Prediction of Peruvian Companies' Stock Prices Using Machine Learning

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Abstract

Nowadays, the challenges that covid-19 has generated to the financial community that operates within the stock market has generated a greater uncertainty in the profitability and consequently has made this practice more difficult. To overcome that problem the present study aims to develop a model that facilitates this work; this model uses the SVR regression algorithm and through technical indicators provide us with the possible trend that the stock may take in the future and thus suggest that the investor in question buys, sells or holds the stock in view of that result. As a result of the project, it was proposed to use 7 technical indicators RSI, MACD, ROC, WMA, OBV, the Williams indicator and the stochastic oscillator that determine the current market condition. After validating the model, it was concluded that there are different Peruvian companies that have been able to overcome the difficulties of the pandemic with enough growth potential during this post-covid period.

Keywords
Machine Learning, Stocks, Support Vector Regression, Forecasting,Python, and Stock Market Prices.

1. Introduction
Nowadays it is a very popular practice to invest in company shares, but the uncertainty of these affects the profitability of the financial community and according to Akhtar et al. (2022), Machine Learning tools have been developed to reduce the risk.

According to Demirel et al. (2021), future events depend, in part on current and past data but the financial time series is volatile, non-linear, non-parametric and unpredictable (pp.63-64). There is not much research on how stocks perform during a recession caused by the Covid-19 pandemic; furthermore Albahli et al. (2022), proposes that there are many studies on predicting stock prices, but what an investor really seeks to know is the possible trend the stock will take in order to decide whether he should buy, sell or hold.

This study has a significant importance since an optimal investment in stocks can contribute to the economic improvement of the country (Kumar et al., 2022). Our main research question: Is it feasible to predict stocks in

Peruvian companies with growth potential during the Covid-19 pandemic, using the Support Vector Regression (SVR) algorithm as Machine Learning in the Lima Stock Exchange (BVL)?
The application of SVR would be shown to directly influence the decision to buy or sell high potential stocks of companies with stock market presence in the LSE during the covid-19 pandemic throughout the year 2022.

1.1 Objectives
To satisfy the need of people interested in trading company shares on the Lima Stock Exchange (BVL) during the covid-19 pandemic throughout 2022, making use of Support Vector Regression (SVMR) for the prediction of stocks with potential and thus decrease their financial risk.

- Determine the most predominant stock indicators for stock prediction.
- To evaluate the viability of (SVR) as a tool for the prediction of Peruvian companies' shares in BVL.

2. Literature Review
Qu and Zhang (2016) argue that the Support Vector Machine (SVM) has achieved remarkable generalization performance. This obtained multiple applications in estimation in Support Vector Regression (SVR), therefore, it is present in most time series forecasting problems. They also claim that the Kernel function used in SVR plays a fundamental role in capturing the nonlinear dynamics of the time series under study. One of the common kernels, in this case, the kernel of the radial basis function is first derived mathematically and is applied in almost all time series forecasting problems.

According to Miranda Henrique et al. (2018), he concludes that, using a fixed training set on daily prices, smaller prediction errors can be obtained with respect to the training test set when using linear kernel. The Support Vector Machine (SVM) has a variable called Support Vector Regression (SVR), both have the same algorithms. SVR can be used in both linear and nonlinear regressions. To better understand it is important to know some concepts such as kernel, hyperplane, support vector and boundary lines. SVR works by predicting continuous ordered variables, while SVM is a classifier that predicts discrete categorical labels.

Support Vector Regression can improve its accuracy and versatility as demonstrated by Fan et al. (2020) proposing an improvement in Support Vector Regression (SVR) by adapting its fixed parameters. For Nahil and Lyhyaoui (2018), they conclude that the Polynomial Kernel function takes more time to train for SVR, giving not so expected and inferior results compared to the Gaussian Kernel function, where it also selects the parameters that offer better performance.

A frequent problem in stock predictions is the high noise in financial time series that affects in the data set and its information, Ouahilal et al. (2017) mentions that different noise filtering techniques that are usually used in macroeconomics can be applied such as Hodrick-Prescott Filter, Baxter King and Christiano-Fitzgerald.

