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An Optimized Support Vector Machine (SVM) based on Particle Swarm Optimization (PSO) for Cryptocurrency Forecasting

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Abstract

Forecasting accurate future price is very important in financial sector. An optimized Support Vector Machine (SVM) based on Particle Swarm Optimization (PSO) is introduced in forecasting the cryptocurrency future price. It is part of Artificial Intelligence (AI) that uses previous experience to forecast future price. Analysts and investors generally combine fundamental and technical analysis prior to decide the best price to execute their trades. Some may use Machine Learning Algorithms to execute their trades. However, forecasting result using basic SVM algorithms does not really promising. On the other hands, Particle Swarm Optimization (PSO) is known as a better algorithm for a static and simple optimization problem. Therefore, PSO is introduced to optimize the algorithms of SVM in cryptocurrency forecasting. The experiment of selected cryptocurrencies is conducted for this classifier. The experimental result demonstrates that an optimized SVM-PSO algorithm can effectively forecast the future price of cryptocurrency thus outperforms the single SVM algorithms.

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1. Introduction

Forecasting market behavior with the goal of getting best decision and maximum profit-making is one of the most difficult tasks for any investor. Cryptocurrency, a digital currency that is completely decentralized and works based on peer-to-peer transactions [1]. There often question, is there any ways that can help to predict future price based on the historical data. To address this question, researcher train predictive models on sets of cryptocurrencies for certain period. Research on the cryptocurrency field is still limited. Mostly, research in this field is focusing on a single cryptocurrency rather than broader areas such as technological advancement, government participation in market regulations as well as market development [2]. In this section, types of cryptocurrency and reviews in financial market are presented. Section 2 presents the literatures of SVM and PSO in financial market and other applications. The methodology is explained in Section 3. The experimental result and analysis are in Section 4 while Section 5 is the conclusion of this paper.

1.1. Cryptocurrency Market Review

Cryptocurrency market's financial term is known as stock market. To maximize financial return, the field of cryptocurrency market prediction has grown in a very fast period and has more exploded with the advent of high frequency, low latency trading hardware including machine learning algorithms[1]. [3] in his paper says, cryptocurrency, also knowns as a subset of digital currency turns to be an essential type of digital currency. Cryptocurrency used the block chain technology, an open distributed ledger to record transactions. Thus, it does not need any intermediate party and have increased capacity, secured and faster transaction which sometimes cannot be done in the normal systems.

1.2. Cryptocurrency Types

Litecoin (LTC) and Ethereum (XRP) are among the largest alternative block chain technologies, known as altcoins and were invented after Bitcoin (BTC). Altcoins may have different purposes of development but are using general methodology based on decentralized P2P network, with the assumption of no network failure and no internet interruption [4]–[7]. Bitcoin was introduced in 2008 as a peer to peer online transaction system, or e-money which requires digital signatures from all parties involved (sender and receiver) without any involvement of monetary organization and this has solved the problem of double-spending issue [8]–[10]. Bitcoin is known as a type of cryptocurrencies that has cryptographic function in its creation [11]. Bitcoin (BTC) transaction is a payment system that works based on a verified cryptographic thus lessen chances of fraud money [12]. Recently, it turns to be the most well-known currency in volume trading which then makes it as the most favorable investment for investors [13] as it locks the transaction individually based on the sender, receiver as well as the transaction volume [2].

Litecoin (LTC) was introduced in 2011 [14] that offers a quicker transaction rate as fast as less than a minute and intelligent enough to handle higher volume of transactions compared to Bitcoin [10]. The network technology was designed to support repeated block generation which resulted in a reduction of block generation time [10], [14]. Previous block generation requires 10 minutes to generate a block, with the Litecoin, it reduced to only 2.5 minutes per block and has adopted a different hashing algorithm [14]–[16]. Litecoin is considered as the 'silver standard' of crypto coin and turn into a second most accepted by both miners and exchanges [15]. It uses Scrypt encryption algorithm and developed to bid the Bitcoin network transaction confirmation speed and uses an algorithm that was resilient to the advancement of hardware mining technologies.

Vitalic Buterin has invented the Ethereum (XRP), also known as ether, and funded by the online crowdfunding [14]. Ethereum is a decentralized block-chain based technology that runs Turing-complete to build and execute smart contracts or circulated systems [14], [15]. Ethereum has no boundaries on its circulation, can be traded in cryptocurrency exchanges, not to be one of the payment systems but its intention is merely to be used in the Ethereum network [15], [17].

NEM is a blockchain notarization also known as a 'peers' or P2P, a set of computers that are interconnected to each other and used to pay for the online transactions as well as do the online messaging function. NEM is jointly owned with a registered version of NEM, named Mijin, it then makes NEM to become as the first public or private blockchain combination [14].

Ripple, an open source digital technology, a P2P system produced by Jed McCaleb and partner, Chris Larsen. There is one organization that governs the Ripple. Ripple offers another medium of security mechanism [2], [14] in its transactions. The development of Ripple is based on Byzantine Consensus Protocol and currently having s maximum number of 100 million [14]. It is reported that the payment transaction of Ripple takes only 4 seconds.

