Soft Computing
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APPLICATION OF SOFT COMPUTING

A secure and intelligent public distribution system (SIPDS) based on deep learning and Ethereum using predictive analytics for supply chain services

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Abstract

This research introduces Secure and Intelligent Public Distribution System (SIPDS), a novel blockchain-based solution that enhances the efficiency of public distribution systems. SIPDS comprises two primary components: one leveraging blockchain technology for data security and the other employing advanced tools for predictive analysis. Initially, we established a secure and intelligent distribution system on the Ethereum platform. By utilizing a specialized blockchain approach, we developed tools capable of harnessing the power of smart contracts and predictive analytics. These tools systematically analyzed data from the Public Distribution System (PDS), uncovering patterns and refining predictive models through deep learning techniques. To assess the model's performance, we utilized key metrics such as Mean Absolute Error (MAE), Root-Mean-Square Error (RMSE), and R^2 score. These findings provided valuable insights into the overall effectiveness of our predictive model.

Keywords Public distribution system · Blockchain innovation · Deep learning · Ethereum · Digital contract · Forecast analytics

1 Introduction

One of the world's paramount concerns is ensuring food safety, which encompasses the accessibility, suitability, reliability, and consumption of nutritious essentials for everyone, at all times, and also the affordability of maintaining a healthy lifestyle (Benton 2016). India employs the Public Distribution System (PDS) to provide agricultural products and essential commodities to disadvantaged populations. However, the PDS encounters various challenges, including inefficiencies in identifying designated recipients, wastage, and procedural issues (Niehaus et al. 2013).

A public distribution system requires critical characteristics like information sharing, reliable results, data protection, integrity, and simplicity (Hussien et al. 2019). Blockchain, known as a decentralized and secure ledger, records and safeguards irreversible data from online transactions. This technology, also referred to as Distributed Ledger Technology (DLT), ensures authenticated transactions through decentralization and cryptographic hashing mechanisms (Khan et al. 2020; Jamil et al. 2020). In the Ethereum blockchain, every payment activity undergoes secure agreement by two participants to uphold its confidentiality and authenticity. A digital contract outlines how the distributed system can be accessed. Both parties reach an agreement on how each business transaction should be stored in a block, containing relevant information and data about the exchange. Additionally, for inclusion in the network, every block must undergo validation using a smart contract.

Afterward, robust encoding algorithms are applied to secure and protect the blockchain. Because it stores the

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majority of collected information in a shared manner, the most crucial aspect of blockchain innovation is ensuring privacy and preventing unauthorized alterations to transaction records (Khan and Byun 2020). Unlike centralized systems, which are susceptible to cyber-attacks, the blockchain provides transactional data confidentiality and integrity through decentralization and cryptographic hashing. Compared to current record-keeping systems, the blockchain system is more reliable and trustworthy. Implementing a smart contract for the conventional methods enhances performance and reduces operational expenses. However, it is important to note that the substantial electricity consumption required to maintain a legitimate distributed ledger is one of the key drawbacks of blockchain architecture (Golosova and Romanovs 2018). This innovative technology significantly impacts the data science industry, particularly in the management and manipulation of raw data (Engin and Treleaven 2019). Various data analytics approaches are utilized to extract meaningful insights from past distribution data, essential for the PDS to formulate effective future strategies, including prospective commodity supply requirements and expanded commodity allocation management across all components. Multiple machine learning (ML) methods are available for assessing information from previous PDS data, including techniques like data analysis and categorization, to name a few.

Modern machine learning techniques enable the creation of reliable and flexible forecasting models that use recently acquired knowledge to predict future outcomes (Iqbal et al. 2020). Prediction methods are essential components of any machine learning system, serving as a tool for companies to foresee future needs based on inferred information. Within computer technology, Deep Learning (DL) approaches, particularly Deep Neural Networks (DNNs), have taken precedence, introducing a new class of deep learning algorithms with applications in various fields. Among these, DNNs stand out as one of the most robust DL models, aiming to enhance the feature representation approach in learning models, thereby replacing current methodologies (Das et al. 2020).

The Public Distribution System (PDS) presents a highly intricate and disorganized structure, characterized by partial integration and the involvement of numerous intermediaries. This complexity leads to an ineffective business environment. Additionally, the effectiveness of food security initiatives is impeded by improper handling, insufficient infrastructure and a lack of adequate marketing facilities. These challenges create obstacles to achieving sustainable food security. The oversight of the Public Distribution System (PDS) is inadequate, allowing for further wastage, theft, and corrupt practices, which contribute to inefficient food distribution. Such circumstances also give rise to broader issues such as corruption, malnutrition, and heightened poverty levels. Consequently, the enhancement of PDS requires technological modernization. One promising avenue is the integration of technologies like blockchain, which can be employed within PDS and similar initiatives to ensure and oversee the attainment of sustainable food security. Therefore, a PDS system was deployed on blockchain with deep learning technology to ensure tracking of goods at every stage of distribution and forecasting analytics for sales prediction.

1.1 The contribution of the method

Blockchain technology ensures data quality and availability in food security by employing features like immutability, consensus mechanisms, and decentralization. Immutability guarantees that once data are added, it cannot be altered, maintaining historical accuracy. Consensus mechanisms validate data accuracy before inclusion, while decentralization stores copies across the network, boosting availability. Cryptography secures data, and smart contracts enforce rules for consistent data. This transparent and accountable system promotes traceability and trust in food supply chains.

Our proposed System for Secure and Intelligent Public Distribution (SIPDS) is established on the Ethereum permissioned blockchain infrastructure, allowing only authenticated entities (central, FCI, state, district, taluks, and ration shops) to engage in communication. This enhancement will increase transaction speed and reduce latency within the blockchain network.

- The aim of utilizing digital contract-based data treatment is to scrutinize PDS records stored on the blockchain for uncovering critical details essential for effective resource management in commodity distribution.
- Furthermore, the predictive module, based on smart contracts, leverages newly acquired information to refine robust Deep Learning-based forecasting models for predicting commodity distribution frequency across all components on a routine basis.
- Additionally, our suggested SIPDS boasts a user-friendly interface, features DL-based forecasting analytics for accurate sales predictions, and operates within a permissioned blockchain network.
- By restricting access to historical transaction records and associated digital details, the proposed SIPDS ensures security.
- This secured system is also compact, with the web application interfacing with the blockchain network through a RESTful API.

- The performance of the predictive analytics model has been evaluated during the creation of the REST API server using a range of metrics, including MAE, RMSE, and R^2 score.

2 Literature review

This section summarizes previous research on the proposed SIPDS including a review of blockchain-based frameworks in selecting the best blockchain platform for a public distribution system.

2.1 Blockchain in PDS

This chapter describes background research and equivalent perspectives for the planned SIPDS. PDS is currently facing a lot of topics in purpose of offering effective distribution services and analyzing PDS data and developing better future strategies. The most fundamental difficulty for the PDS is data security, data interoperability, and poor record administration, all of which can improve the PDS's commodities distribution services. The second task is to evaluate PDS data to try to uncover hidden insights and information, which is critical for making brighter future choices and demonstrating the benefits of data analytics. The third problem is to ensuring that all electronic transactions of the federal government, state governments, district offices, ration shops, and customers are documented in the system. To address these issues, various researchers are working to create dependable and intelligent apps for the public distribution system in practice to improve services. The emergence of blockchain technology has paved the way for a transformation in the way commodity supply data are handled safely and efficiently across a distributed network.

Information and Communication Technologies (ICTs), including the Internet of Things (IoT), big data analytics, and artificial intelligence (AI), are being assimilated into industrial processes. This integration enhances the efficiency of decision-making, accountability, and efforts against corruption. ICTs always had the potential to transform the whole manufacturing process by allowing new technologies to boost the productivity of current supply chain activities (Yeo and Grant 2019). Especially with wireless networks and Radio Frequency Identification (RFID), traceability and food safety can be ensured throughout the distribution process. The uses of blockchain innovation are often divided into two categories in the literary works: financial as well as none. It is utilized in a variety of economic applications, like payment systems, virtual currencies, and finance servicing (Cappa and Pinelli 2020). It has a tremendous implication on the payment of economic goods, such as fiat currency, securities, financial derivatives, and stock exchanges. There are various non-financial applications for blockchain innovation. It encompasses the medical industry, which encompasses applications like online clinical care, health service administration, personalized medicine, and medication counterfeiting (Farouk et al. 2020), among others. Also, it is designed for applications like e-voting, identity, and security mechanisms to enhance government. It also offers the capabilities, to enhance improve, and simplify tasks in especially in corporate industries such as inventory management, and also in educational and authenticity validation applications (Zhu et al. 2020). Furthermore, a large amount of publications in the field of blockchain-based production capacity applications are given, including increasing monitoring and traceability, enhanced data organization across the whole supply chain (Behnke and Janssen 2020), improved stock and process appraisal, and smart transport technologies Numerous business models built on IoT and blockchain applications are currently gaining traction. Numerous business plans IOT-based and blockchain apps are growing rapidly these days. By boosting openness, traceability, and transparency in supply chain networks, blockchain system can help enable more adaptable value chains (Kshetri 2018). We explain how blockchain is applied to detect fake goods in the electronics industry. Behnke and Janssen (2020) Examine into the demands and capabilities of blockchain logistics. There have been a number of example research studies on the application of blockchain emerging technologies in logistics system management. Data mining approaches have recently sparked increased research in a variety of study disciplines, including healthcare, academia, and financial services, to mention a few. The authors of Bin et al. (2013) proposed a prediction model for predicting the dangers in products using restricted approximate sets of resources. DM approaches were used by the authors of a study published in Palaniappan and Awang (2008) to effectively unearth secret information and insights via vast amounts of facts.

