

Blockchain technology in pharmaceutical supply chain : Ensuring transparency, traceability, and security

A. S. Shete *

Department of Pharmaceutics

Krishna Institute of Pharmacy

Krishna Vishwa Vidyapeeth (Deemed to be University)

Karad

Maharashtra

India

Sunil Bhutada [†]

Department of Information Technology

Sreenidhi Institute of Science and Technology

Hyderabad

Telangana

India

M. B. Patil [§]

Department of Pharmaceutics

Krishna Institute of Pharmacy

Krishna Vishwa Vidyapeeth (Deemed to be University)

Karad

Maharashtra

India

Praveen H. Sen [‡]

Computer Science and Business Systems

St. Vincent Pallotti College of Engineering and Technology

Nagpur

Maharashtra

India

* E-mail: amol.shete@rediffmail.com (Corresponding Author)

[†] E-mail: sunilb@sreenidhi.edu.in

[§] E-mail: manemadhuri786@gmail.com

[‡] E-mail: senpraveen.it@gmail.com

Neha Jain [@]

*Department of Computer Engineering
Marathwada MitraMandal College of Engineering
Pune
Maharashtra
India*

Prashant Khobragade [#]

*Department of Computer Science and Engineering
G H Raisoni College of Engineering
Nagpur
Maharashtra
India*

Abstract

Transparency, traceability, and security are three major challenges that blockchain technology has addressed in the pharmaceutical supply chain, making it a disruptive solution. The incorporation of blockchain technology to produce an immutable, decentralized ledger that documents the full path taken by pharmaceutical products from producer to end-user is examined in this abstract. The solution ensures tamper-resistant records by utilizing smart contracts and cryptography concepts, hence mitigating the risk of counterfeit medications. Transparency is improved via real-time supply chain visibility, which gives stakeholders the ability to monitor batch information and confirm product authenticity. Blockchain's decentralized structure improves security by reducing the possibility of fraud and unauthorized access. By means of blockchain implementation, the pharmaceutical business may create a strong, dependable, and effective supply chain ecosystem, thereby promoting safer and more dependable medicine access for patients across the globe.

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1. Introduction

The supply chain of the pharmaceutical business is radically changing as a result of the use of blockchain technology. This introduction explores the various benefits that blockchain provides for security, traceability, and transparency in the pharmaceutical supply chain. Conventional supply chain models frequently encounter difficulties including theft, counterfeiting, and inefficiency, which have detrimental effects on patient

[@] E-mail: neha.juet@gmail.com

[#] E-mail: prashant.khobragade@raisoni.net

safety and the reputation of the sector. Blockchain presents a strong answer to these problems by offering a decentralized, unchangeable ledger that tracks each transaction involving the movement of pharmaceuticals. The potential of blockchain technology to produce a transparent, [1] tamper-proof record of a drug's entire lifecycle from production to distribution to end-user possession is what essentially drives its influence. Each transaction is safely connected to the one before it by the use of cryptographic hashing and consensus procedures, creating an irreversible chain of data. This lowers the possibility of fake medications reaching the market by improving pharmaceutical traceability and ensuring reliable data recording. In order to further automate and streamline procedures and guarantee that contractual responsibilities are fulfilled without the need for middlemen, smart contracts self-executing contracts with the terms of the agreement directly put into code are being used.

Pharmaceutical supply [2] networks need real-time visibility, and blockchain offers a solution by giving all parties access to a single, shared version of the truth. At any stage of the supply chain, this transparency enables producers, retailers, authorities, and even customers to confirm the legitimacy of pharmaceutical items. Furthermore, real-time access to batch information, expiration dates, and other crucial data enhances decision-making and reduces the risks connected to out-of-date or compromised items. In the pharmaceutical sector, where human health is at risk, security is critical. Because blockchain technology is decentralized and employs encryption techniques, security is improved by averting single points of failure and protecting private data. The use of blockchain technology [3] in the pharmaceutical supply chain creates a basis for an ecosystem that is more reliable and trustworthy while also reducing the dangers of fraud and unauthorized access. The adoption of blockchain technology in the pharmaceutical supply chain signifies a paradigm change in favor of a system that is more transparent, traceable, and safe. This introduction lays the groundwork for a thorough examination of how blockchain solves certain issues facing the pharmaceutical sector, ultimately resulting in a more secure and dependable global healthcare system.

