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RESEARCH ARTICLE

Secure Remote Sensing Data With Blockchain Distributed Ledger Technology: A Solution for Smart Cities

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ABSTRACT Particularly in the context of smart cities, remote sensing data (RSD) has emerged as one of the hottest study topics in information and communication technology (ICT) today. The development of machine learning (ML) and artificial intelligence (AI) has made it possible to solve a number of issues, including automation, control access, optimization, monitoring, and management. Simultaneously, there are significant issues with the design and development of the process hierarchy, including inadequate training records, centralized architecture, data privacy protection, and overall resource consumption restrictions. The development of Distributed Ledger Technology (DLT), on the other hand, provides a decentralized infrastructure that allows systems to eliminate centralized data-sharing procedures of smart cities while transferring from network node to network node, and third-party access control solves machine learning issues. To process an ideal data delivery mechanism for the smart cities analytical model, the paper employs Partial Swam Optimization (POS) in conjunction with a secure blockchain distributed consortium network. This work makes three contributions. Firstly, it offers a safe transmission method that combines blockchain and machine learning to optimize the path for reliable data delivery across secure channels. Second, neighborhood encryption sequences are carried out using NuCypher proxy re-encryption-enabled value encryption, a public key cryptographic approach that avoids cypher conversion. Third, Artificial Neural Networks (ANNs) can solve the data deliverance classification problem in smart cities by optimizing record management and preservation.

INDEX TERMS Blockchain, artificial intelligence (AI), machine learning (ML), smart cities, data optimization, remote sensing.

I. INTRODUCTION

Nowadays, the Internet of Things (IoT) has enabled a variety of land-surface applications to automatically access the processes of futuristic land-related services for each user in smart cities. Remote Sensing Data (RSD) is one of the challenging prospects throughout this process. It includes land data management, land records organizations in terms of square size allocation, and different structured-based land surface change applications, for example, frequent changes

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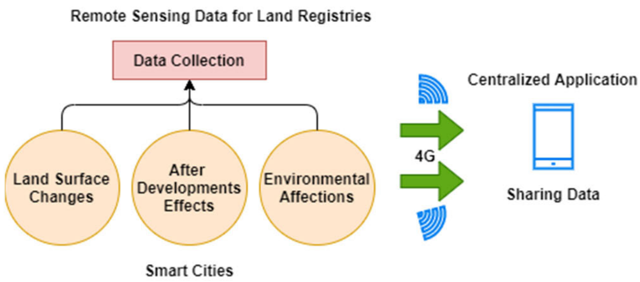

FIGURE 1. The recent working objective of remote sensingenabled application for smart cities.

via signal observations using drone sensors, examinations, predictions, tracking, monitoring, and maintenance of individual aspects [1], [2]. In this manner, the existing process hierarchy is not considered the standardized way to schedule transactions, due to the lack of scalability, privacy, security, and fault tolerance. However, the real-time applications of E-Land-Surface provide information-gathering facilities with the help of land IoT tools. It can be analyzed further by sending it to a cloud structure, where information can be accessed by malicious attackers or insiders [3]. For this reason, this procedure addresses an unsecure manner for record-keeping and management. In addition, several key observations highlight the hierarchy is highly vulnerable, such as receiving many dedicated interactions. The list of cyberattacks which have most occurred throughout recent times are (i) denial of service (DoS), (ii) distributed denial of service (DDoS), (iii) ransomware, and (iv) traditional methods that affect efficiency while services deliverance [4].

Recently, various articles addressed different types of malicious attacks on land registration portals. According to the report of the Department of Excise and Authority USA, it is noted that the rate of cyberattacks increased by almost 30,000 between 2018-2022 [5], [6], [7]. More than this, the involvement of insiders, such as staff, third-party vendors, and co-manager causes data breaches, which create violations. However, the current infrastructure of the Internet of Things is at risk. Due to the occurrence of eavesdropping attacks, most of the time it would be because of Wi-Fi interconnectivity, Bluetooth, Zigbee, or through DDoS [7]. In addition, the existing lifecycle of cloud-enabling technologies is not as efficient as per the standard of data protection. In this manner, the classic edge has become highly interesting for hackers to attack the data of land registry or related information of smart cities [8] (like the interconnection between centralized applications via 4G for scheduling data collections), as shown in Figure 1.