According to Gaspareniene et al. (2021), years ago the economic indicators of a country were used to project the movement or trend that a stock index would take; such as the inflation rate, where a high inflation rate causes a cooling in the economy and consequently would decrease or stop the growth rate of the stock price; but we cannot take into account these indicators for the study in question since it was discovered that the correlation between these and the stock is minimal; it was shown that at least of 27 economic indicators only three really have a direct relationship.
In contrast, Zmuk and Josic (2020) demonstrated that the best way to forecast stock market indices is by making use of historical data and the use of Machine Learning algorithms; as the forecast turns out to be more accurate; to involve historical data two requirements are needed which consist in having access to long time series and that it will not make a large number of time series breaks, as well as periods without data access.

A combination of using historical data as the independent variables and Machine Learning turns out to be very optimal; it is described by Albahli et al. (2022) using both resources and focusing on predicting the trend and reversal points of stocks instead of predicting price changes can be really effective for investors.

Between the use of Machine Learning (ML) and artificial neural networks (ANN) for stock prediction, Cao (2021) states that the former involves models that are becoming increasingly complex due to the number of variables involved and artificial neural networks and decision trees work better for prediction. In the same way, there are other positions regarding prediction in the area of finance; as stated by Durairaj and Mohan. (2021), a model for prediction must be hybrid to really possess competent accuracy.

We have to have as a basis what independent variables we are going to use, since these are the ones that will predict the future behavior of the trends that could adopt the shares; there is a different point of view between what types of independent variables should be used for the prediction of shares, in its majority are usually used characteristics of a share such as its closing price, opening, volume and volatility as considered by Umer (2019), who employed them and demonstrated their effectiveness in a stock prediction system using ML algorithms; but more specifically momentum indicators are usually used with Support Vector Machine (SVM) and its variants such as Support Vector Regression (SVR); the former mostly used for classification and the latter for regression. We quote Cao (2021), who relied on momentum indicators to forecast the price of a stock used only three momentum indicators, MACD, KDJ, and DMI, his prediction model obtained a higher accuracy by 25% compared to other models. But it is necessary to emphasize that his model is quite different from this one since his model is mixed and makes use of LASSO, random forests, R language, among others.

In the work of Nti et al. (2020), they report using the Simple Moving Average (SMA), Exponential Moving Average (WMA), Moving Average Convergence/Divergence (MACD), Relative Strength Index (RSI), Balance of Volumes (OBV), stochastic oscillators (%K and %D), Accumulated Ratio (AR), and Volume Ratio, and obtained an accuracy of 93,7%. From the point of view of Asghar et al. (2019), one of the biggest obstacles in modeling an ML algorithm are the quality of input data and an efficient selection or inclusion of predictor variables, which is a totally subjective issue; the variables it uses are opening price, closing price, high, low, profitability volatility and trading volume.

3. Methods

In the study in question a CRISP-DM methodological approach will be implemented, this methodology together with a study involving the artificial branch such as Machine Learning (ML) provides a broader understanding since it has holistic approach and its execution to analyze data, by the type of data handled during the study has a quasi-experimental scope and a quantitative approach since data such as stock prices are not fixed and can change depending on different factors.

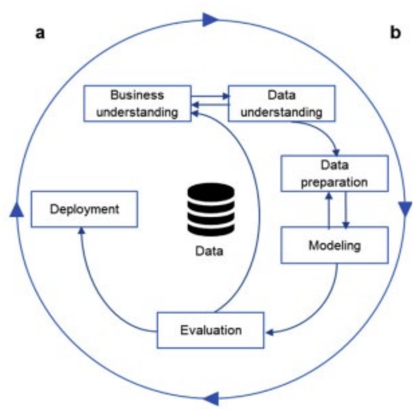

Figure 1. Crisp-DM Methodology

The data (Figure 1) for the analysis were collected from a TradingView platform to visualize the movement of different financial assets such as shares or stock market indexes, here we find the movement and price of the shares of Peruvian companies belonging to the Lima Stock Exchange (BVL); The data collected has an extension of no more than 5 years; for this analysis only companies listed on the Lima Stock Exchange (BVL) were taken into account, there are currently 262 companies listed, only 28 are listed today, using the formula for calculating the finite sample populations, a sample of 20 companies was determined; SPSS was used to randomly select 20 companies belonging to different sectors.

$$n = \frac{28 * 1{,}96^2 * 0{,}05 * 0{,}95}{0{,}05^2 * (28 - 1) + 1{,}96^2 * 0{,}05 * 0{,}95} \cong 20$$

During this stage an abnormal behavior of the shares was revealed compared to previous years caused by the COVID-19 pandemic. For example, as of January 2020 the shares of ALICORP S.A.A. went from a value of 9.00 PEN to 5.10 PEN, there was a reduction of approximately 44%. Another event is that of FERREYCORP S.A.A., there was a downward trend after the origin of COVID between January and April 2020, a drop of 45% in its share price.

