

Blockchain Centered Traceability and Bitcoin Prediction for Food Crops Supply Chain

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ABSTRACT Blockchain technology makes agricultural supply chain management transparent, immutable, decentralized, and secured. All the actions are stored in disseminated shared record which makes the supply chain tamper proof and traceable from farmhouse to table which ensures food crops sold are safe. Farmers are granted with agri-insurance for buying seeds and in the course of natural calamities. Successful agreement guarantees cryptocurrency evidence of distribution when products are delivered, with automated bitcoin payments to all parties. The end user can outlook the complete information from the origin to the end of the food crop production journey. The proposed system that deals with agricultural food crops use blockchain technology which provides safety, agreement, dispersed ledger, speedy payout and decentralization, by accomplishing profit to each and every registered stakeholder and increase confidence among farmers since the transactions are transparent in blockchain system. Also, the recommended system has a User-friendly Interface to view and perform all the transaction activities. Moreover, to forecast the bitcoin price, we propose an ensemble deep learning method by combining Long Short-Term Memory(LSTM), Bidirectional Long Short-Term Memory(Bi-LSTM) and Gated Recurrent Unit(GRU) methods which helps the farmers and stakeholders to buy and sell their crops at the right time.

INDEX TERMS Blockchain, Traceability, Decentralized, LSTM, Bi-LSTM, GRU, Agri-Insurance, Bitcoin, and Distributed Ledger

1. Introduction

Blockchain is a serverless technology in decentralized network environment with immutable distributed ledger for storing transactions which establish communication among multiple computers. It is made up of series of ordered blocks that contains a variable-length list of transaction information. In agriculture, blockchain is used to track from the source and trace each step throughout the provenance of crops from farm to table. Food crops supply chain network is accountable for production to depletion drive of food crops from farmer to end user and the aforementioned objective is to meet the requirements of customer. Blockchain technology combines cryptography to ensure data integrity and permanence, a peer-to-peer design that eliminates centralizing middlemen and collective governance rules that allow any player to view transactions and verify their legality. As a result, blockchain offers greater transaction confidence, transparency and fluidity in multi-stakeholder systems. All operations and transactions across the agricultural supply chain can be managed and integrated in real time using this technology. Blockchain is the effective technology to identify fraud in food by guaranteeing traceability and truthfulness in food supply chain assuring geographic and biological origin is suggested by J.F. Galvez et al. [1]. In [2] Affaf Shahid et al. discussed the features of blockchain and suggested a broad explanation for agri-food chain deployed using ethereum blockchain.

Murat Osmanoglu et al [3] recommended a solution for estimating return of agricultural products. In addition to that, authors proposed yield commitment system which lets the farmers to disclose farming plans with other actors of the marketplace. Meghna Maity et al [4] proposed the traceability of supply chain for sausage material and food scare reduction using stochastic models with batch dispersion using blockchain technology. The proposed system clearly defines the relationship between the stakeholders which aids to know the relationship and moreover the working of the food crop supply chain system. A solution recommended by Jun et al. [5] towards the construction of a reliable, self-organized, eco-friendly smart agriculture that includes every participants in the system, even though they don't trust each other. Prince Waqas Khan et al. [6] defined an IoT-Blockchain system for food safety using digital-ledger and transparency. A hybrid model is recommended by the authors using LSTM and GRU for prediction. Zheshi Chen et al [7] recommended an approach for forecasting the bitcoin daily price by

traditional Machine Learning techniques, Random Forest Method, XGBoost Method and LSTM. Xin Zhang et al. [8] projected a blockchain system which improves the storage efficacy in grain supply chain using blockchain. The system grounded on Hyperledger fabric can share and interchange the information by ensuring security and trustworthiness which ensures tamperproof.

The proposed work on food crops supply chain recommends a complete solution which combines food crop traceability and forecasting bitcoin. Food crop traceability is accomplished including crop insurance coverage to purchase seeds and in the course of natural disasters to farmers using blockchain technology. We suggest an ensemble method for bitcoin prediction based on Long Short-Term Memory (LSTM) algorithm, Bidirectional Long Short-Term Memory (BiLSTM) algorithm, and (Gated Recurrent Unit)GRU algorithm. Bitcoin prediction benefits stakeholders to sell their product at the right time.

The prime novelty of the paper can be outlined as follows:

- A generic application framework is built using blockchain technology for food crops supply chain which ensures decentralization, immutability, traceability and transparency among stakeholders.
- Implementation of food crops supply chain framework accomplishes the following functionalities: (i) farmer can purchase seeds from the seed supplier (ii) farmer has the facility to claim agri-insurance for buying seeds and Weather Based Crop Insurance Scheme(WBCIS) (iii) farmer can sell the food crops (iv) Govt.Panel can provide prudent recommendations to the farmer to increase the yield (v) producer buy the crops from farmer, refines and produce the finished goods (vi) distributor sell the goods to retailer (vii) retailer sell the products directly to the customer (viii) the last entity is the customer who can trace the complete information of the product.
- The price of bitcoin can be predicted using an ensemble method based on Deep Learning techniques, LSTM, Bi-LSTM and GRU. When compared with existing deep learning algorithms, ensemble method gives high accuracy. Since the bitcoin price prediction is transparent, stakeholders can predict the right time to sell and buy the products without the intervention of intermediaries. Malpractices can be avoided such as usage of false weight and measurements, adulteration, black-marketing and hoarding.

The remaining sections are structured in this way: Section 2 presents related work of agricultural traceability management applications and bitcoin prediction. Section 3 demonstrates the framework and flowchart for blockchain traceability process and bitcoin prediction procedure. Section 4 discuss how the price of bitcoin can be forecasted. Section 5, describes the implementation results and discussion of blockchain based traceability for food crops and bitcoin prediction system. Section 6 describes the evaluation metrics for bitcoin price prediction. Section 7 projected the comparison of proposed food crops traceability supply chain with existing traceability system. Lastly, section 8 has conclusion and impending scope.

2. Related Work

This portion describes the literature review which focused on agriculture traceability blockchain systems and bitcoin price prediction in supply chain networks. The term "distributed database" describes a system in which each node generates and maintains files independently rather than a central authority transmitting files to different nodes or computer.

Khaled Salah et al. [9] offered a blockchain framework that assurances soybean traceability. Moreover, ethereum smart contract and IPFS is used to combine business transactions and workflows in supply chain. However, the authors do not address about Proof of Delivery and payment on successful delivery of goods. Since blockchain is a decentralized system, and e-agriculture needs automated payment, mechanism for payment on delivery of data need to be considered. A novel hybrid model is proposed based on Hidden Markov model, ARIMA and LSTM. However, the current system does not suggest the stakeholders to buy and sell their products at the right time to gain more profit which is recommended in the proposed work using ensemble method based on LSTM, BiLSTM, and GRU neural networks. Siddhi Velankar et al. [10] presented, cryptocurrency called bitcoin used for digital payout. The bitcoin price is predicted by means of Machine Learning algorithms. Furthermore, Bayesian Regression technique and Random Forest method is used. Patel Jay et al. [11] offer a long-term dependency that monitors the type of information to be eliminated and the new information to be included in LSTM memory cell. The cell status is accepted by the network and hence they are saved and altered.

Huisu Jang et al. [12] suggested blockchain is the only technology used to generate blocks that is directly used for trading of biotin, which influence the demand and supply of bitcoin. Fernández-Caramés et al. represented the cultivation of raw resources and the finished goods delivery to clients, each stage of the manufacturing process in agriculture is considered as a link in the supply chain [13]. As a result, it denotes the oversight of all production, transformation, distribution, and marketing operations that end in the delivery of a desired product to a customer. Liang, G et al. [14] proposed a method which ensures the marketing

function is a vital portion of agricultural supply chain. Agricultural marketing entails the purchase and sale of agricultural goods. Konstantinos Demestichas et al [15] discussed a solution for traceability in agri-food domain using blockchain technology. However, the current system focuses only on traceability but the stakeholders are not benefitted. The proposed system provides a complete solution including insurance for the planters to purchase seeds and in the course of natural disasters. Moreover, by using the bitcoin prediction, all the stakeholders are profited by knowing the right time to sell and buy their products.