Stellar, like Ripple offers and entire substitute of security instrument and implemented based on Byzantine Consensus Protocol. Stellar has implemented a new technology to process the financial transactions including open source, scattered and unlimited ownership [2], [18].

2. Prior Works

2.1. Optimized PSO

PSO was introduced in 1995 by Kennedy and Eberhart based on social simulation model known as a stochastic optimization algorithm [19]. Research and applications on Particle Swarm Optimization (PSO) has increased rapidly since its formation and this has resulted in many improved PSO algorithms in various types of optimization problem. In PSO, the hyper parameter is optimized by two features; algorithm and its function [20], [21]. PSO algorithms simulates the behavior of a bird flock by simulating the accuracy of intervals between birds and members which could be depend on the physical appearance and its performance [19]. Each bird in the area of searching is called a particle, also considered as a single resolution. Each particle has its own function value to be evaluated and optimized and lead by the velocity of the best particle [19], [22]. This has been applied in PSO algorithms to solve the optimization problems or to improve the original PSO. Lots of work and study of the effectiveness of PSO compared to other machine learning and swarm intelligence algorithm for engineering and computer science problem have been done by researchers to evaluate its performances [11], [23]. Based on the result, it shows that the optimized algorithm has outperformed the other algorithms in both sets of experiments.

In [24], their work uses the modified algorithm based on PSO to reduce the fitness of the Mean Squared Error (MSE). The result proves the proposed algorithm is capable to forecast accurate future price of the tested classifier. The study in the stock market forecasting proposed an algorithm based on SVM optimized by the PSO for the selection of the best features among the available indicators that derived from the technical analysis part [21], [25]. [25] decided to use various indicators from technical analysis including correlation between different stock prices to forecast the future stock price. This is done by applying the PSO algorithms to select the most beneficial input features among all available indicators and resulted that the PSOSVM outperformed the individual SVM method.

[19] has classified the PSO into internal and external modification. Internal modification refers to the modifications of the basic components in PSO. In order to improve the convergence and the quality of PSO, various modifications have been developed including the introduction of inertia weight, velocity clamping, constriction and models as well as various ways of defining global and local greatest positions. Meanwhile, external modification refers to all modifications made using multiple of swarms or methods that will split the swarm. [26] combined PSO-SVM to forecast agriculture water consumption.

PSO-SVM claimed to be simpler to adjust compared to other method named GA with minimum adjustment on its parameters. A study of reservoir annual inflow forecasting is very significant for reservoir management to ensure enough effectively used of water supply and resources. Result of the study shows that the optimum SVM-PSO model has outperformed the ANNs in terms of future forecasting [27].

[28] in their study suggest a model for predicting water consumption with Least Square Support Vector Machines which is optimized by Hybrid Intelligent Algorithm (LS-SVM). PSO algorithm features has been applied in water consumption prediction to improve the searching speed of the optimization using a comprehensive searching algorithm. This has resulted a better prediction of water consumption, but it is subject to the defined parameters.

3. The Proposed Method

This paper uses five (5) years daily prices from 2013 through 2018 for all data models and is prepared from price of a daily trading for all six types of cryptocurrencies. This covers the open/close as well as highest/lowest price of the day. Data may varies based on the datasets available from the source.

