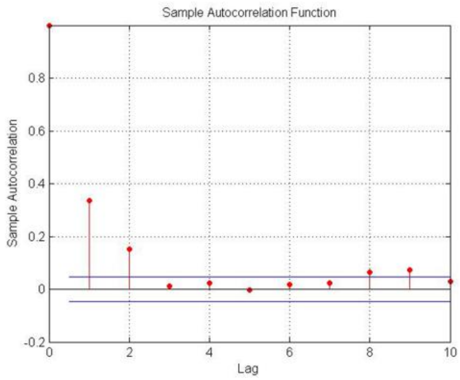

Fig. 1 The correlogram of logarithmic yields of up to 10 previous values

The groups of selected technical indicators were examined in more detail in [12].

In essence, since the response variable predicts the stock market trend (either its increase or decrease), the explanatory features need to measure changes as well. Furthermore, it is necessary to evaluate the level of importance of each individual indicator. The sensitivity analysis is a process which determines whether an input variable influences the output of the method or not. Namely, the input variable can be omitted if there are no noticeable changes between running the model with and without it.

Trend indicators. Based on the aforementioned criteria, the EMA trend indicator was selected in [11]. It assigns greater significance to the more recent changes in prices and enables the calculation of an almost infinite number of steps (for example EMA150, EMA250). In [11] it was shown that for shorter periods of time (5 to 25 days), the analysis of the value trend of the stock index and securities results in indicators which appropriately measure the sensitivity of the change in value. As a result, the selected period for calculating the EMA transformation was the previous 10 days.

Oscillating indicators. According to analyses conducted in [12, 16], we selected the Moving Average Convergence-Divergence (MACD). As an indicator which measures the strength and direction of the trend and momentum, the MACD is effective in optimizing investment strategies on emerging markets.

As was shown in Table 1, the MACD is obtained through a combination of three movement averages. The standard combination of movement averages which determine the MACD is 12-26-9, where the first line is obtained as the difference between the 12-period EMA and 26-period EMA. The other line, which represents the signal line, approximates a 9-period EMA of the first line.

The macroeconomics variable. As an improvement of the previously created models, in this paper one of the macroeconomic variables of the model used to predict the stock index was the exchange rate of the euro towards the dinar, expressed in logarithmic returns [17].

The connection between macroeconomic variables and the price of securities on the capital market gained special importance with the publication of [10], which represents the basis for the claim that there is a long-term connection between these variables. Recent empirical studies focused on analyzing these relations on the developing capital markets, considering that the volatility of these markets is significantly conditioned by the economic activity of the state, and the political and international business environment.

The value of the local currency in relation to the more stable foreign currency is one of the determinants of international investments, and its influence depends on the international economic activity of a country and the state of its balance of payments. The decrease in the value of the local currency increases the risk of the foreign currency exchange rate and decreases the return which foreign investors achieve on their investment in securities. In depreciation periods of the local currency, the capital is removed from the local market and transferred into foreign currency, which has a negative impact on the value of securities on the local capital market. Considering the fact that foreign investors generate a significant part of the demand on the Belgrade stock exchange, the risk of the foreign currency exchange rate influences the liquidity of the market and the value of securities. In this paper, we used the intermediate exchange rate between the euro and the dinar, and the data were taken from the website of the National Bank of Serbia. We also used the logarithmic transformation of the value of the euro expressed in dinars and the logarithmic return.

The detailed mathematical formulations for the applied transformations and indicators are given in Table 1.

Table 1 Input features

Features	Formula
Closing price	CPt, t= 1,2, ... N
Logarithmic return	rt=logCPt – logCPt-1
EMA_N	EMA= $r_t * k + EMA_{t-1} * (1-k)$; $k = 2/(N+1)$
MACD	MACDt = EMA12 –EMA 26
rt-1	rt-1=logCPt-1– logCPt-2
rt-2	rt-2=logCPt-2 – logCPt-3
FER	FERt=logEURt – logEURt-1
	EUR – the intermediate exchange rate of the euro towards the dinar,
	FER– the logarithmic yield to the intermediate exchange rate of the euro

The abovementioned transformations contribute to the stationary nature of the series, which additionally increases the effectiveness of the machine learning algorithm.

The data scaling was carried out so that the attributes with a greater numeric value would not be dominant in comparison to those with a smaller numeric value. The second reason is the increase in speed of the numerical calculation. The scaling of the data in the range [-1, 1] was carried out linearly.

