Blockchain Non-Fungible Token for Effective Drug Traceability System with Optimal Deep Learning on Pharmaceutical Supply Chain Management

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ABSTRACT

In recent times, the number of fake drugs has increased dramatically, which has resulted in millions of victims severely affected by poisoning and treatment failures, resulting in a need for Drug Supply Chain (DSC) traceability. The DSC is generally reluctant to share traceability data and includes several parties having heterogeneous interests. Moreover, existing provenance and traceability systems for DSCs need more trust, data sharing transparency, and separated data storage. By realizing decentralized, trustless systems, a decentralized Blockchain (BC)-based solution is proposed to tackle these constraints. BC is an immutable, decentralized, shared network that allows management directly through a peer-to-peer (P2P) network without the necessity of a central authority to check transactions. This study proposes a new Blockchain Non-Fungible Token-based Drug Traceability with Enhanced Pharmaceutical Supply Chain Management (BNFTDT-EPSCM) model. The proposed BNFTDT-EPSCM model presents transparent and more secure reporting of changes in the operating condition of transported pharmaceutical products to prevent drug recalls. The Ethereum BC enables transactions and computational services using the cryptocurrency Ether (ETH). Simultaneously, an enhanced Byzantine fault-tolerant consensus (RB-BFT) leverages a reputation system to address reliability issues of primary nodes and reduce communication complexity inherent in the Practical Byzantine algorithm (PBFT). The BNFTDT-EPSCM model presents a decentralized solution using Non-Fungible Tokens (NFTs) to improve the traceability and tracking capabilities of the standard serialization process. In addition, the BNFTDT-EPSCM model employs a Deep Belief Network (DBN) approach to perform the inbound logistics task prediction process. Finally, the Tasmanian Devil Optimization (TDO) method is utilized to enhance the hyperparameter tuning of the DBN approach. A detailed set of simulations was executed to examine the effectiveness of the BNFTDT-EPSCM approach, demonstrating a higher throughput at the highest user count of 6000 and achieving 551.22 TPS, significantly outperforming existing models.

Keywords-drug; blockchain; peer-to-peer; deep learning; non-fungible token; Tasmanian devil optimization

I. INTRODUCTION

The development of research, plans, and discussions of Blockchain (BC) technology has recently attracted the interest of researchers and medical experts [1]. BC acts as a decentralized ledger, allowing secure and permanent recording of transactions that cannot be altered once recorded [2]. Its immutability and capacity to manage extensive records make it essential in finance, healthcare, and military medical research [3]. In the pharmaceutical supply chain, challenges include transparency issues, complex product tracking [4], and the delivery of expired products. To maintain trust, consistent documentation of raw material origins is crucial [5]. Counterfeit medications also pose significant risks, potentially leading to ineffective treatments or harmful effects [6]. Integrating IoT technology with BC offers a solution that allows automatic monitoring of manufacturing and

transportation processes [7], with all transactions being time-stamped and traceable.

Smart Contracts (SCs) facilitate digital agreements, helping to reduce transaction costs [8]. NFTs enhance traceability by providing unique identifiers for drugs, allowing secure tracking of ownership and transaction history [9]. This integration improves security and traceability, fostering trust among stakeholders. BC and IoT technologies enable the pharmaceutical industry to address critical challenges and enhance operational integrity [10]. In addition, SCs will allow an NFT owner to manage the terms and conditions of subsequent token owners. The increasing demand for secure and transparent systems in sensitive industries highlights the need for innovative solutions. Utilizing BC technology can enhance traceability and accountability in pharmaceutical supply chains. This ensures that transactions are immutable and easily auditable, fostering trust among consumers and stakeholders.

