Integrating Machine Learning to IOTA: A Secure Intelligent Stock Market Model

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***Abstract*—Worldwide stock markets are investigating the best feasible alternative that can enhance trading efficiency while reducing danger and improving safety. Today, nearly all prominent stockmarkets such as the New York Stock Exchange, the London Stock Exchange, etc. are searching for a feasible alternative for a decentralized and safe stock exchange model. Because of its intrinsic capacity to provide a decentralized, safe network, the use of blockchain has recently been suggested to tackle these problems. However, blockchain suffers from problems with scalability, velocity and increased transaction fees. In this paper, we introduce a method centered on Distributed Acyclic Graph (DAG) for stock exchange management using IOTA. To create the model more smart and safe in the future, we train a neural network model using the Long Short-Term Memory Neural Network (LSTM), which can forecast future stock price fluctuations. When a customer creates a transaction, he gets a forecast of stock price variability. Once the transaction is verified, the transaction is added to the distributed IOTA network ledger. The model offers a fair and stable and safe stock exchange industry. The LSTM model achieves 99.71% accuracy with a mean square error of 0.0004 on the test dataset.**

***Index Terms*—Blockchain , Commerce , IOTA , Stock Exchange , LSTM , FinTech**

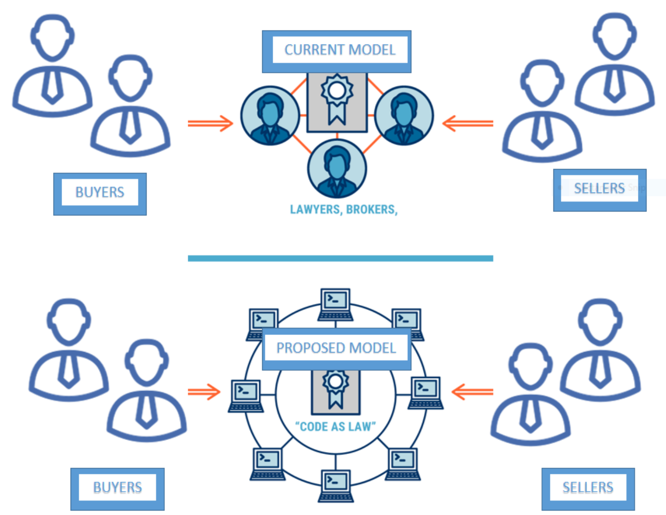

Fig. 1: Current Vs Proposed Model

I. Introduction

The origins of stocks and stock markets date back to the 11th century, when businessmen traded on brokerage debts. It gained momentum in the 13th century when Venice merchants began selling [1] government securities. Stock trading has since developed and drastically altered. Today, the biggest economy revolves around stock markets where millions of worth of everyday assets are traded. In principle, a stock exchange is a key authority that mediates in stock trading in the form of stocks, bonds and other financial instruments between brokers, stock traders and investors [2]. Additionally, traditional stock exchange acts as a facilitator for issuing and redeeming such financial instruments, including the payment of dividends [3], [4].

In recent decades, the stock market has moved away from over the counter trading and has become excessively dependent on computerized systems to handle the enormous number of transactions within the constraints of time. Even though these automated systems claim to be secure and have a lot of focus on ensuring the authenticity of the deal, these systems are still highly susceptible to tampering. This is because they serve as central and singular points of failure, which if compromised, can lead to disaster [5]. Stock exchanges spend lavishly to maintain and secure their operations, which in turn lead to high transaction fees borne by the buyers and sellers on the market [6].

The current stock markets are strewn with issues of centralized architectures. In such markets, central components gather all the data and register them at one central server. In such a scenario where the third party owns the network over which transactions are happening, the network can become an easy target for attackers, and since the server is a single point of failure, this system is susceptible to even more damage [7]. Also, having a central authority managing every transaction in the order provides for the authority to control and set the prices for processing transactions and other fees. Furthermore, the existing system is heavily dependent on intermediaries, also called brokers in the market jargon who act on behalf of the client in exchange for a fee. Another major issue with the traditional method is the long processing times and long settlement delays. This virtually destroys the dynamic nature of the stock markets.

Many researchers started on blockchain-based stock market solution. Blockchain will solve the major issues faced by the stock markets such as insider trading, third-party involvement, price control, security vulnerabilities, fairness, and centralization. However, the significant problems associated with the blockchain is its lack of scalability and relatively slow transaction times. Therefore it is now seen that conventional blockchain system fail to fulfill the requirements of stock market model [8]. Therefore we propose a solution to all these problems as mentioned above as shown in Fig. 1.

New York Stock Exchange and London Stock Exchange are working to create an intelligent stock market model that would be publicly available to all and provide real-time stock market prediction to a user providing a fair and equal ground to all the stakeholders. Stock market prediction determines the company stock's value in the future. Accurate prediction of future price of a stock can help in increasing the profit significantly. In the case of a centralized system to have a predictive model is more manageable; however, as already discussed, such an approach is highly insecure. So in this paper, we propose a stock market prediction market, which is entirely decentralized and secure.

The flow of the paper is as follows. Next section discusses the related works. Part III describes the proposed model. Section IV discusses the machine learning model. How transactions are added to the IOTA platform is discussed in section V. Section VI presents security analysis, and section VII discusses the simulation and results. Finally, the conclusion is presented in section VII.