2. Proposed Architecture Pharmaceutical Supply Chain Management

Blockchain is fundamentally an immutable, decentralized ledger that offers security, traceability, [4] and transparency along the whole supply chain. Smart contracts are integrated into the architecture to automate and

enforce agreements, eliminating the need for middlemen and increasing operational effectiveness. For real-time data gathering and monitoring, IoT device integration is essential. These gadgets which include RFID tags and temperature sensors are systematically placed at different stages of the supply chain, from production plants to pharmacies and distribution hubs. They make sure that pharmaceutical items are handled and kept according to guidelines by constantly recording and transmitting vital information. This real-time monitoring lowers the risk of spoiling or contamination by preventing the distribution of tainted goods and enabling quick response to any deviations from ideal conditions [5].

A safe and intuitive [6] user interface is another feature of the architecture that makes it possible for all parties involved manufacturers, distributors, regulators, and customers to obtain pertinent data on the blockchain. By guaranteeing a single, shared version of the truth, this promotes cooperation and trust among participants. The system also makes use of advanced analytics to extract useful information from the vast amount of data produced by Internet of Things devices. Supply chain efficiency may be increased overall, inventory management can be optimized, and possible interruptions can be foreseen with predictive analytics. The [7] suggested design includes access controls and encryption mechanisms to improve security and protect private information on the blockchain. Because blockchain technology is decentralized, there is less chance of a single point of failure, and a breach at one node won't affect the system as a whole.

3. Smart Contract

Smart contracts, which use computer code to automate procedures and do away with middlemen, mark a paradigm shift in the execution and enforcement of agreements. Being maintained in a distributed ledger, they guarantee security and immutability when operating on blockchain platforms [8]. Despite their potential, they face difficulties during development, particularly when using Solidity, a programming language that is very unfamiliar and has a steep learning curve. Because it involves all peer nodes, transaction execution can also take a while. To mitigate this, performance can be enhanced by selectively distributing smart contracts to particular nodes. Our methodology leverages popular languages such as Java and Node.JS to reduce the learning curve and improve the system's performance [9]. Overcoming these obstacles is essential for smart contracts to be widely used since they offer a more

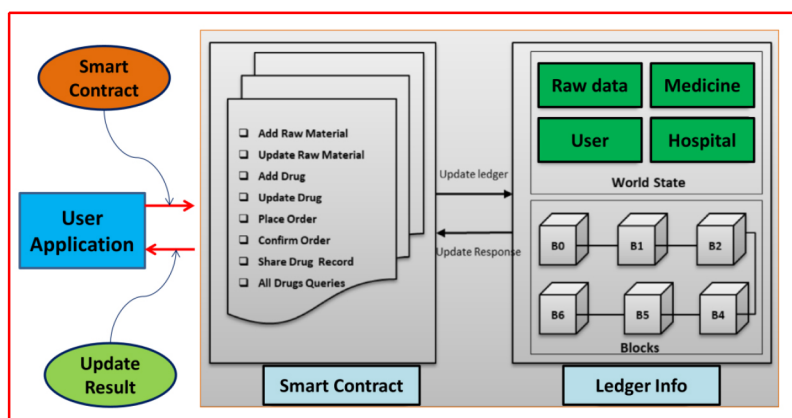


Figure 1

Overview of Smart contact

decentralized, safe, and effective means of conducting business and upholding agreements in the digital era. Smart contracts are redefining traditional contractual frameworks as shown in Figure 1.

4. Machine Learning for Drug Prediction

The application of machine learning (ML) to drug prediction has become a potent tool in pharmaceutical research, transforming the process of finding and developing new drugs. To identify possible medication candidates with the intended therapeutic qualities, machine learning algorithms examine enormous databases, including those including molecular structures, genomic data, and clinical information. These algorithms find patterns and relationships in complicated biological data by using methods including ensemble methods, support vector machines, and deep learning. Machine learning (ML) expedites the process of identifying possible drug candidates, lowers development time and expense, and improves prediction accuracy for safety and efficacy of drugs. Additionally, it makes personalized medicine easier by customizing care according to each [10] patient's unique needs. With its capacity to interpret complex biological interactions, machine learning (ML) has the potential to identify new therapeutic targets, identify innovative medications, and revolutionize the healthcare industry, as illustrate in Figure 2, by introducing more effective, focused, and individualized therapeutic approaches.