This study proposes a new Blockchain Non-Fungible Token-based Drug Traceability with Enhanced Pharmaceutical Supply Chain Management (BNFTDT-EPSCM) model. The proposed BNFTDT-EPSCM model presents a transparent and more secure reporting of changes in the operating condition of transported pharmaceutical products to prevent drug recalls. The Ethereum BC enables transactions and computational services using the cryptocurrency Ether (ETH). Simultaneously, an enhanced Byzantine Fault-Tolerant (RB-BFT) consensus leverages a reputation system to address reliability issues of primary nodes and reduce communication complexity inherent in the Practical Byzantine algorithm (PBFT). The BNFTDT-EPSCM model presents a decentralized solution using Non-Fungible Tokens (NFTs) to improve the traceability and tracking capabilities of the standard serialization process. Based on BC, these NFTs leverage the benefits of both technologies. In addition, the BNFTDT-EPSCM model employs a Deep Belief Network (DBN) approach to perform the inbound logistics task prediction process. Finally, the Tasmanian Devil Optimization (TDO) method is utilized to enhance the hyperparameter tuning of the DBN approach. A detailed set of simulations was carried out to evaluate the BNFTDT-EPSCM approach. The key contributions of the BNFTDT-EPSCM model are listed below.

- Introduces an RB-BFT model that employs a reputation system to improve the reliability of primary nodes. This method significantly mitigates communication complexity, making the consensus process more efficient and strengthening the overall performance of the BC network.
- Ethereum BC enables secure transactions and computational services with the cryptocurrency ETH, fostering a decentralized platform that benefits from its established infrastructure. Additionally, an NFT model enhances traceability and tracking in the serialization process, effectively addressing counterfeiting and misidentification threats.
- A DBN is incorporated for predictive modeling in inbound logistics, improving forecast accuracy and operational efficiency. Utilizing the TDO for hyperparameter tuning additionally enhances the performance of DBM, enabling improved adaptation to complex data patterns and resulting in more reliable predictive outcomes.
- This novel integration improves reliability and transparency and utilizes advanced technologies to address critical industry challenges. The model underscores a novel synergy that optimizes efficiency and trust among stakeholders.

II. RELATED WORKS

In [11], an innovative four-tier architecture was introduced, including parallel side chains, Zero-Knowledge Proof (ZKP), and Interplanetary File Systems (IPFS). In [12], a pharmaceutical cold chain supervision algorithm was presented that depended on BC, cloud storage, and IoT. In [13], a DL-based technique was introduced, called Epsilon Greedy Consensus-based Hadamard Deep Authentication (EGC-HDA), using pharmacological SCM through EGC block validation and the Hadamard Gradient LSTM authentication method. In [14], a comprehensive and broad literature review was presented on this topic, and an efficient SCRM technique was used. In [15], a model was proposed that used AI and BC, recording entire individual transactions in BC by employing SCs and creating a DApp using the React model. In [16], a BC-assisted network was introduced, which also developed mathematical models of forward and backward supply chains.

In [17], a new BC-based multilevel security and authentication application was presented, which integrated a BC-enabled QR code watermarking layer for verification and authentication. In [18], a combined five-layer BC and IoT-based smart tracking and tracing (BIoT3) environment was introduced, presenting a real-world roadmap that followed the layers of the BC infrastructure model. In [19], a new BC-Enabled Unique Identification System (BEUIS) technique was developed. In [20], a system was proposed that employed an IMEFC architecture. In [21], an Ethereum-based solution was presented that uses SCs and data immutability. In [22], a BC-based medical prescription management system was proposed, incorporated with IoT. In [23], Vacledger was proposed, which is a BC framework for the traceability and counterfeit detection of COVID-19 vaccines. In [24], PharmaBlock was presented, which is a BC-based system with an Early Warning System (EWS) and a marketplace for detecting and disposing of near-expiry drugs.

Previous studies have proposed BC solutions for pharmaceutical supply chains, but issues such as complex architectures, connectivity vulnerabilities, and user trust persist. Furthermore, the lack of empirical validation in real-world settings and ongoing interoperability, regulatory compliance, and infrastructure investment challenges hinder widespread adoption and practical implementation.

III. THE PROPOSED METHOD

This study presents a novel BNFTDT-EPSCM model that offers transparent and more secure reporting of changes in the operating condition of transported pharmaceutical products to prevent drug recalls. Ethereum is a decentralized BC platform that enables the creation and execution of SCs, which are self-

executing contracts with the terms of the agreement directly written into code. Figure 1 shows the entire procedure of the BNFTDT-EPSCM approach.

