Application of Three Different Machine Learning Methods on Strategy Creation for Profitable Trades on Cryptocurrency Markets

Mohsen Asgari¹, Seyed Hossein Khasteh²

¹Artificial Intelligence Department, Faculty of Computer Engineering, K. N. Toosi University of Technology
²khasteh@kntu.ac.ir

Abstract— AI and data driven solutions have been applied to different fields with outperforming and promising results. In this research work we apply k-Nearest Neighbours, eXtreme Gradient Boosting and Random Forest classifiers to direction detection problem of three cryptocurrency markets. Our input data includes price data and technical indicators. We use these classifiers to design a strategy to trade in those markets. Our test results on unseen data shows a great potential for this approach in helping investors with an expert system to exploit the market and gain profit. Our highest gain for an unseen 66 day span is 860$ per 1800$ investment. We also discuss limitations of these approaches and their potential impact to Efficient Market Hypothesis.

Keywords— Market Prediction, Financial Decision Making, k-NN Classifier, Extreme Gradient Boosting, Random Forest, Quantitative Computation

I. INTRODUCTION

Artificial Intelligence has widely been applied to different areas in the last decade and there have been reported a lot of improvements in results by using its applications. One of the very interesting areas of application is financial markets. There could be a lot of improvements in exploiting these markets by means of artificial intelligence and machine learning. Some cases of these applications include Loan Application Scoring, Credit Evaluation, Sovereign Credit Ratings, Mortgages Choice Decision, Portfolio Management, Financial Performance Prediction and Market Direction Prediction (Bahrammirzaee).

In this paper we focus on the Market Direction Prediction problem and we look at it as a data science problem.

One of very innovative usages of new technology in finance are cryptocurrencies. As we read in (Hileman et al. 2) "The findings are both striking and thought-provoking. First, the user adoption of various cryptocurrencies has really taken off, with billions in market cap and millions of wallets estimated to have been ‘active’ in 2016. Second, the cryptocurrency industry is both globalised and localised, with borderless exchange operations, as well as geographically clustered mining activities. Third, the industry is becoming more fluid, as the lines between exchanges and wallets are increasingly ‘blurred’ and a multitude of cryptocurrencies, not just bitcoin, are now supported by a growing ecosystem, fulfilling an array of functions." which has been quoted from a survey by Cambridge Center for Alternative Finance in 2017, a year which is not even comparable to what is the prevalence of blockchain based technologies now. As of the time of writing this, only BTC makes a market cap of $1,042,689,199,152 and a 24 hour circulating volume of $57,794,818,577 (“Today's Cryptocurrency Prices by Market Cap”). As the dominance of BTC is 50 percent (“Today's Cryptocurrency Prices by Market Cap”) at the moment, the total market cap of cryptocurrencies registered in Coin Market Cap database can be estimated as about more than 2 thousand billion US Dollars. This impressive amount of money shows a great potential for this innovative use of technology with increasingly facing new challenges (like expensive transaction fees) and tackling them over with innovative solutions (like MicroCache (Almashaqbeh et al.)).

The main goal of the methods described in this article are to determine if the price of the analysed cryptocurrencies will move higher or lower in the
coming four hours. To do that we use a data channel directed to the Binance cryptocurrency exchange free available API and receive the data from the exchange’s database. Then we run some preprocessing procedures on them and get them ready to be used as entry to our machine learning models.

Three different machine learning methods have been used in this work. The first one being kNN as an example-base learner and the last two ones being Random Forest and Gradient Boosting methods as tree-base learners. These models have been discussed in the “Methods and Materials” section.

Data used for these analyses are mostly Open, High, Low, Close and Volume data from three different cryptocurrency markets: ETH-USDT, LTC-BTC, ZEC-BTC. It has been augmented by technical indicators to make better learning data for the models.

After explaining the models and the data, we explore the implementation of these models in the “Proposed Method” section.

At the “Experimental Results” section we look at the performance of these models in predicting the next four hour movement of the market in the test data, which our learned models have not been exposed to.

At the “Discussion” section we look at the performance of our models and we discuss some different and debatable aspects of these methods and the whole strategy creation system and their relation to Efficient Market Hypothesis. There are some improvements which can be made to this work and we mention some of them in the “conclusion and future works” section.

II. RELATED WORKS

In this section we introduce three different surveys done on the topic of market direction prediction and also point to the previous usages of the implemented methods in other studies.

First Survey (Bustos and Pomares-Quimbaya 8) shows a comprehensive taxonomy of stock market prediction algorithms based on machine learning and their categories. This survey has also a performance comparison of the stock market forecast models (Bustos and Pomares-Quimbaya 10) which has 47 different models compared with each other. Based on findings of this article the interest in using Market Information and Technical Indicators as inputs to models have increased in the past few years. It also shows more attention to ensemble methods for this topic recently. Another interesting finding in this survey is better accuracy obtained by using Technical Indicator and Social Networks data combined together in comparison with other data sources as input.

Second survey (Obthong et al.) points out advantages and disadvantages of using 23 different machine learning models with each other, which include k-NN and Random Forest. k-NN, described as a Classification and Forecasting Algorithm, has been noted to have advantages of being robust to noisy training data and being very efficient if the training datasets are large. It also points to the issue of determining the best k for this algorithm and its high complexity in computation and memory limitations as its disadvantages. k-NN can be sensitive to the local structure of the data based on the findings in this survey (Archana and Elango van) (Jadhav and Channe). In the same survey, random forest has been categorized as another Classification and Forecasting algorithm and for its advantages we read: “Robust method for forecasting and classification problems since its design that is filled with various decision trees, and the feature space is modelled randomly, automatically handles missing values and works well with both discrete and continuous variables”. RF algorithm has been disadvantaged by the following points “Requires more computational power and resources because it creates a lot of trees and requires more time to train than decision trees” (Obthong et al. 5) (Pradeepkumar and Ravi).