However, blockchain DLT is envisioned in almost every domain of the enterprise and its environments, especially in smart cities [9]. The role of blockchain technology in Land-Surface applications for the sake of smart cities' data security and privacy is critical. It is because the data is executed across a cloud, which can be used to calculate and preserve data while eliminating the need for centralized cloud-enabling or third party-related authentications. The technology inspires many distributed application developers to design and deploy privacy concerning E-Land-Surface modules [10]. On the other side, there is no intelligent gateway associated with calculating the request of authentication, memory, and security checks while loading records of the land registry with their stakeholders' details by the system. The purpose of choosing blockchain is to provide secure (using NuCypher Proxy Re-Encryption) and smooth scheduling processes, computation, and storage, which directly affects the increased resource usage. To tackle such types of challenging problems, the DLT system needs to collaborate with Artificial Intelligence, especially Machine Learning (ML) mechanism [11]. The possible integration manages the optimization of blockchain storage media, the optimal pathway of block transmission while transactions are scheduled over the consortium network and allows to redesign of a local computing environment using fog-enabling systems, which retain security [12].

To protect existing data delivery processes for the purpose of reducing network resource usage with privacy, there is a need to incorporate the path optimization concept with it [13]. For this purpose, Partial Swam Optimization (PSO) is used to schedule individual delivery records and assigns an optimal path direction. Basically, PSO is a potential computational method that optimizes data iteratively. It improves the candidate solutions about a given set of values in terms of quality. The mechanism initiates by getting a population of candidate solutions for a particular problem, analyzing dubbed particles, and searching the suitable pathway in the search space in accordance with the mathematical formula of particle positions and weight. For instance, the application of E-Land-Surface is collaborating with metaheuristic approaches with ML techniques to eliminate optimal path selection, data optimization, and classification-related issues [14], [15]. While aligning and initializing interoperable transactions between chains, it is highly recommended to restructure the architecture.

The critical prospect of this study is to create a secure lifecycle for remote sensing data of land surface in smart cities, which includes capturing distanced data by wireless sensors network (WSN), IoT-enabling data acquisition, and scheduling local computation through fogs. To reduce the loss between the process of data collection and computation, the collaborative approach of ML with a metaheuristic computation mechanism is used, such as ANN with POS. The purpose is to provide a dynamic structure for optimal pathway selection and deliverance and preserve the transaction of remote sensing data. Through this, it is critical to maintain a secure channel where the data can be traced for the sake of real-time monitoring; it is also because to analyze what factors are involved between nodes, which directly affects the procedure of executions. In this regard, a blockchain DLT is used to provide a protected infrastructure to the process hierarchy of remote sensing data towards storage using the NuCypher Proxy Re-Encryption mechanism with cloud-enabled distributed storage. The proposed model eliminates the blockchain hash calculation procedure because it consumes more computational costs while transactions are scheduled. This paper contributes to six different folds that are highlighted as follows:

- A thorough examination of the research gaps in the E-Land-Surface applications at this time is covered.
- The creation of the suggested computational and safe machine learning approach for blockchain-based remote sensing data optimization.
- A consortium network with two communication channels—one off-chain and one on-chain—that serves both a public and private chain environment.
- The current blockchain distributed application (B-DApp) infrastructure benefits from the integration of computational method (PSO) with artificial neural networks (ANN) to select the best pathway, optimize data, and classify information.
- Custom consensus protocols with four distinct chain codes have been created, developed, and implemented to automate validation and verification throughout the E-Land-Surface transaction delivery process.
- In the end, this paper highlights and separates open research problems recently involving the domain of smart cities, which is not yet been addressed.