Figure 2. Alicorc1

Figure 3. Ferreyc1

Here we show (Figure 2 and figure 3) a noticeable decline in stock price due to the recession caused by the pandemic, this decline can be explained by the assumption that a company's performance is directly related to its stock price.

The next step is data preparation, it is notable to state that Schnell et al. (2019) highlight that here the data as a whole must be transformed so that it can be actionable, data selection, data discarding and data generation are used and further for data mining methods such as Artificial Neural-Networks (ANN), Decision Tree (DT) and Support Vector Regression (SVR).

It is of knowledge that there is always a loss or lack of historical stock data so Asghar et al. (2019) support with three different methods, averages values and places them in the missing place, randomly selects or else fills the missing place with a previous value; it is mentioned that the third method is the optimal one, and this process will be done with the code.

The model is based on which independent variables will be used, since these are the ones that will predict future behavior, and in this study we use momentum indicators.

Within the variety of technical indicators, we select indicators that involve different attributes to determine the future behavior of a stock, such as volume, volatility and their moments of downward or upward trends.

- Exponential Moving Average (WMA)

$$WMA = \frac{Precio_1 * n + Precio_2 * (n+1) + .. Precio_n}{\frac{n*(n+1)}{2}}$$

This is an indicator that anticipates the possibility that a downward or upward trend could occur.

- Relative Strength Index (RSI)

$$RSI = 100 - \frac{100}{1 + \frac{Prom.Ganancia}{Prom.Perdida}}$$

The RSI which compares gains to losses is intended to suggest when the market is overbought or oversold.

- Stochastic Oscillator

$$S = \left(\frac{Precio\ de\ Cierre - Valor\ Mínimo(14\ periodos)}{Valor\ Máximo(14\ periodos) - Valor\ Mínimo(14\ periodos)}\right) * 100$$

Similar to the RSI, it indicates whether the market is overbought or oversold.

- Williams %R

$$Williams\ \%R = \frac{Máximo(14\ periodos)\ -\ cierre\ más\ reciente}{Máximo\ (14\ periodos)\ -\ mínimo\ (14\ periodos)}$$

This percentage will serve to indicate the entry and exit points for investors at certain overbought and oversold levels.

- Moving Average Convergence/Divergence (MACD)

$$MACD = 12PeriodosEMA - 26PeriodsoEMA$$

This indicator, which measures the difference between two moving averages with different calculated time periods, provides us with an idea of whether the market could be trending down or up.

- On Balance Volume (OBV)

$$OBV = OBV_{prev} + \begin{cases} +volumen, & si\ cierre > cierre_{prev} \\ 0, & if\ cierre = cierre_{prev} \\ -volumen, & if\ cierre < cierre_{prev} \end{cases}$$

On-balance volume relates volume to price changes, where a dependency is created.

- Price Rate of Change (PRC)

$$PRC = \frac{\text{Precio de cierre de hoy} - \text{Precio de Cierre"x" de periodos atrás}}{\text{Precio de Cierre de "x" de periodos atrás}}$$

This indicator serves to show the correlated differences between the closing price based on the forecast and the closing price of N previous days.

These indicators are of utmost importance and were selected because they aim to detect when the price of a stock is in an overbought and oversold market; and these two scenarios determine the direction of the trend that the stock may take.

It has been proposed to work with tools from different points of view, in this study the Support Vector Regression (SVR) will be used since it has a parameter that is the Kernel, which is useful in cases where the data are linearly separable.

We will rely on Support Vector Regression (SVR) and its Kernel functions, and as Miranda, B. et al (2018) points out as a conclusion of his research where he compares the Linear, Polynomial and Radial Kernel for the prediction of actions, he determines that the Linear Kernel has smaller prediction errors. $(x^T\ , y)^P$

Table 1. Most used Kernel Tools

MAPE Value	Interpretation
<10	Highly accurate forescasting
10-20	Good forecasting
20-50	Reasonable forecasting
>50	Inaccurate forecasting

In the evaluation stage, the proper functioning of the prediction system is tested and two error indicators must be taken into account:

Root mean square error (RMSE)

$$RMSE = \left(\frac{1}{T}\sum_{i=1}^{T}(di - di)^2\right)^{1/2}$$

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{T}\sum_{i=1}^{T}\left|\frac{di - di}{di}\right|$$

The MAPE values as invoked by Zmuk and Josic (2020) interpreted as follows in Table 2:

Table 2. Interpretation of ASM Value

MAPE Value	Interpretation
<10	Highly accurate forescasting
10-20	Good forecasting
20-50	Reasonable forecasting
>50	Inaccurate forecasting

Where a mean absolute percentage error of less than 10 can be concluded as a good prediction, and one greater than 50 a very inaccurate prediction.