2.2 Platforms using blockchain technology

Blockchain technology, which uses a distributed ledger to securely and reliably store a wide range of data exchanges, is one of the most technological advancements. Blockchain-based architectures come in three flavors: consortium, private, and public. The public blockchain, a fully accessible project, employs proof-of-work consensus processes. The foundation of the private blockchain is a chain of permissioned networks run by a single company. A permissioned blockchain designed for corporate applications is a consortium blockchain or federated blockchain, in which multiple firms collaborate to improve organizational operations utilizing blockchain innovation (Brown et al. 2016). According to a recent review study (Agbo et al. 2019; Sugumaran and Rajaram 2023; Ilakkiya and Rajaram 2023), the Ethereum and Hyperledger Fabric frameworks are frequently utilized to construct corporate applications for supply chain businesses. Ethereum supports and carries out smart contracts that make use of high-level computer languages to enhance the fundamental operation of the blockchain system. Due to these fantastic features, Ethereum is a strong and reliable blockchain foundation for creating PDS implementations. As a result, our suggested SIPDS uses the Ethereum platform to create a secure and intelligent public distribution network based on the blockchain.

3 Designed a blockchain-based, secure public distribution system

The suggested methodology for the blockchain-based SIPDS is outlined in this section. The suggested system is summarized in Section 3.1. Section 3.2 describes the connection framework for the envisioned blockchain-based SIPDS.

3.1 Outline of the proposed SIPDS

SIPDS innovation consists of a number of computer networks which are used to manage commodity distribution and electronically share data. This additionally makes it possible for technological advancement to deliver commodity distribution data to the supply chain sector and professional, allowing them to make more informed judgments. As a result, a blockchain-based SIPDS has been created to protect PDS facts in a distributed manner. Figure 1 depicts a system architecture of the upcoming SIPDS that combines the general framework of blockchain-based, trustworthy PDS administration, data, and predictive modeling. The permissioned blockchain network allows only authorized persons to participate, which is controlled by a central authority. Also, it offers qualified participants with enrollment and authentication certificates. The proposed approach sets itself apart from past systems with this distinctive and novel characteristic.

The suggested blockchain-based model seeks to hold commodity distribution information in a safe and trustworthy distributed ledger. Smart contracts are used in the built framework to check and verify transaction records based on predetermined circumstances. The smart contract is implemented on the blockchain network that enables for the secure and transparent exchange of assets (anything of value) avoiding the usage of third parties. Multi-user categories decide the user's (participant's) function in the proposed blockchain-based SIPDS. A REST API server allows the participants to interface with the created blockchain system. The participants' entire, up-to-date record of information, commodity specifics, commodity distribution documents, customer information, and data analytics. The predictive analytics model can help PDS management build enhanced future actions to obtain market share.

3.2 The proposed blockchain-based SIPDS interaction model

This part outlines the planned blockchain and DL-based SIPDS workflow. The created platform serves as a client interface architecture that supplies a blockchain record and a digital contract as resources for the front-end interface. Figure 2 depicts the planned SIPDS. The user-friendly architecture of the front-end application permits individuals to engage also with blockchain system. Participant's registration and verification, commodity allotment, distribution records, and data analytics report are only a few of the intuitive features supported by the software application for submitting transaction ideas to the built blockchain network. The proposed SIPDS is built on a permissioned network chain. As an outcome, before conducting a commodities transaction also on blockchain network users should authenticate and validate their identities. Users must enroll and undergo authentication in addition to developing a secret key which will be used to validate a digital trade. The process of learning to read and write PDS-related data from a blockchain ledger, which executes and confirms throughout the blockchain network, is referred to as a transaction. The central government will upload commodity and distribution data to the blockchain network via an REST API server. It is also important to note that almost all components can submit transactions like getting commodity specifics data, distribution data, and viewing data analytics reports, among others. In addition, an embedded inference engine is performed to examine and discover confidential message from PDS data that is retrieved from the ledger, as well as to record data analytics outcomes return to the distributed ledger. Furthermore, a prediction model depending on extracted patterns is built using an incorporated predictive analytics component. The predictive analytics component creates predictions and saves them to the blockchain using information from the data analytics module. The off-chain information system is an independent data repository that uses a series of steps to successfully store and retrieve current participant and asset values through the blockchain ledger. A recent collection of data values for component distributions is what the off-