The original data were scaled using a min-max normalization:

$$f_i(\text{norm.}) = \frac{f_i - \min F}{\max F - \min F}\ , \tag{13}$$

where min F and max F are the minimum and maximum values of the feature F, and f_i is the variable in the i^{th} row.

Trend modeling. In the proposed model, the variable being predicted is the future trend of the stock market prices. The feature which serves as a label for the class is a categorical variable used to indicate the movement direction of the logarithmic return on the Belex15 index over time t. If the logarithmic return over time t is larger than zero, the indicator is 1. Otherwise, the indicator is −1. In reality, the market price trend does not constantly follow a straight line; it is volatile, and the line fluctuates up and down repeatedly, rendering it challenging for prediction.

Based on the aforementioned analysis, the following prediction model was created:

$$y_t = SVM(r_{t-1}, r_{t-2}, EMA_{10t-1}, MACD_{t-1}, FER_{t-1})\ . \tag{14}$$

In the given SVM model implementation, it is necessary to determine the value of parameter C, as well as the parameter σ of the Gaussian kernel:

$$K(x, x_k) = e^{\frac{-\|x-x_k\|^2}{\sigma^2}}\ . \tag{15}$$

One of the ways to determine these parameters is the k fold Cross-Validation procedure in combination with a Grid-Search.

In order to form the SVM model, the LibSVM [18], a library for support vector machines was used.

4. Experimental Results

In order to investigate the prediction accuracy of the proposed prediction model, the available data set is divided into two sub-samples. The first sub-sample period begins on October 05, 2005 and lasts until December 31, 2012. It is considered an in-sample period for model training. The second sub-sample of a 252-day period that made up the test set represents a whole trading year, starting from the beginning of 2013 and lasting until the end of 2013. The duration of the tested time span is sufficient to provide reliable prediction results. In addition, the results enable us to include all the forms of the model behavior.

As a general measure for the evaluation of the prediction effect, the Hit Ratio (HR) was used, calculated based on the number of properly classified results within the test group:

$$HR = \frac{1}{m}\sum_{i=1}^{m} PO_i \text{ for } PO_i = \begin{cases} 1 & PV_i = AV_i \\ 0 & PV_i \neq AV_i \end{cases} \tag{16}$$

where PO is the prediction output of the *i* trading day, AV_i is the actual value for the *i* training day and PV_i is the predicted value for the *i* trading day and *m* is the number of data in the test group [19].

It is known that different values of parameters C and σ will influence the accuracy of the SVM classifier. Thus, the SVM parameters C and σ were determined after a 10-fold Cross-Validation in combination with a Grid-Search, which was additionally used to overcome the problem of overfitting the model [20]. The training set is randomly divided into training and test sub-sets, for example in a ratio of 1:9. Then the algorithm for learning is applied on the training sub-set and the quality of the prediction on the test sub-set is evaluated. This procedure is repeated *10* times and we select the C and σ pair which enables the best precision. To form the final training model, the SVM model with the best parameters of C and σ was run on the training set. After the training phase, the accuracy of the model was evaluated on the test data. Pairs C and σ should be subjected to a grid-search exponentially [9], for example $C=2^{-5}, 2^{-3}, \ldots, 2^{15}$, $\sigma = 2^{-15}, 2^{-13}, \ldots, 2^{5}$ .The parameters were chosen as follows: $\sigma^2 = 16$ and C = 8 (Figure 2).

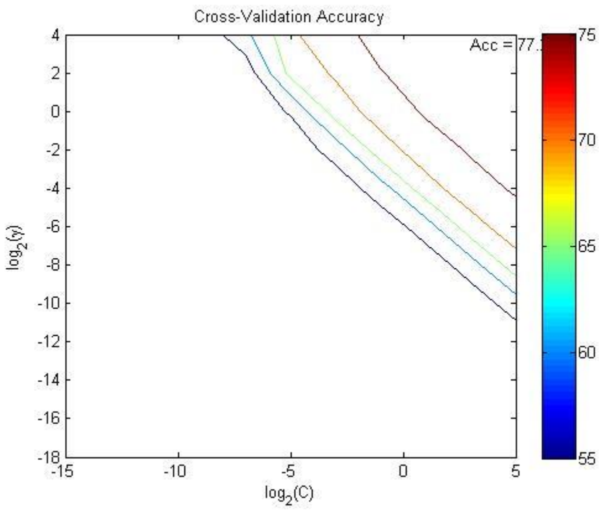

Fig. 2 The optimization of the SVM model parameters

In order to compare the results obtained by the SVM model, an LS-SVM prediction model was also created using the previously selected indicators. The values of the prediction obtained using the random walk (RW) model were also included. We will briefly describe the differences between the selected benchmarking models.