Third survey (Kumar et al.) organises core Computational Intelligence approaches for stock market forecasting in three different classes including: Neural Network, Fuzzy Logic and Genetic Algorithm. It surveys application of these models in markets of 19 different countries. Mostly used data for training models based on this survey are Technical Indicators (Kumar et al. 15). It also shows that more research has been done for American Markets (NYSE & NASDAQ) than other geographical locations. This survey concludes “identification of suitable pre-processing and feature
selection techniques helps in improving the accuracy of stock market forecasting models and computational intelligence approaches can be effectively used to solve stock market forecasting problem with high accuracy. Among them hybrid models are predominant techniques applied to forecast stock market due to combined prediction capability of base models”.

k-Nearest Neighbours algorithm (k-NN) is an instance-base learner model first developed by (Fix and Evelyn). This model has shown a good performance regarding returns in financial markets. Applying this model to Jordanian Stock Market has been reported to yield Total Squared RMS error of 0.263, RMS error of 0.0378 and the average error of -5.434E-09 for “AIEI” symbol (Alkhatib et al). Another scheme of applying k-NN has been reported in (Chen and Hao) by the name of “FWKNN”. It has been concluded in that research: “The experiment results clearly show that FWSVM-FWKNN stock analysis algorithm where the classification by FWSVM and the prediction by FKNN, is robust, presenting significant improvement and good prediction capability for Chinese stock market indices over other compared model”.

Random Forests have been used since the late 90s to overcome the over fitting problem in decision trees (Ho and Kam). A variation of this algorithm has been applied to cryptocurrency market direction detection problem on 60 minutes data in (Akyildirim et al). Their out-of-sample accuracy on BTC, ETH, LTC and ZEC has been reported 0.52, 0.53, 0.53 and 0.52 respectively. They have used mostly OHLC and indicator-based data for their model training. They also have concluded that their used algorithms “demonstrate the predictability of the upward or downward price moves” (Akyildirim et al 27).

Gradient Boosting is a relatively old popular machine learning method in dealing with non-linear problems (Friedman). Later a more efficient variant of it has been developed by (Chen and He) known today as Extreme Gradient Boosting (XGBoost) algorithm. It has been reported (Alessandretti et al. 4) this method has been used in a number of winning Kaggle solutions (17/29 in 2015). XGBoost has been applied to the Bitcoin market in (Chen et al. 12) and its accuracy has been reported 0.483. Another experiment on XGB-based methods has yielded 1.1

* 10³ BTC (for their method 1) and ~ 95 BTC (for their Method 2) starting from 1 BTC (Alessandretti et al. 7).

III. METHODS AND MATERIALS

In this section we first look at the data used in this project, then we get acquainted with three different methods which have been used to make the models for the prediction task.

1. Used Data

Binance is a cryptocurrency exchange that provides a platform for trading various cryptocurrencies. As of April 2021, Binance was the largest cryptocurrency exchange in the world in terms of trading volume (Coin Market Cap).

Binance provides a free to use API for data gathering. This API is conveniently available to use in python language. We use this API to gather Time stamp (in second precision), Open, High, Low, Close and Volume for a 4 hours period dataframe. This procedure runs for all three different assets that we study: ETH-USDT, LTC-BTC and ZEC-BTC. Data gets gathered from mid-2017 until April 2021. This makes our raw input data.

2. First Classifier: k-Nearest Neighbours Vote

Neighbours-based models are type of instance-based learning or non-generalizing learning. They don’t attempt to construct a general internal model, but simply store instances of the training data (hence called lazy learners). Classification is computed from a sort of majority vote of the nearest neighbours of each point: the point we are trying to classify is assigned to the data class which has the most representatives within the nearest neighbours of the point. Using distance metrics can sometimes improve the accuracy of the model. (Pedregosa et al.) These models are also beneficial for regression problems.

Suppose we have pairs \((X_1, Y_1), (X_2, Y_2), \ldots, (X_n, Y_n)\) taking values in \(\mathbb{R}^d \times \{1, 2\}\), where \(Y\) is the class label of \(X\), so that \(X|Y = r \sim P_r\) for \(r = 1, 2\) (and probability distributions \(P_r\)). Given some norm \(|\cdot|\) on \(\mathbb{R}^d\) and a point \(x \in \mathbb{R}^d\), let \((X_{(1)}, Y_{(1)}), (X_{(2)}, Y_{(2)}), \ldots, (X_{(n)}, Y_{(n)})\) be a reordering of the training data such that \(|X_{(1)} - x| \leq \ldots \leq |X_{(n)} - x|\).
Now, by voting on $X_{(i)}$ starting from $i = 1$ and going increasingly for $i$, we can do the classification task.

We use Scikit-learn implementation (Pedregosa et al.) of k-NN classifier in this project.

3. Second Classifier: Random Forest

Random forests or random decision forests are classified as ensemble learning methods. They can be applied to classification, regression and other tasks that operate by constructing an assembly of decision trees at training time and returning the class that is the mode of the classes (for classification) or mean/average prediction (for regression) of the individual trees (Ho). “Random decision forests correct for decision trees' habit of over fitting to their training set” (Friedman et al. 587-588). Random forests generally perform better than individually assisted decision trees, but their accuracy could be lower than gradient boosted trees. However, data characteristics can affect their performance (Piryonesi and El-Diraby).

The training algorithm for random forests applies the general technique of bootstrap aggregating, or bagging, to tree learners. Given a training set $X = x_1, \ldots, x_n$ with responses $Y = y_1, \ldots, y_n$ bagging repeatedly ($B$ times) selects a random sample with replacement of the training set and fits trees to these samples:

for $b=1, \ldots, B$:

I. Sample, with replacement, $n$ training examples from $X,Y$; call these $X_b,Y_b$.

II. Train a classification or regression tree $f_b$ on $X_b,Y_b$.

After training, predictions for unseen samples $x'$ can be made by averaging the predictions from all the individual regression trees on $x'$:

$$\hat{f} = \frac{1}{B} \sum_{b=1}^{B} f_b(x')$$

or by taking the majority vote in the case of classification trees.