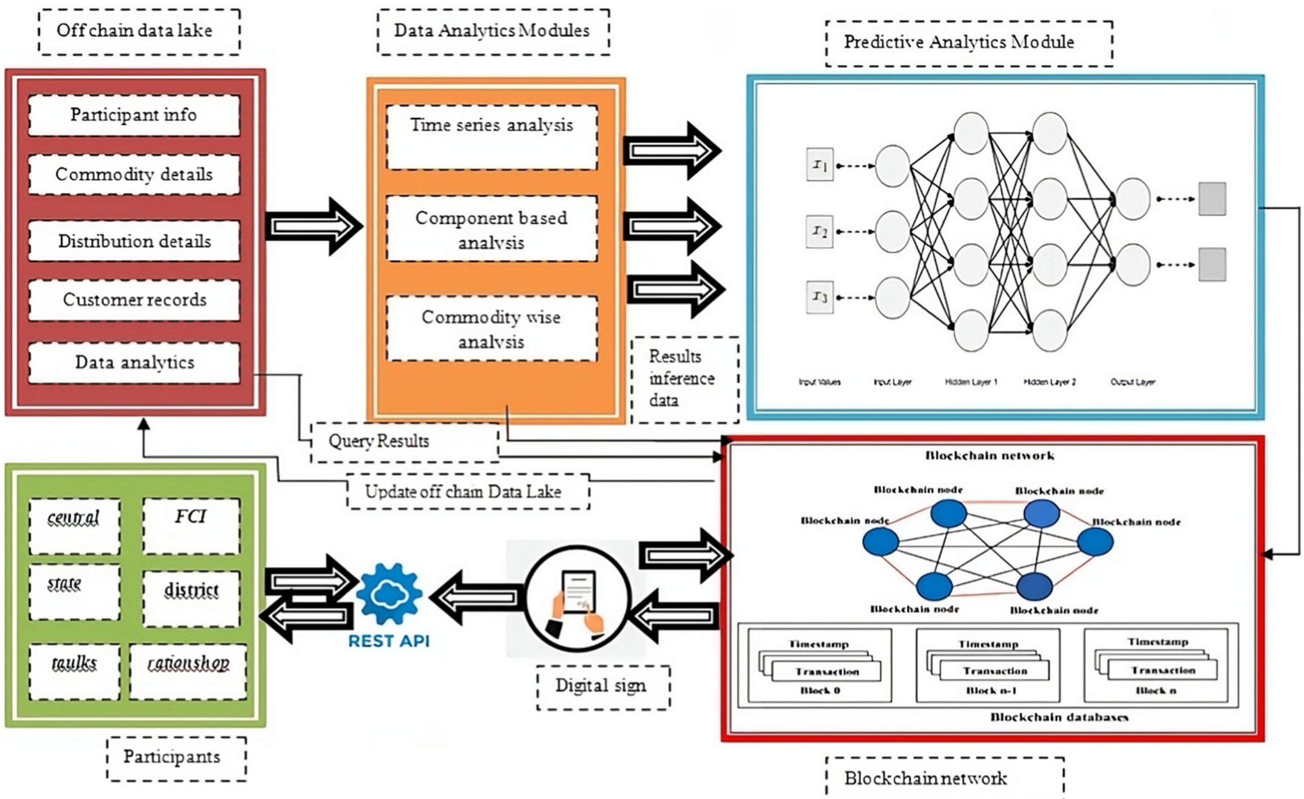


Fig. 1 The proposed blockchain-based SIPDS block diagram

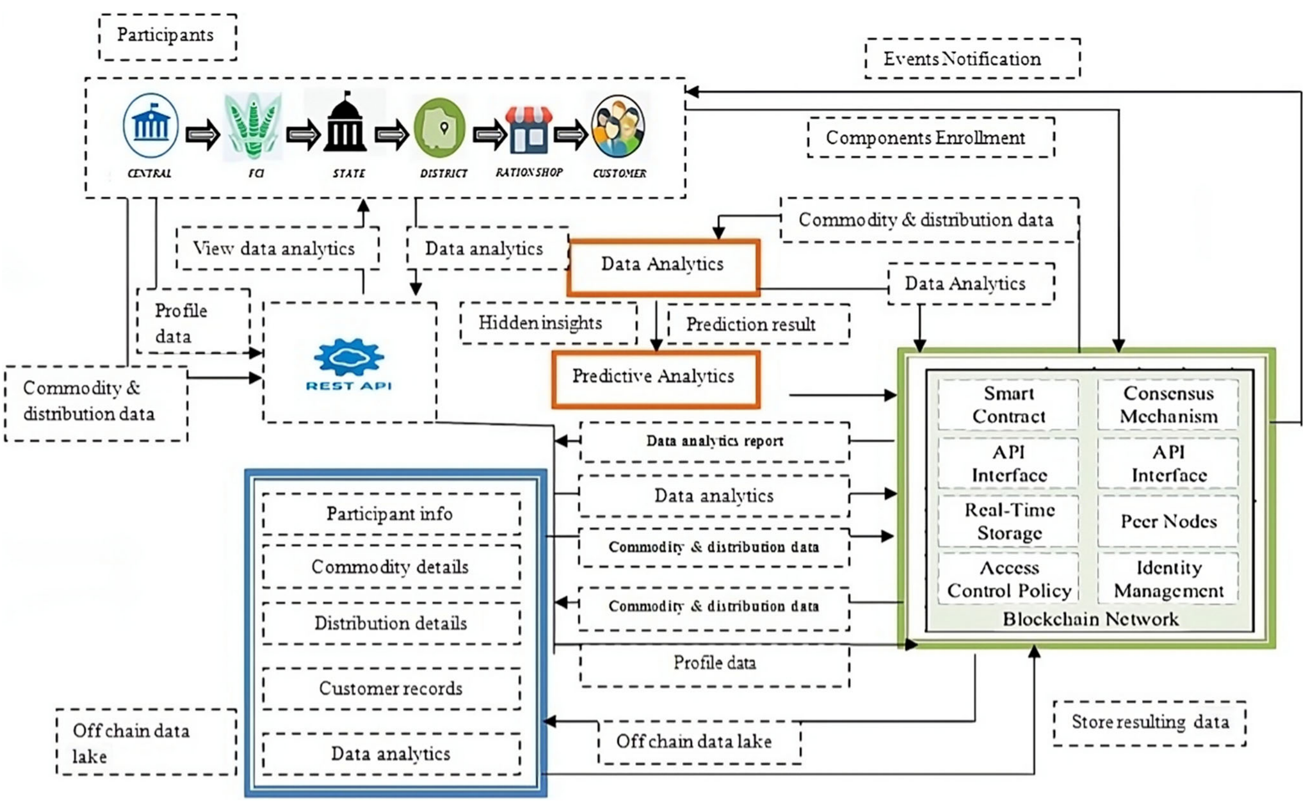


Fig. 2 The suggested blockchain-based SIPDS workflow

chain database logger is designed to keep track of. A notification notice is then sent to the user interface by an event manager to let users know if the process was successful or not.

3.3 Planned predictive analytics framework based on public distribution system data

The proposed predictive analytics model for projecting future sales of the public distribution system is described in this paper, PDS can use this tool to help them develop successful organizational strategy and procedures Data collection, preprocessing, data mining techniques to remove essential patterns, data standardization to give reliable information, and training and testing deep learning classifiers are all steps in the proposed method.

3.3.1 Data collecting for PDS

Data from the Tamilnadu public distribution system were utilized in this study. (https://tnpds.gov.in/ and https://tn.data.gov.in/). The collection was collected over a 3-year period and contains 50,000 distribution records (2019–2021 (up to May)).

3.3.2 Data preprocessing

Data preprocessing is a crucial step in converting raw facts into reliable information within the data mining and knowledge extraction process. Unfortunately, the data from the public distribution system do not meet the required quality for implementing DL approaches to unveil hidden insights. To enhance the reliability of PDS data, it is imperative to remove irrelevant and untrustworthy information. To streamline the acquired dataset, the following steps are taken: identifying and eliminating redundant records and unnecessary data attributes, a process facilitated by our proposed SIPDS system.

3.3.3 Analysis of patterns

Engineering patterns is a pivotal stage when employing deep learning techniques to reveal concealed attributes within a preprocessed dataset. These extracted features prove highly influential in augmenting the training accuracy of DL-based models. To unveil hidden insights using DL approaches in our suggested SIPDS, we leveraged the following features: commodity distribution day, commodity name, and allocation quantity of specific commodities, along with state, district, and taluks details. Time-series features offer a diverse set of intriguing data that can be harnessed for forecasting analytics.

Initially, utilizing time-series analytics, such as year wise, month wise, and day wise, our suggested model investigates the distribution date attribute in extracting the frequency of commodity distribution data. Second, we apply time-series analytics to examine commodity-specific distribution attributes on a year, month, and daily basis. Figure 3 illustrates the distribution of commodities in FCI and Tamilnadu, employing time-series analytics on both a weekly and daily scale. Likewise, Fig. 4 utilizes a time-series model to examine the distribution of commodities across multiple taluks and registered ration stores on an annual basis. It monitors the allocations on a daily and monthly basis, as well as whether or not sales of specific items were high. The monthly analysis, spanning from January to December, provides a detailed overview of average frequency distribution per day. Through data analytics, PDS uncovers concealed insights and trends, enabling more informed decision-making. These data often reveal which products have been most in demand and which district component has seen the highest sales.

3.3.4 Data normalization

Certain data characteristics values, like year-wise and month-wise frequency of the commodity distribution, induce skewness in our created dataset. To avoid skewness, all of these data attributes must be normalized within a specific range to obtain consistent values. Numerous methods for normalizing data have been proposed, including decimal scaling normalization, z-score normalization, and min–max normalization, to mention a few. The min–max normalization method was utilized in this study to normalize many of the data features that result in inaccuracies in their values. This procedure is used to change normalized characteristic levels from 0 and 1 and retain the accuracy of data attribute values. For normalize facts with results in a particular length such as [0, 1], implement Eq. (1)

$$\text{MinMax} = \frac{x_i - \min(A)}{\max(A) - \min(A)}. \tag{1}$$

3.4 Algorithms used in the proposed method

This subsection describes the suggested regression-based predictive analytics models. Three widely used recurrent neural network models are Bidirectional LSTM, Gated Recurrent Unit (GRU), and Long Short-Term Memory (LSTM) (BiLSTM).