II. Related Works

The current stock exchanges understand the limitations of centralized architecture. With the advent of blockchain and its PoTEential to disrupt long-established centralized systems, the tech industry is set up for a new revolution. Blockchain has already shown a deep impact on how we transact and keep a record of money and finances. Its PoTEential to simplify stock trading in a global market is the focus of today's community. Although still a topic of research and a long way from being perfect, blockchain technologies, are seen as an area of exploration by several companies and startups [3], [9].

Institutions dedicated to the stock market have begun dabbling with the cryptocurrency markets. Banking heavyweight Morgan Stanley is estimated to have invested 2 billion dollars into cryptocurrencies from hedge funds over the last year. TraderView [10], a social community providing tools for stock traders, has listed many major cryptocurrency pairs on its site. Also, Robinhood [11], an app that introduced stock trading to a new generation of investors, announced plans to collaborate with ethereum and bitcoin on its platform. However, adding cryptocurrency to stock exchange does not fundamentally address the root of the stock market centralized structure. Although it provides, a broader and broader domain, yet the security vulnerabilities still exist. Nasdaq stock market, which is the 2^{nd} largest global stock exchange is working on using blockchain to change its working fundamentally. Recently, it agreed with blockchain startups for testing the shared trading in its private network. The information on shares was kept a secret to public [12]. Blocko Inc, a blockchain startup in Korea, has the mission of making the enterprise based on blockchain. It handles all the complexities in implementing blockchain technology in stock market companies [13]. The blockchain-based stock market solutions are also in the building phase and require a lot of endeavors to be successful. The main problems with blockchain are the issues of scalability, miners, and validating nodes. Each entity must maintain a history of all the transactions until that time, which puts storage and computational limitations to participate in the model.

Some stock exchanges such as the New York Stock exchange and London stock exchange are working on making the stock exchange intelligent. The idea is that transactions would be able to predict the future values of the stocks. Stock market prediction task is difficult and cumbersome due to time series degree of variation. Jegadeesh et al. [14] studied how different predictive signals influence the market. Neural networks have an excellent capability in learning patterns and subtle changes. Krauss et al. [15] employed deep learning and random forest for dynamic stock market prediction. However, many solutions exist that have achieved good accuracies for stock market prediction, but none of the approaches have been applied for a decentralized system model.

We propose a decentralized stock market solution using IOTA. When a user makes the transaction, he calls a smart contract to make his transaction. A smart contract is simply a computer protocol that allows the performance of trackable and irreversible transactions without the involvement of third parties. In our solution, the Smart contract as part of protocol gets the live prediction of stock values, and it finally makes a transaction to IOTA platform. IOTA is based on DAG-based structure, where each node can add its transaction anywhere in the graph. It eliminates the need for storage requirement and the need for separate validating nodes or transaction fees. This is because each node is a validating node. The major contributions of this paper are as follows:

- This paper proposes a completely secure and decentralized stock market model on IOTA platform.
- Smart contracts are deployed on IOTA platform. These smart contracts via a decentralized system can be accessed by all and can be stored securely. Smart contracts eliminate the need for any intermediary entities providing a secure way to access the LSTM model.
- Our model incorporates an LSTM based machine for a stock market prediction that achieves an accuracy of 99.71% on New York Stock Exchange dataset.

III. Proposed Method

When a buyer wants to buy the stocks, he makes a transaction by calling a smart contract, specifying the company and the number of shares that need to be transferred. Smart contracts are a computer code running on a platform containing a set of rules under which the users to that smart contract agree to work with each other. If and whenever the provisions of the agreement are satisfied, the deal is processed further. Smart contracts on receiving the information access the machine learning model (a separate entity from Smart contact) for getting the future prediction.

The machine learning model is trained on previously built transactions in the distributed ledger. Machine learning model receives the information of the company the user is interested in investing. The description of the model is explained in the next section. Model outputs a matrix of the number of days