T. Phaladisailoed et al [16] discussed various Machine Learning algorithms to predict the price of bitcoin with high accuracy. The current system considers only open, close, high, and low features. Chao Lin et al [17] propose a permissioned architecture using ethereum based blockchain that allows to host rule with integrated cryptographic primitives and PBFT consensus protocol to avoid transaction fee and reward for mining. Fernández et al [18] devoted a review on how to develop, when to use and how to adapt blockchain for the needs of IoT based applications.

The ConvLSTM model and 3D-CNN were created by the authors of [19] to anticipate agricultural output at the county level. The study aims to estimate the yield of soybeans, and to distinguish between the ConvLSTM and 3D-CNN models, which both estimate crop productivity. The inventors of [20] have put forth a blockchain-based architecture that can automate the settlement of insurance claims and control the scope of coverage for motor insurance companies. The feasibility of enhancing food monitoring systems with blockchain technology has been investigated by experts in [21]. Authors in [22] propose a blockchain-based insurance scheme for smart communities. The smart city managers, insurance providers, customers, users, detectors, and other gadgets make up this system. According to this paradigm, a person's public key serves as their identity. The authors in [23] summarized the methods of gathering the traceability data—form entry, label scanning, and sensor transmission and methods of visualising the traceability data. But in the proposed Blockchain centered traceability system's user interface includes the complete information. Moreover, the user can apply for insurance and to forecast the price of bitcoin.

3. Blockchain Based Food Crops Traceability

Figure 1 demonstrates the proposed structural design for blockchain centered traceability in food crops supply chain and bitcoin prediction grounded on LSTM, BiLSTM and GRU algorithms.

Blockchain is a distributed ledger technology that allows transaction records to be stored in an open, secure, and immutable manner across a network of computers. Blockchain data is arranged into blocks, with a list of transactions contained in each block. A block is composed of a header information and a body(the actual transactions). A chain is formed when each block contains a hash of the previous block's header. By making it computationally impossible to alter any block in the chain without also altering all of the blocks that follow after it, this assures immutability. Consensus mechanisms are those that makes nodes to a consensus regarding the state of the blockchain at that moment. Consensus mechanisms in a decentralised network are protocols that enable nodes to agree on the blockchain's current state. They ensure that all participants view the ledger identically. This blockchain-based traceability system makes use of the Proof-of-Work(PoW) consensus method which allows nodes to solve difficult mathematical puzzles becomes the miner. Proof-of-Work verifies and adds blocks to the chain. Miners employ processing power in the process of competing to solve these difficulties.

3.1 Framework of Food Crops Traceability System and Bitcoin Prediction

This section describes the framework scheme of proposed blockchain centered food crops traceability system which has eight entities/stakeholders.

- i. **Supplier / Seed Seller:** Supplier or seed seller is responsible for selling good breed seeds to farmers. Once registered in the blockchain network, the Seed Seller can login and upload seed details.
- ii. **Farmer / Harvester:** Farmer, who is in charge of everything from seeding to harvesting. The farmer can login, view the seeds, selects the required seeds and make payment. The farmer can login can upload the food crops details after harvesting.
- iii. **Agri-Insurance:** Farmers can apply agri-insurance for buying seeds. The Govt.Panel check the information given by the farmer and approve or reject the application. During natural calamities, the farmer can apply WBCIS.
- iv. **Govt. Panel / Authorities:** Set standards, regulations, laws, rules, and policies that all concerned parties must follow throughout the process. The farmers can get wise recommendations from the Govt.Panel to increase the crop production.
- v. **Manufacturer / Producer:** Raw materials are converted into product or finished goods. The valid producer can buy the food crops from farmer, make payment and produce the finished goods. The finished goods details are uploaded in the blockchain network.

- vi. **Distributor / Wholesaler:** The distributor is responsible for shipping the producer's processed goods from manufacturer to merchants. The distributor who is responsible for shipping the product to dealers or retailers can select the finished goods uploaded by the producer.
- vii. **Retailer / Dealer:** Retailers are in charge of selling things, whether they are sold in small neighborhood stores or enormous supermarkets. The retailer buys and sell the products from distributor in small quantities to customer. Retailer upload the product details for the customer to buy.
- viii. **Customer / End User:** End user is the final link in the chain who can purchase products from dealer in small quantity and when the QR code is scanned, the end-user can track and trace every step in the manufacturing lifecycle.

Figure 2 depicts the flowchart for the proposed blockchain based traceability, insurance and bitcoin prediction framework which describes the entire proposed system.

3.2 Design of Food Crops System

The design of the food crops traceability system consists of all the stakeholders in the blockchain network, their functions, associations and interactions among the stakeholders. Figure 3 illustrates the communication between seed seller, farmer, agri-insurance, and Govt.Panel in the blockchain network.

Seed seller can register by invoking the method `seedseller_register()` and once registered, seed seller can login, when `seedseller_login()` method is invoked. Seed seller can upload the seed details by executing the method `seedseller_upload()`. Seed details with image gets uploaded. Insurance company register in the blockchain network using `insurance_register()`. Farmer can apply insurance to buy seeds by executing `apply_insurance_buyseeds()`. The information given by the farmer is validated using `approve_status(action)`. Farmers can also apply for Weather Based Crop Insurance during natural calamities by invoking the method `apply_insurance()`. The applied farmer's information can be accessed by the Govt.Panel and check with the nearby weather station. The interaction between farmer, producer and distributor is explained in figure 4.

The farmer executes the function, `farmer_upload_product()` to upload the cultivated crop after harvesting. New producer can register and login by executing `producer_register()` and `producer_login()`. Distributor buy the manufactured products from producer and ships to the retailers without any modification. New distributor can register using `distributor_register()` and login using `distributor_login()`. Distributor upload the product details for the retailer to buy by executing the function `distributor_upload_product()`.

Figure 5, describes the communication between distributor, retailer and customer in the blockchain network. Retailer is in charge of selling products directly to customer or end-user. New retailer can register by invoking `retailer_register()` and login using `retailer_login()`. Retailer can view the products using `retailer_view_cart()`. The required products can be selected by the retailer, add to cart and make payment using `distributor_payment()`. The retailer can upload the products for the customer to buy using `retailer_upload_product()`. The customer is the last chain of product flow in agri-supply chain management. The products they buy will be used by them without reselling to any other parties. So customers are the main key for the sustainability of a product. New customer can register and login in blockchain network using `customer_register()` and `customer_login()`. Customer scan the QR code to trace details of the product such as product name, product description, transaction ID, company name, certifying agency, fertilizer used, soil type, variety, harvest time, agricultural operations, and security information such as Blockchain Address, Hash Address, Previous Block Hash by executing the function `QRcode_scanner()`.

To build a blockchain network, NodeJS is used. Java Script is used to create interactive web pages. Dynamic web pages and bitcoin prediction procedures are developed using Python. Visual Studio Code is a code editor used for the development operations and building web applications.

4. Bitcoin Price Prediction Procedure

4.1 Bitcoin: A decentralized digital cash that is used globally and transferred between nodes in the blockchain network for digital payment. Bitcoins are used for online transactions to buy products. The transactions are validated by the computers in the blockchain system and recorded in the disseminated ledger.

4.2 Prediction: Bitcoin's price varies like stock market. It is essential to predict the price of bitcoin to make right investment decision and the stakeholders can sell and buy the products at the precise time to acquire profit. To forecast the bitcoin price, an ensemble method based on LSTM, Bi-LSTM and GRU is used.

4.3 Input data

The input data is classified as internal information and external information. The internal information is gathered by the parameters of bitcoin and the external information is obtained from the public. The input data is taken from publicly available dataset through internet as mentioned here, 'https://www.marketwatch.com/investing?mod=top_nav', '<https://in.investing.com/crypto/bitcoin/historical-data>' and also some real time dataset. This information includes date, time, opening, bid, ask, and closing of OHLC (Open, High, Low and Close) and finally the volume of trades.