This bootstrapping procedure leads to better model performance because it decreases the variance of the model, without increasing the bias. This means that while the predictions of a single tree are highly sensitive to noise in its training set, the average of many trees is not, as long as the trees are not correlated. Simply training many trees on a single training set would give strongly correlated trees (or even the same tree many times, if the training algorithm is deterministic); bootstrap sampling is a way of de-correlating the trees by showing them different training sets.

The number of samples/trees, $B$, is a free parameter. Typically, a few hundred to several thousand trees are used, depending on the size and nature of the training set. An optimal number of trees, $B$, can be found using cross-validation, or by observing the out-of-bag error: the mean prediction error on each training sample $x_i$, using only the trees that did not have $x_i$ in their bootstrap sample (James et al. 316-321).

We use Scikit-learn implementation (Pedregosa et al.) of random forest classifier in this project.

4. Third Classifier: eXtreme Gradient Boosting

Gradient boosting is a machine learning technique for regression and classification problems, which like random forest, produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees. When a decision tree is the weak learner, the resulting algorithm is called gradient boosted trees, which usually outperforms random forest (Piryonesi and El-Diraby) (Friedman et al.). It builds the model in a stage-wise fashion like other boosting methods do, and it generalizes them by allowing optimization of an arbitrary differentiable loss function.

Like other boosting methods, gradient boosting combines weak "learners" into a single strong learner in an iterative fashion. It is easiest to explain in the least-squares regression setting, where the goal is to "teach" a model $F$ to predict values of the form $\hat{y} = F(x)$ by minimizing the mean squared error $\frac{1}{n} \sum_i (\hat{y}_i - y_i)^2$ where $i$ indexes over some training set of size $n$ of actual values of the output variable $y$. So we have following definition:

$$\hat{y}_i = \text{The Predicted Value} \ F(x)$$

$$y_i = \text{The Observed Value}$$

$n = \text{The Number of Samples in } y$

Now, let us consider a gradient boosting algorithm with $M$ stages. At each stage $m$ ($1 \leq m \leq M$) of gradient boosting, suppose some imperfect model $F_m$ (for low $m$ this model may simply return $\hat{y}_i = \hat{y}$, where the right-hand side is the mean of $y$). In order
to improve $F_m$, our algorithm should add some new estimator, $h_m(x)$. Thus,

$$F_{m+1}(x) = F_m(x) + h_m(x) = y$$

or, equivalently,

$$h_m(x) = y - F_m(x).$$

Therefore, gradient boosting will fit $h$ to the residual $y - F_m(x)$. As in other boosting variants, each $F_{m+1}$ attempts to correct the errors of its predecessor $F_m$.

A generalization of this idea to loss functions other than squared error, and to classification and ranking problems, follows from the observation that residuals $h_m(x)$ for a given model are the negative gradients of the mean squared error (MSE) loss function (with respect to $F(x)$):

$$L_{MSE} = \frac{1}{2} (y - F(x))^2$$

$$h_m(x) = - \frac{\partial L_{MSE}}{\partial F} = y - F(x).$$

So, gradient boosting could be specialized to a gradient descent algorithm, and generalizing it entails "plugging in" a different loss and its gradient (Li).

Now, with having an overview of boosted trees, one may ask what are XGBoost trees? XGBoost is a tool motivated by the formal principle introduced. More importantly, “it is developed with both deep consideration in terms of systems optimization and principles in machine learning”. “The goal of this library is to push the extreme of the computation limits of machines to provide a scalable, portable and accurate library” (Chen and Guestrin). We use this library for our implementations of the solution.

IV. PROPOSED METHODS

In this section we look at our proposed methods for market direction problem in cryptocurrency markets. First, we fill in details about our raw data gathering procedure. Then at the second subsection, we elaborate on our pre-processing steps for the obtained raw financial data. We also explain the dataset creation part of the scheme at this subsection. The third step, sums up the definition of our three different models. We also make some concise points about hyper parameters of each model. Last subsection looks at evaluation of results and concludes the strategy creation part of the system. Figure 1 (look at page 7) shows a comprehensive view of the whole system, green lines indicate train phase and red lines indicate exertion phase.

1. Raw Data Gathering

At the time of doing this research, Binance has made available, access to its historical records (for Open, High, Low, Close and Volume) through its API for time frames bigger than one minute. We gather 4 hour period data to a Pandas dataframe since its first available timestamp (which is usually mid 2017). The data includes OHLCV for ETH-USDT, LTC-BTC, ZEC-BTC. We use 95% of the data for training and the remaining 5% to evaluate the models.

2. Pre Processing and Dataset Creation

After gathering the data, we augment it with some famous Technical Indicators in finance. Typically these indicators are some mathematical functions which take some arguments from real time or past data and they create some insights about “technical” moves of the market. Name and formula for these technical indicators has been reported in the Appendix A.

After augmentation we have a dataframe including all relevant data for each record. Now, two things must be done to make it a suitable dataset for our models: 1- We need to encapsulate all the features used for identifying a data point for each one of them, 2- We need to label each datapoint.

For this project we use the last financial records plus 59 records proceeding it as its features. These records are in a 4 hour period and all of the produced features are numerical. We normalize them by using the Feature Scaling method. Each value gets divided to its maximum value minus its minimum.

To encapsulate the feature data for each datapoint we take all the 60 rows (and 19 parameters at each row) from our augmented dataframe and put all those variables inside another array named X. So, each $X_i$ will be a data point with 1140 parameters.