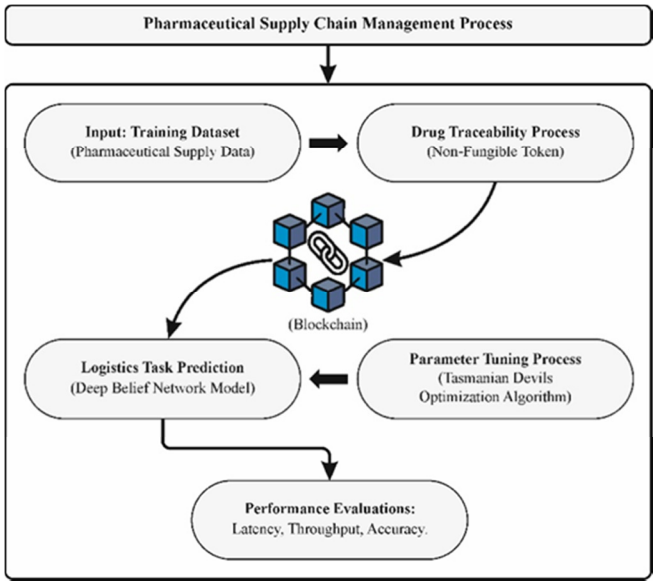

Fig. 1. Overall process of the BNFTDT-EPSCM approach.

A. Proposed NFT-based Drug Traceability

Serialization in the pharmaceutical industry comprises assigning a unique QR code to each package for traceability, created through NFTs on the BC [25]. The SC manages these NFTs, enabling the owner to add events and transfer ownership as needed. The SC allows hierarchical packaging management, where the owner must append dispatch events before sending items to the next actor in the dispersion network. The UpdateOwner and AppendEvent functions are exclusive to the NFT owner, ensuring secure data handling and preventing unauthorized changes. Upon minting, the creator appends status updates for effective anti-counterfeiting. When a pharmaceutical package is shipped, ownership is transferred, a "delivered" event is logged, and the NFT is burned by sending it to an inaccessible address upon patient delivery, averting further modifications.

B. Enhanced Practical Byzantine Model

The RB-BFT model addresses low consistency and communication difficulties in PBFT by integrating a reputation-based approach consisting of three key components: node detection and selection, a reputation model, and an improved consensus procedure [26]. It uses a credit estimation technique to assess node behavior, choosing nodes with higher trust levels as primary nodes to improve system security. A supervisory node monitors reputation scores and serves as a backup. The RB-BFT employs a deposit mechanism, requiring nodes to deposit a value tied to their initial reputation, establishing a normalized score between 0 and 1. A score of 1 indicates high reliability, while scores above 0.6 are acceptable, scores above 0.9 denote excellent reputation, and scores below 0.4 are considered malicious, with the supervisory node updating scores after each consensus round based on performance.

C. DBN-based Classification

The BNFTDT-EPSCM model incorporates the DBN model to perform the inbound logistics task prediction process. RBM consists of a Visible Layer (VL) and a Hidden Layer (HL) [27]. The VL controls input and the HL obtains high-level semantic features from input data. The hidden and visible units are binary variables with one or zero layers. An entire network is a bipartite graph without connection within the HL or VL. The hidden unit is $h = [h_1, \dots, h_m, \dots, h_k]$ and the visible unit is $v = [v_1, \dots, v_m, \dots, v_k]$. In the energy-based method, the joint configuration energy of VL and HL of v and h for RBM is determined as:

$$E(v,h,\theta) = -\sum_m b_m v_m - \sum_n a_n h_n - \sum_{mn} w_{mn} v_m h_n \quad (1)$$

where $\theta = (w_{mn}, a_n, b_m)$ shows the parameter of RBM, a_n and b_m imply the bias vectors of hidden and visible units, correspondingly, w_{mn} stands for the weighted among the hidden unit h_n and the visible unit v_m. The joint probability dispersion of v and h is calculated as:

$$P(v,h,\theta) = \frac{1}{Z(\theta)} e^{-E(v,h;\theta)} \quad (2)$$

where $Z(\theta) = \sum_v \sum_h E(v,h,\theta)$ stands for the normalized factor. The probability function of v and h is provided as follows:

$$P(h_n = 1|v) = g(\sum_{m=1} w_{mn} v_m + a_n) \quad (3)$$

$$P(v_m = 1|h) = g(\sum_{n=1} w_{mn} h_n + b_m) \quad (4)$$

where $g(x) = 1/(1 + exp(x))$ implies the logistic function. The RBM approach is trained by iteration, and the parameter $\theta = (w_{mn}, a_n, b_m)$ is attained by the subsequent Gradient Descent (GD) model:

$$\theta = \theta + \eta \times \frac{\partial \ln[\prod_{m=1}^{k} p(v|\theta)]}{\partial \theta} \quad (5)$$

where η refers to the rate of learning. The GD approach struggles with higher-dimensional data, while RBM's training efficiency was notably improved using the Contrastive Divergence (CD) method:

$$(v_m h_n)_{data} - (v_m h_n)_{rec} = \frac{\partial \ln p(v|\theta)}{\partial w_{mn}} \quad (6)$$

In this context, $(\cdot)_{data}$ is the expectation of the trained data, $(\cdot)_{rec}$ is the expectation of the reconstructed model, with conditions for DBN weights and biases defined as follows:

$$\Delta w_{mn} = \eta((v_m h_n)_{data} - (v_m h_n)_{rec}) \quad (7)$$

$$\Delta a_m = \eta((v_m)_{data} - (v_m)_{rec}) \quad (8)$$

$$\Delta b_n = \eta((h_n)_{data} - (h_n)_{rec}) \quad (9)$$

The RBM parameters are fine-tuned for optimal local performance, allowing the DBN to explore a deep hierarchical representation, with both layers treated as a single RBM.

D. Hyperparameter Tuning Using the TDO Model

Finally, the TDO model is employed to enhance the tuning of the DBN method [28]. TDO starts its iterative process with hunter agents known as Tasmanian Devils (TDs), creating a randomly generated population in the search space, where each agent depicts a variable vector. This initialization is stated as:

$$X_{ij} = x_j^{\min} + rand.\left(x_j^{\max} - x_j^{\min}\right), \quad i = 1,2,\dots,M, \quad j = 1,2,\dots,n \tag{10}$$

In TDO, a $rand$ value is generated between zero and one, with x_j^{min} and $x_j^{\max}$ referring to the bounds for the j^{th} dimension. The candidate's performance is assessed using the Objective Function (OF), with the optimal member updated in each iteration via feeding strategies, as each TD either searches for food or tends to it to enhance performance.

1) Eating Carrion: Exploration Stage

The TD occasionally consumes native carrion, exploring optimal positions. The target for the i^{th} TD is randomly selected:

$$C_i = X_k,\ i = 1,2,\dots,M,\ \ k \in \{1,2,\dots,M | k \neq i\} \tag{11}$$

where C_i denotes the selected carrion by the i^{th} TD, and k is arbitrarily selected from one to M. Affording to the certain carrion, the novel position of TD is defined as follows.

$$x_{ij}^{new,S1} = \begin{cases} x_{ij} + r \cdot \left(c_{ij} - I \cdot x_{ij}\right), & F_{C_i} < F_i \\ x_{ij} + r \cdot \left(x_{ij} - c_{ij}\right), & \text{otherwise} \end{cases} \tag{12}$$

$$X_i = \begin{cases} X_i^{new,S1}, & F_i^{new,S1} < F_i \\ X_i, & \text{otherwise} \end{cases} \tag{13}$$

where $X_i^{new,S1}$ describes the original position of the i^{th} TD employing the initial tactic, $x_{ij}^{new,S1}$ is the group of the j^{th} dimension, $F_i^{new,S1}$ states the value of OF for the novel status, F_{C_j} represents the OF for the elected carrion, r signifies the arbitrary number within the range of zero and one, and I indicates the number of random integers, which is one or two.