The transaction date is represented as date attribute, the highest price of the share that the buyer confirms is the bid rate. The ask feature is lowest price that seller is ready to receive. On a particular day, the high attribute is maximum bitcoin price and low attribute is minimum price happened. Volume attribute is number of bitcoins used to buy and sell goods on that date.

4.4 Data Preprocessing

Data preprocessing is the procedure in data mining and analysis process. Here raw data from the database is taken as input and then it is transformed into an understandable format for machine learning. Machines read data as 1s and 0s. So it is necessary in all data sets, to remove NaN values, null values and then it must be replaced by the appropriate attribute. Data cleaning method is done to preprocess these information. After this, all data sets are merged into single dataset, according to the time magnitude.

$$X_{norm} = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (1)$$

4.5 Feature Extraction and Feature Selection

The preprocessed input is given as input for feature selection process. Here all the entities are of numeric values. Feature Selection is one of the dimensionality reduction techniques. It is used to select the efficient features from large volume of data. Feature choice is used to choose a subcategory of appropriate attributes from the original features using the available feature selection algorithm.

Feature selection is also used to decrease the dimension of features, select optimum information needed for learning, in addition increase built models. To solve the problems of high dimensionality data, feature selection is used. Feature importance was found using a Mutual Information (MI) based feature selection. The attributes in the dataset are the features needed for predicting the price of bitcoin. From these features the important features that are needed for predicting bitcoin price is identified using MI method.

4.6 MI based feature selection

In MI based feature selection technique optimal method is used for finding the feature subset. For removing the repetitive or the duplicate features occurred in the subset filtering is used. The basic principle of this feature selection is based on the MI theory. The MI technique measure the dependence information of each feature. It is computed using the following formula

$$p(tx) = \sum (ty, ak)ak \quad (2)$$

$$MI(ty, ak) = p(ak, tz) \log 2(p(ak, tz) p(ak) p(ty)) \quad (3)$$

Where probability of the word tx is represented as $p(tx)$ and probability of ak containing the word tx is represented as $p(ak, tx)$.

5 Proposed ensemble method using LSTM, GRU and Bi-LSTM for Bitcoin Price Prediction

5.1 LSTM

LSTM cell finds long term dependencies and comprises of hidden state and a cell state. These are maintained by the structures called gates. The gate is the sigmoid function of the inputs. LSTM cell has 3 gates: input, forget, and output.

The new input is stored in the cell. It is then passed to the input gate. It is shown in the equation 4 and 5. The forget gate takes the decision to remove the information that is already present in the cell state. It is shown in equation 6. Finally, the output gate is used for filtering the output and decides the final cell output. This is represented in the equation 7.

$$a_t = \sigma(W_a \cdot [o_{t-1}, y_t] + b_d) \quad (4)$$

$$d_t = \tanh(W_d \cdot [o_{t-1}, y_t] + b_d) \quad (5)$$

$$f_t = \sigma(W_f \cdot [o_{t-1}, x_t] + b_f) \quad (6)$$

$$o_t = \sigma(W_o \cdot [s_{t-1}, x_t] + b_o) \quad (7)$$

$$S_t = o_t \cdot \tanh(c_t) \quad (8)$$

Where d_t represents cell state, o_t represents output gate, g_t represents hidden state.

5.2 GRU

GRU was developed from LSTM. The structure of GRU is easier than LSTM. The number of prior and previous state is defined by the reset door. The prior state is for current data and the previous state is from fix gate. The over fitting is minimized by the addition of regularization in all the layers. The Input Gate and Forget Gate are combined to produce Update Gate. It comprises of twofold doors namely the Update and Reset.

The connections between the input and output can be represented by the following equations:

$$P_t = \sigma(W_p [g_{t-1} \cdot y_t]) \quad (9)$$

$$q_t = \sigma(W_q \cdot [g_{t-1} \cdot x_t]) \quad (10)$$

$$h_t = \tanh(W_h [Y_t \cdot g_{t-1} \cdot y_t]) \quad (11)$$

$$g_t = (1 - P_t) \cdot g_{t-1} + z_t \cdot g_t \quad (12)$$

Where p_t and q_t denotes Update and Reset Gate output, W_p and W_q denotes Reset and Update gate weights, $\sigma(\cdot)$ is the sigmoid function, $\tanh(\cdot)$ is hyperbolic tangent functions.

5.3 Bi-LSTM

The bi-LSTM was developed for training the neural network with the inputs of past and future. Two LSTM layers are linked together to form the bi-LSTM. Here the inputs are functioned and processed. Bi-LSTM process all the input element with finite sequences. This processing is done by the past and the future context. Two values are saved in hidden layer. One for forward calculation, and a transpose for reverse calculation. The outcome is based on this forward and reverse calculation and reverse calculation.

$$a_h^t = \sum_{l=1}^L x_l^t w_{lh} + \sum_{h':t>0}^H b_{h'}^{t-1} w_{h'h} \quad (13)$$

$$a_h^t = \theta_h(a_h^t) \quad (14)$$

5.4 Proposed Ensemble Method

The ensemble approach for deep learning is referred as combination of different networks. In ensemble learning all the networks are trained with random weights on same dataset. Then the networks involved in the ensemble model are processes separately to find their identification of results. Then based on the average of the model's identification the output is declared. The computation cost of these models is very high rather than using a single model. To create an ensemble there must be minimum three to maximum of 10 trained models.

To create ensemble model LSTM, Bi-LSTM, GRU is used. Different input data can be used for training each model in the ensemble network. The three models make their predictions on their own way. These predictions are finally combined to produce the result. This prediction can be combined based on weighting, averaging and stacking. Here stacking is used. So, the stacking of LSTM, Bi-LSTM and GRU ensemble model is taken to provide the outcome. The dataset has many examples for crop price with number of rows and columns. The dataset is distributed in the ratio 70:30 for training and testing. Stacking ensemble learning is done to forecast the bitcoin price. Figure 6 shows the sample stacking ensemble learning architecture.

Algorithm 1 Ensemble Method

Input: Feature values

Output: Predict price of bitcoin

Step 1: Import data from dataset

Step 2: Data pre-processing is initiated to set of null values as Nan

Step 3: Exploratory data analysis is done

Step 4: Build the ensemble model by combining LSTM, Bi-LSTM, and GRU models

Step 5: Data preparation for Training and Testing

Step 6: To forecast close price of Bitcoin, consider Close and Date

Step 7: Bitcoin price is predicted Using Ensemble training and testing

Step 8: Analysis on the ensemble model

Algorithm 1 describes the step by step procedure of ensemble method used to predict the price of Bitcoin. Here 3 neural network models are taken namely the LSTM, Bi-LSTM and GRU. In stacking model each model predicts an output then a meta learner is created with the logistic regression and weak learner. Then final output is predicted.

6. Results and Discussion

6.1 Setting Network Nodes

The nodes which are ready to connect in blockchain system are permitted to execute at the command line interface. These blockchain nodes are responsible for keeping track of the distributed ledger and function as a communication center for the activities involved in the blockchain network. The nodes that are agreed to connect in the blockchain network are executed in the command line interface.

6.2 Initiating Transactions

Initiating transactions broadcast the transaction data to every nodes that take part in blockchain structure. Genesis Block generated with few random values and that block data is transmitted to every nodes. The block data is transmitted to all nodes in the network of blockchain system.

6.3 Synchronization of Node

Synchronization of nodes is performed after broadcasting because the nodes are not aware of each other. To perform synchronization, all the nodes are registered in blockchain system. The transactions transmitted through postman tool can be transmitted to all registered nodes. Now the proposed blockchain network is in synchronization. When the network is in synchronization, we need to send the Pending Transactions or verify the transaction using /broadcast API call. The transaction information will be added into block, once the transactions are mined. This mining data is also transmitted to all registered nodes in blockchain system. A block will be generated with new index and new timestamp. Transactions data already added in the

pending transactions are currently stored inside transactions[] after mining. The Seed Seller upload the details of seed with the image of the seed from Seed Seller Login.

Table 1 shows the seed transaction details using blockchain with the block parameters previous hash address, new hash, timestamp, date and id. First block for product transaction is genesis block which do not have previous hash address is described as 0. The newly created block is linked to previous block which forms chain of transactions. If any transaction is altered makes the hash to change. This hash address acts as a unique finger print for that transaction block and behaves as a mechanism which prevents tampering.

