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Deep Learning Based Autonomous Transport System for Secure Vehicle and Cargo Matching

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Abstract: The latest 6G improvements secured autonomous driving's realism in Intelligent Autonomous Transport Systems (IATS). Despite the IATS's benefits, security remains a significant challenge. Blockchain technology has grown in popularity as a means of implementing safe, dependable, and decentralised independent IATS systems, allowing for more utilisation of legacy IATS infrastructures and resources, which is especially advantageous for crowdsourcing technologies. Blockchain technology can be used to address security concerns in the IATS and to aid in logistics development. In light of the inadequacy of reliance and inattention to rights created by centralised and conventional logistics systems, this paper discusses the creation of a blockchain-based IATS powered by deep learning for secure cargo and vehicle matching (BDL-IATS). The BDL-IATS approach utilises Ethereum as the primary blockchain for storing private data such as order and shipment details. Additionally, the deep belief network (DBN) model is used to select suitable vehicles and goods for transportation. Additionally, the chaotic krill herd technique is used to tune the DBN model's hyperparameters. The performance of the BDL-IATS technique is validated, and the findings are inspected under a variety of conditions. The simulation findings indicated that the BDL-IATS strategy outperformed recent state-of-the-art approaches.

Keywords: Blockchain; ethereum; intelligent autonomous transport system; security; deep belief network

1 Introduction

With the tremendous growth of modern communicating, sensing, computing, and analyzing devices and techniques, the last few years have witnessed industry growth and tremendous academic efforts in intelligent autonomous transportation systems (IATS) [1], imposes more convenient and safer transport facilities along with major impact on all the aspects of daily lives with smart vehicles and transport services. Due to the growing complexity, uncertainty, and diversity of strategies, behavior, and mechanisms included in the ecosystem, however, IATS currently have proved higher degree of social complexity rather than the expected intelligence, leaving several persistent problems that have not been resolved. One serious problem is the security risk caused by IATS evolving trends toward centralization [2]. The rapidly evolving technology includes cloud computing and Internet-of-Things (IoT) allow most of the information, decisions analyses and processed by cloud-based platforms or centralized authorities, that is considered as IATS' "Achilles' heel" and currently not available because of malicious attack, simply improper operations or performance limitations. Another problem is the lack of mutual trust amongst IATS entities [3]. Consequently, assets and money could not "flow" from one entity to other directly and smoothly without a trusted intermediary, which results in increased social complexity of IATS, hierarchical structures, and diversified mechanisms [4]. Fig. 1 demonstrates the structure of ITS.