The rest of this paper is organized and structured as follows: In Section II, various previously published related works are analyzed, where the role of machine learning for remote sensing data is highlighted, along with metrics of the current research gaps evaluations. The fundamental knowledge, problem definition, problem descriptions, and related mathematical notations of the proposed work are discussed in Section III. However, Section IV presents the design of the proposed model, working hierarchy, chain codes, and consensus protocols. The implementation challenges with the open research issues for technological maturity are elaborated in Section V. Conclusively, in Section VI, the details of futuristic developments are discussed.

II. RELATED WORK

The description of this section is categorized into two different ways, including machine learning (ML) for remote sensing data and the integration of blockchain technology is with.

A. COMPUTATIONAL, AI, AND ML METHODS FOR REMOTE SENSING DATA

Particle Swam Optimization (PSO) is one of the popular path optimization techniques, which uses a set of random particles and defines the best solution [16]. All particle is provided in search space, such as distance position from a corresponding and best position, as calculating the distance from the optimal particle of a swam. The depiction of particles helps in network transmission, for example, the way of closing particles, the global optimization process, and determining fitness function that helps in the solution of optimization problems. The strategy to use PSO is to categorize search into two domains, such as local and global best [17]. The predefined working of POS estimates the individual position of a particle. Whereas the global positioning search attains overall information, while the movement of the particle is compared to the best positioning particle in the swam. However, Table 1 presents the use of PSO for path selection, schedule in accordance with an optimal criterion, and data movement with the shortest deliverance hierarchy of remote sensing transactions are highlighted as follows:

B. MACHINE LEARNING INTEGRATES WITH BLOCKCHAIN DLT

Recently, the blockchain DLT is growing desirable that has attracted global attention, including the manufacturers, productive staff, and related societies of smart cities [24]. However, most of the blockchain DLT applications are currently used as only fund/assets transfer options and exchanging information via a distributed network based on chaincode. For this reason, it is considered an ideal platform where business operations and industrial transactions are performed securely. The main target of the current smart cities is to provide security and privacy in terms of creating a relationship between vendors and other stakeholders regarding land registries, land surface changes, monitoring aftereffects of developments, and dynamic decision-making. To do this, the technology supports industrial units for futuristic developments based on the overall industrial chain values [25]. On the other side, the lifecycle of an existing solution affects automation, most importantly optimization of scheduled operations throughout the process. For instance, the technology also disturbs because of a few additional fluctuations, such as flexibility, safety, cost of resource consumption, and productivity. To create a secure intelligent environment, the sensor data comes from the deployed monitoring devices of the land surface that possibly contain changing conditions, human effects, and development aftereffects. Analysis of these day-to-day large-volume data in dynamic time processing is quite a complex task [26]. The branch of AI comes to resolve data management and optimization-related tasks of smart cities. In the procedure to optimize data, ML provides steps to passing off, such as data aggregation of land-surface, generating information in accordance with their classifications, and predictive maintenance [27], [28]. However, ML predictive maintenance deals with a large number of records to develop a process for structured redundancies.

However, the trends of current investigating protocols can leverage timely, where the scheme of ML accurately estimates data loss while scheduling data management and optimization according to the hierarchy of lifecycle [26], [27]. Whereas the control of land-surface monitoring is to be possible while associating features of ML techniques when designing and developing the DApp. This can include dependencies of generated records via system/IoT sensors

TABLE 1. Computational methods for remote sensing data related works.