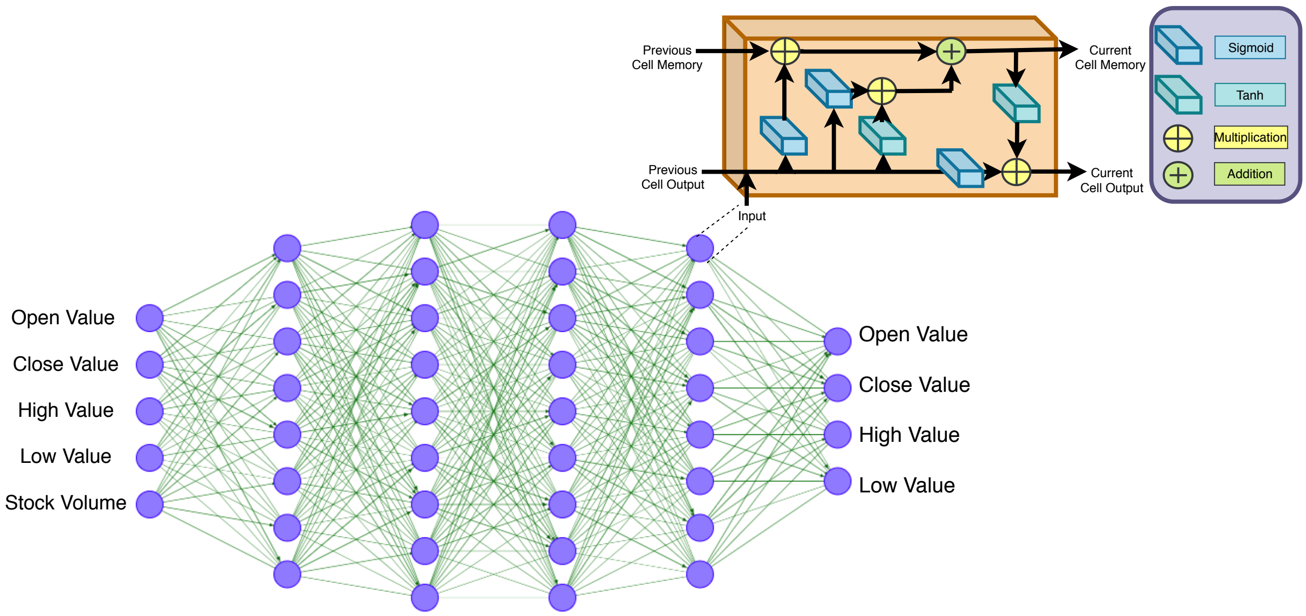

Fig. 2: Neural Network architecture using LSTM Cell

vs. stock price variation to the smart contract. Smart contract returns the matrix to the user and waits for the user to confirm the transaction. On the user's confirming the transaction, the transaction gets added to the IOTA network. The process of a transaction's being added to the IOTA network is described in detail in section VI.

IV. Architecture & Methodology of Machine Learning Model

With the growth of artificial intelligence domain, systems are evolving to become smarter. Current studies on stock exchange market use machine learning models with handcrafted features. However, manually creating these features is a complex and cumbersome task. Some of the solutions proposed such as [16], [17] have come up in predicting the stock market using neural networks, backpropagation networks, convolutional networks with highest prediction accuracies achieved through Recurrent Neural Networks (RNN). RNN's are very useful in learning the short term dependencies and correlations. However, the problem with the stock exchange model is that they can't take a long history into account [18]. So we employ Long short-term memory neural network (LSTM) model for making the stock market predictions.

Sepp Hochreiter and Juergen Schmidhuber to enhance the RNN, proposed Long Short-Term Memory (LSTMs) to solve the vanishing gradient problem faced in RNN's [19]. LSTM has much better performance over RNN due to their remembering the inputs for a longer duration of time. LSTM deals with the exploding and vanishing gradient problems. LSTM can be seen as a computer memory. Like an ordinary computer, it can read, write, and delete the information based on the relevance of data. The cell structure of the LSTM has been presented in Fig. 2. It has a cell that is made up of gates. Gates are small decision units having binary decision capability. It decides whether the information should be stored in a cell or not. It also assigns an essential factor in every piece of information by giving them weights. As shown in Fig. 2, LSTM has gates of 3 kinds: input gate (for input), forget gate (delete the information) and output gate (resultant information). These gates, like traditional nodes in neural networks, can decide whether to block or pass the information. The weights are adjusted similar to that in RNN. These gates are sigmoid and analog with the output range from 0 to 1. This is the reason that they can make the iterative process of making guesses using error backpropagation.

LSTM is an extension of RNN. Vanilla RNN is an LSTM with all input and output gates as 1, and forget gate as 0. In LSTM there are three gates, where the input denoted by i, the forget gate is indicated by f and the output gate represented by o. W is a recurrent connection at the current and previous hidden layer. U denotes weight matrix that connects the inputs to the existing hidden layer. C indicates hidden, which is evaluated based on the previous hidden state and the current input. It defines how last memory is combined with new input. At gates, the sigmoid function is used. Sigmoid function normalizes the value of inputs between the range 0 to 1. Then it multiplies the input vector i, element by element with weight matrix U, which is of the same size as of input vector. This operation ensures that only a degree of input is "let through" to output. The input gate controls the probability with which the newly computed states are passed to the output. Forget state works similarly, which decides the likelihood of the previous state to be passed to the output. Output gate defines the internal state that is exposed to higher layers.

These memory cells enable the network to associate memories effectively and to refer to entries remote in time. Thus they are capable of dynamically learning the structure of data over time with better predictability.

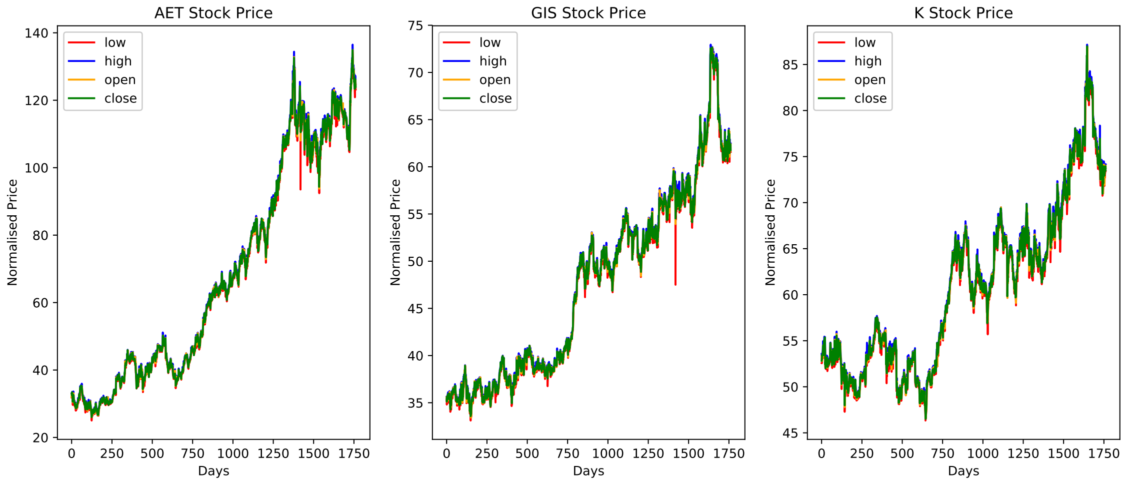

Fig. 3: Stock Market Prices for 3 companies “AET”, “GIS”,“K”

