Can ANN-GARCH model prove statistically significant over the state of the art in forecasting the price volatility of the Ethereum?

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***Abstract*—With a market capitalization of the US $18 billion, Ethereum is the second most popular cryptocurrency traded. With such a significant market share, it has captured the interests of many, from academicians to investors to the blockchain application developers. Even after being so popular, research in this area of cryptocurrency is scarce. This research paper is targeted to answer the question if ANN-GARCH model proves statistically significant over the state of the art in forecasting the price volatility of the Ethereum. This research will contribute to the academic community in having a better understanding of this new asset along with the insight if hybridization techniques can work well with such a volatile asset. Variations of GARCH and ANN will be statically tested to get the answer to the proposed question. This research looks promising with the features of ANN for detection of nonlinearity combined with volatility prediction GARCH to accurately predict the volatility.**

I. Introduction

As one of the major asset class, cryptocurrencies are gaining huge popularity among the academicians and investors. With market capital more than $170 billion and increasing, cryptocurrencies are becoming major part of global economy (CoinMarketCap, 2019). With the rise in market capital, there is also rise in number of cryptocurrencies which are making their way to the market. Apart from major players, such as Bitcoin, Ethereum, Ripple, there are more than 2000 cryptocurrencies in circulation (CoinLore, 2019). The first cryptocurrency, Bitcoin, is designed to transact money anonymously with full transparency, thus challenging the working of traditional financial institutions. This asset class is new and has started becoming popular in recent days. Also, this asset class is very loosely regulated thus making it more uncertain and volatile for prediction. These factors make it very fascinating for researchers and academicians to explore this modern space.

Ethereum which is the second most popular cryptocurrency has a market capitalization of $18 billion (CoinMarketCap, 2019). Ethereum is a unique cryptocurrency in itself. It can be transacted for execution of applications along with transfers as payment. Lot of research is being done in for predicting the prices and volatility of Bitcoin but relatively less efforts are put in towards analysis of Ethereum. Thus making it vital for this research.

This research is aimed towards finding an answer to the following question:

Can ANN-GARCH model prove statistically significant over the state of the art in forecasting the price volatility of the Ethereum?

Artificial Neural Network (ANN) and General Auto-Regressive Conditional Heteroskedasticity (GARCH) are the two machine learning techniques used in this research for forecasting the volatility. Nonlinear effects of volatility can be detected by using ANN which are not captured by GARCH and its derivatives (Kristjanpoller and Minutolo, 2018). Thus improvising on traditional GARCH and its variations, hybridization looks promising in delivering the statistically significant results for forecasting.

To understand the Ethereum as a cryptocurrency and how the hybrid models perform on such volatile asset class, following objectives are defined:

*1) **Building models for forecasting volatility of Ethereum with variations in ANN configurations and suitable GARCH derivatives.***

*2) **Comparing these models with each other to find the best fit model.***

*3) **Comparing the best fit model with the state of the art in the Ethereum volatility forecasting space.***

*4) **Highlighting the key differences between Ethereum and Bitcoin.***

This research will only consider the facts presented in the literature review for attaining the 4th objective. It will be very interesting to see the behavioural similarities and differences between the two major cryptocurrencies.

The next section of this paper will shed light on literature reviewed in the space of cryptocurrency. It will also consist of review on the use of such hybrid models previously and their findings. Lastly, it will talk about the state of the art in forecasting volatility of Ethereum. Following this will be the proposed methodology to carry out this research followed by the results. Final section will include conclusion and discussion about the future work.

Limitation of this research will be, as the number of iterations and layers are increased in ANN, it may become overfit for this dataset.

II. Related Work

According to the researchers Pichl and Kaizoji (2017), there is very limited research regarding cryptocurrencies in the past. Most of which revolves around bitcoin and it seems to be increasing every year. As discussed in the earlier section, cryptocurrency market is very loosely regulated, thus there are few researchers who are exploring this space and trying to standardize the regulations which can help governments (Böhme et al., 2015). In this paper, researchers talk about various risks and how cryptocurrencies like Bitcoin can be used for illegal activities. Similarly, Lu and Tu (2015) speak about their concerns about capital movement and active Bitcoin market in China. They also speak about how imposing regulations by People's Republic of China has helped in stopping capital flight completely.

On the other hand researchers such as (Brière, Oosterlinck and Szafarz (2015) talk about investment opportunities of the cryptocurrencies such as bitcoin and how it can help in making a portfolio stronger. They talk about how bitcoin is proved to have great returns in short period of time. Their research consists of only the upward trend thus missing out the major trench during 2017. Bhattacharjee (2016) compares about the forecasted returns of Dollar, Euro and Rubel's across the Bitcoin. Researcher uses GARCH (1,1) and GARCH(1,2) to forecast the volatility testing thus concluding, the returns on fiat currencies were likely to remain constant whereas bitcoin has shown high volatility.