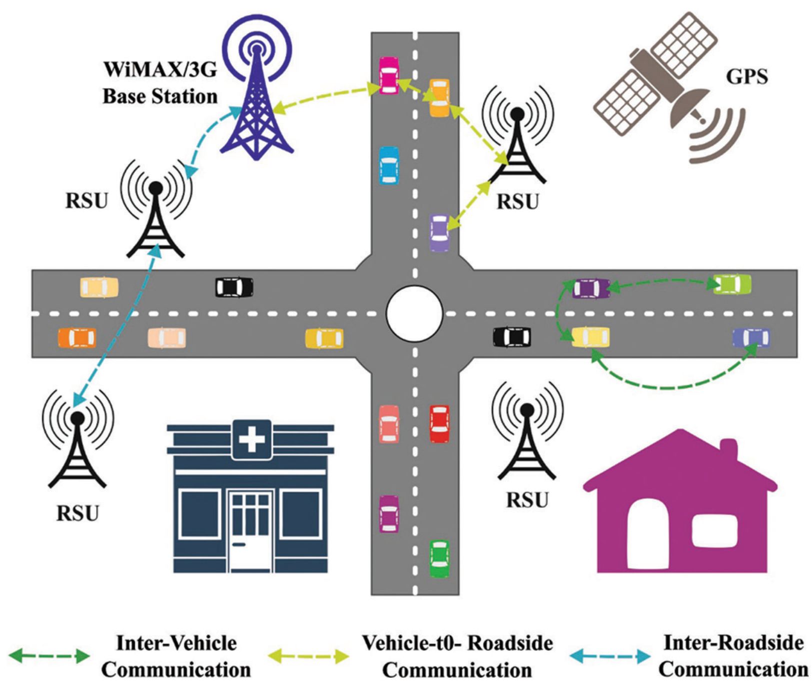

Figure 1: ITS architecture

The more commonly discussed topic interms of applications of the BT in transportation is logistics; indeed, several studies were introduced in the last few years. In a globalized world, many industries must design effective and longer supply chains to achieve success [5]. It implies that the difficulty of tracing and delivering goods should be fulfilled with a satisfactory informatics system. The blockchain serves various functions by protecting data and goods from malicious attacks in multiple agent supply chains [6]. Blockchain gives the opportunity of managing product storage quality at the time of guaranteeing and transportation the origin of product, thus creating trust between the suppliers. Many important issues can be resolved in supply chain management (SCM) by a blockchain, namely avoiding counterfeiting, flexibility, risk reduction, reports on stopped goods, speed of transfer, cost, and quality control [7].

Major enterprises, like Maersk and IBM, have built partnerships to examine blockchain implementation. Many stakeholders could depend on the blockchain to gain trust and to handle the fluctuation of data [8]. The supply chain and Traceability could be improved, adding values to the final products: all the transfers of goods could be validated and recorded by the consensus of each blockchain entity. The major challenges in supply chain BT application are to resolve the difficulty of ensuring that the physical layers (that is real goods) correspond to the digital layers (i.e., information that are stored) [9]. The usage of certified smart objects of IoT can brighten the future of this type of system. Several enterprises have invested in the supply chain application of BT, namely SKUchain, Provenance, Blockverify, and Jiocoin (launches its crypto-coin) that has created services to prevent forging of properties.

This article focuses on the design of blockchain with deep learning enabled IATS for secure cargo and vehicle matching (BDL-IATS). The BDL-IATS technique applies Ethereum as the fundamental blockchain for storing confidential data such as order details, cargo details, etc. Besides, the deep belief network (DBN) model is utilized to recommend vehicle and cargo matching during transportation. Moreover, the chaotic krill herd algorithm is applied for the hyperparameter tuning of the DBN model. The performance validation of the BDL-IATS technique takes place and the results are inspected under varying aspects.

Section 2 discusses the related works to the research study and Section 3 discusses proposed research methodology and Section 4 performance analysis and comparison with existing system and Section 5 discusses conclusion with future findings.

2 Related Works

2.1 Blockchain Technology

In cargo logistics transportation, the logistics turnover amongst connects is delayed, the data chain of total system was incomplete, and data transparency was minimal. Accordingly, loopholes from logistics transportation are prone to appear. To the stable function of logistics transportation method from logistics company. When it fails, massive security loopholes are created from the system like system breakdown and collapse. When the logistics method was integrated into the decentralized blockchain platforms, the potential issues of typical logistics management method is resolved; therefore, the logistics management method appears that natural adaptabilities to blockchain technology. Fig. 2 illustrates the framework of blockchain.

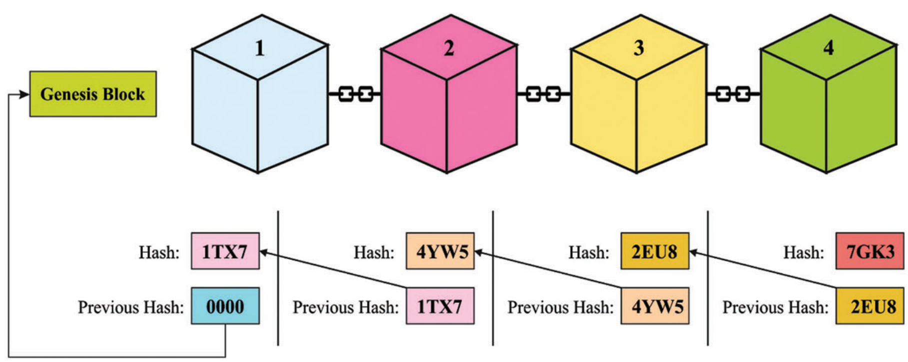

Figure 2: Structure of blockchain

The blockchain is a decentralization distributed storing that is combining kept by every participating node; in the meantime, the participating node is attain real-time data from the network. During this manner, the blockchain data tamper-proof and trustworthy features are combined as to logistics management. The data from the blockchain is allocated with joining nodes from the network in real time that is important to Logistics Companies. Only if the upload data has been attained by another node from time is the quick and smooth function of logistics transfer is make sure. During the case of meeting business scenario, blockchain is resolve the issues of data asymmetry and lack of trust. Concurrently, utilizing appropriate recommendation techniques enhances the turnover rate of trucks and cargo from the truck-finding state.