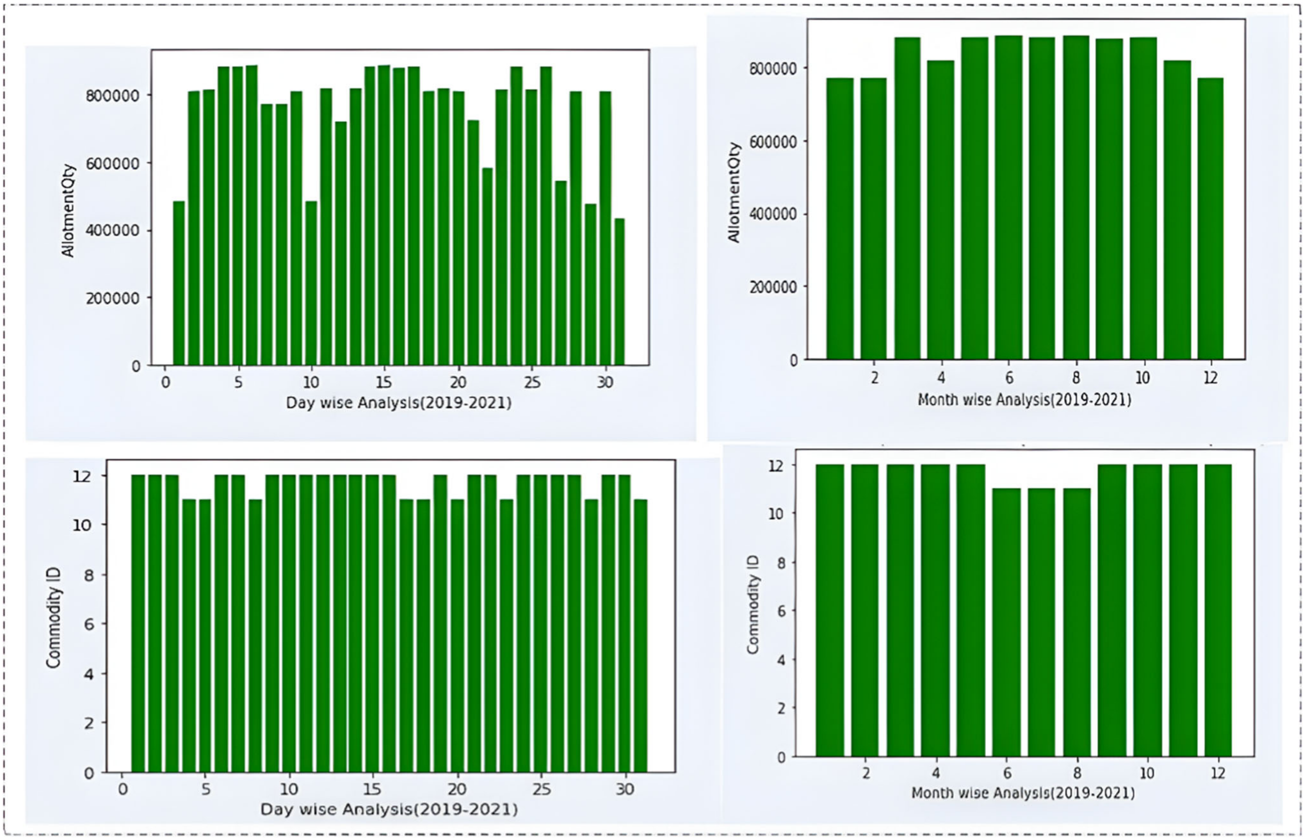


Fig. 3 Analyze time-series of distribution (central government to FCI & State)

3.4.1 Long short-term memory (LSTM)

Due of its flexibility and incorporation of activation functions into every level, neural networks are effective at extracting nonlinear aspects for long memory data. In the study, standard LSTM with forget gates was chosen as an extra inputs for FFC open price prediction to represent exogenous variables. F. Gers was the first to introduce LSTM. A forget gate, input gate, input candidate gate, and output gate are all represented by interacting neural networks in Fig. 5, as can be seen. The output value of the forget gate is between 0 and 1. A forget gate function is a function that retains the necessary cell state information for prediction as an equation while forgetting the unneeded cell state from an earlier time cycle (Eq. 2)

$$f_t = \sigma W_f \cdot [h_{t-1}, x_t] + b_f. \tag{2}$$

The σ function that represents the activation functional also known as sigmoid, which allows the framework to be nonlinear

$$\sigma(X) = \frac{1}{1 - e^{-x}}. \tag{3}$$

The next phase results in the creation of a new cell state, C_t, which transitions to a different time step as a renewal cell state. This new cell state is created by the combination of the input gate and input candidate gate. As activation functions at the input gates and input candidate gate, respectively, the sigmoid activation function and the hyperbolic tangent function are used, to provide output ii select and new cell state C_t^r, as shown in the equations. The tanh function is a parabolic tangent function that returns values ranging from -1 to 1

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_t), \tag{4}$$

$$C_t^r = \tanh(W_c[h_{t-1}, x_t] + b_c). \tag{5}$$

The output of the tanh function, a parabolic tangent function, ranges from -1 to 1

$$\tanh(X) = \frac{e^x - e^{-x}}{e^x + e^{-x}}. \tag{6}$$

3.5 Gated recurrent unit (GRU)

Recurrent neural networks were significantly better at managing and processing sequential data than various kinds of neural networks. RNNs, unlike standard neural networks, concentrate on altering state neurons to acquire contextual relationships inside and among sequential input.

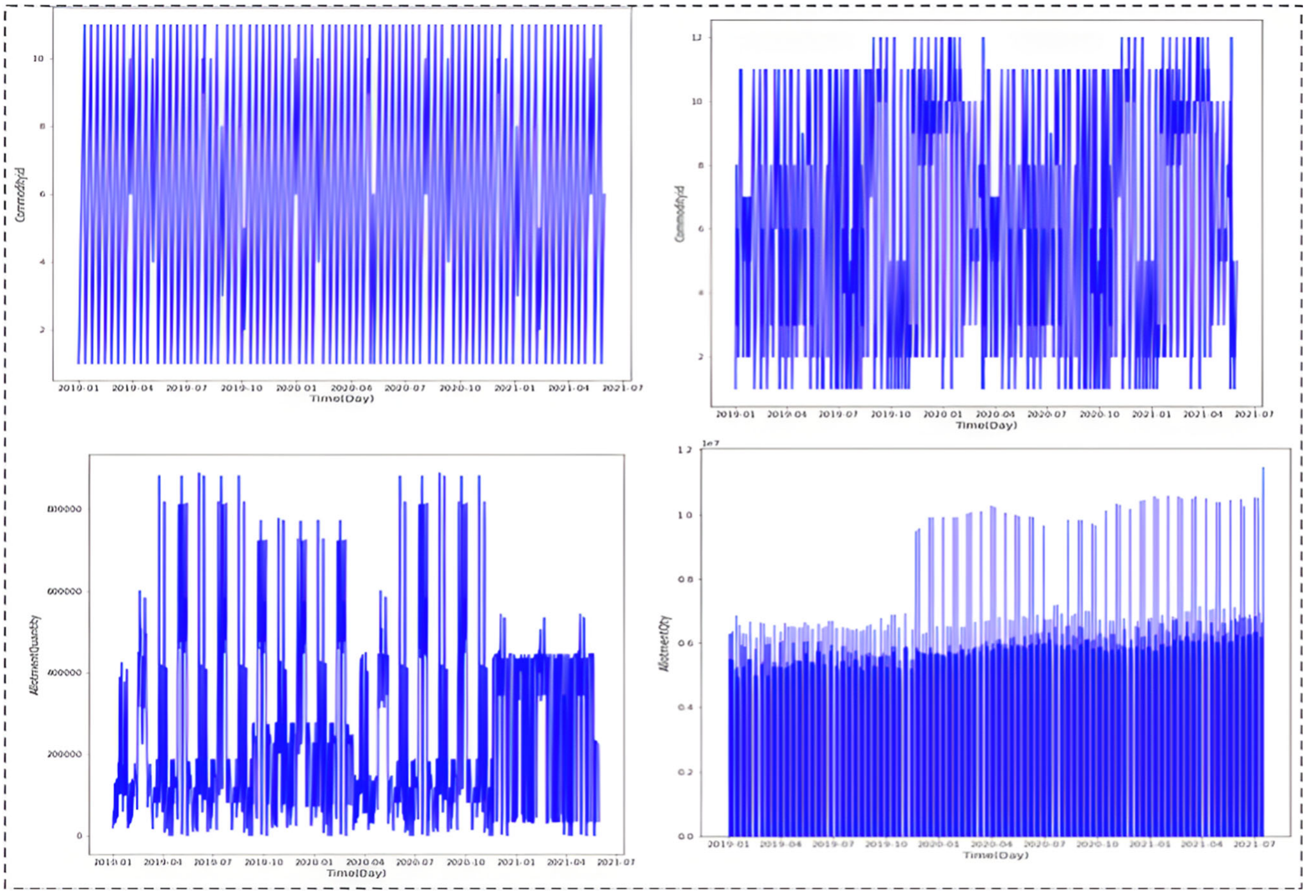


Fig. 4 Analyze time-series of distribution-year wise

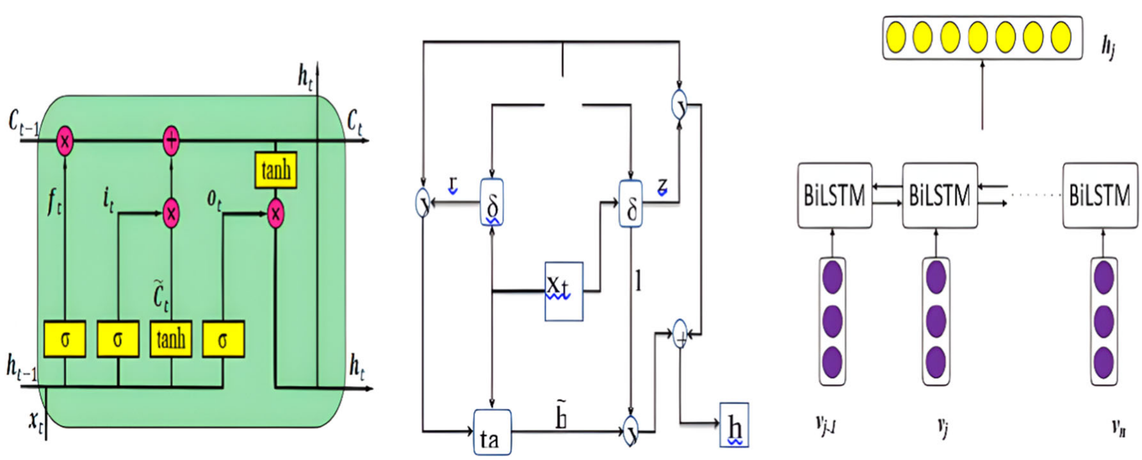


Fig. 5 LSTM, GRU, and BiLSTM architecture

The occurrence of disappearing and bursting gradients, which make training RNNs difficult, is a limitation of such recurrent networks. In typical recurrent neural networks, the disappearing and explosion of gradients are a problem that GRUs can overcome. LSTM models are the most extensively used RNNs, as they have been proven to deliver state-of-the-art efficiency in a broad variety of various computational applications.