Major Contribution (s)	Method/Methodology	Gap Analysis	Similarity and Difference with the Proposed Model
The integration of Internet of Things (IoT), machine learning, and intelligent sensors for remote sensing data of agriculture [18]	This paper classified the role of sensors and their suitable usage in the field using a support vector machine (SVM). In this manner, the authors separated assessment according to the operational condition, such as soil quality, crop monitoring, harvesting, weeding, and spearing as follows: • ESP-32 • DHT-11	• Interoperable cross-chaining limitations • Scope of data protection issues	• Public chain • Hash-encryption SHA-256 mechanism used • Wireless sensor inter-connectivity
Spectral convolution network for hyperspectral image classification and remote sensing [19]	The author of this paper proposed a model named "HRSIC", a novel spatial feature information classification using ResNet connections. However, the aim of this is to reduce the cause of degradation and increase depth.	• Outsource computation is required • High resource consumption • Complex deep network structure	• No security features are discussed • Permissionless network • Image-based remote sensing classification
An efficient prediction from remote sensing data by transfer learning mechanism [20]	A new paradigm called YieldNet, a customized convolutional model based on neural networks, utilized that objective to transfer learning between a large-scale crop yield prediction using the share weight of the backbone feature extractor.	• No standard is used to schedule transactions of remote sensing • A local data preservation strategy is used	• Real-time decision-making platform for stakeholder to maximize yield potential • Unsecure channel for data transmission
Fractional crops remote sensing data classification using convolutional deep network [21]	This paper proposed FGCN, a predefine convolutional network involve with fractional Gabor features, which is an efficient fusion method that comprehensively extracted multi-features in the remote sensing data.	• Semantic change features problem • Light detection and ranging data processing limitations • Cost of data optimization	• A multi-sensor platform is proposed • Consume more computation because of complex network structure while training
Risk assessment of futuristic disaster in smart cities using remote sensing data classification with multicriteria approach [22]	The importance of remote sensing data in risk assessment and futuristic developments is presented by E. Psomiadis et al. The main objective of this study is highlighted as follows: • Remote sensing data utilized to create geographical information system for efficient classification of flooded areas, impacts, and related disasters	• Upstream and downstream of data transmission via the centralized network related problem • Cost of network bandwidth • No data privacy mechanism follows	• Fog-enabling computation is required for high-resolution orthophoto images • Leck of record keeping and preservation mechanism used

and discarding the involvement of humans in real time. Meanwhile, it is also significant for designing a secure channel of land registries in accordance with the adaptation of standards of open communications. On the same end, a stakeholder's satisfactory environment is required, where the model gets a request for an update or related feedback and preserve in an organized ledger. In the end, the collaboration of AI, ML, and Blockchain DLT is the main focus of this study

TABLE 1. *(Continued.)* **Computational methods for remote sensing data related works.**

Scene classification by remote sensing data classification using deep learning network for dynamic monitoring [23]	A scene classification framework using network search architecture is proposed. It is based on multi-objective neural networks. There are some additional features discussed as follows: • Automatic search • Powerful evolutionary coding for searching • Flexible and reliable hierarchy is designed	• Computational complexity • Performance errors in terms of search network and balance particle choices	• Hierarchical extraction processes • Scene classification • A complex data structure is presented

that can solve different problems of smart cities, including analysis of land surface changes records, land registries and monitoring, traceability, predictive developments, and ledger management related [25], [27].

III. PRELIMINARIES

This section discusses the problem statement, problem description, problem formulation, primary knowledge, and notations that help to understand why this topic considers the current real-world problem. To do this, there is a need to elaborate on the basic remedies of the proposed work are as follows:

A. NOTATION AND PROBLEM DESCRIPTION

In this context, there are a few assumptions that are crucial to describe for pathway optimization mechanism using PSO: (i) customize opposition-based learning that use to optimize the rate of convergence, (ii) opposite population, (iii) recent population, and (iv) optimal candidate solutions. While designing an efficient model for transactional pathway optimization, there is a need to reorganize an opposite population and the recent population from the original one. For identity generations, the identification of the optimal candidate (shortest path for schedule) solutions from the customized population in accordance with the defined problem is presented. Assume that P ϵ P [a, b] is a discrete number, where the opposite population from this input number P' is as follows:

$$\mathrm{P}' = a + b - P \tag{1}$$

However, in the analysis of dimensional search space, a distributed (d-dimensional) is derived that potentially describes the expansion in the opposite population, as follows:

$$\mathrm{P}'' = a' + b' - P' \tag{2}$$

where, in this case, P' consider the change with respect to P in accordance with the d-dimension.