2) Eating Prey: Exploitation Phase

The TD searches for prey in two stages: assessing potential victims and then hunting and feeding after targeting. Equations (14-16) define the first stage, with the TD's position updated based on another population member randomly chosen as the target. The prey selection procedure is stated below.

$$P_i = X_k, i = 1,2,\dots,M, k \in \{1,2,\dots,M | k \neq i\} \tag{14}$$

where P_i denotes the prey nominated by the i^{th} TD, and k is elected randomly from one to M. Affording to the nominated prey, the second stage is executed to attain the novel location of the TD, as shown below.

$$x_{ij}^{new,S2} = \begin{cases} x_{ij} + r \cdot \left(p_{ij} - I \cdot x_{ij}\right), & F_{p_i} < F_i \\ x_{ij} + r \cdot \left(x_{ij} - p_{ij}\right), & \text{otherwise} \end{cases} \tag{15}$$

$$X_i = \begin{cases} X_i^{new,S2}, & F_i^{new,S2} < F_i \\ X_i, & \text{otherwise} \end{cases} \tag{16}$$

where $X_i^{new,S2}$ describes the new position of the i^{th} TD by employing the second plan, $x_{ij}^{new,S2}$ refers to the element of the j^{th} dimension, $F_i^{new,S2}$ states the value of OF for the novel status, and F_{P_i} indicates the main function of the selected prey.

The TD simulates hunting within a defined neighborhood range, using (17-19) to establish its position and pursue prey, Equation (17) represents the neighborhood, and (18) determines the new position.

$$R = 0.01\left(1 - \frac{t}{T}\right) \tag{17}$$

$$x_{ij}^{new} = x_{ij} + (2r - 1) \cdot R \cdot x_{ij} \tag{18}$$

$$X_i = \begin{cases} X_i^{new}, & F_i^{new} < F_i \\ X_i, & \text{otherwise} \end{cases} \tag{19}$$

where R describes the neighborhood radius, t describes the iteration count, and T represents the maximal iteration size. X_i^{new} represents the novel location of the i^{th} TD in the neighborhood of X_i, x_{ij}^{new} expresses the j^{th} element of X_i^{new}, and F_i^{new} designates the new value of an OF of X_i^{new}. In addition, the TDO is deployed to define the hyperparameter involved in the DBN approach. The MSE assumes that the primary function is shown as follows:

$$MSE = \frac{1}{T}\sum_{j=1}^{L}\sum_{i=1}^{M}\left(y_j^i - d_j^i\right)^2 \tag{20}$$

where M and L represent the outcome value of layer and data, and y_j^i and d_j^i imply the accomplished and suitable magnitudes for the j^{th} unit from the output layer of networks in time t.

IV. RESULTS ANALYSIS

This section examines the overall analysis of the BNFTDT-EPSCM method concerning various aspects [16, 29]. The data utilized for the simulation comprises parameters such as class, drugId, name, batchNo, description, itemCondition, quantity, and owner. The proposed technique was simulated by employing Python 3.6.5 on a PC with an i5-8600k, 250GB SSD, GeForce 1050Ti 4GB, 16GB RAM, and 1TB HDD. The parameter settings were as follows: learning rate: 0.01, activation: ReLU, epoch count: 50, dropout: 0.5, and batch size: 5.

Figure 2(a) shows that the BNFTDT-EPSCM technique achieved greater performance with lower latency (LAT) values across diverse user counts [30]. With 1000 users, it attained 0.244 s, while the other models recorded higher LAT values, and this trend continued with 4000 and 6000 users, where the BNFTDT-EPSCM technique consistently outperformed other methods. Figure 2(b) shows that the BNFTDT-EPSCM approach achieved optimal performance with low latency (LAT) values, recording 1.298 s for 1000 users, better than competitors such as RSCMS-HBE (1.528 s). This trend continued with 1.745 s at 4000 users and 2.192 s at 6000 users. Figure 2(c) showed that the BNFTDT-EPSCM approach maintained lower LAT values, achieving 1.396 s with 1000 users and 1.388 s with 6000 users. Figure 2(d) accentuates the superior THRO of the BNFTDT-EPSCM model, attaining 104.54 for 1000 users and rising to 551.22 at 6000 users, outperforming other models.