The GRU architecture is depicted in Fig. 5. GRU is a basic model of the LSTM that uses simply 2 gates to build candidate memory from existing input and past memory state. A GRU cell to take the contents of the prior hidden state h_{t-1} and the given input x_t at every time step t gives the computed current state after manipulating them using reset and update gates. h_t toward the upcoming time cycle is depicted in Fig. 9. A generic GRU cell is defined by the formulas below

$$s_t = \eth(W_s x_t + U_s h_{t-1} + b_s), \tag{7}$$

$$r_t = \eth(W_r x_t + U_r h_{t-1} + b_r), \tag{8}$$

$$\tilde{h_t} = \tanh(W_h x_t + U_h(h_{t-1} \otimes r_t) + b_h), \tag{9}$$

$$h_t = s_t \otimes h_{t-1} + (1 - s_t) \otimes \tilde{h_t}, \tag{10}$$

where s_t denotes the vectorized form of the update gate, r_t indicates the vectorized form of the reset gate, and h_t signifies a linear extrapolation of the old state h_{t-1} and the present candidate storage h_t using the update gate result. To reduce ranging between zero and one, sigmoid activation ($\eth$) is used on both the update and reset gates. The parabolic tangent activation tanh() is used to calculate h_t. Hadamard product is denoted by the symbol $\otimes$ (element-wise multiplication). x_t is the present input supplied into the network; W_s, W_r, and W_h are trainable weights of feed-forward connections, whereas U_s, U_r, and U_h are weights of recurrent connections. The bias vectors are b_s, b_r, and b_h.

3.6 Bidirectional LSTM (BiLSTM)

Long-term dependencies are more well captured by the LSTM structure, a well-known cyclic neural net structure, than by regular RNN. By addressing the problem of long-term dependence, it might be simpler for RNN to recognize and utilize additional dependency links. The LSTM is an enhanced RNN model that incorporates internal gates to address the slope problem. The LSTM is a recursive neural network that uses the input and output of the preceding unit to generate an outcome matrix, so it can be used as the input for the unit after it. Finally, categorization is done using the output of the hidden layer.

Every cell in an LSTM introduce an innovative formation that be primarily made up of four elements, as was previously stated: input gate i_t, output gate o_t, forget gate f_t, and memory unit c_t. The calculation is expressed by the equations (11–16)

$$f_t = \sigma\left(W_{(f)}x_t + U_{(f)}h_{t-1} + b_{(f)}\right) \tag{11}$$

$$i_t = \sigma\left(W_{(i)}x_t + U_{(i)}h_{t-1} + b_{(i)}\right) \tag{12}$$

$$o_t = \sigma\left(W_{(o)}x_t + U_{(o)}h_{t-1} + b_{(o)}\right) \tag{13}$$

$$c_t = \tilde{c} + i_t \odot \tanh\left(W_{(c)}x_t + U_{(c)}h_{t-1} + b_{(c)}\right) \tag{14}$$

$$\sim\ = f_t \odot c_{t-1} \tag{15}$$

$$h_t = o_t \odot \tanh(c_t), \tag{16}$$

where x_t is the input at time, σ is the sigmoid activation function, and denotes the element multiplication. c_t is utilized to avoid gradient disappearance or explosion, allowing LSTM to acquire longer information reliance. I_t and o_t represent the input and output gates, which are required to control the memory unit's input and output.

However, back-to-front information cannot be encoded using LSTM. The bidirectional LSTM network was suggested to make use of past and forward properties over a specified time period. BiLSTM, which is created by combining forward and backward LSTM, may deliver more relevant information and have a quicker and more effective learning potential. Figure 5 depicts the BiLSTM's construction. This module uses BiLSTM to examine how the capsule layer influences the network features' ability to fit and their ability to generalize to the new data set.

3.7 Suggested blockchain and DL-based SIPDS implementation

This part explains the PDS deployment framework, which forecasts future sales using blockchain-based technologies and predictive analytics. The implementation environment is separated into two sections, including the development of a public distribution system based on blockchain innovation and the application of analytics forecasting to identify future commodities sales.

3.7.1 The suggested blockchain-based SIPDS implementation environment

The planned blockchain-based system undergoes separate front-end and back-end development phases. Table 1 outlines the structure for the back-end development of the proposed reliable public distribution system. The method and a series of experiments are executed on a Windows computer using an online tool in the Remix IDE environment for generating smart contract code in the Solidity language. Additionally, Ethereum, an open-source platform for creating blockchain runtimes, is utilized. The design and development process also involves the use of Sublime Text, which allows for the creation of blockchain applications compatible with both local and web-based servers. To retrieve data from the blockchain-based application, a RESTful API is employed. Table 1 lists the tools and technology needed to implement PDS's GUI. To create dynamic performance of the front-end application, the following technologies are employed in the development of a web-based implementation: HTML5, CSS3, Bootstrap, and JQuery. When a client utilizes the web-based implementation, actions like POST, GET, PUT, and DELETE

Table 1 Suggested blockchain-based SIPDS development environment

Components of the system	Explanation
Operating system	Windows 7
CPU	AMD PRO A4-4350B R4, 5 COMPUTE CORES 2C + 3G 2.5 GHz
Memory	4.00 GB
Remix IDE	0.10.3
Ethereum	2.0
Sublime text	3.2.2
Python	3.6.9

Components of the system	Explanation
Operating system	Windows 7
CPU	AMD PRO A4-4350B R4, 5 COMPUTE CORES 2C + 3G 2.5 GHz
Memory	4.00 GB
Programming language	HTML5, CSS5, JQuery
Front-end library	Bootstrap
Client SDK	Google chrome & Firefox

are triggered, which subsequently cause those methods to respond to the client's HTTP request.

3.7.2 Predictive analytics model implementation and experimentation setup

This section explains how to build up the predictive analytics framework to estimate product growth. Table 2 shows the suggested DL-based predictive analytics module's deployment environment. In addition, our research employs deep learning technologies along with BiLSTM, LSTM, and GRU to anticipate the frequency of commodity distribution for each component of a public distribution mechanism in the prospective.

Two operational phases are included in the methodologies mentioned above: training the learning model and evaluating the learned model with diverse datasets. As a result, the prepared dataset needs to be broken into two subsections: testing and training. Different strategies, such as K-fold and holdout, are available to divide data into subsets. The prepared structure is divided into two sections with a 70–30 split using the sklearn python module. Apply the proper formula (7) during testing and training to determine a divided input proportion. To obtain prediction results, ReLU (from hidden layers to input layers) and softmax were first used as activation functions in our proposed model (between the output and last hidden layers). The training procedure employs the dropout technique, which involves removing nodes from hidden layers at random. To able to preserve the outcome for every neuron throughout the hidden layer, our suggested model employs a dropout rate of 0.5, and that is a common number. The proposed blockchain-based SIPDS' execution outcomes are shown in this subsection. The front-end user interface displays the proposed SIPDS basic functions, including central government, state government, districts, taluks, and ration shops profiles, distribution record history of each component, commodity supply/stock, and data analytics. Every component's personal data are provided by the central government profile management.

4 The results of the suggested SIPDS's prediction

The experimental findings of the suggested forecasting component for future sales prediction utilizing multiple regression models are shown in this part.

Table 2 The proposed DL-based predictive analytics module's development setup

Components of the system	Explanation
Operating system	Windows 7
CPU	AMD PRO A4-4350B R4, 5 COMPUTE CORES 2C + 3G 2.5 GHz
Memory usage	4.00 GB
language for programming	Python
IDE (platform)	Colab

4.1 Time-series analysis for commodity and quantity forecast

The section shows the results of commodity and quantity-wise forecasting with time-series and additional data components. The regression models are used in this study to forecast future sales of the commodity on a daily level using the excellently python library sklearn, which is critical for PDS organization to build upcoming business goals and plans to successfully handle their requirements. To evaluate the predictive power of the created regression models, we also employed statistical measures including mean absolute error (MAE), root-mean-square error (RMSE), and R^2 score.