Dumitrescu (2017) in their research talks about in detail advantages and disadvantages of cryptocurrencies. Paper covers four major advantages which are personal data protection, how it can lower the transaction fees, fast and transparent transactions will avoid fraudulent and overhead charges and even after being volatile at this stage, how it will reach a point where it will be immune to inflation. This research also highlights some of the key concerns, such as lack of solid anonymity, Ponzi schemes around cryptocurrencies, and the trust issues it faces due to its newness.

In the research paper, authors discuss about the uniqueness of the Ethereum as a cryptocurrency (Wang et al., 2019). They state substantial amount of the funds and accounts for Ethereum are managed by smart contracts. Though their research focuses on how to reduce the costs for executing smart contracts, they briefly talk about the factors affecting the Ethereum pricing.

In the whitepaper published on Ethereum, the author speaks about how Ethereum is an updated version of cryptocurrency with advanced features such as withdrawal limits and financial contracts. The underlying protocol says to be Turing-complete which would theoretically allow any type contract to be designed for transaction or application. Author claims to have this protocol open ended so that people can use it for developing non-financial applications as well (Buterin, V. ,2014). With all this said, it seems that the pricing of Ethereum is not only based on economic factors, but also based on variety of other factors including creation of smart contracts, developing new decentralized applications. Thus making it very novel in itself.

Talking about the research carried out in this domain, it mostly carried on Bitcoin which is the leading cryptocurrency. Few researchers have carried out the research on the social media sentiment and popularity of the Bitcoin. Number of Reddit posts and the education level of the person were the few parameters considered for their research. They found an interesting fact that the around 60 % of the people were from middle school (Narman, Uulu and Liu, 2018). In another research, 500,000 tweets consisting of altcoins over a period of 71 days were analysed to predict the short term returns using machine learning techniques such as linear regression (Steinert and Herff, 2018).

One of the researcher applied GARCH model on Bitcoin, Gold and US Dollar to compare its results in a portfolio management. She found out that the portfolio consisting with bitcoin yielded more profits thus suggesting the inclusion of cryptocurrency in the portfolio (Dyhrberg, 2016). But this research was carried out when the Bitcoin prices were at its paramount. Thus their claim of suggesting Bitcoin inclusion for risk averse users stands questioned.

In one of the papers, authors fitted twelve GARCH models to the seven most popular cryptocurrencies at that time. Their research concluded that IGARCH and GJRGARCH models were best fit for forecasting the volatility of majority of these cryptocurrencies. They suggested that the this asset is good for the individuals who can afford taking risk. Their research uncovered an important facts that for some cryptocurrencies, IGARCH(1,1) model was best fit where as for other GJRGARCH(1,1) was best fit whereas for Ripple GARCH(1,1) was best fit (Chu et al., 2017). This also suggests that the prices and volatility of the underlying cryptocurrencies vary. Due to data constraints, they did not consider Ethereum for this research thus invoking curiosity about the same for our research paper.

One of the authors used GARCH variations for fitting the Bitcoin prices and found that AR-CGARCH had the optimal fit. They have included long-run as well as short run component of conditional variance to obtain the results (Katsiampa, P., 2017). hey measured the results based on Akaike information criterion (AIC) and Bayesian information criterion (BIC).Outcome of this research was similar to that done by Bouoiyour and Selmi (2016).

In another research, authors performed an econometric analysis on the Cryptocurrency Index. They found that TGARCH(1,1) was best fit with respect ot the AIC, BIC and log likelihood. They also compared it with traditional ARIMA Models (Chen et al. , 2016).

Using the Artifical Neural Network (ANN) for doing analysis on time series data for forecasting has been in use since decades. One of the early spotting of use of ANN too was to predict stock returns of IBM. Although, the results of early studies were not that great, but it provided researchers with foundation to build upon (White, H., 1988). On the other hand, some of the researchers analyzed stock markets in big cities like London and New York for which they used ANN in combination with GARCH model. This combination was able to predict the volatile components. They found the interesting fact that Neural Networks can capture the volatile components which GARCH model alone was not able to capture (Kryzanowski, Galler and Wright, 1993).

In one of the papers, author proposed hybrid models along with neural networks and time series model for stock market prediction. Direction and deviation are the points considered for prediction of the price index volatility. This model gave accurate results when applied to South-Korean market (Hyup Roh, 2007). One of the researcher, combined the artificial neural network model with hybrid asymmetric volatility approach which showed improved results in determining the prices of financial derivative in Taiwan's market (Tseng et al., 2008).