To label each datapoint we define a threshold to determine if retrospectively we would have entered the market at that timestamp, after 4 hours we would make profit or loss? This threshold gets defined using the fees per each cryptocurrency exchanger. At the time of doing this research the least possible fee to exchange in the market in Binance was 0.15 percent (0.075 percent to exchange from A symbol to B symbol and 0.075 to exchange from B to original A symbol). So, we define our threshold in
this project as about 0.15 percent of the price movement in the 4 hour period. To sum up, if an asset’s value changes more than this threshold in a positive direction, we label it as “1” and otherwise we label it as “0”. This way per any label=1 if we had entered the market at that point we would make profit.

3. Model definition-Model Training

At this subsection we look at the libraries and hyper parameters involved in each model. We also note each model’s training time. A more elaborate discussion about the hyper parameters is held in the Discussion section.

kNN model and random forest have been implemented using open source machine learning library Scikit-learn. Scikit-learn features various classification, regression and clustering algorithms including support vector machines, random forests, gradient boosting, k-means and DBSCAN, and is designed to interoperate with the Python numerical and scientific libraries NumPy and SciPy. (Pedregosa et al.) An important design note about scikit-learn is its unified interface for its models. If user’s data suffices this interface requirements, it’s easy to use and change models to use for the same data.

XGB has been implemented using XGBoost. XGBoost is an optimized distributed gradient boosting library designed to be highly efficient, flexible and portable. It implements machine learning algorithms under the Gradient Boosting framework. XGBoost provides a parallel tree boosting (also known as GBDT, GBM) that solve many data science problems in a fast and accurate way (Chen and Guestrin).

Hyper parameters involved in kNN classifier are as follows:

- **Number of Neighbours:** Depended on The Dataset (5 for ETHUSDT, 20 for LTCBTC, 100 for ZECBTC)
- **Weight Function Used in Prediction:** Distance
- **Algorithm Used to Compute The Nearest Neighbours:** Auto: will attempt to decide the most appropriate algorithm between BallTree, KDTree and Brute Force based on the values passed to fit method.

- **Leaf Size:** 30
- **The Distance Metric to Use for The Tree:** Minkowski
- **Power Parameter for The Minkowski Metric:** 2

Hyper parameters involved in Random Forest classifier are as follows:

- **The number of trees in the forest:** Depended on The Dataset (700 for ETHUSDT and ZECBTC, 1000 for LTCBTC)
- **The Function to Measure The Quality of A Split:** gini
- **The Maximum Depth of The Tree:** Nodes are expanded until all leaves are pure or until all leaves contain less than the minimum number of samples required to split an internal node samples.
- **The minimum number of samples required to split an internal node:** 2

Hyper parameters involved in XGB classifier are as follows:

- **Booster:** gbtree
- **Eta (alias: Learning Rate):** 0.3
- **Minimum Loss Reduction Required to Make A Further Partition on A Leaf Node of The Tree (The larger gamma is, the more conservative the algorithm will be.):** 0
- **Maximum Depth of A Tree:** 6
- **Lambda (L2 regularization term on weights. Increasing this value will make model more conservative.):** 1
- **Alpha (L1 regularization term on weights. Increasing this value will make model more conservative.):** 0
Training and evaluation of the models in this project has been done using Colab virtual machines by google. Training time takes the most for Random Forest with an average of 167.97 seconds. Second place goes to XGB with an average of 46.85 seconds and finally kNN takes only 1.06 seconds on average to be trained for these datasets.

4. Evaluation and Strategy Creation

To evaluate each model in this project we use two different methods: Accuracy of The Model and The Profit Obtained by The Model. By accuracy in this context, we mean how many times the predicted label for the market direction matches with the real direction of the market. To discuss how we calculate the obtained profit, we need to understand how we use the models to create the strategy.

Strategy Creation procedure is pretty straightforward. We took 60 rows of records from now and past data and then we decide if the price will go up enough to cover the exchange’s fee? If we predict it will, we enter the market and after 4 hours we retry this operation to decide for the next 4 hours. If the next 4 hours still shows an adequate positive movement, we keep the buy position and if it does not, we sell what we have bought. Now, our profit is the difference between the values of bought and sold assets. It will accumulate this positive or negative profit through the test span. Notice that our position size stays the same at each buying or selling trade. At the final step of the strategy we sell whatever we have. Another evaluative indicator for strategy assessments in financial markets is Profit Factor, which is defined as: “The gross profit divided by the gross loss (including commissions) for the entire trading period”. We calculate this metric for each model and each asset. In the next section we look at the results of our experiments with our models.

V. EXPERIMENTAL RESULTS

Here we look at three different cryptocurrencies that we study, separately. This section has three subsections relative to each cryptocurrency pair. At each subsection, first, we have a graph of the pair’s price movements through the time span that we scrutinize it. Then, we have a graph that shows the normalized returns of that pair through the time. The mentioned graph shows what we are trying to predict. The third graph is the pair’s price movements through its test phase (which makes 5% of our data). Then we report the accuracy of each model on their test data and we look at their performance as their profits through the test time. This performance is assessed with a cumulative reward graph which shows how much money we have earned with a fixed position at each time we entered or exited the market. Finally, we have some information regarding the test of models and a distribution graph of each model’s (positive or negative) profits.
A. ETH-USDT:

Figure 2. Close Price for ETH-USDT from 2017-07 to 2021-07

Figure 3. Normalized Return for ETH-USDT from 2017-07 to 2021-07
Figure 4. Normalized Close Price for ETH-USDT in Test Data

Figure 5. Performance of The k-NN Model for ETH-USDT in Test Data

Figure 6. Performance of The XGB Model for ETH-USDT in Test Data
Figure 7. Performance of The Random Forest Model for ETH-USDT in Test Data

| Testing Accuracy | 0.519900 |
|------------------|----------|
| Net Profit       | 575.810  |
| Number of Winning Trades | 105 |
| Number of Losing Trades | 82 |
| Total Days in Test | 66 |
| Percent of Profitable Trades | 56.15% |
| Avg Win Trade    | 29.680   |
| Avg Los Trade    | -30.983  |
| Largest Win Trade| 177.820  |
| Largest Los Trade| -161.700 |
| Profit Factor    | 1.23     |