The random walk uses the current value to predict the future value, assuming that the later value in the following period (y_{t+1}) will be equal to the current value (y_t).

The LS-SVMs, proposed by Suykens in [21], include a set of linear equations which are solved instead of QP for classical SVMs. Therefore, LS-SVMs are more time-efficient than standard SVMs, but are characterized by a lack of sparseness. In order to form the model we used the library LS-SVMlab [22].

Table 2 shows a comparison of the hit rates obtained using the SVM method and the abovementioned benchmark models.

Table 2 Prediction accuracy of different prediction models

Model	Hit rate
RW	0.5000
LS-SVM	0.5437
SVM	0.5516.

The results indicate that both of the prediction models outperform the random walk process. The hit rate of the proposed SVM predictor at the level of the entire set of the test group is 0.5516 and represents an increase of approximately 1% in comparison to the LS-SVM model. Based on the obtained trend prediction, we can define the trading signals. The buy signal is generated if the method indicates an increase in the trend for the next day in comparison to today, and the sell signal is generated if the method indicates that the trend will decrease the following day. As a result, it is important to mention that in the field of stock market trend prediction, every increase in efficiency in comparison to the current range is considered an exceptional contribution, while the market itself reflects a high financial gain [19].

Table 3 represents the hit-rate of the proposed model based on temporal sequences which correspond to the real frameworks of trading on the Belgrade stock exchange, the weekly, biweekly, monthly and quarterly work regime.

Table 3 Time sequence comparison of the models

Time sequence	RW	LS-SVM	SVM
0-5	0.6000	0.6000	0.6000
0-10	0.8000	0.8000	0.8000
0-20	0.7000	0.7000	0.7000
0-40	0.6000	0.6750	0.6750
0-60	0.6000	0.6167	0.6333
0-80	0.6125	0.6000	0.6125
0-100	0.6100	0.6200	0.6300
0-120	0.6083	0.6417	0.6500
0-140	0.5714	0.6214	0.6286
0-160	0.5438	0.5813	0.5938
0-180	0.5389	0.5833	0.6000
0-200	0.5200	0.5450	0.5650
0-220	0.5113	0.5520	0.5656
0-240	0.5125	0.5542	0.5667
0-252	0.5000	0.5437	0.5516

In the first trading month, the rate of the hits is identical for all models, which is again in favor of the previously noted strong correlation in the available data series. Based on the results presented in Table 3, it is clear that the SVM method continuously and without oscillations outperforms the LS-SVM method. The obtained results indicate the good predictive abilities and stable characteristics of the proposed prediction model and confirm its good generalization characteristics.

It is important to note that in this paper, the research focused on the prediction rate of the price index of the emerging market of the Republic of Serbia, and that it led to competitive results within those observed for the prediction of market indices and the price of financial instruments on developed markets [1, 3, 19].

5. Conclusion

The aim of this study was to test the prediction precision of an SVM-based stock market trend prediction model as a widely implemented model for the recognition and monitoring of trend movements on the small emerging market of the Republic of Serbia.

The next step would include the testing of the proposed models on the constituents of the Belex15 index and a comparison of the achieved results. This would enable us to focus on the generalizing characteristics of the selected indicators and the classifier itself.

In addition, in order to increase the stability of the prediction model after designing several different prediction models, a hybrid prediction model could be designed, where the outputs from several models would be combined into a final model.

Further improvements to the model would include the adjustment of the model parameters by means of a more sensitive and advanced parameter setting. This would include the introduction of a significantly higher number of input parameters and the application of some of the comprehensive methods for features selection.

Considering the fact that the prediction model is used only for data which are easily accessed in all stock markets, the model adds practical components to stock prediction, and an evaluation of its real applicable value would also be of interest. In that sense, the proposed model should also be tested for the profitability of prediction-based trading strategies with the currently available tools and trading strategies in economic sciences.

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