Therefore,

$$d - dimension = p''(P'1, P'2, P'3, .., P'n) \tag{3}$$

and P [a', b'], a' = 1, 2, 3, ..., search dimension; similarly, b' = 1, 2, 3, ..., search dimension. Thus, in analyzing oppositional-based optimization, there is a need to initialize the process of opposition-based learning during the procedure of PSO implication.

On the other end, the privacy of data while optimizing the path for traveling is critical. To incorporate private data during the process of path scheduling towards the transmission, the method of orthogonal-PSO plays a vital role in selecting the best position and load data in a protected manner. The operation of secure selection and loading is described as follows:

A population of positions generation

$$A' = A'1, A'2, A'3, \ldots, A'n, \tag{4}$$

with the transmission speed V' in the selection of dimension is created.

In this whole scenario, oppositional-based learning helps to evaluate the initial solution and the total estimating candidate solution for the purpose of the best choice. To do this, an inverse solution is designed that aims to compare generated identical solutions with random newly generated solutions. Meanwhile, the development of opposition-based learning improves the traveling cost because calculates estimations dynamically.

$$\mathrm{A}'' = A''1, A''2, A''3, \ldots, A''n \tag{5}$$

whereas

$$\mathrm{A}'' = min + max - A' \tag{6}$$

However, eq 5 and 6 elaborate the working operation of inverse solution A' ϵ [min, max] and their implication with the oppositional-based population in the d-dimension.

By choosing the best position, the fitness value of the final selection for the desired positions is calculated as follows:

$$\mathrm{fitness(f)} = max(l) \tag{7}$$

where,

$$\mathrm{l} = \log_{10}(\mathrm{e}^2/\mathrm{k}) \tag{8}$$

$$\text{additionally,}\ \mathrm{k} = \text{sum of } ((\mathrm{I}_1(\mathrm{b, c})$$

$$- \mathrm{I}_2(\mathrm{b, c}))/\text{sum of average}) \quad (9)$$

where (b, c) describes the row and column denoted as the loaded protected data. Substantially, 'l' is designed to help assess the fitness of the desired positions.

After all these, the path selection of data transmission is adopted based on the process of global and local values estimated by the evaluation metrics of P'', A'', and fitness (f). The calculative criteria of finding and updating best selection is highlighted as follows:

$$\mathrm{A}''(\text{best f}) \rightarrow (\mathrm{a}+1) = best(local[P'']) \rightarrow (global[p'']) \quad (10)$$

B. PROBLEM FORMULATION

To protect the data, the newly implemented NuCypher Proxy Re-Encryption (NCPRE) mechanism is playing a crucial role, where an individual transaction encodes/proxies their transactional data records and then operates in terms to threshold traverse details either 0 or 1 bits (means binary formation). The purpose is to design this with the proposed model is that it solves many-to-many data sharing and exchanging data in a very fine manner. Instead of encrypting data every time, a number of logs are encrypted only a single time under the data key known "owner key". In case of data inputs align sequentially, the model load and comprise data in the node is mentioned as follows:

$$D = \sum_{d=1}^{n} NCPRE(d) + (bits(load * comprise)) \quad (11)$$

where 'd' is the data point which is presented in the form of binary.

Using these generated proxies of re-encryption, the authorized system's expert can delegate and revoke access to as many logs in accordance with the need. In this manner, no attacks can occur because NCPRE creates temporary keys, which reduces data on risk in the distributed environment compared to the traditional golden key used in a centralized system. However, there is a fixed size of node transactions schedule, where the loading data is maximized the bits into 4MB node according to the following criteria:

$$NCPRE' = \mathrm{D/n},\ 1 <= \mathrm{NCPRE}' <= 4 \quad (12)$$

Concurrently, the proposed model operated the data management, organization, optimization, and classification before preserving the processed logs in the cloud-enabled distributed storage using the ANN mechanism. The pre-train and fine-tune phases are designed, which aim to compose output logs in a sequential manner. Initially, for the training phase, a predefine ANN strategy is employed, which helps to design an input flow control infrastructure for data logs from the primary to the desired layer through the multi-neural nets hidden layers. It enables the system to provide a required initiation in accordance with the hierarchy proposed by the model for process scheduled data that represents system conviction. On the other side, a fine-tuning phase is designed