Table 1. Information Regarding k-NN Test on ETH-USDT

| Testing Accuracy | 0.547264 |
|------------------|----------|
| Net Profit       | 860.940  |
| Number of Winning Trades | 120 |
| Number of Losing Trades | 90 |
| Total Days in Test | 66 |
| Percent of Profitable Trades | 57.14% |
| Avg Win Trade    | 36.302   |
| Avg Los Trade    | -38.836  |
| Largest Win Trade| 174.820  |
| Largest Los Trade| -158.100 |
| Profit Factor    | 1.25     |

Table 2. Information Regarding XGB Test on ETH-USDT
|                     |                  |
|---------------------|-----------------|
| Testing Accuracy    | 0.562189        |
| Net Profit          | 672.80          |
| Number of Winning Trades | 166        |
| Number of Losing Trades | 125        |
| Total Days in Test  | 66              |
| Percent of Profitable Trades | 57.04%   |
| Avg Win Trade       | 29.782          |
| Avg Los Trade       | -34.168         |
| Largest Win Trade   | 135.050         |
| Largest Los Trade   | -158.100        |
| Profit Factor       | 1.16            |

Table 3. Information Regarding Random F Test on ETH-USDT
B. LTC-BTC

Figure 11. Close Price for LTC-BTC from 2017-07 to 2021-07

Figure 12. Normalized Return for LTC-BTC from 2017-07 to 2021-07
Figure 13. Normalized Close Price for LTC-BTC in Test Data

Figure 14. Performance of The k-NN Model for LTC-BTC in Test Data

Figure 15. Performance of The XGB Model for LTC-BTC in Test Data
Testing Accuracy | 0.585956
---|---
Net Profit | 0.0005090
Number of Winning Trades | 46
Number of Losing Trades | 40
Total Days in Test | 66
Percent of Profitable Trades | 53.49%
Avg Win Trade | 0.00006
Avg Los Trade | -0.00005
Largest Win Trade | 0.00024
Largest Los Trade | -0.00019
Profit Factor | 1.24

Table 4. Information Regarding k-NN Test on LTC-BTC

Testing Accuracy | 0.520581
---|---
Net Profit | 0.0006720
Number of Winning Trades | 88
Number of Losing Trades | 91
Total Days in Test | 66
Percent of Profitable Trades | 49.16%
Avg Win Trade | 0.00004
Avg Los Trade | -0.00003
Largest Win Trade | 0.00024
Largest Los Trade | -0.00024
Profit Factor | 1.22

Table 5. Information Regarding XGB Test on LTC-BTC
| Description                      | Value        |
|----------------------------------|--------------|
| Testing Accuracy                 | 0.467312     |
| Net Profit                       | 0.0004430    |
| Number of Winning Trades         | 71           |
| Number of Losing Trades          | 65           |
| Total Days in Test               | 66           |
| Percent of Profitable Trades     | 52.21%       |
| Avg Win Trade                    | 0.00006      |
| Avg Los Trade                    | -0.00006     |
| Largest Win Trade                | 0.00027      |
| Largest Los Trade                | -0.00029     |
| Profit Factor                    | 1.12         |

Table 5. Information Regarding Random Forest Test on LTC-BTC

Figure 18. Distribution of Profits for XGB in LTC-BTC

Figure 19. Distribution of Profits for k-NN in LTC-BTC

Figure 20. Distribution of Profits for Random Forest in LTC-BTC
C. ZEC-BTC

Figure 20. Close Price for ZEC-BTC from 2017-07 to 2021-07

Figure 21. Normalized Return for ZEC-BTC from 2017-07 to 2021-07
Figure 22. Normalized Close Price for ZEC-BTC in Test Data

Figure 23. Performance of The k-NN Model for ZEC-BTC in Test Data

Figure 24. Performance of The XGB Model for ZEC-BTC in Test Data
Figure 25. Performance of The Random Forest Model for ZEC-BTC in Test Data

| Metric                        | Value       |
|-------------------------------|-------------|
| Testing Accuracy              | 0.521277    |
| Net Profit                    | 0.0003430   |
| Number of Winning Trades      | 21          |
| Number of Losing Trades       | 22          |
| Total Days in Test            | 66          |
| Percent of Profitable Trades  | 48.84%      |
| Avg Win Trade                 | 0.00004     |
| Avg Los Trade                 | -0.00002    |
| Largest Win Trade             | 0.00015     |
| Largest Los Trade             | -0.00010    |
| Profit Factor                 | 1.63        |

Table 7. Information Regarding k-NN Test on ZEC-BTC

| Metric                        | Value       |
|-------------------------------|-------------|
| Testing Accuracy              | 0.518617    |
| Net Profit                    | 0.000293    |
| Number of Winning Trades      | 46          |
| Number of Losing Trades       | 49          |
| Total Days in Test            | 66          |
| Percent of Profitable Trades  | 48.42%      |
| Avg Win Trade                 | 0.00005     |
| Avg Los Trade                 | -0.00004    |
| Largest Win Trade             | 0.00045     |
| Largest Los Trade             | -0.00021    |
| Profit Factor                 | 1.14        |

Table 6. Information Regarding XGB Test on ZEC-BTC
| Parameter                        | Value     |
|---------------------------------|-----------|
| Testing Accuracy                | 0.510638  |
| Net Profit                      | 0.0007550 |
| Number of Winning Trades        | 87        |
| Number of Losing Trades         | 85        |
| Total Days in Test              | 66        |
| Percent of Profitable Trades    | 50.58%    |
| Avg Win Trade                   | 0.00004   |
| Avg Los Trade                   | -0.00004  |
| Largest Win Trade               | 0.00020   |
| Largest Los Trade               | -0.00014  |
| Profit Factor                   | 1.25      |

Table 9. Information Regarding Random Forest Test on ZEC-BTC

Figure 26. Distribution of Profits for k-NN on ZEC-BTC

Figure 27. Distribution of Profits for XGB on ZEC-BTC

Figure 28. Distribution of Profits for Random Forest on ZEC-BTC
VI. DISCUSSION

In this section we discuss how our models have been performing through different market conditions, we also delve into the question “Have our models beaten the market?”. We talk about how these results challenge the Efficient Market Hypothesis (EMH) in the context of cryptocurrency markets and how one can implement practically these models and exploit the market. We also note the limitations and differences between response times of our models.