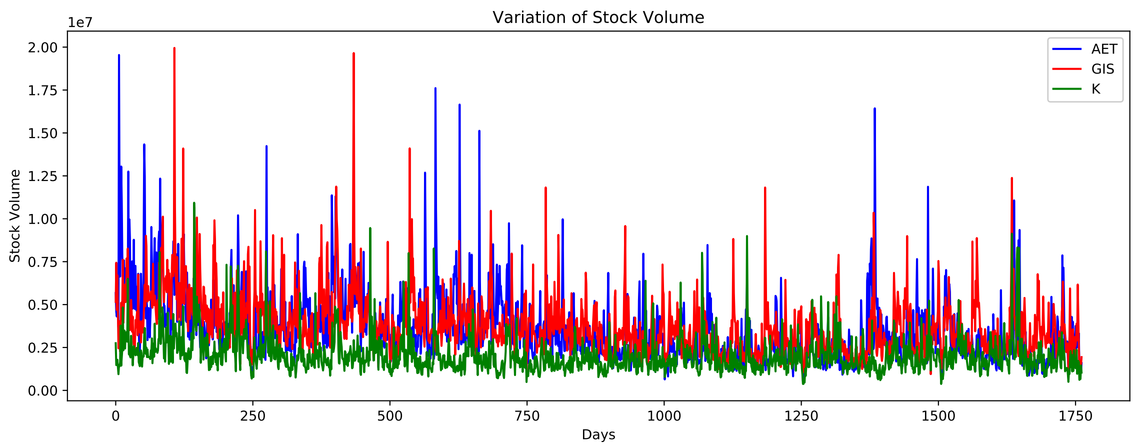

Fig. 4: Stock Volume for 3 companies “AET”, “GIS”,“K”

A. Methodology

Stage 1: Raw Data: This stage involves collecting historical stock data from the distributed ledger to use that for predicting the stock prices in the future. For training and testing purpose we have used New York stock exchange dataset. The dataset contains five columns for 501 companies: open, close, high, low, and stock volume for 6 years. The variation of stock price vs. the number of days and stock volume vs. the number of days for three companies is depicted in fig. 3 and 4, respectively. The 3 companies are Aethon Minerals Corp (AET), General Mills (GIS) and Kellog (K).

Stage 2: Data Preprocessing: Normalizing the data helps the algorithm inefficiently converging to the global/ local minimum efficiently. The pre-processing stage involves

- Data discretization
- Data transformation
- Date cleaning
- Data distribution

Stage 3: Training Neural Network LSTM takes a 3-D array as input having the following fields [batchsize, timesteps, Features].

- **Batch Size**: Using small batch size reduces the speed of training while using a larger batch size reduces the model’s ability to generalize to different data, and it also consumes more memory. We have set batch size as 50.
- **Time Steps:** It is the number of days back in time which the networks see to predict the result. We set it to 1394 days.
- **Feature:** The features for a company are in the form of vector consisting of date, open, high, low, close, and volume.
- **Optimizer:** We chose to use Adam optimizer as it uses a different learning rate for every parameter and every iteration. It provides a more sound descent since the gradient update uses moments of weights.

The features are fed into a network with random biases and weights. The LSTM model comprises of six layers with the

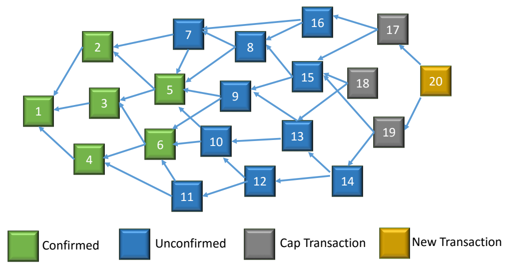

Fig. 5: Distributed acyclic structure of IOTA when a new transaction is added. The blocks are the transactions, and an arrow from transaction 9 to 5 depict that transaction 9 validates transaction 5. Green blocks are confirmed transaction, blue blocks are still unconfirmed, grey blocks depicts caps and yellow block represents new transaction.

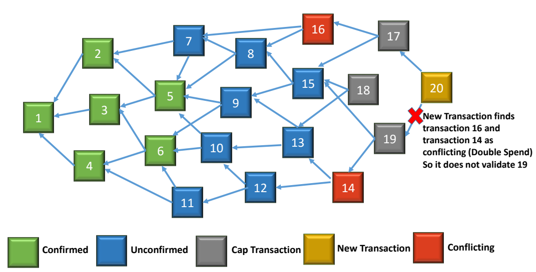

Fig. 6: A scenario when new transaction finds transaction 16 and transaction 14 as conflicting due to double spending. So it does not validates transaction 19. Hence as network grows, gradually the conflicting transactions will be separated from main chain.

first layer being a sequential layer, followed by four layers as LSTM layers and the final layer (i.e., the output layer) having linear activation function (as shown in Fig. 2).