Tokody et al. [10] examined the question improved from connection to the control and communication of autonomous vehicle and vehicle systems. An improvement of autonomous intelligent vehicles and vehicle systems was dependent upon the more progress of co-operating intelligent transportation methods for achieving smart mobility. The investigation purposes for finding such techniques and processes that use the safety development of gradually difficult cyber-physical system (CPS) and system components utilized from autonomous intelligent vehicle and transport system, because of the feature of safety and operational risk. Kamal et al. [11] presented a few optimizing security techniques employing symmetric encryption to secure multimedia information transmission amongst vehicles. An important feature of this optimizing technique is that utilize a lesser count of information for generating fingerprint. The techniques convert approximately 3.7×10^5 instances of data as to 3600 instances for generating the fingerprints. The Fast Fourier Transform (FFT) was utilized for fetching the maximal 3 peak value of signal from the frequency domain. The centralized server authenticates the data transmission by relating the HASH of the fingerprint and also keeps the transaction file.

Kumar et al. [12] presented a privacy-preserving based secured structure for providing combined of privacy and security from C-ITS structure. The presented structure offers 2 levels of security as well as privacy utilizing blockchain and Deep Learning (DL) methods. Primary, the blockchain component was planned for securely transmitting the C-ITS data amongst AVs-RSUs-TCCs, and smart contract based enhanced Proof of Work (ePoW) approach was developed for verifying data integrity and mitigating data poison attacks. Secondary, the DL technique was developed that contains Long Short Term Memory-Auto Encoder (LSTM-AE) approach to encoder Cooperative Intelligent Transport Systems and Services (C-ITS) data as a novel format for preventing inference attacks. The encoding data was utilized by the presented Attention-based RNN (A-RNN), to intrusive event detection from C-ITS structure.

In Zhou et al. [13], a blockchain based IATS was presented. This system utilizes Ethereum as basic blockchain for recording sensitive data like system order, cargo, and personal data on blockchain, making sure the non-tampering and reliable of data. Concurrently, system management component, order management component, transportation management component, warehouse management component, and transaction management components are introduced. Meanwhile, the Light Gradient Boosting Machine (LightGBM) technique was employed for recommending vehicles and cargos equivalent in transportation. Yu et al. [14] examined DL based traffic safety solutions to both autonomous and manual vehicles from 5G enabled ITS. During this method, a driving trajectory as well as natural driving data sets were utilized as network input to long-term memory network from the 5G enabled ITS: the probability matrix of all intentions are computed by softmax function. Afterward, the last intention probabilities are achieved by fusing the mean rule from the decision layer. Maskey et al. [15] presented the Blockchain based structure with outlier detection for preventing malicious activity by vehicle but maintaining integrity from sharing data. The Outlier Detection was planned for residing before the consensus procedure, for identifying and preventing contribution of malicious vehicle from consensus procedure or block mining. During the presented Blockchain based ITS (BITS) with Outlier Detection for Smart City, it can be utilized ML for detecting the anomaly from the data [16].

3 The Proposed Model

This article has developed an effective BDL-IATS technique for secure cargo and vehicle matching in the IATS environment. The BDL-IATS technique has employed applies Ethereum as the fundamental blockchain for storing confidential data such as order details, cargo details, etc. Moreover, the CKHA with DBN model is utilized to recommend vehicle and cargo matching during transportation.

3.1 Design of IATS Based on DBN Model

Deep Belief Network (DBN) is a Deep Neural Network (DNN) collected of s several RBM and Back Propagation Neural Network (BPNN) stack [17] that utilizes an unsupervised greedy learning technique for adjusting the connection weight of all RBM layers and supervised learning manner for optimizing the network parameter. All RBM has of visible layer $V_k = (v_1,\ v_2,\ \ \cdots,\ v_n)$ and hidden layer $H_k = (h_1,\ h_2,\ \ \cdots,\ h_m)$. The visible layer V_1 and hidden layer H_1 procedure RBM_1, the hidden layer H_1 as visible layer of RBM_2 and hidden layer H_2 procedure RBM_2, etc. The weight amongst connection neurons, $W_k = \{w_{i,j}\} \in R^{n\times m}$ is the connected weight amongst the visible as well as hidden layers of k^{th} RBM, and $A_k = \{a_i\} = R^n$ and $B_k = \{b_j\} = R^m$ implies the visible as well as hidden layer biases of k^{th} RBM. Therefore, only 3 parameters were needed for determining an RBM. In order to DBN technique with normal charging voltage, the energy function of their internal RBM was determined as:

$$E(V_k,\ H_k|\theta_k) = -A_k^T V_k - B_k^T H_k - V_k^T W_k H_k \tag{1}$$

where V_k and H_k stands for the binary state of every unit from k^{th} visible as well as hidden layers. The lower energy function represents the most ideal state of networks, i.e., the lower forecast error to the EV charging voltage. With regularize and development of the energy function, the joint probability distribution of RBM is attained as:

$$P(V_k,\ H_k|\theta_k) = \frac{\exp(-E(V_k,\ H_k|\theta_k))}{Z(\theta_k)} \tag{2}$$

$$Z(\theta_k) = \sum_{v_k, H_k} \exp(-E(V_{k'} H_k|\theta_k)) \tag{3}$$

where $Z(\theta_k)$ signifies the partition functions that implies the sum of every feasible state energy function of the group of V_k and H_k node from the normal charging voltage DBN technique, and is utilized as the main purpose of the optimized technique. Based on the structural features of RBM, the probability that i^{th} units v_i of visible layer V_k and j^{th} unit h_j of hidden layer H_k are activated are written as:

$$P(v_i = 1|H_k) = \sigma\left(a_i + \sum_{i=1}^{m} h_j w_{ij}\right) \tag{4}$$

$$P(h_j = 1|V_k) = \sigma\left(b_j + \sum_{i=1}^{n} v_j w_{ij}\right) \tag{5}$$

where $\sigma(x) = 1/(1 + e^{-x})$ refers to the sigmoid activation functions.

The DBN trained technique to normal charge voltage has 2 phases of pre-trained and fine-tuned. During the pre-trained step, RBM_1 obtains data on EV needed voltage, needed current, charging current, and temperature, and trained all RBMs from bottom-up order utilizing a layer-by-layer greedy learning technique for achieving the removal of high level feature of input data and the upgrade of connection weight of trained networks [18]. The resultant data is forecasted charging voltage. During the fine-tuned step, the BPNN gets the forecasted charging voltage as input and actually measured charge voltage as outcome, and always modifying and optimizing the network parameter from top to bottom from the method of supervised learning.

3.2 Hyperparameter Tuning of DBN Model

For tuning the hyperparameters of the DBN model, the CKHA is utilized and thereby optimized the overall performance of the network. KH is a novel generic stochastic optimized method to the global optimized issue. It can be simulated as performance of a krill swarm. Once the hunting to the food and communicate with everyone, the KH method repeat the execution of 3 actions and follows search way that progress the main function values [19]. The time relied place was mostly defined as 3 movements:

1. Foraging action;
2. The movement inclined by other krill;
3. Physical diffusion.

Even KH method adapts the Lagrangian method as demonstrated in the subsequent model:

$$\frac{dxi}{d_t} = N_i + F_i + D_{i'} \tag{6}$$

where N_i, F_i and D_i implies the foraging motions that are controlled by another krill and the physical diffusion of krill's i correspondingly. A primary motion F_i cover 2 parts: the present food place and data on the preceding place. In order to krill i, it is express this motion as under:

$$F_i = V_f \beta_j + w_f F_i^{old} \tag{7}$$

where:

$$\beta_i = \beta_i^{food} + \beta_i^{best} \tag{8}$$

and V_f implies the foraging speed, w_f represents the inertia weights of foraging motion from zero and one is the final foraging motion.

The direction managed by the secondary effort N_i, a_i has been measured by 3 effects: target, local, and repulsive effects. To krill i, it could be expressed as under:

$$N_i^{new} = N^{\max} a_i + w_n N_i^{old} N_i^{new} = N^{\max} a_j + w_n N_i^{old}, \tag{9}$$

where $N^{\max}$ stands for the maximal induced speeds, w_n signifies the inertia weight of secondary motion from zero and one is the final motion controlled by other krill [20].