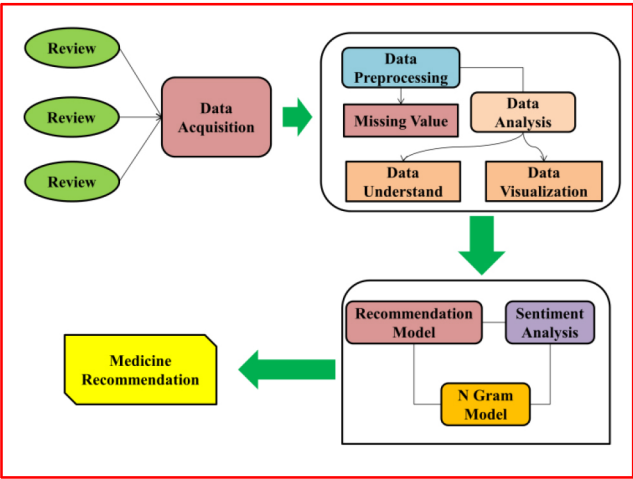


Figure 2

ML based System Architecture for Medicine Recommendation

5. Methodology

5.1 Dataset

Our suggested system’s drug recommendation module makes use of a substantial dataset that we obtained from reliable pharmaceutical websites, Drug.com and Druglib.com, which are accessible through the UCI Machine Learning datasets repository. This dataset includes comments and reviews from patients about their interactions with different medications. Our project intends to improve the precision and dependability of medication recommendations by utilizing the extensive data from Drug.com. It also intends to offer consumers insightful information derived from actual patient evaluations and comments.

5.2 DL Model

a. BERT (Bidirectional Encoder Representations from Transformers):

1. Input Representation:

Given a sequence of words or subwords $x_1, x_2, \dots, x_n$, BERT tokenizes and converts them into tokens

$$[CLS], x_1, x_2, \dots, x_n, [SEP],$$

Where, [CLS] and [SEP] are special tokens representing the start and end of a sequence.

2. Token Embedding:

Each token is represented by an embedding vector e_i . Token embeddings are concatenated with positional embeddings p_i to consider the order of words:

$$h_i = e_i + p_i.$$

3. Segment Embeddings:

For input sequences containing two segments, each token is assigned a segment embedding s_i , indicating the segment it belongs to. Segment embeddings are added to token embeddings:

$$h_i = h_i + s_i.$$

4. Attention Mechanism:

The self-attention mechanism computes attention scores α_{ij} between each pair of tokens. For token i , the output o_i is a weighted sum of the input token embeddings, where the weights are determined by the attention scores:

$$o_i = \sum_{j=1}^n a_{ij} h_j$$

5. Encoder Layers:

BERT consists of L layers of encoders, each with a multi-head self-attention mechanism and a feedforward neural network. The output of the l -th layer is given by:

$$H^l = \text{Layer Norm}(\text{Multi Head Self Attention}(H^{l-1}) + H^{l-1}).$$

6. Pre-training Objectives:

Masked Language Model (MLM): Randomly mask tokens, predict the masked tokens using softmax:

$$P(\text{masked token} | \text{context}) = \text{softmax}(W_o \text{ReLU}(W_h h_i)).$$

Next Sentence Prediction (NSP): Predict whether a pair of sentences is consecutive or not using a sigmoid activation:

$$P(\text{Is Next} | \text{pair of sentences}) = \text{sigmoid}(W_{sh}[\text{CLS}]).$$

b. LSTM:

1. Input Gate:

Calculate the input gate it :

$$it = \sigma(W_{iix}t + b_{ii} + W_{hih}(t-1) + b_{hi})$$

Calculate the input modulation candidate $C \sim t$:

$$C \sim t = \tanh(W_{icx}t + b_{ic} + W_{hch}(t-1) + b_{hc})$$

Element-wise multiplication of it and $C \sim t$:

$$cell_in = it \odot C \sim t$$

2. Forget Gate:

Calculate the forget gate ft :

$$ft = \sigma(W_{fix}t + b_{if} + W_{hfh}(t-1) + b_{hf})$$

Element-wise multiplication with the previous cell state C_{t-1} :

$$cell_forget = ft \odot C_{t-1}$$

3. Output Gate:

Calculate the output gate ot :

$$ot = \sigma(W_{iox}t + b_{io} + W_{hoht} - 1 + b_{ho})$$

Calculate the new cell state:

$$cell_out = \tanh(cell_in + cell_forget)$$

4. Element-wise multiplication with ot :

$$C_t = cell_out \odot ot$$

5. Hidden State:

Calculate the new hidden state ht :

$$ht = \tanh(C_t) \odot ot$$

6. Result and Analysis

Important performance metrics of the system are shown in Figure 3, which also provides information about query transaction latency and



Figure 3

(a) Representation of system response (b) Representation of Latency in query transaction using blockchain Technology

responsiveness. A visual summary of the system’s response to user inputs may be seen in subfigure (a), which shows the representation of system response. The system’s behavior as the user load rises is demonstrated by the graph, which depicts the dynamics of response times. Subfigure (b) explores query transaction latency, providing insight into how long it takes the system to process and react to user queries.