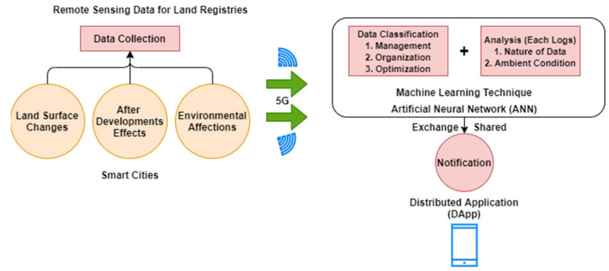

FIGURE 2. The proposed process hierarchy.

with customized parameters (as discussed in eq (13)) to analyze that the data are loaded under the size of node eq (12) and follow the hierarchy of data management, organization, and optimization, as shown in Figure 2.

$$NN(pre-train(PT), fine-tune(FT)) = \sum_{i=1}^{n} ANN\ PTiFTi \sum_{j=1}^{n} ANN\ PTjFTj - \sum_{i=1}^{n} aPTi \sum_{j=1}^{n} bFTj \quad (13)$$

where i = number of logs and j = number of scheduled logs. And so, $\sum_{i=1}^{n} PTi \sum_{j=1}^{n} FTj$ = logs manage, organize, and optimize.

The classification of logs according to the nature of data is implemented, it is needed due to the requirement to maintain an efficient logs preservation environment. In this scenario, the model associated with the designed ANN classification strategy ($\sum_{i=1}^{n} ANN\ PTiFTi + \mathrm{aPTj}$), is discussed as follows:

$$ANN(classification(FTj = 1|PT)) = (\sum_{i=1}^{n} ANN\ PTiFTi + \mathrm{aPTj}) \quad (14)$$

IV. PROPOSED MODEL

The operational hierarchy of the proposed model is shown in Figure 3. However, this proposed model contributed to four different subsections: such as (i) lifecycle of remote sensing data, (ii) ML-ANN for data classification, (iii) PSO for the shortest path of node transaction, and (iv) blockchain DLT for ledger privacy, and security. Initially (in section I), the system receives remote sensing data from the Internet of Things (IoT)-enabled sensors. After receiving the chain of data, a standard process hierarchy of data collection is required. It contains a mechanism of data capturing, such as stop-and-listen. The main purpose is to capture remote data and store it in static memory. Whereas it can be examined, analyzed, presented, and reported. The advantage of formalizing these steps is to refine individual data points from a number of large data records of smart cities. And so, it helps to schedule processes in terms of management, organization, and optimization. In section II, the classification of data is under the nature of collected points. To analyze these, the remote sensing data for the land registry is categorized into four subdomains. First, data collection captures the data of land surface changes, aftereffects of developments, and

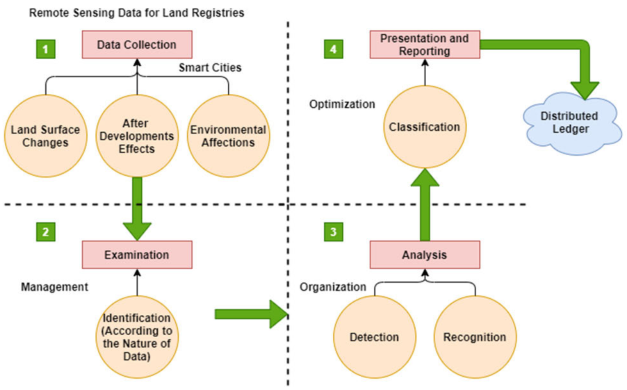

FIGURE 3. **Operational sequences of the proposed model.**

environmental affections and transmits it to the examination, as shown in Figure 4. Second, the examination helps in the process of management, where it separates data logs according to their nature using a machine learning supervised technique.