In order to the i^{th} krill the physical diffusion was an arbitrary procedure. This motion contains 2 modules: a maximal diffusion speed as well as oriented vector. The look of physical diffusion is provided under:

$$D_i = D^{\max} \delta, \tag{10}$$

where $D^{\max}$ signifies the maximal diffusion speeds and δ refers to the oriented vector whose value was an arbitrary number amongst [−1, 1]. Based on the 3 above examined performances, the time-relied place in time t to $t + \Delta t$ is expressed by the subsequent formula:

$$X_i(t + \Delta t) = X_i(t) + \Delta t \frac{dx_i}{dt}. \tag{11}$$

For enhancing search effectiveness and making sure convergence to an optimum solution, the chaos method was combined with KH structure to this study scope [21]. Assuming that Chebyshev map is one of the widely utilized chaotic behavioral maps, it can be feasible for generating chaotic orders quickly and effectually. Also, there is no requirement for retaining long orders. The Chebyshev map utilized under the CKH technique alteration the value of randomized parameters $\omega^{chebychev} = (\omega_d, \omega_f)$ from KH.

The Chebyshev map upgrade parameters ω_d and ω_f as:

$$\omega_j^{chebychev} = \cos\left(j * \cos^{-1}\left(\omega_{j-1}^{chebychev}\right)\right) \tag{12}$$

Eq. (12) takes a chaotic order in range of zero and one. To all independents implementation of Eq. (12), $\omega_0^{chebychev}$ represents the outcome arbitrarily [22,23]. The chaotic value $\omega_j^{chebychev}$ created utilizing a logistical map with 300 runs and $\omega_0^{chebychev} = 0.001$.

During the case of CKH,

$$N_k^{next} = N^{\max} \alpha_k + \omega_{d,j}^{chebychev} N_k^{present} \tag{13}$$

$$F_k^{nexi} = V_f \beta_k + \omega_{f,j}^{chebychev} F_k^{previous} \tag{14}$$

4 Experimental Validation

The proposed research is implemented in NS-3 environment. This section inspects the performance analysis of the BDL-IATS technique with other techniques interms of different measures. Tab. 1 and Fig. 3 offer a comparison study of the BDL-IATS technique interms of accuracy. The experimental results indicated that the BDL-IATS technique has resulted in improved performance with the higher accuracy values. For instance, with 3 hrs, the BDL-IATS technique has accomplished higher accuracy of 3.20% whereas the ItemCF, UserCF, GBDT, and LightGBM techniques have resulted to lower accuracy of 1.10%, 1.62%, 2.14%, and 2.64% respectively. In addition, with 12 hrs, the BDL-IATS technique has accomplished maximum accuracy of 83.26% whereas the ItemCF, UserCF, GBDT, and LightGBM systems have resulted in lesser accuracy of 66.12%, 69.02%, 71.92%, and 78.67% correspondingly. Moreover, with 24 hrs, the BDL-IATS technique has accomplished maximum accuracy of 86.64% whereas the ItemCF, UserCF, GBDT, and LightGBM methods have resulted to lower accuracy of 77.47%, 79.88%, 81.33%, and 84.47% correspondingly.

Table 1: Comparative analysis of BDL-IATS technique in terms of accuracy with existing methods

Accuracy (%)					
Time (hrs)	ItemCF	UserCF	GBDT	LightGBM	BDL-IATS
0	1.10	1.62	2.14	2.64	3.20
3	28.72	29.20	34.27	37.65	38.61
6	47.78	49.96	54.06	57.20	60.09
9	60.57	62.26	65.16	71.43	74.33
12	66.12	69.02	71.92	78.67	83.26
15	69.26	72.16	76.50	81.57	86.15
18	74.57	75.54	78.91	82.78	86.64
21	76.74	78.19	80.85	83.02	86.88
24	77.47	79.88	81.33	84.47	86.64