All our three studied cryptocurrency pairs show different market conditions through our models train phases (i.e. all of them have bullish, bearish and range movements), although frequency of these moves are not equal and this could make effects on the results. Let’s compare test results on late April 2021 fall of ETH-USDT. By comparing Fig 2 and Fig 3 we see k-NN based strategy has not fallen in equity during that span, but figures 4 and 5 shows that XGB and Random Forest have fallen there, although the overall smoothness of the last two models is better. Again, if we take Fig 22 as a reference and compare figures 23 and 25 with it, we see how models have avoided bearish markets. Figure 16 shows a model where, although being positive in the final returns, does not look good for practical usage. Cumulative results in 66 days for all models show a positive return, but is this positive return because of the market or because of our models?

To discuss the above question, we look at what would have happened if we had bought the cryptocurrency in question right after the start of the test time span and we hold it till the last day. For demonstration purposes here we focus on ETH-USDT. For ETH-USDT it means buying an ETH coin for about 1577 $ and selling it for about 2757 $ which yields 1180 $. The point here is with all of our AI based strategies we already cover this profit and our strategy’s profit is the Net Return plus this amount, because at the last step of our strategies we get back to whatever cryptocurrency we have started with. We will have that coin plus whatever we have gained in Net Profit. To sum up, the answer is yes, we beat the market (i.e. the strategy of holding) by using discussed methods.

“The efficient market hypothesis (EMH) is a back-breaker for forecasters. In its crudest form it effectively says that the series we would very much like to forecast, the returns from speculative assets, are unforecastable. The EMH was proposed based on the overpowering logic that if returns were forecastable, many investors would use them to generate unlimited profits. The behaviour of market participants induce returns that obey the EMH, otherwise there would exist a ‘money-machine’ producing unlimited wealth, which cannot occur in a stable economy.” (Timmermann and Granger 1) The point here is, what if some patterns exist in the market dynamics but are not visible to ordinary users and they could only be discovered through artificial intelligence based systems? If that would be the case, it’s obvious that our formulation of EMH should change accordingly. Maybe the hidden patterns inside a market can be exploited to some extent and this extent is determined by the behaviour of the exploiters. But of course due to laws of thermodynamics there will be a limit for this exploit. It can be definitely said due to the second law of thermodynamics, a system’s entropy increases and this eventually makes that system unstable for exploitation.

There were two important factors of tuning these models: Hyper parameters and Labelling Sensitivity Threshold. Each discussed model has its own hyper parameters and changing them affected the results significantly. Labelling Sensitivity Threshold was another consequential parameter in our experiments. This parameter defines to which extent the return should be, to be considered a positive return for the model. Usually, it should be at least greater than the exchange’s fee to denote a profitable trade, but tweaking with it yields different results. One can use grid searching in available values for these tunings. There may be a need to reconfigure them from time to time.

As it has been shown in this project, models perform differently in different markets. Beside the generated profit, each machine learning model can have its own pros and cons. For example, in our experiments, k-NN usually took about 7.5 seconds to predict the label where Random Forest took about 0.13 seconds and XGB took only 0.008 seconds.
These differences will make each of them preferable to another based on the contexts.

All of what has been discussed till now are theoretical arguments, implications of these models look very attractive but it definitely will bring up new issues and more research needs to be done. Many exchanges nowadays allow automatic traders to act in their provided markets. One can use these exchanges data and process them inside the introduced schemes and decides and trades based on them in hope of profit. As cryptocurrency markets are almost always available (i.e. 24/7) using a dedicated server can find trade opportunities and acts on them automatically.

VII. CONCLUSIONS AND FUTURE WORKS

The impact of artificial intelligence’s applications in many areas are promising for a more efficient and prosperous future. In this study we looked at three different machine learning approaches to help investors to make their decisions in some new emerging international markets in a more data driven and autonomous manner. We also addressed a simple strategy creation framework to use these models. Although all of our models showed positive returns in comparison to baseline strategy (i.e. holding the assets) and a maximum of 1.60 profit factor for ZEC-BTC by k-NN in 66 days and a minimum profit factor of 1.12 for LTC-BTC by Random Forest, it’s obvious more research needs to be done in this area. The resulting strategies still lack “smoothness” in their equity graphs and hence showing large potential risks to be implemented. Designing a full autonomous trading system surely involves more concerns than the ones we had simplified in this research work, like market liquidity issues. We also discussed how these new and uprising technological advancements can cast a shadow on some long lasting hypothesis in finance like Efficient Market Hypothesis.

As we can see, there seems a predictability potential in a highly complex system like financial markets by means of machine learning. For future works, our suggestions include:

1. Combining Fundamental Information with Technicals to improve the accuracy
2. Ensembling different approaches in machine learning to decrease the bias of the whole system
3. Using social networks data streams to obtain an accumulated view on public opinion on different assets
4. Using Deep neural networks to feature extraction from raw data
5. Using Deep Reinforcement Learning to design sophisticated strategies directly to enhance performance
6. Using machine learning approaches for risk management in a collateral system to decision making

Besides what we have discussed about financial markets, it seems machine learning models can be used in many other chaotic natured problems which share some of their data characteristics with financial data. These fields could include supply chain support, Business affairs with public opinions, public views on political issues and many other use cases.
REFERENCES

AKYILDIRIM, ERDINC, ET AL. “PREDICTION OF CRYPTOCURRENCY RETURNS USING MACHINE LEARNING.” ANNALS OF OPERATIONS RESEARCH, VOL. 297, 2021, PP. 3–36.