Figure 6a is applied to assess commodity distribution over all components and compare the prediction efficiency of the BiLSTM, LSTM, and GRU algorithms using the MAE and RMSE performance measures. In aspects of MAE and RMSE, the prediction error of the BiLSTM algorithm for all components is 1.097 and 1.467, 1.236 and 2.954, 2.478 and 2.923, respectively. When comparing multiple DL models, the prediction mistake can be seen to decrease. Similarly, Fig. 6b is applied to do a quantity-wise evaluation of all components and examine the prediction efficiency of the BiLSTM, LSTM, and GRU algorithms using the MAE and RMSE performance metrics. In aspects of MAE and RMSE, the prediction error of the BiLSTM algorithm for all components is 1.432 and 1.643, 1.634 and 1.234, and 2.345 and 2.087, respectively. When compare to various DL models, it may be shown that the prediction error decreases.

The performance evaluation and appraisal of the approaches are shown in Fig. 7. The R^2 value serves as a gauge for the prediction's accuracy. Figure 7a displays the DL model's prediction performance in a commodity-wise distribution with the highest R^2 scores for each of the major components, which are 0.90, 0.92, and 0.91, respectively. When compare to different DL models, it is shown that the prediction error increases. Figure 7b depicts the DL model's prediction performance in allotment quantity-wise distribution, with all components scoring 0.95, 0.94, and 0.96, respectively, in regards of maximum R^2 score. In a similar manner, when evaluated to alternative DL models, the prediction error increases.

I have added some figures based on current and future commodity forecasts, as well as allocation quantity forecasts. This prediction is valid for each component. Figure 8 shows how standard DL models like BiLSTM, LSTM, and GRU can be used to compare actual and predicted commodity distributions. When compared to other traditional models, the BiLSTM model properly predicted. Figure 9 shows how classic DL models like BiLSTM, LSTM, and GRU may be used to compare real and predicted quantity-wise distributions. The BiLSTM model has the highest accuracy and the best future results, as seen in the following prediction examples.

4.2 Performance evaluation

To convey the performance of the regression models, we included performance metrics including mean absolute error (MAE), root-mean-square error (RMSE), and R^2 score in this work. Machine learning provides a range of

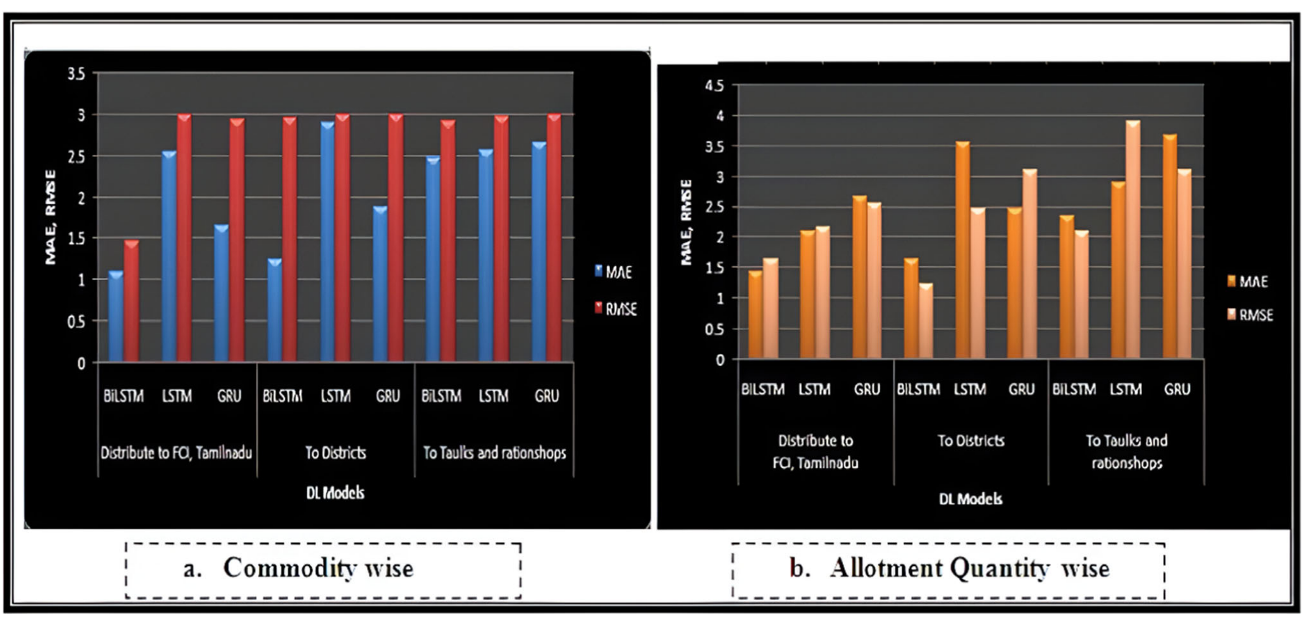


Fig. 6 Assessment of regression model performance using MAE and RMSE

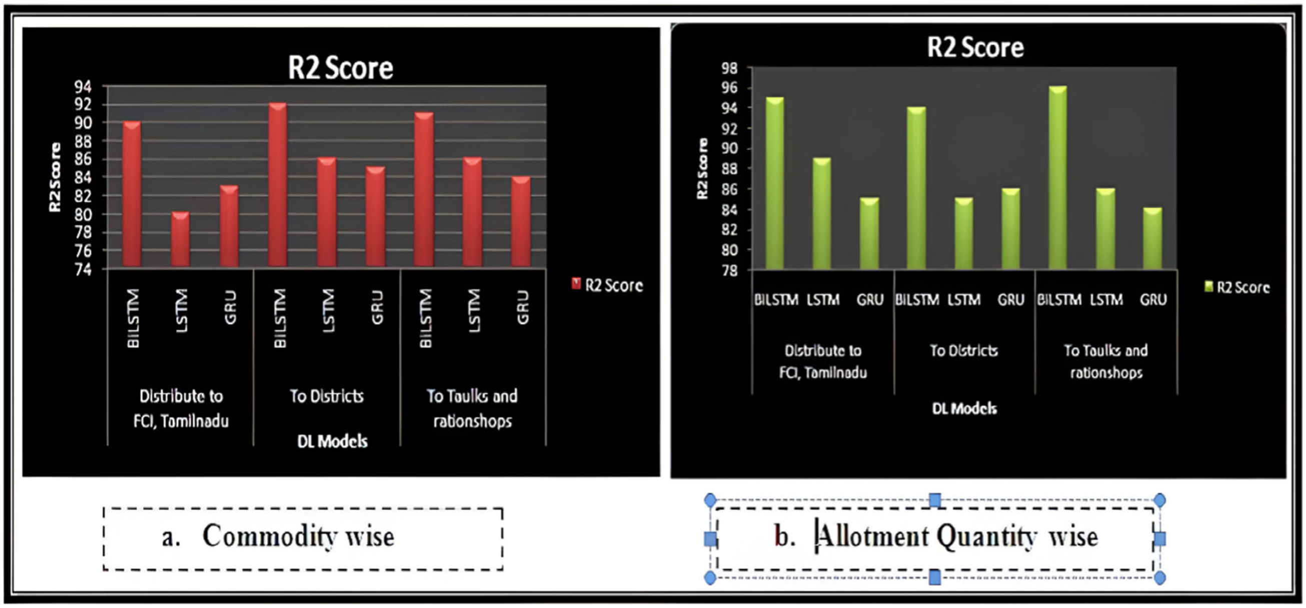


Fig. 7 Using R^2 Score, assess the effectiveness of the regression models

performance indicators for improving the appropriateness of predictive models.