The Weather Based Crop Insurance Scheme is an Insurance protection scheme for notified food crops during natural calamities. Farmers claim agri-insurance for high rainfall, high wind speed, and reason for natural calamity is flood. The end user can scan the QR code for product traceability. On scanning the QR code by customer, the particulars about product with description, traceability ID, company name, certifying agency, fertilizer used, soil type, and harvest time are displayed. Moreover, customer can view the agricultural operations and the security information results of the QR code scan depicts the security details such as block chain address, previous block hash and transaction ID.

6.4 Metrics for Evaluation

To guarantee that the model is legitimate and to measure its performance, the system is tested with the authenticated dataset.

6.4.1 Experimental Results

An experiment is designed to find an optimal algorithm with maximum accuracy and the ability to handle large volume of data to implement the bitcoin forecasting feature. This section first discusses the datasets used in the research and the performance metrics used for evaluation. It is followed by results analysis with comparison.

6.4.2 Datasets and Performance Metrics

Dataset used for the experiment consists of 10 agricultural categories: wheat, rice and soybean, Channa, Green gram, Bengal gram, Toor dal, Urad dal, Peas, Masoor dal based on weekly field price of 12 years (2009-2021) for each commodity. Table 2 shows the price statistics of raw data in the dataset.

a. MSE

The regression line's closeness can be computed using mean squared error. Forecasted result is much better when the MSE is very low. The Mean Square Error is calculated using the following formula

$$MSE = \left(\frac{1}{n}\right) * \sum (actual - forecast)^2 \quad (15)$$

Where n = number of items

b. RMSE and MAPE

The accuracy of predictions can be calculated and measured by using mean absolute percentage error (MAPE) and the root mean squared error (RMSE).

$$RMSE = \sqrt{\frac{\sum_{i=1}^M (R_i - P_i)^2}{M}} \quad (16)$$

$$MAPE = \frac{1}{M} \sum_{i=1}^M \left(\frac{|R_i - P_i|}{R_i} \right) * 100\% \quad (17)$$

Where R_i is the real cryptocurrency price and P_i is the predicted cryptocurrency price and M is the total number of samples. The statistical distribution of raw data price is described in Table 2.

6.4.3 Results Analysis

Test has been conducted in two series, one with time-series data and other with multivariable data for 12 years dataset from December 2008 to March 2021. Both the experiments are compared with the existing machine learning models. From literature review, 5 algorithms namely Support Vector Regression (SVR) recommended by Awad et al., LSTM suggested by Hochreiter et al., Auto Regressive in Moving Average (ARIMA) by Box et al., XGBoost proposed by Chen et al. and Prophet by Taylor et al. are used for comparison. Table 2 shows the average MSE on the price prediction of each model for series 1 experiment.

From the results in the first experiment attempt, ARIMA is proved as an efficient among the existing models, because of its minimum value on MSE average. But the proposed method achieves still lowest average MSE of 0.25. Table 3 shows MSE results for series 1 experiment and table 4 shows the MSE results obtained for series 2 experiments. In the second experiment attempt, LSTM obtained the lowest MSE amongst the existing models. The proposed method still reduces the MSE to 0.22 by 0.20 decrease from ARIMA model.

Figure 7 and 8 shows the MSE bar chart comparison of proposed and existing models for both the experiments. By observing the two experiment attempts, proposed system partakes the capability of scalability. The LSTM model accomplishes lesser MSE in second attempt than the first attempt. While for other models such as SVR, XGBoost and Prophet, there is no improvement compared to the first experiment attempt. It shows that all the models have a lack of capability on handling high complexity of data. The proposed method is efficient while comparing with other models. It handles large dataset, provides software maintainability and scalability. As a conclusion of the experiment, this method is chosen as the key model in forecasting the commodities price, as it has shown to be superior compared to other models and holds the greatest potential to be further improved when more data becomes available.

In table 5 the RMSE and MAPE values for the proposed ensemble method using all the 10 commodities is shown. The average RMSE of proposed method is 18.957 and average MAPE is 0.502. In the table 6, LSTM obtained the lowest RMSE amongst the existing models. The proposed method still reduces the RMSE to 18.9575 by a large decrease from ARIMA, Bi-LSTM, LSTM model. The proposed model accomplishes lesser RMSE and MAPE while for other models such as LSTM, GRU, Logistic Regression, Multi-linear Regression, LDA, Bi-LSTM there is higher RMSE and MAPE results.

7. System Comparison

Table 7 depicts the analogy of the proposed food crops traceability system with other existing traceability methods.

7.1 WBCIS and Automated Payment

The registered farmer can apply insurance to buy seeds and the Govt. Panel approves by verifying the information provided by the farmer. Automated payment is triggered to the seed seller from the insurance company. The farmer can also claim WBCIS during natural calamities.

7.2 Government Authorities

The registered farmers can get wise suggestions from the Government Authorities to increase the crop yield.

7.3 Authenticated Stakeholders

The stakeholders of the blockchain based food crops supply chain are insisted to register in the blockchain network. So only authenticated stakeholders are allowed to do any transactions in the blockchain network.

7.4 Transparency And Information Sharing

The transactions performed by the stakeholders are broadcasted to each and every nodes in the blockchain system which guarantees transparency one of the prime feature of blockchain technology.

7.5 Security and Trustworthiness

The transaction information that is broadcasted will be secured with the help of cryptography, consensus algorithm and decentralization. Each block contains a unique hash address. If there is a change in the data, the hash address changes which

makes the block invalid. Since the transactions are distributed, there is no single node failure and hard to corrupt which ensures trustworthiness.

7.6 Bitcoin Prediction

The price of bitcoin can be forecasted using ensemble method which combines LSTM, Bi-LSTM and GRU deep learning neural network which contributes high accuracy. By forecasting the price of bitcoin, all the stakeholders can find the right time to sell and buy the products.

7.7 Traceability

The customer or end user can track and trace from farming to table such as product details, the agricultural operations, manufacturing process, security information like unique hash address of a product, transaction id.

A few challenges arise with scaling a blockchain network, particularly when handling massive volumes of data. Processing a large number of transactions per second (TPS) on blockchain networks can be achieved by storing the hash address of the node alone in the blockchain and transaction data can be stored in Interplanetary File System(IPFS). By dividing files into smaller units, distributing them over a network of nodes, and offering a content-addressed method for retrieval.

IPFS facilitates decentralized and distributed file storage. For any alteration to a file's content results in a new address which guarantees that the data is unchangeable. IPFS generates unique content identifiers for files using cryptographic hash algorithms. The data integrity is preserved by this content addressing, and any changes made to the content produce a new hash, making it tamper-evident. The IPFS network's nodes automatically cache content, which might result in faster file retrieval times and better performance.

8. Conclusion

A de-centralized framework is designed and implemented using blockchain technology to achieve transparency, fault-tolerant, immutable, tamper proof distributed data for food crops traceability system which ensures the end user can view the complete information from the source of the crop to finished goods journey. Furthermore, the same framework serves the farmer to claim insurance for buying seeds and agri-insurance during natural disasters. The price of bitcoin is also forecasted so that the farmers can find the right time to sell their crops. Since the system is distributed and the transactions are transparent, all the entities are profited without loss.

The product and information flow of proposed framework demonstrate that, the recommended system is beneficial in the field of food crop safety. The conceptual framework and interactions between the stakeholders are designed using sequence diagrams. The system collects and analyses credit assessments of merchants in blockchain based food crops supply chain with an ensemble method based on LSTM, Bi-LSTM and GRU models. Finally, the aim of improving food crop safety across the whole food crops supply chain has been achieved. This work can be further extended as how blockchain technology may assist agricultural food chains to become more profitable in the long run. Moreover, the farmer can be given facility to claim for other types of agricultural insurances.