ALESSANDRETTI, LAURA, ET AL. “ANTICIPATING CRYPTOCURRENCY PRICES USING MACHINE LEARNING.” COMPLEXITY, 2018.

ALKHATIB, KHALID, ET AL. “STOCK PRICE PREDICTION USING K-NEAREST NEIGHBOR (KNN) ALGORITHM.” INTERNATIONAL JOURNAL OF BUSINESS, HUMANITIES AND TECHNOLOGY, VOL. 3, NO. 3, 2013, PP. 32-44.

ALMA SHAQBEH, GHADA, ET AL. “MICROCASH: PRACTICAL CONCURRENT PROCESSING OF MICROPAYMENTS.” LECTURE NOTES IN COMPUTER SCIENCE, VOL. 12059, 2020.

ARCHANA, S., AND K. ELANGOVAN. “SURVEY OF CLASSIFICATION TECHNIQUES IN DATA MINING.” INTERNATIONAL JOURNAL OF COMPUTER SCIENCE AND MOBILE APPLICATIONS, VOL. 2, NO. 2, 2014, PP. 65-71.

BAHRAM MI RZAEE, ARASH. “A COMPARATIVE SURVEY OF ARTIFICIAL INTELLIGENCE APPLICATIONS IN FINANCE: ARTIFICIAL NEURAL NETWORKS, EXPERT SYSTEM AND HYBRID INTELLIGENT SYSTEMS.” NEURAL COMPUTING AND APPLICATIONS, VOL. 19, NO. 8, 2010, PP. 1165-1195.

BUSTOS, O., AND A. POMARES-QUI MBAYA. “STOCK MARKET MOVEMENT FORECAST: A SYSTEMATIC REVIEW.” EXPERT SYSTEMS WITH APPLICATIONS, VOL. 156, 2020.

CHEN, TIANQI, AND CARLOS GUESTRIN. “XGBOOST: A SCALABLE TREE BOOSTING SYSTEM.” PROCEEDINGS OF THE 22ND ACM SIGKDD INTERNATIONAL CONFERENCE ON KNOWLEDGE DISCOVERY AND DATA MINING, 2016.

CHEN, TIANQI, AND TONG HE. XGBOOST: EXTREME GRADIENT BOOSTING. R PACKAGE VERSION 0.4-2 1.4. 2015.

CHEN, YINGYUN, AND YONGTAO HAO. “A FEATURE WEIGHTED SUPPORT VECTOR MACHINE AND K-NEAREST NEIGHBOR ALGORITHM FOR STOCK MARKET INDICES PREDICTION.” EXPERT SYSTEMS WITH APPLICATIONS, VOL. 80, 2017, PP. 340-355.

CHEN, ZHESHI, ET AL. “BITCOIN PRICE PREDICTION USING MACHINE LEARNING: AN APPROACH TO SAMPLE DIMENSION ENGINEERING.” JOURNAL OF COMPUTATIONAL AND APPLIED MATHEMATICS, VOL. 365, 2020.

FIX, AND EVELYN. DISCRIMINATORY ANALYSIS: NONPARAMETRIC DISCRIMINATION, CONSISTENCY PROPERTIES. VOL. 1, USAF SCHOOL OF AVIATION MEDICINE, 1985.

FRIEDMAN, JEROME, ET AL. THE ELEMENTS OF STATISTICAL LEARNING. VOL. 1, NEW YORK, SPRINGER SERIES IN STATISTICS, 2001.
FRIEDMAN, JEROME H. “Greedy Function Approximation: A Gradient Boosting Machine.” *ANNALS OF STATISTICS*, VOL. 29, NO. 5, 2001, PP. 1189-1232.

FRIEDMAN, JEROME H., ET AL. “10. Boosting and Additive Trees.” *THE ELEMENTS OF STATISTICAL LEARNING*, 2ND ED., SPRINGER, 2009, PP. 337–384.

HILEMAN, ET AL. *GLOBAL CRYPTO CURRENCY BENCHMARKING STUDY*. VOL. 33, CAMBRIDGE CENTRE FOR ALTERNATIVE FINANCE, 2017.

HO, TIN KAM. “Random Decision Forests.” *PROCEEDINGS OF 3RD INTERNATIONAL CONFERENCE ON DOCUMENT ANALYSIS AND RECOGNITION*, VOL. 1, 1995, PP. 278-282.

HO, TIN KAM. “The Random Subspace Method for Constructing Decision Forests.” *IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE*, VOL. 20, NO. 8, 1998, PP. 832-844.

JADHAV, SAYALI D., AND H. P. CHANNE. “Comparative Study of K-NN, Naive Bayes and Decision Tree Classification Techniques.” *INTERNATIONAL JOURNAL OF SCIENCE AND RESEARCH (IJSR)*, VOL. 5, NO. 1, 2016, PP. 1842 - 1845.

JAMES, GARETH, ET AL. *AN INTRODUCTION TO STATISTICAL LEARNING WITH APPLICATIONS IN R* NEW YORK, NY, SPRINGER, 2013.

KUMAR, GOURAV, ET AL. “Stock Market Forecasting Using Computational Intelligence: A Survey.” *ARCHIVES OF COMPUTATIONAL AND MATHEMATICAL ENGINEERING*, VOL. 146, NO. 2, 2020.

**COMPUTATIONAL METHODS IN ENGINEERING**, VOL. 28, 2021, PP. 1069–1101.

LI, CHENG. *A GENTLE INTRODUCTION TO GRADIENT Boosting*. COLLEGE OF COMPUTER AND INFORMATION SCIENCE, NORTHEASTERN UNIVERSITY.