V. Adding Transaction to IOTA platform

Once the LSTM model predicts the variation of future stock price variation, the user can change his transaction or can go ahead with the actual transaction. Once the user confirms a transaction, it is added to the network. The following steps are followed while adding a transaction to the network

A. Blocks & Transactions

Every transaction is a block instead of a combination of transactions in our system. The transaction includes stock details and digital asset records. The records such as the amount / stocks, buyer or vendor id, other entity details time stamp are associated with a valid transaction. Each node is equipped with a valid, personal digital signature. In order to ensure accuracy and authenticity, the information will subsequently be encrypted and signed by user. The signature can be verified by all the other nodes, but not fabricated or forged.

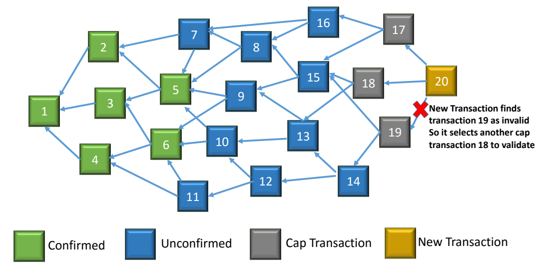

Fig. 7: When new transaction come, it validates the a transaction at random. If the transaction is invalid, it randomly chooses another transaction to validate. For instance, transaction 20 finds transaction 19 as invalid, so it chooses transaction 18 to validate.

B. Validation Phase

The transaction is shared among all authorized nodes. IOTA removes dependence on separate mining nodes. In the conventional blockchain, depending on the architecture chosen, the verifying nodes may vary. Any node could be a mining node or a verifying node in public blockchain. Although only chosen approved nodes can play that role, in the consortium blockchain model. These approved nodes have sufficient computational resources to achieve quicker consensus. However, this results in a requirement of separate transaction fees to be paid to the mining node. Yet, in our model, when a user makes a transaction, he has to validate two other transaction or blocks, as shown in Fig 5. The impetus to validate other transactions is that its transaction is added only when it validates two different transactions. Thus no separate transaction fees are required.

C. Validation of new transactions

This is a critical question, as it is which is heart of consensus mechanism. “ Cap” is used for non-verified end blocks. In Fig 5, the caps can be seen in blue. When a fresh transaction arrives, it is attached at the end of DAG. As other transactions come, the cap transaction is validated. Selection of nodes to be approved (cap) is done by picking from all caps at random.

D. Design Structure

The transactions are inserted in the form of a directed graph instead of a generic link list data structure. We design a directed acyclic graph as shown in fig. 5 to prevent loops as well as deadlock. A directed acyclic graph (DAG) is a graph that doesn’t have cycles. One can move from one node to another, but can’t return to starting node irrespective of the path taken. From one vertex to another, there is a directed edge. These vertexes here refer to blocks or transactions. An edge is considered as block validation. So a directed edge from block ’2’ to block ’z’ validates that transaction ’2’ has tested transaction z. The advantage of this structure is that it is possible to attach transactions very quickly at different locations in the graph. Another advantage is that a user can attach transaction to any sub-section of DAG, without requiring to store the entire DAG network.

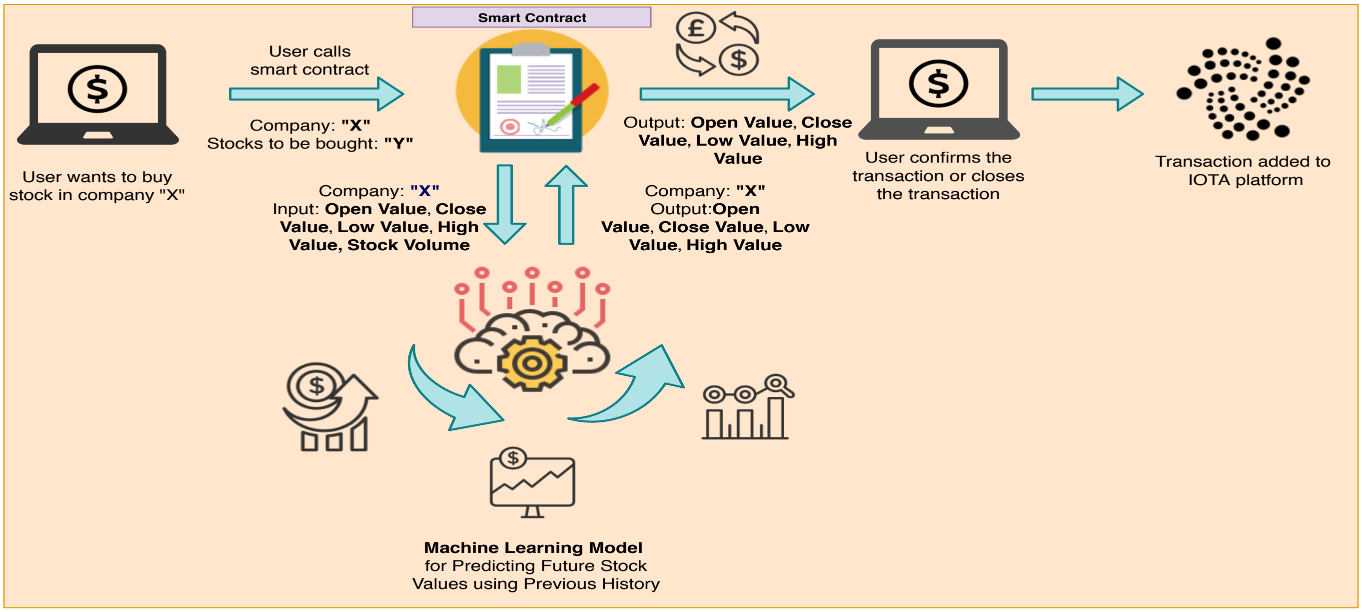

Fig. 8: When a user makes a transaction, the smart contract is invoked. A smart contract takes values from the user and makes use of a machine learning model to predict the future value of stocks in which the user is investing and gives its prediction. User can choose to continue with transaction or change. Finally, the transaction is added to the IOTA platform