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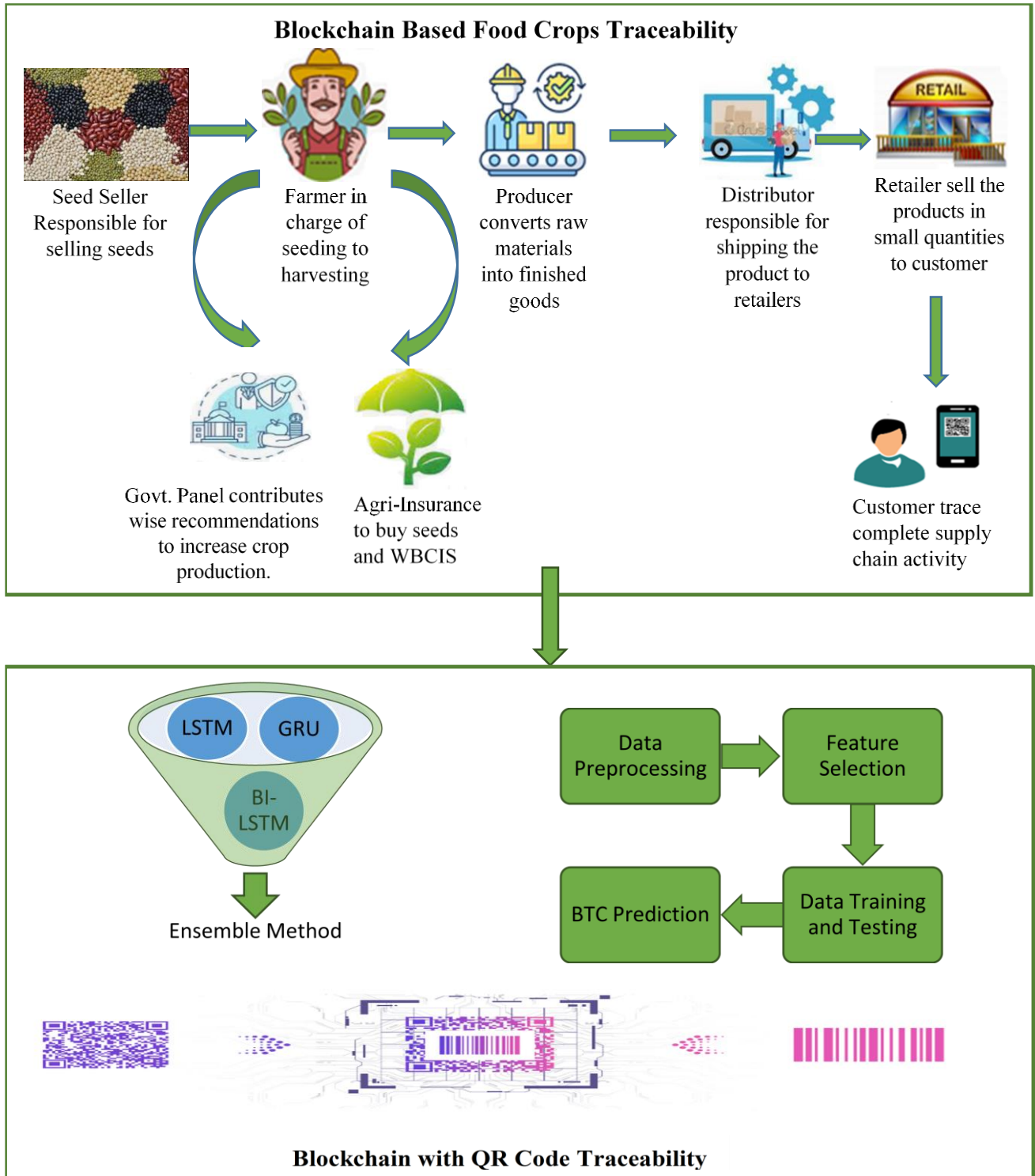


Figure 1. Architecture for Blockchain centered Food crops Traceability and Bitcoin Prediction

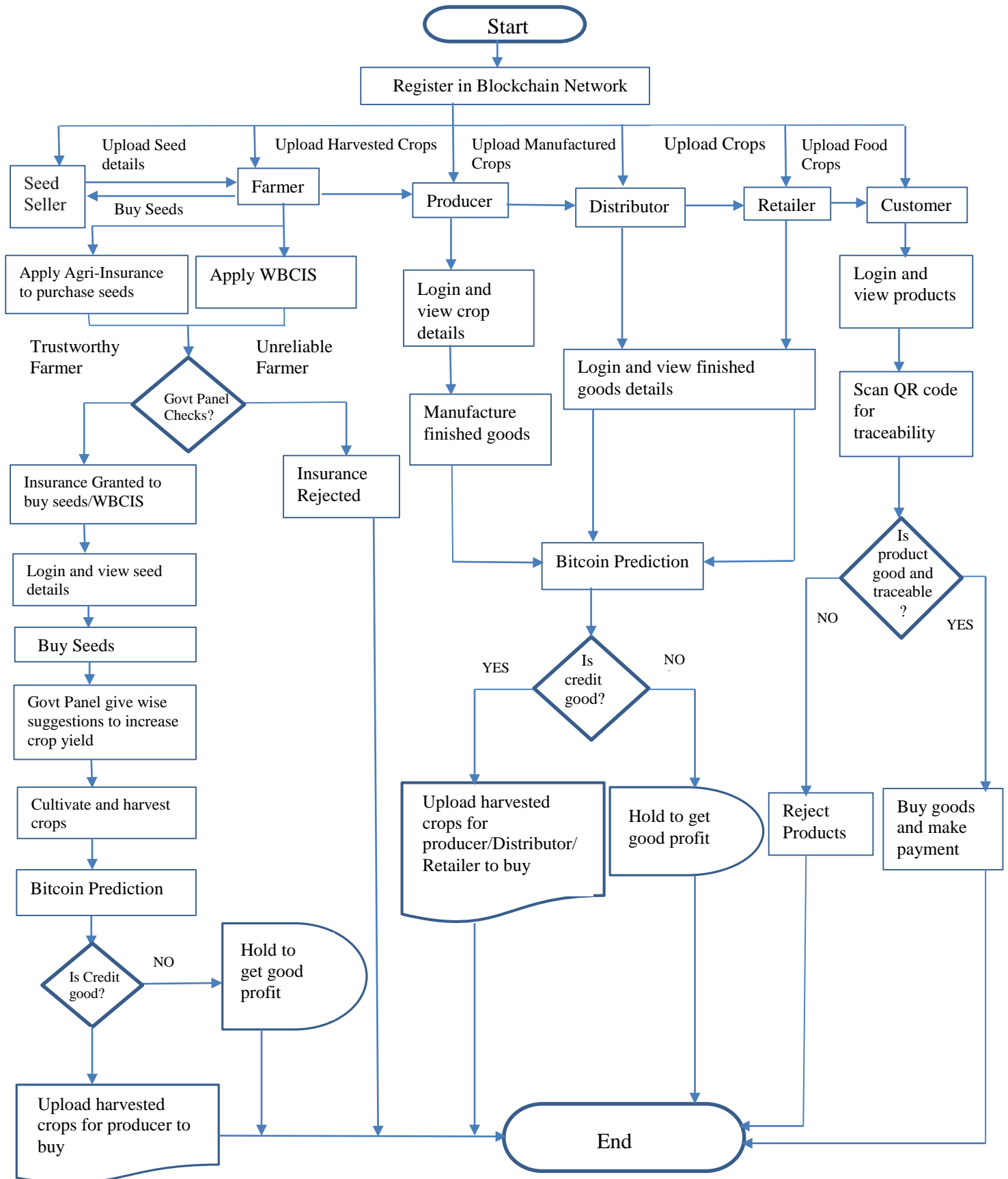


Figure 2. Flowchart for the proposed Blockchain based Food crops Traceability and Bitcoin Prediction