Finally, in the implementation stage it can be observed how accurate the model is with the Confusion Matrix, which is a tool that helps to visualize the performance of a supervised learning algorithm. In practical and accurate terms, the matrix allows to observe the types of hits and misses the previous model is having.

When modeling the code, four possible outcomes can be obtained, which are:

- True positive (VP): The value is positive and the test predicted that it would be positive.
- True negative (TN): The value is negative and the test predicted it would be negative.
- False Positive (FP): The value is negative and the test predicted that it would be positive.
- False Negative (FN): The value is positive and the test predicted it would be negative.

From these four options emerge the metrics of the confusion matrix, which are:

- Accuracy: Refers to the closeness between the true result and the estimated result. It is defined with the following formula:

$$(VP + VN)/(VP + FP + FN + VN + VN)$$

- Accuracy: It refers to the dispersion of the values obtained; the smaller the dispersion, the higher the accuracy. It is defined with the following formula:

$$VP/(VP + FP)$$

- Sensitivity or Recall: It is the rate of true positives. It is defined by the following formula:

$$VN/(VN + FP)$$

- Specificity: It is the rate of true negatives. It is defined with the following formula:

$$VN/(VN + FP)$$

4. Data Collection

The data collected comes from TradingView which is a trading platform that has historical data from companies around the world, these are composed of the closing, opening, low and high price per day, these data are what the model needs to yield a result.

Here we can observe the data of the company BROCALCI (Table 3).

Table 3. Data Collection

Companies	open	high	low	close	volume
13/07/2016 08:20	6,3	6,4	6,3	6,4	6170

5. Results and Discussion

5.1 Numerical Results

The companies that were accepted by the model were the following in Table 4:

Table 4. Model 1 and Model 2

Companies	Model1 score	Model2 score
BVL_DLY_AENZAC1, 1D	0,95	0,77
BVL_DLY_BBVAC1, 1D	0,96	0,81
BVL_DLY_CASAGRC1, 1D	0,92	0,8
BVL_DLY_CPACASC1, 1D	0,92	0,6
BVL_DLY_BUENAVC1, 1D	0,92	0,62
BVL_DLY_CORARAREC1, 1D	0,91	0,72
BVL_DLY_SIDERC1, 1D	0,91	0,61
BVL_DLY_ENGIEC1, 1D	0,9	0,74
BVL_DLY_INRETC1, 1D	0,95	0,69
BVL_DLY_PML, 1D	0,96	0,78
BVL_DLY_CVERDEC1, 1D	0,96	0,7
BVL_DLY_BROCALC1, 1D	0,94	0,72

BVL_DLY_UNACEMC1, 1D	0,95	0,63

In the case of the company Sociedad Minera El Brocal S.A.A., the model gives us two models with score 0,94 and 0,72, this means that it was accepted by the model and determine that it is viable to invest in this stock because it will enter in an upward trend.

5.2 Graphical Results

The company Sociedad Minera El Brocal S.A.A showed the following results (Figure 4):

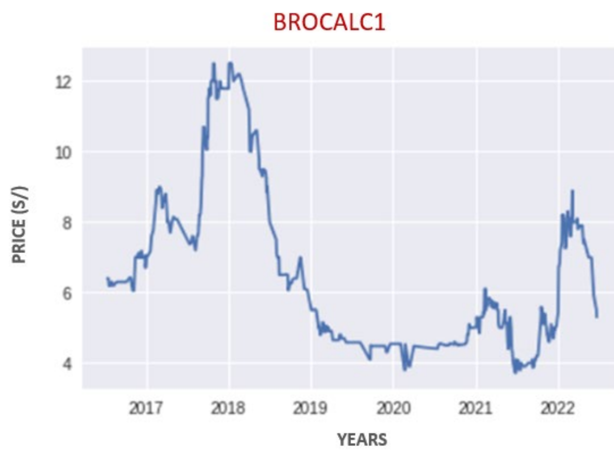

Figure 4. Brocal Results

It was possible to test the initial hypothesis, if it is possible to predict the shares of Peruvian companies with growth potential during the post-covid 2019 stage using Machine Learning.