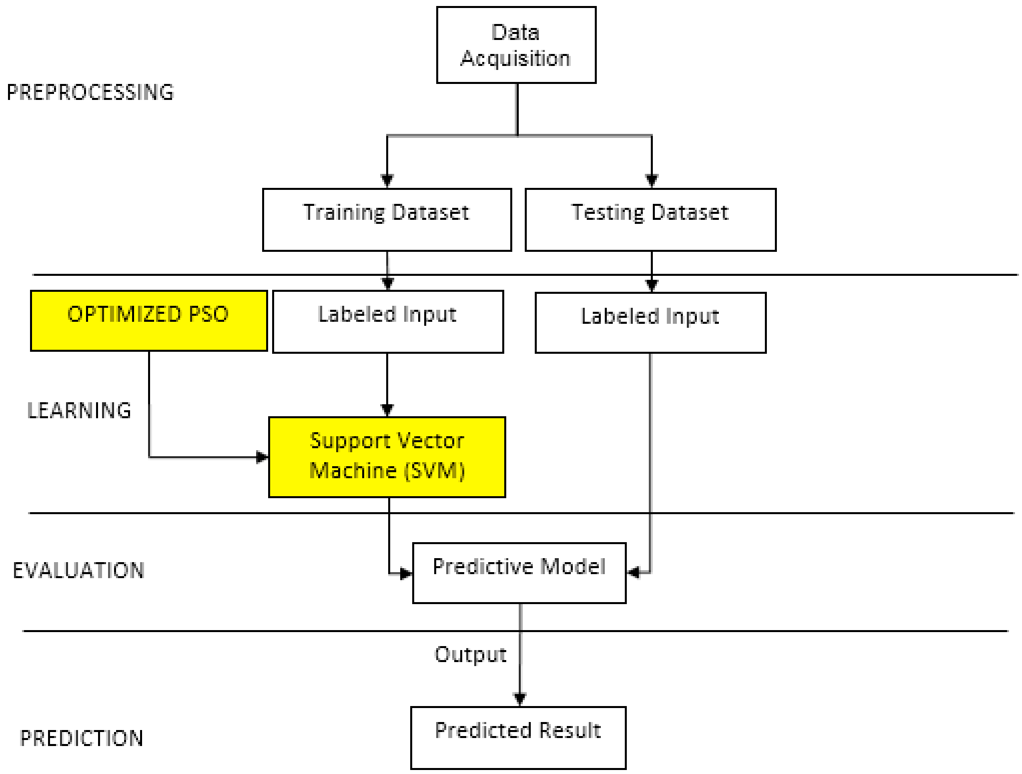

Fig. 1. Flowchart of Optimization SVMPSO

Table 1. Variable Description.

Variable	Description
Open Price	The opening price of a selected cryptocurrency of the trading day
Close Price	The closing price of a selected cryptocurrency of the trading day
High Price	The highest price of a selected cryptocurrency of the trading day
Low Price	The lowest price of a selected cryptocurrency of the trading day

3.1. Data Description

Getting the most accurate forecasting price based on the optimized SVM-PSO becomes the objective of this paper. Figure 2 shows training and testing dataset. The training dataset consist of a figure (as per #Observations) followed by testing dataset in the next segment. Several classifiers are then used to predict the testing dataset (testing value = 364).

Table 2. Training and Testing Dataset

Cryptocurrency	Training Dataset			Testing Dataset		
	From	To	#Observations	From	To	#Observations
Bitcoin, BTC, XBT	28-Mar-13	16-Jan-17	1388	17-Jan-17	16-Jan-18	364
Ether or “Ethereum”, ETH	7-Aug-15	16-Jan-17	526	17-Jan-17	16-Jan-18	364
Litecoin, LTC	28-Apr-13	16-Jan-17	1358	17-Jan-17	16-Jan-18	364
Nem, XEM	1-Apr-15	16-Jan-17	657	17-Jan-17	16-Jan-18	364
Ripple, XRP	4-Aug-13	16-Jan-17	1262	17-Jan-17	16-Jan-18	364
Stellar, XLM	5-Aug-14	16-Jan-17	896	17-Jan-17	16-Jan-18	364

4. Experimental Result and Analysis

The result section begins by observing performance measures for each cryptocurrency types according to classifiers and it serves as a control for the rest of the discussion. Table 3 and 4 show the performance accuracy in correspondence to classifiers on the cryptocurrency market capitalization. Table 3 shows performance measures by various classifiers while Table 4 shows the standard SVM vs SVM with optimized parameter selections with PSO. The maximum value is 97%, which means that any alphas over 97% have p-value of 0.01 or less.

Table 3. Performance Measures by various classifiers

Classifiers	Performance Accuracy (%)					
	Bitcoin	Ethereum	Litecoin	Nem	Ripple	Stellar
SVM	78.90	**95.50**	**82.40**	47.70	70.00	58.70
ANN	**79.40**	78.00	75.80	**77.80**	81.40	89.80
DL	61.90	69.40	62.80	57.20	60.90	70.70
BoostedNN	81.20	81.60	72.20	77.40	**81.50**	**92.80**

Table 4. Performance Measures by various classifiers

Classifiers	Performance Accuracy (%)					
	Bitcoin	Ethereum	Litecoin	Nem	Ripple	Stellar
SVM	78.90	95.50	82.40	47.70	70.00	58.70
Optimized SVM-PSO	**90.4**	**97**	**92.1**	**57.8**	**82.8**	**64.5**

Several different classifiers were trained with the same set of features. In this case, the datasets were evaluated using classification accuracy. The comparison of all classifiers generated by different methods are based on the same dataset. Then, it will be fair for all classifiers to perform the testing and training.

The classifiers with best performance are then testified. The results show that SVM classifier works well for Ethereum followed by LiteCoin. While, Optimized-SVM is seen works best for Ethereum followed by Bitcoin. However, among all, Optimized SVM-PSO classifier performs the best compared to the other classifiers with the performance accuracy of 97%.

For comparability, same data sets and period of 364 days were chosen for all classifiers. The Optimized SVM significantly outperformed the other classifiers. Thus, the Optimized SVM-PSO is considered as reliable forecasting model for the six selected cryptocurrencies.

5. Conclusion

The paper concentrates on the performance of an Optimized SVM-PSO of six cryptocurrencies. It starts by explaining the cryptocurrency market review as well as type of cryptocurrencies in the financial market. The performance measures for all classifiers over the selected cryptocurrency and outcome is presented in Figure 3. The outcomes show that SVM-PSO outperformed other classifiers with the accuracy of 97%. It then confirms that accurate forecasting result also depends on the population and quality of training dataset.

Results which obtained earlier through SVM vs optimized SVM-PSO were then be evaluated. From the comparative analysis done in the next section, SVM-PSO shows comparable value over the other cryptocurrencies for this period.

In future, the model will be enhanced on the accuracy rate of the forecasted price. Future work will concentrate on the data preprocessing by including the sentiment data prior to the testing and training experiments.

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