Third, the hierarchy of analysis supports data organization, in which it detects and recognizes partial points of data records and matches them. It is because of data category is created category using the ANN mechanism, as discussed in eq (13) and (14). Finally, the process of presentation and reporting received an optimized and classified data log, which loads on the node (which is a fixed size of 4MB) and executes, as shown in Figure 3. On the other side, section III of the proposed model is designed with the purpose to minimize the traveling cost by selecting the best path for data traveling/transmission. In this manner, the PSO algorithm is used to estimate the optimal solution of data delivery by evaluating the local and global selection from the original population with the help of the orthogonal-PSO strategy. However, for secure transmission, a consortium blockchain-enabled distributed network is deployed. In this, two channels of intercommunication for transaction handling are proposed, such as implicit transaction (on-chain) and explicit transaction (off-chain). To automate the transaction over the consortium network, a chaincode/smart contract with four functions is implemented and deployed. Along with that, a customized PoS consensus develops that handles participating nodes' identity, participation information, ledger, and sharing protocols for privacy protection. To tackle all the requests, an administrator/manager panel is designed (known as Distributed Application (DApp)) that makes the system more reliable in terms of accessing, logs sharing, managing, and preserving logs as required. In the end, a cloud-enabled distributed ledger storage (dynamic memory) is structured (where only processed logs are stored) that is considered one of the cost-efficient immutable data preservation infrastructures.

A. CHAINCODE AND CONSENSUS PROTOCOLS

Table 2 presents the working sequences of the designed chaincode. However, this code is created and deployed with four different functions for automating remote sensing data collected from the devices. In this manner, the secure lifecycle of data capturing is implemented, including (i) data collecting (dCollect()), (ii) scheduling (dSchedule()), (iii) examining (dExamine()), (iv) storing (dStore()), (v) organizing (dOrganize()), and (vi) optimizing (dOptimize()), that aiming to collect land surface records via B-DApp using the collaborative mechanism of ANN with PSO. A Land-Surface Manager is only responsible that managing the overall process of B-DApp. Initially, the chaincode initiates dEnroll() function while checking the entire chain of stakeholder participation; if the devices are already enrolled, then the system passes through the proposed lifecycle of remote sensing. Other than that, the function dEnroll() runs in terms of verifying and validate the request for device registration. After all these processes, transactions are initiated from dCollect() to dOptimize as per the designed formation in a secure manner, shown in Table 2. For instance, the data transmitted from one end to another are fully proxy re-encrypted using the NuCypher threshold mechanism.

The function MLedger() is created with the objective to construct the optimized logs in the immutable cloud-enabled blockchain DLT storage. It is completely a cost-effective data storage infrastructure because there is no additional third-party preservation involvement occur throughout, such as IPFS, Filecoin, etc. However, the transactions go from either implicitly or explicitly depending on the nature of inter or outer transactional requests. For this purpose, ANTran() function is designed that use to redirect the newly added activities. Every transaction is scheduled in accordance with the FSNode(), a fixed-size node that is capable of transferring data toward delivery. On the other side, another important function UTLogs() is created, which is dependent on the consensus protocols, such as miner = max stakes, sub-miner = number of stakes, verify and validate = request execution, and update transaction = calculate 51% votes. The main task of UTLogs() is to get the request for an update from the stakeholders, and after analysis it activity gets updated and shared among them as per the designed rules, shown in Table 2.

V. RESULTS AND DISCUSSION

The major assumptions of the simulations are discussed as follows:

- Intel Core i7 (11 generation-H processor) is used
- 16 GB DDR4 3200 MHz RAM
- Iris-Xe Shared Graphics
- 512 SSD with 1 TB HDD
- Python 10.7.3 version with OpenCV library is used
- Tested on the Benchmark dataset (Virat2020-UrbanYork) [29], [30], [31], [32], [33], [34], [35]

Initially, the experimental analysis of the proposed model applied on the real-time cameras for finding the land surface changes and aftereffects of developments in the smart cities.