(1) The mean absolute error (MAE) is used to gauge how well a prediction model is working by calculating the mean of the exact variance among instances of actual and anticipated data. Equation (17) is applied to compute it

$$\text{MAE} = \frac{\sum_{i=1}^{n} |Y_i - \hat{Y}_i|}{n}. \tag{17}$$

(2) Root-mean-square error (RMSE)

The square root of the MAE is the root-mean-square error (RMSE). It is calculated using the square root of the average squared difference among exact and anticipated data instances to evaluate the prediction model's overall performance. The range of RMSE is 0 to 1, with 0 indicating that the regression model functioned accurately on unknown data and a big value indicating that the prediction process has a high inaccuracy. Equation (18) is applied to compute it

$$\text{RMSE} = \frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)|^2}{n}. \tag{18}$$

(3) R^2 score or R-squared

In a regression model, a statistic meter is used to show how much the two variables vary from one another (i.e., dependent and independent variables). The R^2 score ranges from 0 to 1. The number 0 denotes the regression model's lowest performance, while 1 denotes the model's best performance across the unseen data samples. Equation (19) is used to compute the R^2

$$R^2 \text{ Score} = \frac{\sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n} \left(Y_i - \overline{Y}\right)^2}, \tag{19}$$

where

$$\overline{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i. \tag{20}$$

Table 3 shows the proposed SIPDS' performance evaluation and comparison findings with existing DL models including GRU, LSTM, and Bi-LSTM. In comparison to GRU, LSTM, and BiLSTM, the outcomes of the proposed SIPDS model were the most exciting and noteworthy. When related to other DL models, the BiLSTM performs enhanced in regards of R2 score. In comparison to GRU and LSTM, the suggested BiLSTM has a reduced prediction error. Using time-series data to estimate future sales, our suggested BiLSTM model showed the most promising prediction results. The BiLSTM model beat other classic DL models like GRU and LSTM in terms of prediction performance.

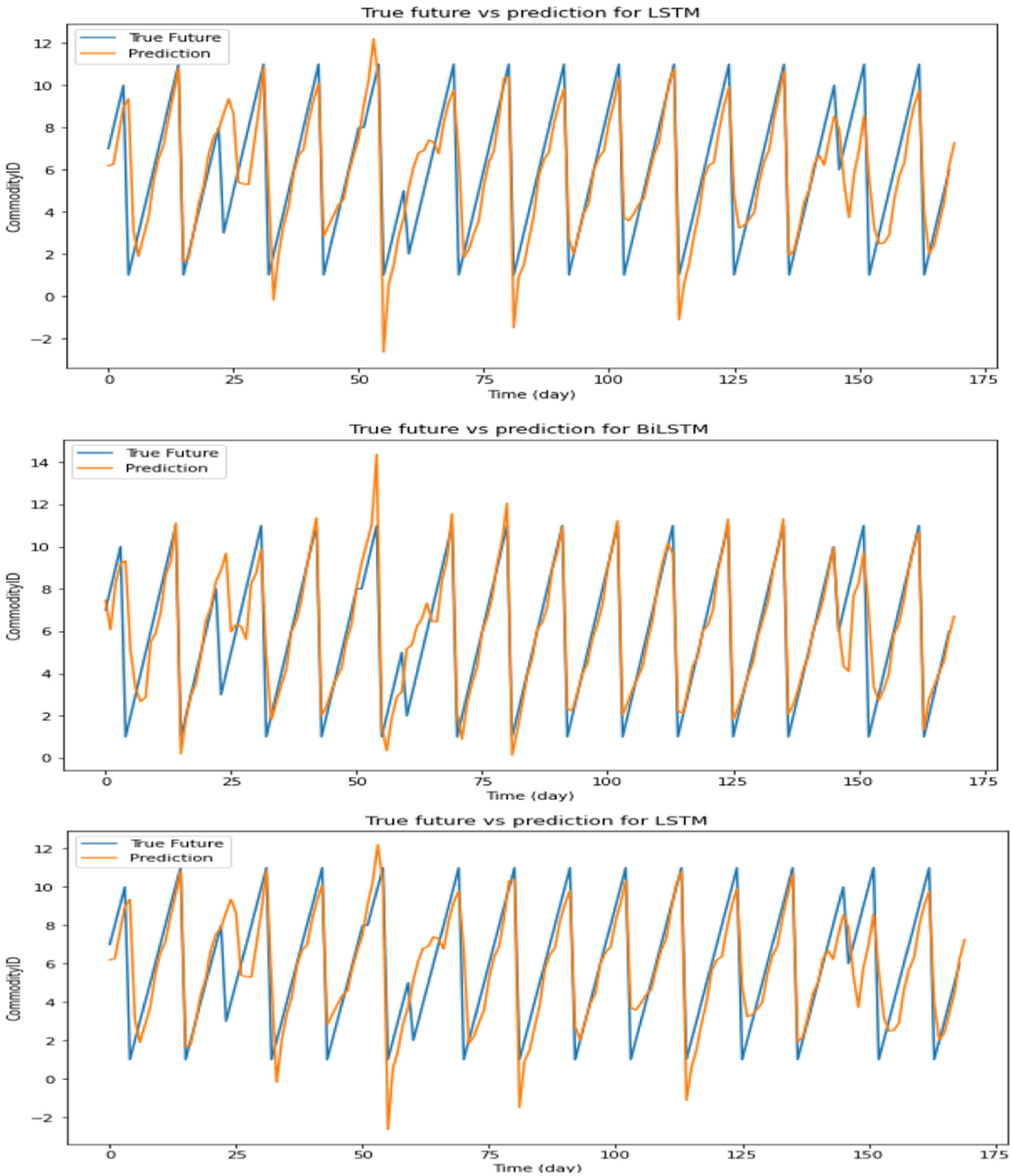
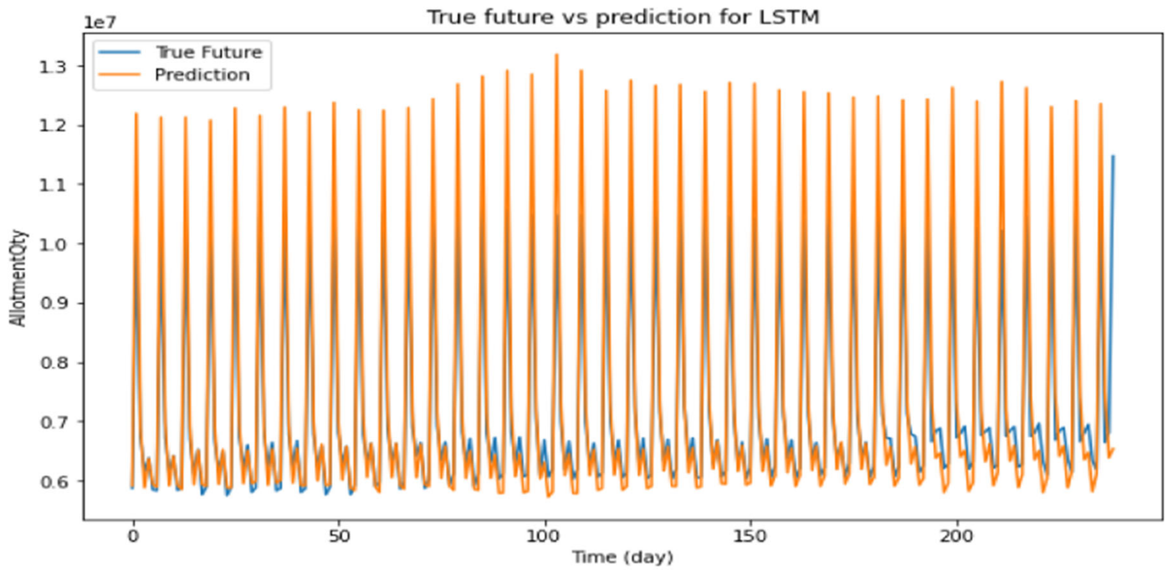
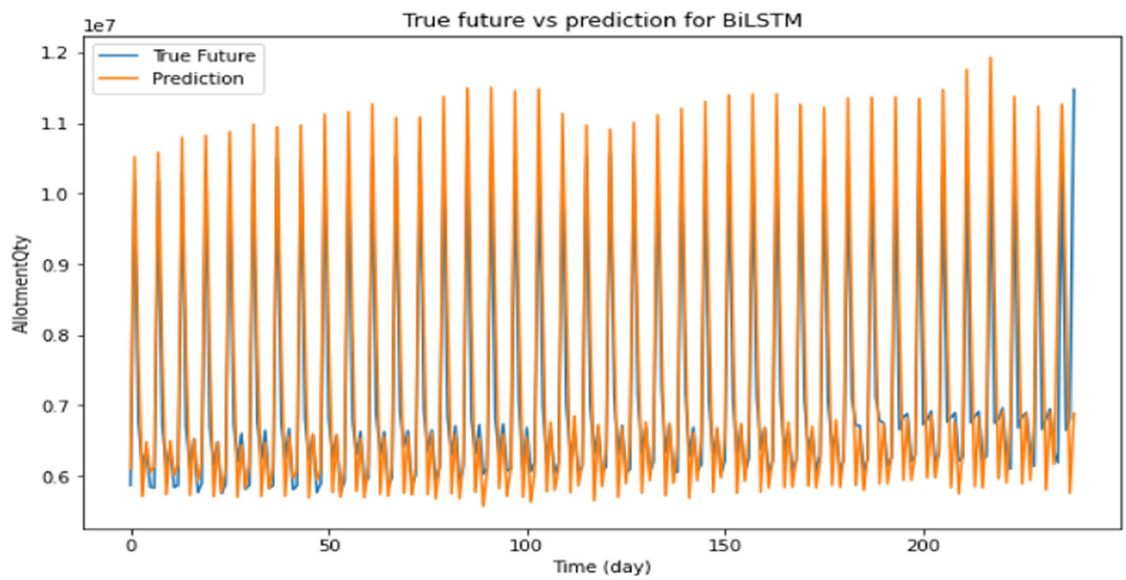