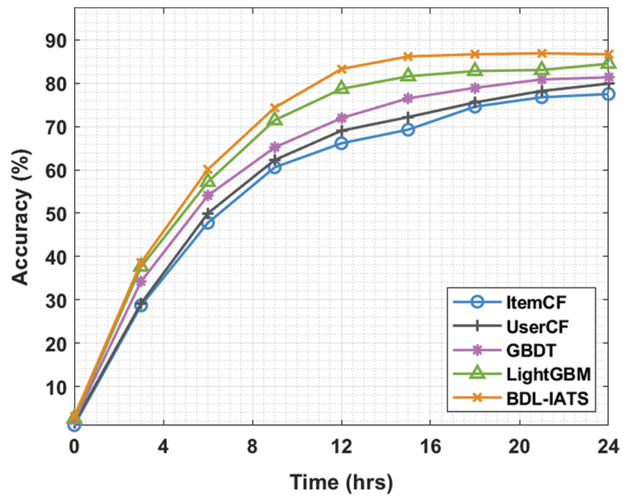

Figure 3: Accuracy analysis of BDL-IATS technique

Tab. 2 and Fig. 4 give a comparison study of the BDL-IATS method with respect to precision. The experimental results indicated that the BDL-IATS technique has resulted in improved performance with higher precision values. For instance, with 3 hrs, the BDL-IATS technique has accomplished higher precision of 48.83% whereas the ItemCF, UserCF, GBDT, and LightGBM approaches have resulted to lower precision of 32.87%, 34.72%, 38.19%, and 44.66% correspondingly. Besides, with 12 hrs, the BDL-IATS system has accomplished higher precision of 80.98% whereas the ItemCF, UserCF, GBDT, and LightGBM methods have resulted to lower precision of 62.48%, 64.79%, 68.26%, and 75.43% respectively. Eventually, with 24 hrs, the BDL-IATS algorithm has accomplished superior precision of 82.14% whereas the ItemCF, UserCF, GBDT, and LightGBM techniques have resulted to lower precision of 68.72%, 70.34%, 75.43%, and 79.36% correspondingly.

Table 2: Comparative analysis of BDL-IATS technique in terms of precision with existing methods

Precision (%)					
Time (hrs)	ItemCF	UserCF	GBDT	LightGBM	BDL-IATS
0	3.03	3.03	3.49	3.03	5.11
3	32.87	34.72	38.19	44.66	48.83
6	48.60	50.91	54.15	61.09	66.87
9	57.62	60.39	64.10	71.96	78.44
12	62.48	64.79	68.26	75.43	80.98
15	65.25	67.57	72.19	78.67	81.91
18	67.80	69.42	74.27	78.44	82.60
21	68.26	70.80	75.20	78.67	82.37
24	68.72	70.34	75.43	79.36	82.14

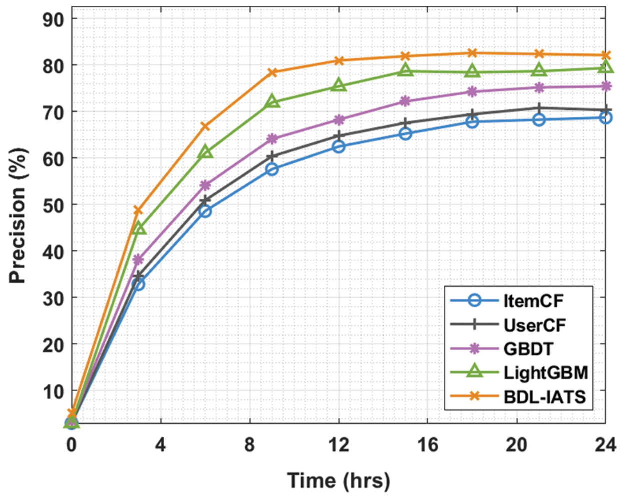

Figure 4: Precision analysis of BDL-IATS technique with existing methods

Tab. 3 and Fig. 5 provide a comparative study of the BDL-IATS technique in terms of recall. The experimental results designated that the BDL-IATS technique has resulted in higher performance with superior recall values. For instance, with 3 hrs, the BDL-IATS approach has accomplished higher recall of 46.42% whereas the ItemCF, UserCF, GBDT, and LightGBM techniques have resulted to lower recall of 32.90%, 35.08%, 37.48%, and 40.75% respectively. Followed by, with 12 hrs, the BDL-IATS approach has accomplished higher recall of 78.91% whereas the ItemCF, UserCF, GBDT, and LightGBM methods have resulted to lower recall of 57.98%, 60.59%, 63.43%, and 71.49% correspondingly. Moreover, with 24 hrs, the BDL-IATS algorithm has accomplished higher recall of 81.52% whereas the ItemCF, UserCF, GBDT, and LightGBM techniques have resulted in minimum recall of 64.08%, 66.91%, 69.53%, and 75.64% respectively.