E. Validation

Transaction validation is performed by inspecting the balance of the user. A transaction or block is considered confirmed when the majority of the transaction validates it. IOTA is based on the idea that more the network spams, faster is the confirmation of the transactions. Therefore its scalability increases with an increasing number of users. If malicious nodes validate a malicious transaction, the chances of their being validated decreases, thus it avoids malicious transactions to be confirmed.

F. Proof-of-Time

Spanning and Sybil attacks are avoided by incorporating time difference between the transactions that a user can make. Proof of work is used in blockchain to verify a transaction. Proof-of-work is spending some of the computational resources, which is necessary for node to gets its transaction validated before its added to blockchain. However, in here, it has limitations on who can be the mining node and therefore not scalable option. Decreasing the PoW computational task also impacts the network's privacy and makes it more vulnerable to ASIC assaults.So we introduce, Proof of Time Expenditure (PoTE) rather than Proof of Work (PoW). Whenever user makes a transaction, user must validate 2 other transaction. Also user can make another transaction after only a specified time. Since each transaction has a timestamp, the attacker can't fool the network by changing the time. PoTE also makes it expensive for an attacker to "surpass" the transaction of honest.

G. Consensus

Blockchain employs "longest chain" rule to reach consensus. Validated transaction are added only if they are validated by validating nodes. Every miner must devote computational resources, frequently known as proof-of-work. The consensus, however, is based on the most complicated chain in the intelligent chain. Whenever a node wishes to add a fresh transaction, the prior current transactions must be validated. The more directly or indirectly a transaction is checked, the safer it is. Unlike Blockchain, where a bifurcation of positions exists between the miners and the system users, all entities have an equal chance. The consensus mechanism is shown in fig. 7.

The end to end system model is summarised in Fig. 8. When a fresh transaction discovers a cap transaction invalid, it selects another cap for validation randomly. Transaction 20, for example, considers transaction 19 invalid, so it chooses to validate transaction 18.

VI. Informal Security Analysis

Figure 5 shows the At the moment of the present transaction, IOTA network. There are two cap operations to verify each new transaction. If the transaction validates both caps, they will be implemented into the IOTA network. However, if a transaction is discovered to be invalid, another cap as shown in fig will be selected randomly. 7.

1) **Spam & Sybill Attack Resistant** A malicious user can not send multiple transaction numbers simultaneously due to Proof of Time Expenditure that the node must perform.
2) **Model free from any Deadlock** There exists no likelihood of a deadlock because this approach employs a directed acyclic graph.
3) **Proof of No Starvation** Each cap transaction is randomly selected from all the caps. The probability of not selecting a cap after several evaluations is negligible. There is therefore no likelihood of starvation that a cap is not selected.

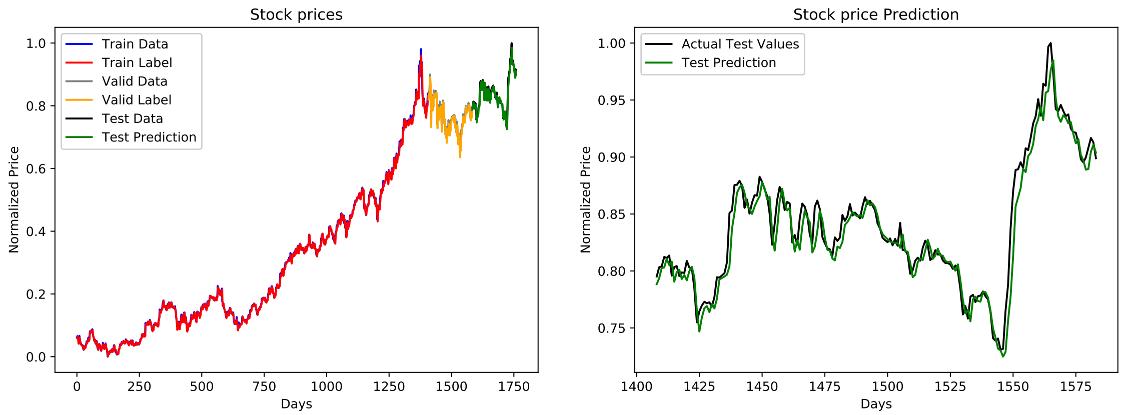

Fig. 9: Stock Market Prediction using LSTM model for stock of company Aethon Minerals Corp (“AET”)