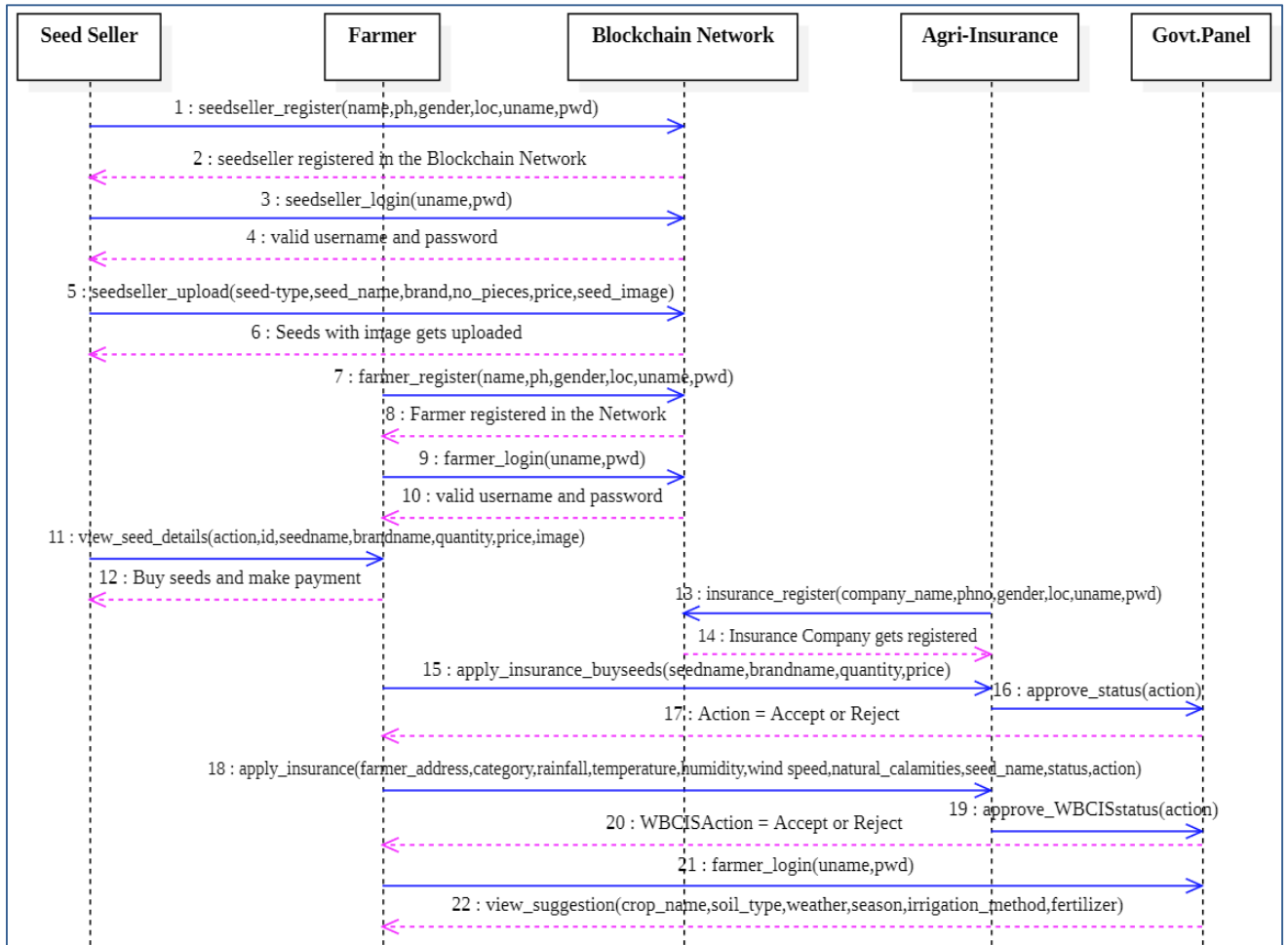


Figure 3. Communication between Seed Seller, Farmer, Agri-Insurance, Govt.Panel

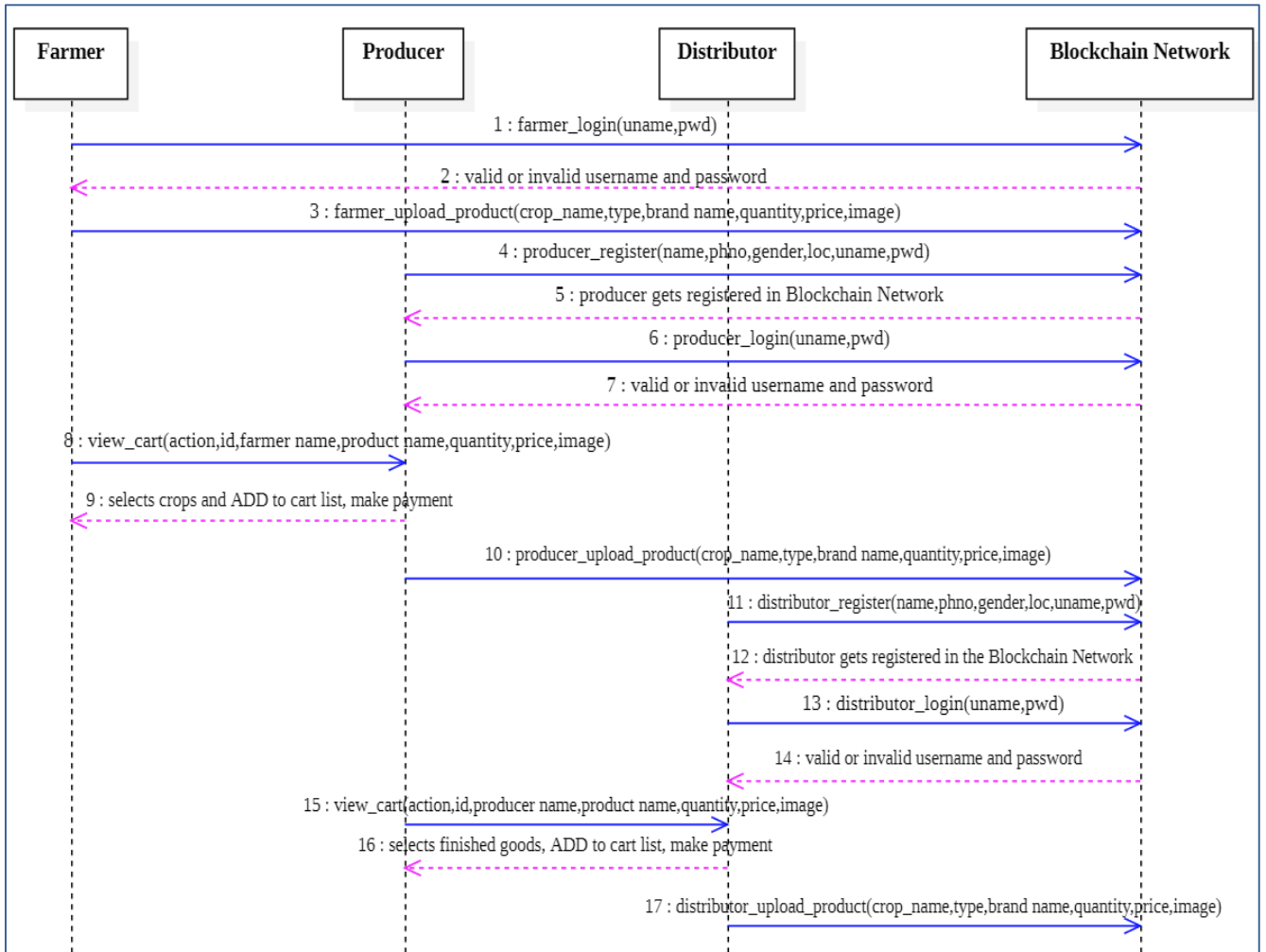


Figure 4. Communication between Farmer, Producer and Distributor

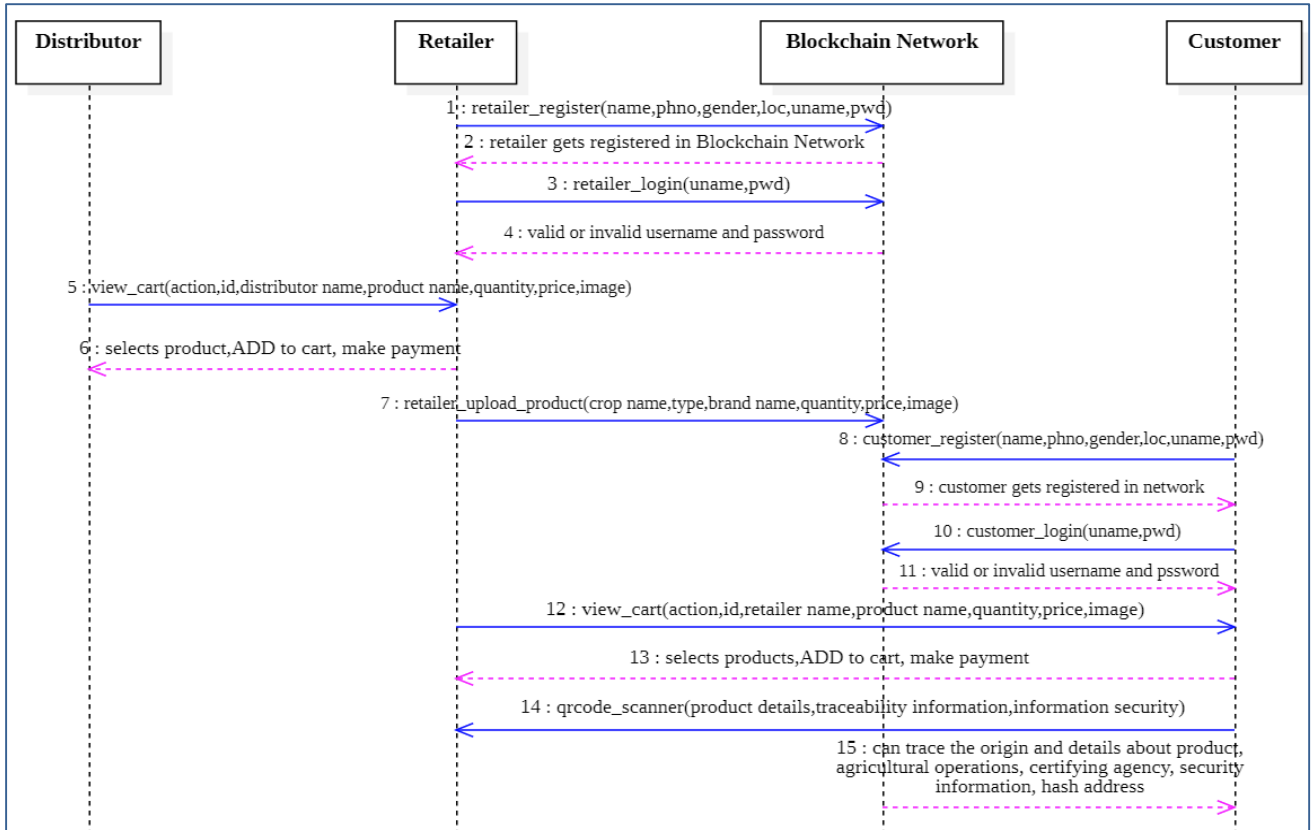


Figure 5. Communication between Distributor, Retailer and Customer