This latency model shows possible bottlenecks and scalability issues as the user base grows across different user categories. In order to identify performance patterns, possible areas for improvement, and set benchmarks for the best user experience, it is imperative that these visualizations be analyzed for system optimization. All things considered, system administrators and developers can benefit greatly from these graphical representations as they provide a thorough grasp of the behavior of the system under various workload conditions and user situations.

The outcomes of drug recommendation utilizing machine learning models LSTM and BERT in particular are shown in Table 1. The metrics for accuracy, precision, recall, and F1 Score are critical measures of how well the models perform in making medication recommendations.

Table 1
Result for Drug Recommendation using ML Model

Model	Accuracy	Precision	Recall	F1 Score
LSTM	89.63	88.56	82.77	89.75
BERT	92.54	91.2	94.23	92.44

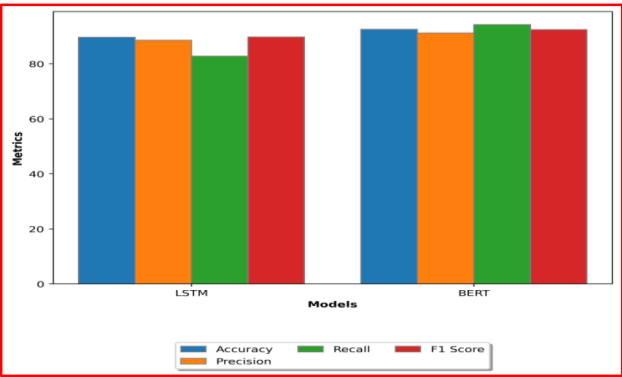


Figure 4
Model Performance Metrics

High accuracy values indicate in Figure 4 shows that the drug recommendations are generally correct; precision highlights the accuracy of positive predictions; recall emphasizes the model’s capacity to identify pertinent instances; and the F1 score offers a balanced metric that takes both precision and recall into account.

The LSTM model demonstrates commendable results as shown in Figure 5 with an accuracy of 89.63%, precision of 88.56%, recall of 82.77%, and an F1 score of 89.75%. However, the performance of the BERT model is even better, with 92.54% accuracy, 91.2% precision, 94.23% recall, and an astounding 92.44% F1 score. Together, these measures demonstrate how well both models propose medications, with BERT surpassing LSTM for every parameter that was examined.

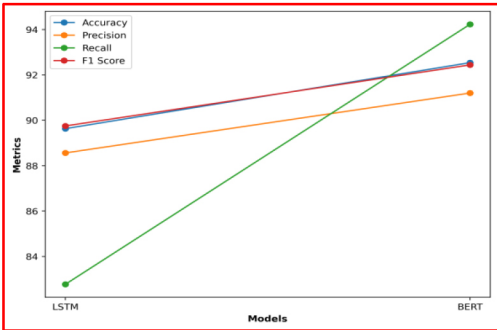


Figure 5
Comparison of Metrics for drug recomondation

The enhanced efficacy of BERT in using contextual information is demonstrated by its higher performance, hence validating its potential to augment drug recommendation systems. These findings offer insightful information to researchers and healthcare professionals that will help them choose and apply machine learning models that will produce the best results for medication recommendations.

7. Conclusion

The incorporation of blockchain technology into the pharmaceutical supply chain is a significant breakthrough that promotes security, traceability, and transparency. Every transaction, from production to distribution, is guaranteed to be permanently recorded by the decentralized and unchangeable ledger of blockchain technology. This boosts traceability and improves transparency by giving stakeholders instant access to reliable information, facilitating the quick identification of pharmaceutical product origins and movements. The supply chain is protected from illegal access and counterfeit medications by the intrinsic security characteristics of blockchain, such as consensus processes and cryptographic validation. This game-changing technology reduces risks, simplifies procedures, and boosts trust throughout the pharmaceutical industry. As the industry adopts blockchain, stakeholder engagement becomes more effective, guaranteeing that consumers receive genuine and safe medications. The pharmaceutical industry's dedication to quality, safety, and the welfare of patients worldwide is further supported by the supply chain, which is strengthened by blockchain technology and emerges as an example of integrity.

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