Table 3: Recall analysis of BDL-IATS technique with existing methods

Recall (%)					
Time (hrs)	ItemCF	UserCF	GBDT	LightGBM	BDL-IATS
0	0.85	1.50	1.50	2.59	2.38
3	32.90	35.08	37.48	40.75	46.42
6	45.98	48.38	51.65	55.58	63.43
9	52.31	54.49	57.32	66.26	72.15
12	57.98	60.59	63.43	71.49	78.91
15	61.03	64.30	67.57	74.11	81.09
18	62.34	65.39	68.88	75.64	81.74
21	63.86	67.35	69.75	75.20	81.96
24	64.08	66.91	69.53	75.64	81.52

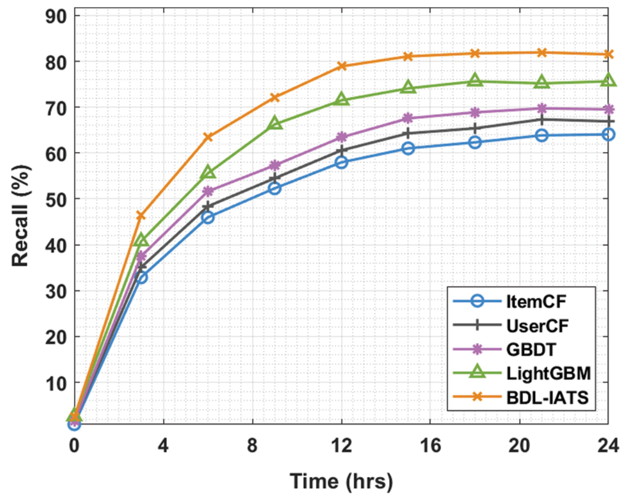

Figure 5: Recall analysis of BDL-IATS technique with existing methods

Tab. 4 and Fig. 6 offer a comparison study of the BDL-IATS technique interms of conversion rate (CR). The experimental outcomes indicated that the BDL-IATS technique has resulted in improved performance with the maximum CR values.

Table 4: Conversion rate analysis of BDL-IATS technique with existing methods

Conversion rate (%)					
Time (hrs)	ItemCF	UserCF	GBDT	LightGBM	BDL-IATS
0	1.69	1.69	2.01	1.91	2.54
3	16.94	17.36	18.53	20.75	21.38
6	23.92	25.30	27.21	29.22	29.85
9	28.16	28.90	30.91	33.66	35.89
12	31.12	32.50	33.87	36.94	38.85
15	33.13	34.09	35.99	37.79	40.23
18	33.56	34.62	36.10	38.43	40.86
21	33.87	35.04	36.31	38.43	40.54
24	34.83	35.15	36.31	38.21	40.76

For instance, with 3 hrs, the BDL-IATS technique has accomplished higher CR of 21.38% whereas the ItemCF, UserCF, GBDT, and LightGBM techniques have resulted to lower CR of 16.94%, 17.36%, 18.53%, and 20.75% correspondingly. Also, with 12 hrs, the BDL-IATS approach has accomplished maximum CR of 38.85% whereas the ItemCF, UserCF, GBDT, and LightGBM techniques have resulted to lower CR of 31.12%, 32.50%, 33.87%, and 36.94% correspondingly. Moreover, with 24 hrs, the BDL-IATS technique has accomplished higher CR of 40.76% whereas the ItemCF, UserCF, GBDT, and LightGBM systems have resulted to lower CR of 34.83%, 35.15%, 36.31%, and 38.21% correspondingly.

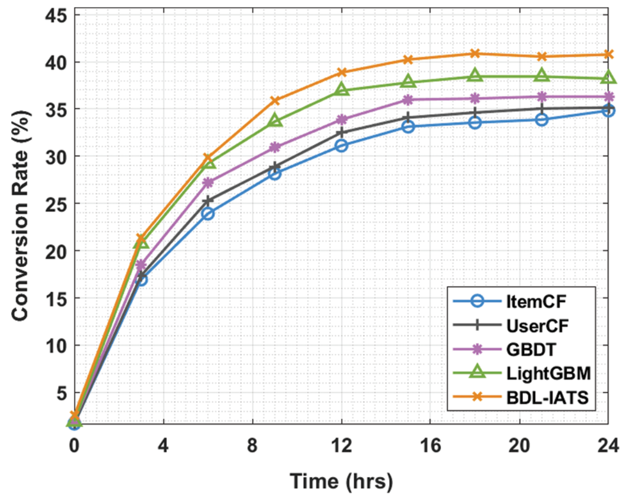

Figure 6: CR analysis of BDL-IATS technique with existing algorithms

Finally, an average response time (ART) analysis of the BDL-IATS technique with recent approaches takes place in Tab. 5 and Fig. 7.