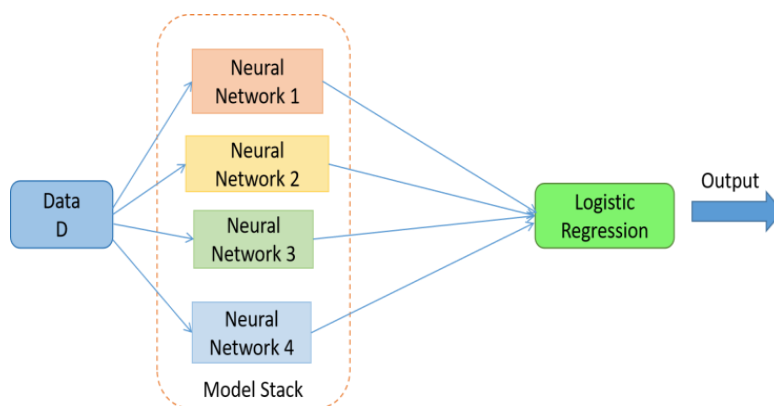


Figure 6. Ensemble Learning Architecture

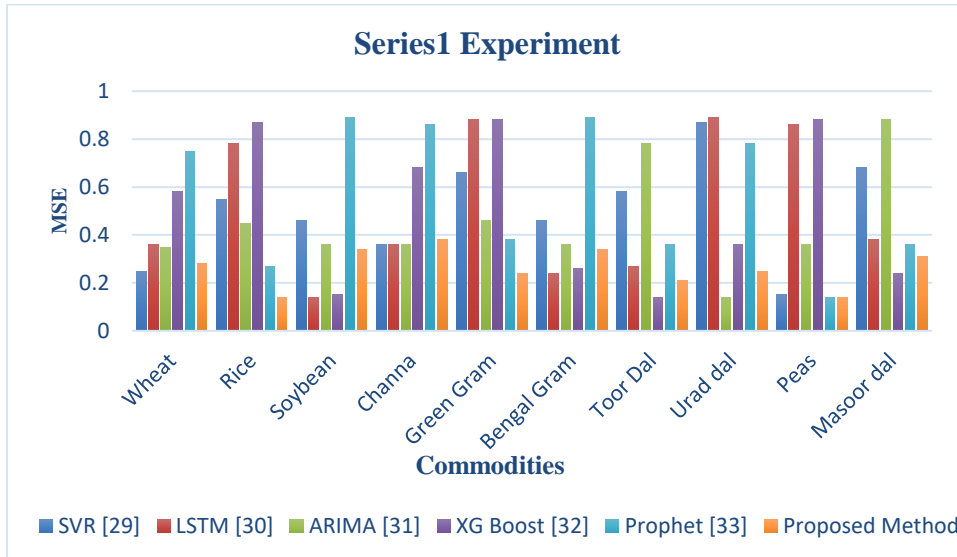


Figure 7. MSE Result Comparison of Proposed Method with Other Methods for Series 1 Experiment

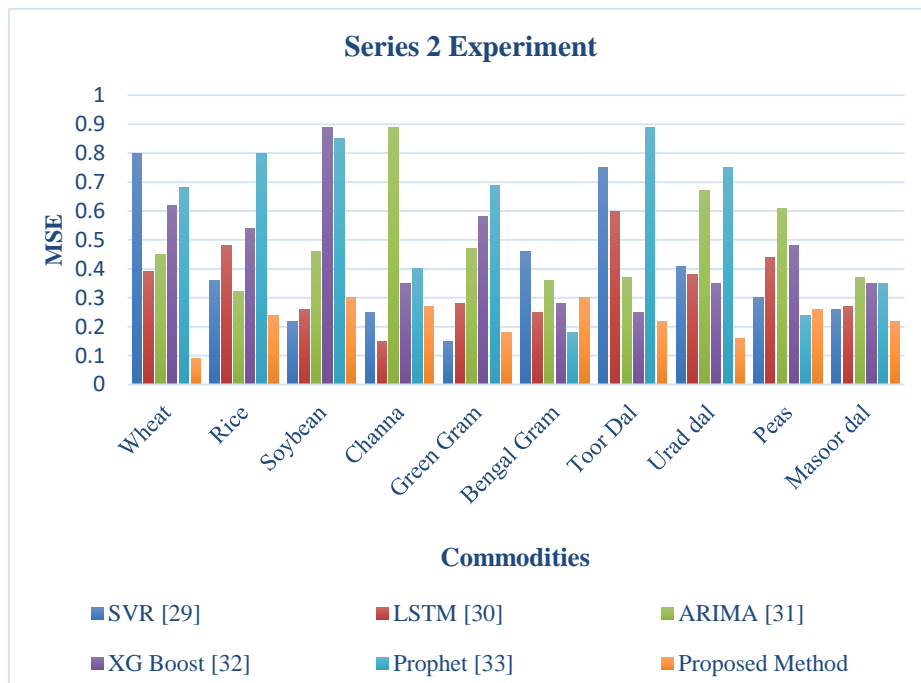


Figure 8. MSE Result Comparison of Proposed Method with Other Methods for Series 2 Experiment