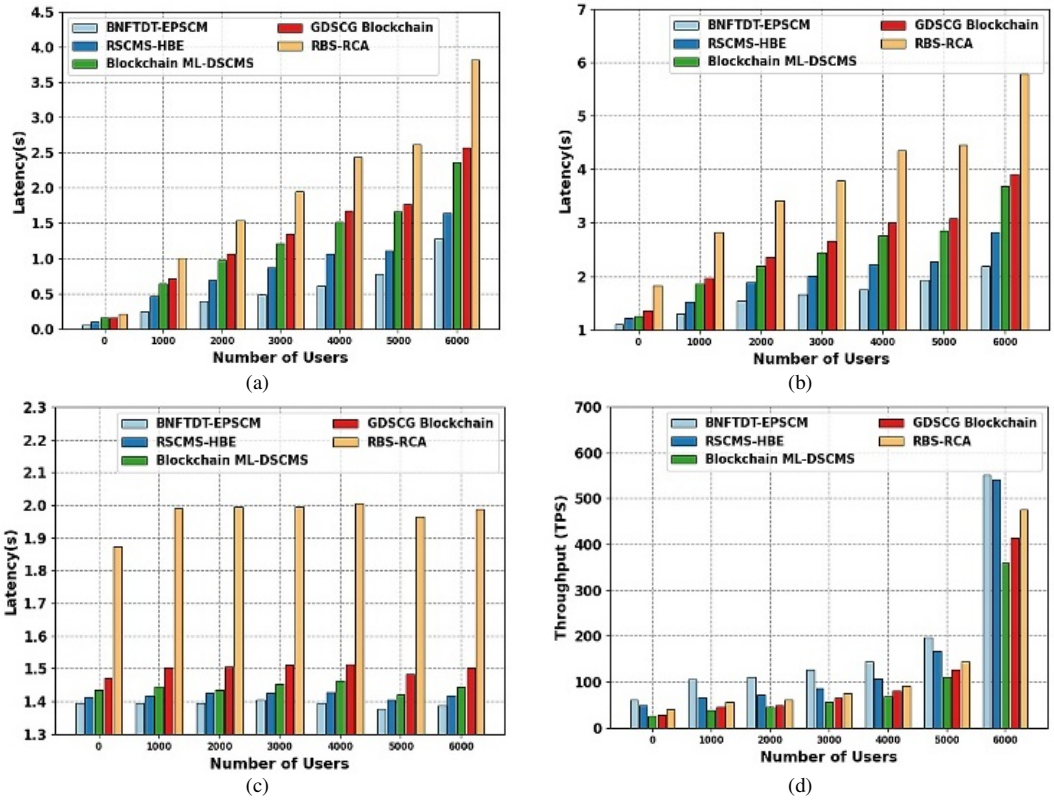

Fig. 2. Comparative analysis of BNFTDT-EPSCM technique under varying latency and throughput.

TABLE I. TOTAL NUMBER OF ORDERS ANALYSIS OF BNFTDT-EPSCM UNDER VARYING NUMBER OF DAYS

Total number of orders				
Number of days	**BNFTDT-EPSCM**	**Original sequence**	**MHA-GRU**	**RNN model**
Day 1	681	676	616	574
Day 2	688	680	666	638
Day 3	696	684	676	658
Day 4	691	682	620	638
Day 5	606	528	598	568
Day 6	693	608	686	648
Day 7	624	578	616	564
Day 8	595	554	528	576

Table I shows that the BNFTDT-EPSCM technique consistently achieved the highest number of orders over several days [27]. It starts with 681 orders on Day 1 and peaks at 696 on Day 3. In comparison, the Original Sequence, MHA-GRU, and RNN models exhibit lower order numbers throughout the observed period.

V. CONCLUSION

This study introduced a novel BNFTDT-EPSCM model, which presents a transparent and more secure reporting of changes in the operating condition of transported pharmaceutical products to prevent drug recalls. In addition, the BNFTDT-EPSCM model provides a decentralized solution based on NFT, which could enhance the trace and track capabilities of the standard serialization procedure introduced. NFTs are minted in the BC and inherit each advantage these technologies provide. Furthermore, the BNFTDT-EPSCM model utilizes the DBN method to perform the inbound logistics task prediction process. Finally, the TDO method is employed to improve the hyperparameter tuning of the DBN method. A detailed set of simulations was executed to examine the performance of the BNFTDT-EPSCM approach, and the experimental validation showed superior throughput at the highest user count of 6000, achieving 551.22 TPS, significantly outperforming existing models. Limitations include scalability, interoperability, user trust in BC, regulatory compliance, and infrastructure costs. Future work may focus on improving scalability, improving integration, and validating efficiency through empirical studies that address security measures and foster stakeholder collaboration.

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