In one of the study, stock market of Istanbul was analyzed by the researcher. He integrated the neural network model with one of the derivatives of GARCH model. The data used for the research was the daily closing values of the ISE National-100 index from October,1987 to February,2008. This data is not only asymmetric and nonlinear but also shown strong volatility clustering. These properties of data makes the research more interesting. They compared the combination of GARCH, EGARCH, SAGARCH, PGARCH, NPGARCH, TARCH, APGARCH, GJR-GARCH, NPGARCH with Artificial Neural Network models. They proposed ANN-APGARCH model which gave improved forecasting results (Bildirici and Ersin, 2009).

It can be seen that there is rapid evolution in forecasting volatile component in financial markets. To improve the results, researchers explored the use of hybrid models. Researchers have started merging artificial intelligence models like support vector machine genetic algorithm with traditional models. As mentioned earlier, many of the researchers have proved that the combination of artificial neural networks with time series forecasting models yielded better results for different stock markets. Thus artificial neural networks play an important role in volatility prediction.

Cryptocurrencies, nowadays, are growing rapidly in world's economy. Researchers are working towards building the prediction models for different digital currencies. In recent studies, machine learning algorithms are applied to predict the price of Bitcoin which is the most popular cryptocurrency. Exchange rate of Bitcoin is highly volatile and hence prediction of same is challenging. It is important to predict the bitcoin rates for financial markets. An algorithm was proposed wherein the recurrent neural networks are combined with Tree classifier which gave the most accurate results in determining Bitcoin's exchange rate (Mallqui and Fernandes, 2019). In another research, returns on bitcoin's intraday trading are predicted using 7 layered ANN model. Different combinations of input, output and hidden layers are compared to investigate the performance of ANN.(Nakano, Takahashi and Takahashi, 2018).

In another research,a new prediction framework to forecast daily prices of bitcoin was proposed. They used Long short-term memory (LSTM) networks in predicting results. They evaluated the performance by using daily bitcoin price data over period of 7 months which consisted of 208 records. The results showed best results when LSTM was combined with AR(2) model instead of tradition LSTM model. This study contributed a new prediction framework for cryptocurrencies (Wu et al., 2018).

III. METHODOLOGY

This research will follow the CRISP-DM (CRoss Industry Standard Process for Data Mining) methodology to ensure the consistency of the research (Wirth, R. and Hipp, J., 2000). Following is the pictorial representation of the steps involved in CRISP-DM.

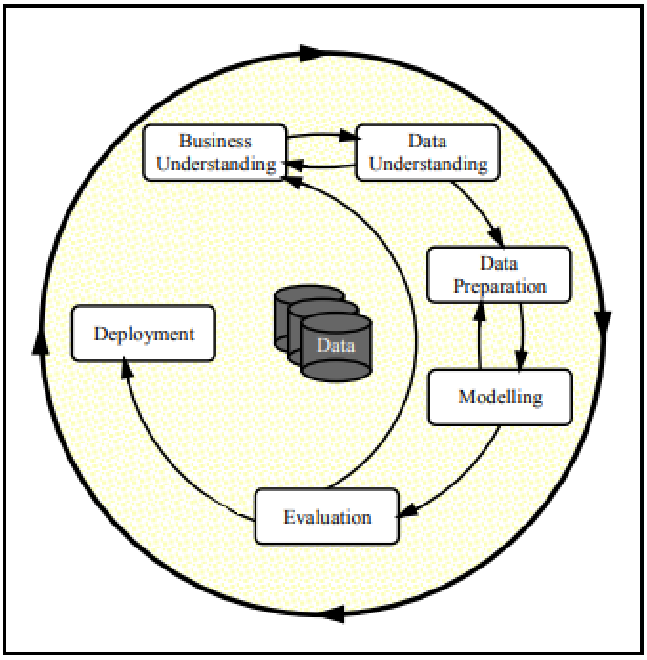

Fig. 1. Cross-Industry Process for Data Mining.

A. Business Understanding

As we have already covered the uniqueness of Ethereum in the above sections, predicting its prices and volatility is major challenge. There are lot many factors which may affect the pricing. Also, there is very little work in place to forecast this asset class. This paper will focus on forecasting the price volatility of Ethereum by using historical data of its stock price.

B. Data Understanding

To move ahead with the research, data is fetched from Quandl. Closing prices of Ethereum with frequency as daily will be considered. This data will be obtained from BTIFinex Exchange (Quandl.com, 2019). Quandl code for the same is "BITFINEX/ETHUSD". Data from 14th March 2016 to 28th February 2019 will be used for this research.