Table 1 Transaction Details

Id	Crop Name	Previous Hash Address	Hash Address	Timestamp
1	Corn	0	232904914109b1950647 89ccab5562ae21cfa6707 cdeb42993e54c10ccab4 0	2023-04-23 10:49:15 182596
2	Rice	232904914109b1950647 89ccab5562ae21cfa6707 cdeb42993e54c10ccab4 0	1B9BC7B7376E6C5C0F1 042DFDD42AC68017D8C EE72988967D7C670D40 C466C85	2023-04-23 10:49:25 112596
3	Sorghum	1B9BC7B7376E6C5C0F1 042DFDD42AC68017D8C EE72988967D7C670D40 C466C85	B93F08E9D0F10D198F2 BB01616FE38DB01F5FEF 03E0E1D19D288E18131 608107	2023-04-23 10:49:52 167259
4	Barley	B93F08E9D0F10D198F2 BB01616FE38DB01F5FEF 03E0E1D19D288E18131 608107	B904432B6DE55A66C7F 785BB5C62F8827DF5CA 7023EAF8B2941254FC7C 9DBB94	2023-04-23 10:49:60 105534
5	Bajra	B904432B6DE55A66C7F 785BB5C62F8827DF5CA 7023EAF8B2941254FC7C 9DBB94	D8C9E5A7DF6C353F63A 126A8BC53BBD7DC75AA D72F040D8CAD71AC611 B0E5130	2023-04-23 11:23:10 144567
6	Ragi	D8C9E5A7DF6C353F63A 126A8BC53BBD7DC75AA D72F040D8CAD71AC611 B0E5130	0596EBDAA3ED354C8B2 C822D148B4BA07BE58A C8F915E8EA3EB9DD0D0 3BB36CA	2023-04-23 11:34:52 123456
7	Brown Rice	0596EBDAA3ED354C8B2 C822D148B4BA07BE58A C8F915E8EA3EB9DD0D0 3BB36CA	2AFC02E139D803289A1 9471652CC5FCD9B827F DF9029B4C88AE76435C 942D453	2023-04-23 10:49:52 182596
8	Rice	2AFC02E139D803289A1 9471652CC5FCD9B827F DF9029B4C88AE76435C 942D453	1B9BC7B7376E6C5C0F1 042DFDD42AC68017D8C EE72988967D7C670D40 C466C85	2022-04-23 11:49:30 167890
9	Barley	1B9BC7B7376E6C5C0F1 042DFDD42AC68017D8C EE72988967D7C670D40 C466C85	B904432B6DE55A66C7F 785BB5C62F8827DF5CA 7023EAF8B2941254FC7C 9DBB94	2023-04-23 12:12:34 134568
10	Corn	B904432B6DE55A66C7F 785BB5C62F8827DF5CA 7023EAF8B2941254FC7C 9DBB94	540647BA037B42DABEE A5ED7A53F8D4CD7304A 118957472D751D3811F 1D76D31	2023-04-23 12:49:52 167588

Table 2. Statistical Distribution of Raw Information Cost

Food Crops	Mean	Minimum	Maximum	Standard Deviation
Wheat	4.49	3.25	5.63	0.77
Rice	5.85	5.18	6.78	0.59
Soybean	3.56	3.05	3.56	0.53
Channa	6.69	3.35	5.53	0.66
Green Gram	5.85	5.18	5.68	0.59
Bengal Gram	2.67	2.05	3.54	0.53
Toor Dal	6.69	3.37	7.63	0.77
Urad dal	7.87	7.38	6.78	0.79
Peas	3.67	3.07	3.76	0.73
Masoor Dal	5.74	2.5	7.3	0.72

Table 3. MSE Results of Series 1 Experiment

Commodities	SVR [24]	LSTM [25]	ARIMA [26]	XG Boost [27]	Prophet [28]	Proposed Method
Wheat	0.25	0.36	0.35	0.58	0.75	0.28
Rice	0.55	0.78	0.45	0.87	0.27	0.14
Soybean	0.46	0.14	0.36	0.15	0.89	0.34
Channa	0.36	0.36	0.36	0.68	0.86	0.38
Green Gram	0.66	0.88	0.46	0.88	0.38	0.24
Bengal Gram	0.46	0.24	0.36	0.26	0.89	0.34
Toor Dal	0.58	0.27	0.78	0.14	0.36	0.21
Urad dal	0.87	0.89	0.14	0.36	0.78	0.25
Peas	0.15	0.86	0.36	0.88	0.14	0.14
Masoor dal	0.68	0.38	0.88	0.24	0.36	0.31
Average	0.50	0.51	0.45	0.504	0.568	0.263

Table 4. MSE Results of Series 2 Experiment

Commodities	SVR [29]	LSTM [30]	ARIMA [31]	XG Boost [32]	Prophet [33]	Proposed Method
Wheat	0.25	0.36	0.35	0.58	0.75	0.28
Rice	0.55	0.78	0.45	0.87	0.27	0.14
Soybean	0.46	0.14	0.36	0.15	0.89	0.34
Channa	0.36	0.36	0.36	0.68	0.86	0.38
Green Gram	0.66	0.88	0.46	0.88	0.38	0.24
Bengal Gram	0.46	0.24	0.36	0.26	0.89	0.34
Toor Dal	0.58	0.27	0.78	0.14	0.36	0.21
Urad dal	0.87	0.89	0.14	0.36	0.78	0.25
Peas	0.15	0.86	0.36	0.88	0.14	0.14
Masoor dal	0.68	0.38	0.88	0.24	0.36	0.31
Average	0.396	0.35	0.497	0.469	0.583	0.224

Table 5. RMSE and MAPE Results of Experiment

Commodities	RMSE	MAPE
Wheat	50.9	0.25
Rice	45.6	0.55
Soybean	34.7	0.46
Channa	23.5	0.36
Green Gram	25.6	0.66
Bengal Gram	0.86	0.46
Toor Dal	0.97	0.58
Urad dal	1.235	0.87
Peas	2.45	0.15
Masoor dal	3.76	0.68
Average	18.95	0.50

Table 6. RMSE and MAPE Results comparison with Existing Methods

Methods	RMSE	MAPE
GRU	174.12	0.24
LSTM	41.03	1.12
Bi-LSTM	29.27	5.99
ARIMA	302.53	4.56
Logistic Regression	66	6.78
LDA	65.3	7.89
Multi-linear Regression	59	8.76
Proposed Method	18.95	0.50

Table 7. Comparison of proposed food crops supply chain with other existing traceability supply chain

Factors	Massimo Conti[29]	M.N.M. Bhutta[30]	S. Wang [31]	H. Juma [32]	G. Perboli [33]	W. Lin [34]	Proposed System
Trustworthiness	Yes	Yes	Yes	Yes	Yes	Yes	Yes
WBCIS	No	No	No	No	No	No	Yes
Data Security	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Authenticated Stakeholders	Yes	No	Yes	Yes	No	Yes	Yes
Government Authorities	No	No	No	No	No	No	Yes
Traceability	Yes	Yes	Yes	No	No	No	Yes
Automated Payment	No	No	No	No	No	No	Yes
Transparency	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Information Sharing	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bitcoin Prediction	No	No	No	No	No	No	Yes

Figure 1: Architecture for Blockchain centered Food crops Traceability and Bitcoin Prediction
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Table 1. Transaction Details

Table 2. Statistical Distribution of Raw Information Cost

Table 3. MSE Results of Series 1 Experiment

Table 4. MSE Results of Series 2 Experiment

Table 5. RMSE and MAPE Results of Experiment

Table 6. RMSE and MAPE Results comparison with Existing Methods

Table 7. Comparison of proposed food crops supply chain with other existing traceability supply chain

Biography

Dr. DAYANA D.S received her PhD from SRM Institute of Science and Technology, Chennai. She has more than 14 years of academic and research experience. Currently she is working as an Assistant Professor in the Department of Networking and Communications, School of Computing, College of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur. Her research interest includes Blockchain, cryptography, Agricultural Traceability, Deep Learning and Networking.

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