Table 5: Average Response time analysis of BDL-IATS technique with existing methods

	Avg. response time (sec)				
Time (hrs)	ItemCF	UserCF	GBDT	LightGBM	BDL-IATS
0	4.99	4.79	4.24	3.76	3.12
3	4.88	4.63	4.18	3.68	3.23
6	4.87	4.68	4.10	3.73	3.20
9	4.94	4.76	4.21	3.81	3.18
12	4.96	4.74	4.29	3.79	3.39
15	4.99	4.80	4.32	3.98	3.25
18	5.04	4.79	4.41	3.87	3.29
21	5.05	4.85	4.45	3.95	3.34
24	5.07	4.87	4.37	3.85	3.17

The results indicated that the BDL-IATS technique has resulted in least ART over the other techniques. For instance, with 3 hrs duration, the BDL-IATS technique has provided lower ART of 3.12hrs whereas the ItemCF, UserCF, GBDT, and LightGBM techniques have obtained higher ART of 4.99, 4.79, 4.24, and 3.76 hrs respectively. In addition, with 12 hrs duration, the BDL-IATS method has provided lower ART of 3.39hrs whereas the ItemCF, UserCF, GBDT, and LightGBM techniques have gained higher ART of 4.96, 4.74, 4.29, and 3.79 hrs correspondingly. Moreover, with 18 hrs duration, the BDL-IATS approach has provided lower ART of 3.29hrs whereas the ItemCF, UserCF, GBDT, and LightGBM techniques have reached higher ART of 5.04, 4.79, 4.41, and 3.87 hrs respectively. Furthermore, with 24 hrs duration, the BDL-IATS technique has offered lesser ART of 3.17hrs whereas the ItemCF, UserCF, GBDT, and LightGBM methods have obtained higher ART of 5.07, 4.87, 4.37, and 3.85 hrs respectively.

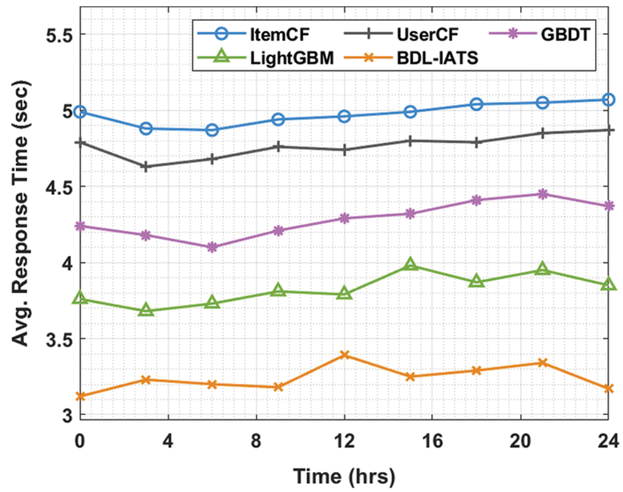

Figure 7: ART analysis of BDL-IATS technique with existing algorithms

By observing the comprehensive result analysis, it can be ensured that the BDL-IATS technique has resulted in enhanced performance over the other methods in the IATS environment.

5 Conclusion

This article has developed an effective BDL-IATS technique for secure cargo and vehicle matching in the IATS environment. The BDL-IATS technique has employed applies Ethereum as the fundamental blockchain for storing confidential data such as order details, cargo details, etc. Moreover, the DBN model is utilized to recommend vehicle and cargo matching during transportation. Furthermore, the CKHA is applied for the hyperparameter tuning of the DBN model. The performance validation of the BDL-IATS technique takes place and the results are inspected under varying aspects. The simulation results reported the better performance of the BDL-IATS technique over the recent state of art approaches. Therefore, the BDL-IATS technique can be utilized as a proficient tool for the IATS environment. In the future, data encryption techniques can be used to achieve secure communication in the IATS environment.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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