Fig. 8 Comparative analysis of commodity sales prediction using BiLSTM, LSTM, and GRU


True future vs prediction for LSTM
1e7
True Future
Prediction
1.3
1.2
1.1
1.0
0.9
0.8
0.7
0.6
AllotmentQty
0
50
100
150
200
Time (day)


True future vs prediction for BiLSTM
1e7
True Future
Prediction
1.2
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0.9
0.8
0.7
0.6
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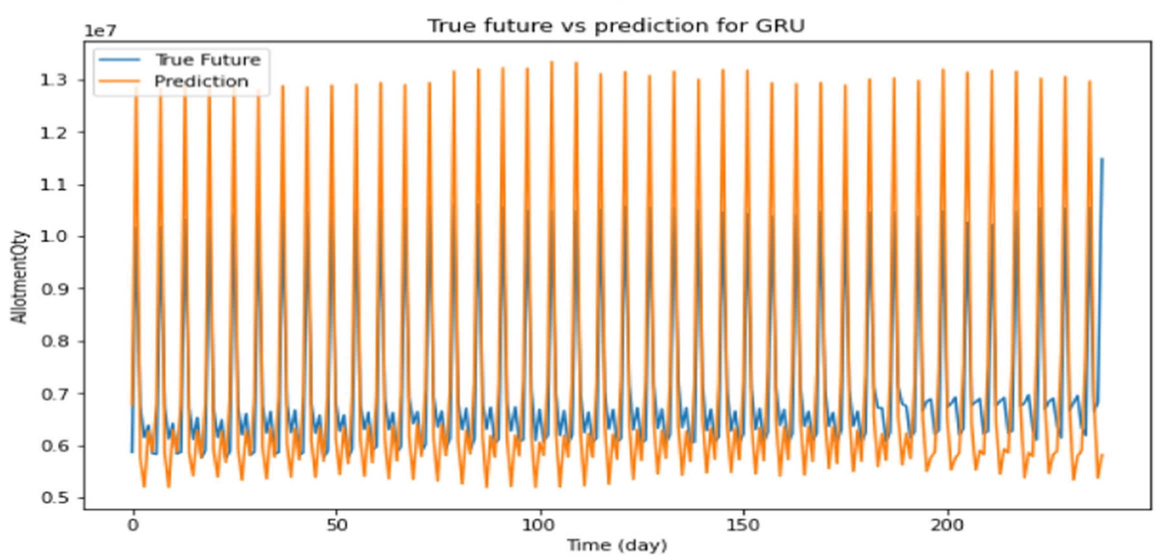
Time (day)


True future vs prediction for GRU
1e7
True Future
Prediction
1.3
1.2
1.1
1.0
0.9
0.8
0.7
0.6
0.5
AllotmentQty
0
50
100
150
200
Time (day)

◀**Fig. 9** Comparative analysis of quantity-wise prediction using BiLSTM, LSTM, and GRU

5 Discussions

The proposed blockchain-based SIPDS is compared to existing techniques in this section. The intended project included a baseline analysis to show the efficacy, reliability, and capabilities of the suggested blockchain-based SIPDS. Table 4 summarizes the conclusions of the comparative analytical analysis. In our proposed work, we only looked at the assessment characteristics that have an impact on the success of blockchain-based systems.

The above important evaluation variables are taken into account: smart contracts, efficiency, blockchain network type, and the system's primary capabilities. These criteria are applied to determine the value and individuality of blockchain-based development systems. Existing solutions are based on permissioned networks and are solely concerned with storing distribution data for all components. The suggested blockchain-based SIPDS is a compact framework, since the user application interacts to blockchain networks via RESTful API and can study the key operations of blockchain technology. Existing models, such as Sugumaran and Rajaram (2023), Ilakkiya and Rajaram (2023), Sooraj et al. (2020), Famnaz and Kumari (2019), Singh et al. (2020), Parameswari and Mandadi (2021), and Pawar et al. (2021), are also built on top of the network's permissioned chain. These systems, on the other hand, are used to keep track of distribution records in a secure and visible ledger. In addition, we apply DL approaches to analyze commodity and allocation quantity data from the PDS to uncover secreted insights and usable knowledge. A permissioned network of blockchain, a client interface, and a DL-focused predictive analytics component for sales prediction are also the foundations of our proposed SIPDS.

6 Conclusion and future work

In conclusion, SIPDS seamlessly integrates the security and reliability of blockchain with the intelligence of deep learning through smart contracts, offering a novel approach to enhancing distribution systems. Utilizing Ethereum as the foundation for our secure blockchain structure ensures data integrity and decentralization. SIPDS operates within a permissioned blockchain framework, promoting transparency and trust among participants. User interaction is facilitated through front-end software via REST server APIs, streamlining accessibility. Our empirical results highlight the remarkable predictive capabilities of the BiLSTM model when compared to the traditional DL models like LSTM and GRU. This superior accuracy in predicting quantity-wise distributions bolsters resource planning and allocation, contributing to heightened service

Table 3 Analyzing and contrasting the classic deep learning models' performance

Commodity wise analysis	DL models	MAE	RMSE	R^2 score
Distribute to FCI, Tamilnadu	BiLSTM	1.097	1.467	0.90
	LSTM	2.545	2.998	0.80
	GRU	1.645	2.934	0.83
To districts	BiLSTM	1.236	2.954	0.92
	LSTM	2.897	2.986	0.86
	GRU	1.878	2.998	0.85
To taluks and ration shops	BiLSTM	2.478	2.923	0.91
	LSTM	2.567	2.978	0.86
	GRU	2.659	2.989	0.84
Allotment quantity-wise analysis	**DL models**	**MAE**	**RMSE**	**R^2 score**
Distribute to FCI, Tamilnadu	BiLSTM	1.432	1.643	0.95
	LSTM	2.094	2.153	0.89
	GRU	2.673	2.543	0.85
To districts	BiLSTM	1.634	1.234	0.94
	LSTM	3.564	2.456	0.85
	GRU	2.456	3.097	0.86
To taluks and ration shops	BiLSTM	2.345	2.087	0.96
	LSTM	2.897	3.897	0.86
	GRU	3.675	3.097	0.84

Table 4 Comparison of the suggested SIPDS based on blockchain

System	Smart contract	Framework	Efficiency	Blockchain network	Functionality
Sooraj et al. (2020)	Yes	Hyperledger Sawtooth	Low	Permissioned	Track the location of commodities
Famnaz and Kumari (2019)	No	Node.js	Low	Permissioned	Built small web-based applications
Singh et al. (2020)	Yes	Hyperledger fabric with big data	High	Permissioned	Conceptual framework for storage and analysis of data across on-chain and off-chain
Parameswari and Mandadi (2021)	Yes	Ethereum & Remix IDE (Online Tool)	Low	Permissioned	Develop only smart contract-based application
Pawar et al. (2021)	Yes	Hyperledger Composer	Low	Permissioned	To achieve the strategic goal of a transparent and trusted Food Subsidy Distribution System
Dayana et al. (2023)	Yes	NodeJS, JavaScript, Python	Low	Permissioned	Circular blockchain technology is employed for traceable agri-food supply chains and accurate Bitcoin price prediction using LSTM, achieving 88.67% accuracy compared to SVM and NB
Sajja et al. (2023)	Yes	–	Low	Permissioned	This article addresses the uses of blockchain technology in food supply chains, agricultural insurance, smart agriculture, and agricultural commodities transactions
Proposed SIPDS	Yes	Ethereum	High	Permissioned	SIPDS including commodity details, distribution records, etc. Smart contract enabled data and predictive analytics

quality, customer loyalty, and profitability. By leveraging predictive analytics, SIPDS empowers proactive commodity demand forecasting and distribution planning. This transformative approach underscores its potential to revolutionize distribution management, fostering a reliable and intelligent ecosystem. This study reaffirms the immense potential of blockchain and predictive analytics in ensuring the integrity and intelligence of distribution data, thereby charting a path toward enhanced efficiency and reliability.

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Data availability Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Declarations

Conflict of interest Conflict of interest is not applicable in this work.

Ethics approval and consent to participate No participation of humans takes place in this implementation process.

Human and animal rights No violation of human and animal rights is involved.

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