This data will be fetched in R. Plot will be generated to understand the data. By looking at the plots we might understand the volatility of the data and general trend. It may help in answering few questions like how often are the sudden spikes in the whole dataset, Is there any pattern which is followed by the data.

C. Data Preparation

Before preparing the data, we might need to run few tests on the data set. Augmented Dickey-Fuller test

(Fuller, W.A., 2009) will be run on the dataset to test for the stationarity with respect to the level of confidence. Along with this Jarque-Bera test for checking the normality will be used to identify the skewness in the data if any.

Data will then be scaled to its logarithmic value so as to fit it for ANN.

After this the data will be decomposed to find the stationarity and seasonality. Once identified, the next step will be run the auto.arima() function to find the p, d, q co-ordinates for the timeseries. These p, d, q will then be passed to the Engle's LM test for ARCH to check for the presence of Heteroskedasticity in the data (Engle, 1982). Once this test is done , rejecting the null hypothesis will prove the presence of heteroscedasticity in the dataset. If non linearity is detected, then ANN proves to be appropriate method.

D. *Modeling*

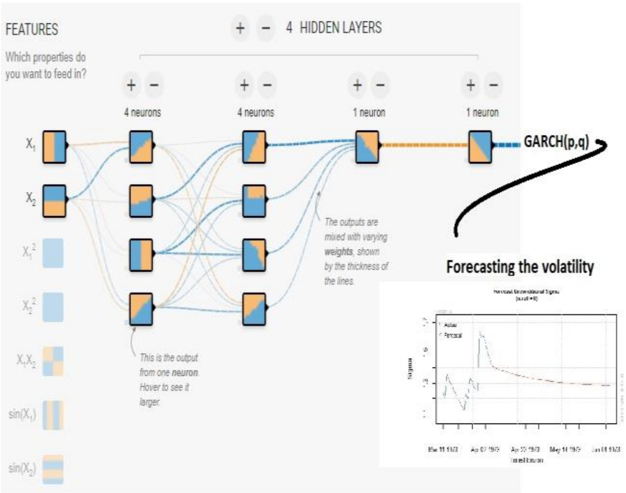

Fig. 2. ANN-GARCH Reresentation.

Engle (1982) put forth the model by taking into consideration, the heteroscedasticity of timeseries data with the ARCH model and the generalization of ARCH model. These models are described by the following equations,

$$r_t = \alpha_0 + \sum_{i=1}^{k}\beta_i r_{t-1} + e_t \qquad ...(1a)$$

$$e_t|\psi_{t-1} \sim N(0, h_t) \qquad ...(1b)$$

$$h_t = c + \sum_{i=1}^{p}\theta_i e_{t-i}^2 + \sum_{j}^{q}\beta_j h_{t-j} \qquad ...(1c)$$

where k is autoregressive order of the mean of the equation, p is order of the lagged squared error and q is the order for the lagged variance (Engle, 1982).

Next GARCH model that will be used is APGARCH (Asymmetric Power General Autoregressive Conditional Heteroskedasticity) model. Power term d is included in the original GARCH model to keep check on the variance in the Eq. (2c). It allows linear relationship thus making itself as a stochastic volatility model with standard deviation d = 1.

$$r_t = \alpha_0 + \sum_{i=1}^{k}\beta_i r_{t-1} + e_t \qquad ...(2a)$$

$$e_t \sim N(0, h_t^{d/2}) \qquad ...(2b)$$

$$h_t^{d/2} = c + \sum_{i=1}^{p}\theta_i(|e_{t-i}| + \omega e_{t-i})^d + \sum_{j=1}^{q}\beta_i h_{t-j}^{d/2} \qquad ...(2c)$$

As few researches have shown that EGARCH model is also noteworthy in volatility prediction of timeseries data, thus EGARCH model is described by the equations below.

$$r_t = \alpha_0 + \sum_{i=1}^{k}\beta_i r_{t-1} + e_t \qquad ...(3a)$$

$$e_t \sim N(0, h_t) \qquad ...(3b)$$

$$\log(h_t) = c + \sum_{I=1}^{P}\theta_i \frac{e_{t-i}}{h_{t-i}} + \sum_{j=1}^{q}\beta_j \log(h_{t-j}) + \gamma\left|\frac{e_{t-i}}{h_{t-i}}\right| \qquad ...(3c)$$

Also, various tests such as AIC (Akaike information criterion), BIC (Bayesian information criterion), CAIC (Consistent Akaike Information Criterion), AICc (corrected Akaike Information Criterion) and Hannan – Quinn criterion. will be used to check the maximum likelihood of the GARCH fit. Lower the values of these tests, higher will be the best fit probability of that GARCH model (Burnham and Anderson, 2004).