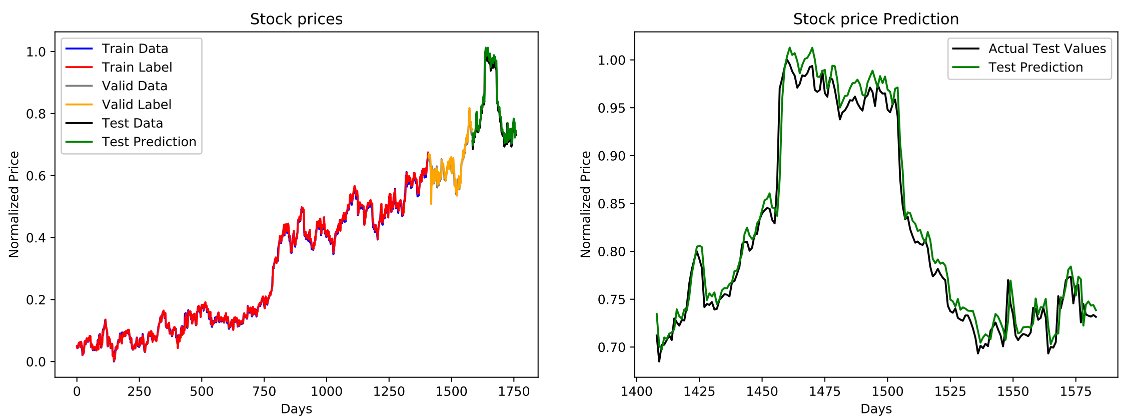

Fig. 10: Stock Market Prediction using LSTM model for stock of company General Mills (“GIS”)

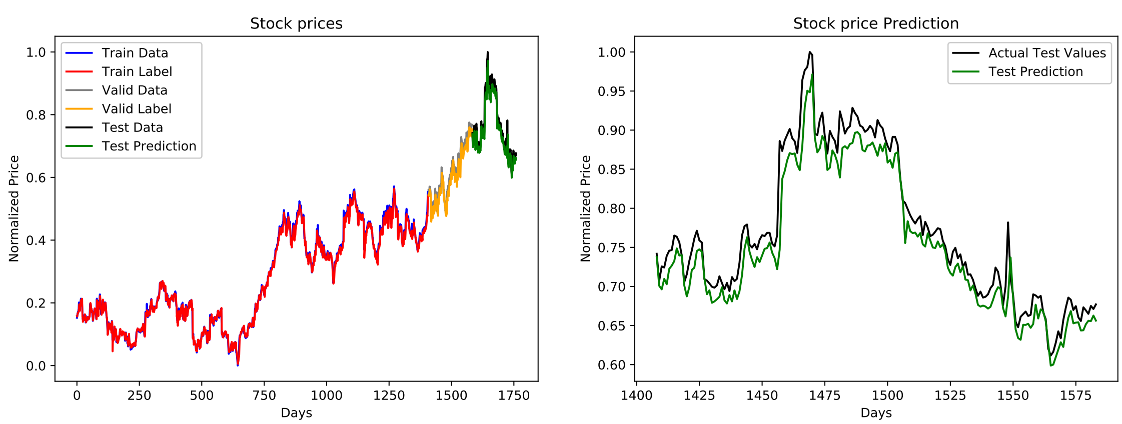

Fig. 11: Stock Market Prediction using LSTM model for stock of company Kellogs (“K”)

4) **Solution to Double Spending Problem** If a transaction checks an invalid transaction, it risks verifying itself as in the scenario of Fig. 6. This scheme is also secure to double expenditure by a malicious user.
5) **Completeness of Consensus Mechanism** Because the caps are selected with priority at random, priority is provided to those who are verified by more number of transaction either directly or indirectly. This results in longer dangle becoming considerably larger, while smaller or side dangle ceases with time & is out of validation process. So the transaction which are validated achieve consensus.

TABLE I

	Training MSE	Test MSE
Aethon Minerals Corp (AET)	0.00007	0.00031
Kellog (K)	0.00006	0.00040
General Mills (GIS)	0.00007	0.00030

VII. Simulation & Results

TOQEN [20] is used to create smart contracts on IOTA platform. Whenever a buyer or seller wants to buy or sell his stocks, he makes a transaction by calling smart contract, specifying the company, amount of stocks that need to be transferred. Smart contract accesses Intelligent agent who is a separate entity from Smart contact and can be accessed only through a smart contract. For training the predicting model, we train the LSTM neural network. We use Network Stock Exchange dataset [21] for training and validating the system. This dataset is publicly available on the Kaggle platform. It is a dataset that spans from 2010 to 2016 and has stock prices for 501 companies such as Kellogs (K), Aethon Minerals Corp (AET), General Mills (GIS), etc. It includes 140 stock split in times for prices for each company. Fig. 3 depicts the opening and closing prices for 3 companies and Fig. 4 illustrates the distribution of stock volume.

The LSTM model was trained with input parameters from the above four parameters in the dataset, as shown in Fig. 2. The number of neurons in the LSTM model has been taken as 200, with four neurons in the last layer. Learning rate has been set to 0.001. Batch size vector for the stock of companies contains 50 was used to train the model for 100 epochs. The feature vector of stock for company contains 4 parameter values i.e. 'open', 'close', 'low', 'high'. The dataset for each company is distributed into 80% being training data, 10% being validation data, and the rest 10% as test data. The total instances for each company in the dataset are 1742, where 1394 are training examples, 174 are validation and remaining are test samples. Stock prices are normalized to increase the adaptive learning of the network.