HTTP://WWW.CHENGLI.IO/TUTORIALS/GRADIENT_BOOSTING.PDF. ACCESSED 24 4 2021.

OBTHONG, MEHTABHORN, ET AL. “A Survey on Machine Learning for Stock Price Prediction: Algorithms and Techniques.” *PROCEEDINGS OF THE 2ND INTERNATIONAL CONFERENCE ON FINANCE, ECONOMICS, MANAGEMENT AND IT BUSINESS*, 2020.

SCITEPRESS - SCIENCE AND TECHNOLOGY PUBLICATIONS. ACCESSED 22 4 2021.

PAREGOSA, FABIAN, ET AL. “Scikit-learn: Machine Learning in Python.” *THE JOURNAL OF MACHINE LEARNING RESEARCH*, VOL. 12, 2011, PP. 2825-2830.

PIRYONESI, S. MADEH, AND TAMER E. EL-DIRABY. “Data Analytics in Asset Management: Cost-Effective Prediction of the Pavement Condition Index.” *JOURNAL OF INFRASTRUCTURE SYSTEMS*, VOL. 26, NO. 1, 2019.

PIRYONESI, S. MADEH, AND TAMER E. EL-DIRABY. “Role of Data Analytics in Infrastructure Asset Management: Overcoming Data Size and Quality Problems.” *JOURNAL OF TRANSPORTATION ENGINEERING*, VOL. 146, NO. 2, 2020.
PIRYONESI, S. MADEH, AND TAMER E. EL-DIRABY. “USING MACHINE LEARNING TO EXAMINE IMPACT OF TYPE OF PERFORMANCE INDICATOR ON FLEXIBLE PAVEMENT DETERIORATION MODELING.” JOURNAL OF INFRASTRUCTURE SYSTEMS, VOL. 27, NO. 2, 2021.

PRADEEPKUMAR, DADABADA, AND VADLAMANI RAVI. “FORECASTING FINANCIAL TIME SERIES VOLATILITY USING PARTICLE SWARM OPTIMIZATION Trained Quantile Regression Neural Network.” APPLIED SOFT COMPUTING, VOL. 58, 2017, PP. 35-52.

TIMMERMANN, ALLAN, AND CLIVE W. J. GRANGER. “EFFICIENT MARKET HYPOTHESIS AND FORECASTING.” INTERNATIONAL JOURNAL OF FORECASTING, VOL. 20, 2004, PP. 15-27.

“TODAY’S CRYPTO CURRENCY PRICES BY MARKET CAP.” COIN MARKET CAP, HTTPS://COINMARKETCAP.COM/. ACCESSED 21 4 2021.

“TOP CRYPTO CURRENCY SPOT EXCHANGES.” COIN MARKET CAP, HTTPS://COINMARKETCAP.COM/RANKINGS/EXCHANGE S/. ACCESSED 24 4 2021.
APPENDIX A: USED TECHNICAL INDICATORS AND THEIR FORMULAS

In this appendix we introduce the technical indicators used in this project and their respective formulas.

Commodity Channel Index (CCI):

\[ CCI = \frac{Typical\ Price - MA}{0.015 \times Mean\ Deviation} \]

where:

Typical Price = \( \sum_{i=1}^{P} \frac{(High + Low + Close)}{3} \)

P = Number of Periods

MA = Moving Average

Moving Average = \( \frac{\sum_{i=1}^{P} Typical\ Price}{P} \)

Mean Deviation = \( \frac{\sum_{i=1}^{P} |Typical\ Price - MA|}{P} \)

We have used this indicator in 14 and 30 periods in this project.

Relative Strength Index (RSI):

\[ RSI_{\text{Step\ one}} = 100 - \frac{100}{1 + \frac{Average\ Gain}{Average\ Loss}} \]

The average gain or loss used in the calculation is the average percentage gain or loss during a look-back period. The formula uses a positive value for the average loss.

Once there is first step data available, the second part of the RSI formula can be calculated. The second step of the calculation smooths the results:

\[ RSI_{\text{Step\ two}} = 100 - \frac{100}{1 + \frac{(Previous\ Average\ Gain \times (Period - 1)) + Current\ Gain}{(Previous\ Average\ Loss \times (Period - 1)) + Current\ Loss}} \]

We have used this indicator in 14 and 30 periods in this project.

Directional Movement Index (DMI):

\[ DX = \left( \frac{|DI^+ - DI^-|}{|DI^+ + DI^-|} \right) \times 100 \]

where:

\[ DI^+ = \left( \frac{Smoothed\ (DM^+)}{ATR} \right) \times 100 \]

\[ DI^- = \left( \frac{Smoothed\ (DM^-)}{ATR} \right) \times 100 \]

DM+ (Directional Movement) = Current High − Previous High

DM− (Directional Movement) = Previous Low − Current Low

ATR = Average True Range

Smoothed (x) = \( \sum_{t=1}^{\text{Period}} x - \frac{\sum_{t=1}^{\text{Period}} x}{\text{Period}} + CDM \)

CDM = Current DM

We have used this indicator with period=14 in this project.

Moving Average Convergence Divergence (MACD):

\[ MACD = EMA_{12\ \text{Period}} - EMA_{26\ \text{Period}} \]

Bollinger Band®:

\[ Boll = \frac{Boll_U + Boll_D}{2} \]

\[ Boll_U = MA(TP,n) + m \times \sigma[TP,n] \]

\[ Boll_D = MA(TP,n) - m \times \sigma[TP,n] \]

where:

Boll_U = Upper Bollinger Band

Boll_D = Lower Bollinger Band

MA = Moving Average

TP (Typical Price) = \( \frac{(High + Low + Close)}{3} \)

n = Number of Days in Smoothing Period (Typically 20)

m = Number of Standard Deviations (Typically 2)

\( \sigma[TP,n] \) = Standard Deviation over Last n Periods of TP