Artificial Neural Network is considered as one of the major machine learning technique in doing analysis on the financial data. Multi-Layer Perceptron(MLP) is feedforward artificial neural network. It has at least 3 layers, viz. input, output and hidden layer in between. It uses nonlinear activation function to classify the data which is nonlinear in nature. MLP may have multiple layers. Total number of layers are denoted by L, whereas total number of neurons per layer are denoted by N and I denotes the total number of input of the network, θ_j^l is the activation function for layer l and unit j, Ψ_1^L is linear activation function for l as layer L and $w_{j,k}^1$ as the weight from i unit if the previous layer to j unit in layer 1. Thus MLP is mathematically denoted by:

$$S_j^1 = \sum_{k=1}^{I} w_{j,k}^1 \qquad \forall j \in N$$
$$A_j^1 = \theta_j^1 (S_j^1) \qquad ... (4)$$

$$S_j^1 = \sum_{i=1}^{N} w_{j,i}^l A_i^{l-1} \qquad \forall j \in N$$
$$A_j^1 = \theta_j^l (S_j^l + b_l) \qquad \forall l \in \{2, \ldots., L-1\} \qquad ... (5)$$

$$S_j^1 = \sum_{i=1}^{N} w_{1,i}^{L-1} A_i^{L-1}$$
$$A_1^L = \Psi_1^L (S_1^L) \quad \dots (6)$$

Equation 4 is for the first layer whereas equation 5 is for the hidden layer and equation 6 for the output layer (Rumelhart, Hinton and Williams, 1986).

Model will be fitted with 1 hidden layer first then gradually increasing it to 2, 3 and finally 4 to observe the changes. Each layer will have 5 neurons and then it will be increased with 5 neurons each iteration to 10, 15 and 20 neurons.

E. *Evaluation*

Mean Square Error (MSE) is used to find the error in the actual and the forecasted values. It is chosen because of its robust nature. Also, Model Confidence Set test (MCS) is used to check for the p-values of the tests for each model. To further sure, we use student's t-distribution test to check statistical significant testing. Along with this General Error Distribution test is used to check for the distribution of error which can be used as a statistically significant measure.

IV. Results

In one of the papers, GARCH, EGARCH and APGARCH models were used. Order of k, p and q were set changed from 0 to 2 with each iteration. The sliding window sizes were kept as 63 days, 126 days, 189 days, 252 days and 278 days. Thus the total number of models formed were 120. Model with EGARCH and sliding windows over 252 days appeared to be best amongt all. Similar kind of result is expected in this research for Ethereum. Mean Squared Error (MSE) is used to identify the best model (Kristjanpoller and Minutolo, 2018). It was also identified that the term period and MSE are inversely proportional. After collinearity test with the traditional indicators, M12, S-RSI and BUB were considered to compare the indicators.

After identifying the 12 best forecasting models, these were then fed to the ANN. Where each time the configurations used were changed from 1,2,3 and 4 hidden layers to 5, 10, 15 and 20 neurons with the sliding window of 252 days. With 1 hidden layer and 10 neurons, the mean squared error was reduced by 3.32%. Interestingly when the number of neurons were increased to 5 and 44 days were the sliding window the MSE reduced by 4.53%. It was found that the best hybrid model with the MSE reduced by 4.99% was the one with 2 layers, 5 neurons. The best hybrid model for the similar kind of research was the one with few layers and few neurons. Similar kind of results are expected in this research paper.

V. Conclusion

Results of this research will be very much worth noticing. It will hugely contribute to the literature in cryptocurrency space apart from Bitcoin which is a big plus point. Also, it will help the academicians to verify the outcome of the hybridisation of GARCH and ANN on highly volatile asset class. It will also help the investors to learn more about the future trends of Ethereum. Also, investors will be able to know the impact of inclusion of Ethereum in a portfolio with respect to the volatility thus measuring the risk of the same.

VI. Future Work

Once these results are obtained, remaining GARCH Derivatives such as GJR-GARCH (1,1), TGARCH, IGARCH (1,1) etc. will be tested. Also, advance Neural Network technique such as Long Short-Term Memory will be tested after successful completion of this research.

There is substantial amount of work that can be done after this research. To test all the variations of ANN and GARCH will require more time. Also, few of the tests such as KPSS can be run on the same set of data and models to double check their significance. It can be used as a benchmarking for carrying out further research in the domain of cryptocurrencies.

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