Fig. 9, 10, and 11 show the stock market prediction using LSTM model for the three companies AET, GIS, K, respectively. Left figure in Fig. 9, 10, and 11 depict the training dataset, train label, validation dataset, validation label, and test data and test prediction. The label for the dataset is the next iteration close value. A forecast of the stock market is made for 200 days. The right side figures in Fig. 9, 10, and 11 depict the actual vs. predicted values based on the proposed stock market model. The neural network predicts all the parameters. In the figure, we achieve an accuracy of 99.71% when the output label is closing value. Table I shows the test mean square error is only 0.0003-0.0004 for all the companies. Finally, the normalized price is converted to original price range and given to the user. The user confirms the transaction and adds the transaction to an immutable distributed ledger.

VIII. Conclusion

In this paper, we propose an Intelligent decentralized stock market model using the convergence of machine learning and DAG-based cryptocurrency. The current prevalent stock exchange mechanism is hectic, cumbersome, and is susceptible to many risks. Therefore the need for the distribution mechanism is felt. Though blockchain solves many problems of the centralized stock market, it is not suitable in this context on account of the rapidly growing transaction rates. Thus, we employ an IOTA based platform to cater to issues such as scalability, speed, and the increasing transaction fees in the blockchain. The paper also incorporates a machine learning model which makes the model more intelligent and provides a future proof solution for the stock market.

References

[1] S. H. Kim and S. H. Chun, "Graded forecasting using an array of bipolar predictions: application of probabilistic neural networks to a stock market index," *International Journal of Forecasting*, vol. 14, no. 3, pp. 323–337, 1998.

[2] M. Crosby, P. Pattanayak, S. Verma, V. Kalyanaraman *et al.*, "Blockchain technology: Beyond bitcoin," *Applied Innovation*, vol. 2, no. 6-10, p. 71, 2016.

[3] M. Hansson, "On stock return prediction with lstm networks," 2017.

[4] A. L. C. Lim and W. W. Wai, "Embracing blockchain applications in fundamental analysis for investment management," *Asia Proceedings of Social Sciences*, vol. 2, no. 2, pp. 111–114, 2018.

[5] H.-j. Kim and K.-s. Shin, "A hybrid approach based on neural networks and genetic algorithms for detecting temporal patterns in stock markets," *Applied Soft Computing*, vol. 7, no. 2, pp. 569–576, 2007.

[6] B. C. Florea, "Blockchain and internet of things data provider for smart applications," in *2018 7th Mediterranean Conference on Embedded Computing (MECO)*. IEEE, 2018, pp. 1–4.

[7] M. R. Islam, I. F. Al-Shaikhli, R. B. M. Nor, and V. Varadarajan, "Technical approach in text mining for stock market prediction: A systematic review," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 10, no. 2, pp. 770–777, 2018.

[8] I. Konstantinidis, G. Siaminos, C. Timplalexis, P. Zervas, V. Peristeras, and S. Decker, "Blockchain for business applications: A systematic literature review," in *International Conference on Business Information Systems*. Springer, 2018, pp. 384–399.

[9] L. Alessandretti, A. ElBahrawy, L. M. Aiello, and A. Baronchelli, "Machine learning the cryptocurrency market," *arXiv preprint arXiv:1805.08550*, 2018.

[10] P. Egger, "An econometric view on the estimation of gravity models and the calculation of trade potentials," *World Economy*, vol. 25, no. 2, pp. 297–312, 2002.

[11] N. McAlone, "The no-fee stock trading app robinhood is now officially worth 1.3 billion dollar," *Business Insider Australia*, 2017.

[12] N. Kshetri and J. Voas, "Blockchain-enabled e-voting," *IEEE Software*, vol. 35, no. 4, pp. 95–99, 2018.

[13] K. Salah, M. H. U. Rehman, N. Nizamuddin, and A. Al-Fuqaha, "Blockchain for ai: review and open research challenges," *IEEE Access*, vol. 7, pp. 10 127–10 149, 2019.

[14] N. Jegadeesh and S. Titman, "Returns to buying winners and selling losers: Implications for stock market efficiency," *The Journal of finance*, vol. 48, no. 1, pp. 65–91, 1993.

[15] C. Krauss and J. Stübinger, "Non-linear dependence modelling with bivariate copulas: Statistical arbitrage pairs trading on the s&p 100," *Applied Economics*, vol. 49, no. 52, pp. 5352–5369, 2017.

[16] W. Chen, C. K. Yeo, C. T. Lau, and B. S. Lee, "Leveraging social media news to predict stock index movement using rnn-boost," *Data & Knowledge Engineering*, vol. 118, pp. 14–24, 2018.

[17] A. M. Rather, A. Agarwal, and V. Sastry, "Recurrent neural network and a hybrid model for prediction of stock returns," *Expert Systems with Applications*, vol. 42, no. 6, pp. 3234–3241, 2015.

[18] B.-S. Lin, W.-T. Chu, and C.-M. Wang, "Application of stock analysis using deep learning," in *2018 7th International Congress on Advanced Applied Informatics (IIAI-AAI)*. IEEE, 2019, pp. 612–617.

[19] F. A. Gers, J. Schmidhuber, and F. Cummins, "Learning to forget: Continual prediction with lstm," 1999.

[20] TOQEN, "Smart contract on iota using toqen," 2019. [Online]. Available: https://github.com/qubiclite/qlri

[21] Kaggle, "New york stock exchange dataset," 2017. [Online]. Available: https://www.kaggle.com/dgawlik/nyse