5.3 Proposed Improvements

The main problem detected is the lack of automation to obtain the data to be entered in the code. Therefore, the proposed improvement is to link the code with the Tradingview page through an Api, in this way the data will be collected automatically. Currently thousands of companies opt for an Api to save on extra costs, one of the main examples is Uber that links its system with google maps (Wu, 2019).

5.4 Validation

The validation of the model goes through the confusion matrix, which yielded the following results in Table 4:

Table 5. Model 1 and Model 2

Companies	Accuracy	Recall	Precision	Specifity
BVL_DLY_AENZAC1, 1D	0,97	0,96	0,98	0,97
BVL_DLY_BBVAC1, 1D	0,96	0,96	0,98	0,96
BVL_DLY_CASAGRC1, 1D	0,95	0,97	0,95	0,9
BVL_DLY_CPACASC1, 1D	0,93	0,95	0,95	0,89
BVL_DLY_BUENAVC1, 1D	0,91	0,94	0,92	0,85
BVL_DLY_CORAREC1, 1D	0,93	0,73	0,94	0,99
BVL_DLY_SIDERC1, 1D	0,93	0,9	0,92	0,95
BVL_DLY_ENGIEC1, 1D	0,92	0,98	0,87	0,84
BVL_DLY_INRETC1, 1D	0,96	0,93	0,93	0,97
BVL_DLY_PML, 1D	0,96	0,98	0,96	0,93
BVL_DLY_CVERDEC1, 1D	0,97	0,97	0,96	0,96

BVL_DLY_BROCALC1, 1D	0,97	0,96	0,98	0,97
BVL_DLY_UNACEMC1, 1D	0,95	0,97	0,95	0,92

As we can see, accuracy, sensitivity, precision and specificity are the four metrics of the confusion matrix that denote the characteristics of the aforementioned Model1 and Model2 scores, the latter, as well as their metrics cannot have a value equal to 1, since it would represent an error, these values must be represented between 0 and 1 being values greater than 0.8 values of an optimal precision.

6. Conclusion

It can be concluded that in this research a price prediction experiment has been conducted using the support vector regression (SVR) model. Technical analysis and fundamental analysis indicators have been used. The data are evaluated by statistical indicators such as RSI, Williams, WMA, MACD and OBV. The model in turn is validated by the confusion matrix which seeks to evaluate the errors and successes of the model. Once the results are obtained, a visual evaluation is made, contrasting the information previously obtained with the results of the matrix and the values that do not pass the matrix will be discarded.

Likewise, the technical indicators that denote greater precision are those that involve moments when the market is overbought and oversold, such as the RSI, MACD, ROC, WMA, OBV, the Williams indicator and the stochastic oscillator, Most of these need a large amount of historical data to be validated since there are technical indicators that use up to 26 periods, so using stocks with historical data of less than 2 years results in values equal to 1 in the confusion matrix metrics, which would denote an error in the model.

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Biographies

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Jose Antonio Espiritu Pera, born in Sanna San Borja clinic, 22 years old, passionate about English and French languages, with an intellectual preference for financial management courses as well as industrial technology. He is a student of industrial engineering at the Universidad de Lima with courses at the Universidad del Pacifico. This is his first publication within the academic field with the purpose of transcending within the research area. It aims to work to deepen the knowledge within the stock exchange of Lima.

José Antonio Taquía is a Doctoral Researcher from Universidad Nacional Mayor de San Marcos and holds a Master of Science degree in Industrial Engineering from Universidad de Lima. He is a member of the School of Engineering and Architecture teaching courses on quantitative methods, predictive analytics, and research methodology. He has a vast experience on applied technology related to machine learning and industry 4.0 disrupting applications. In the private sector he was part of several implementations of technical projects including roles as an expert user and in the leading deployment side. He worked as a senior corporate demand planner with emphasis on the statistical field for a multinational Peruvian company in the beauty and personal care industry with operations in Europe and Latin America. Mr. Taquía has a strong background in supply chain analytics and operations modeling applied at different sectors of the industry. He is also a member of the Scientific Research Institute at the Universidad de Lima being part of the industrial and circular economy groups. His main research interests are on statistical learning, predictive analytics, and industry 4.0.

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