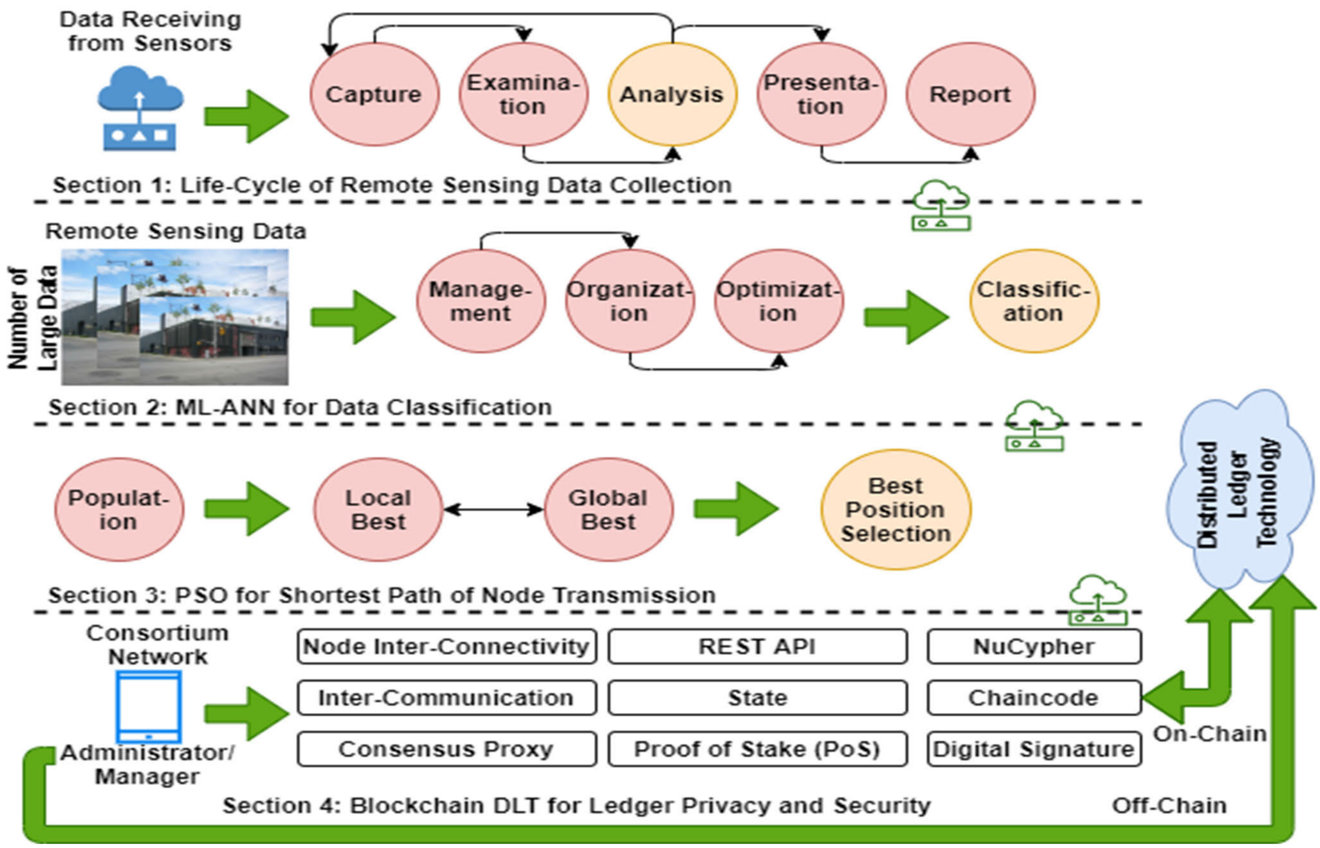

FIGURE 4. The proposed model.

For this evaluation, the system presents outperform in terms of examining the changes and effects drastically, as shown in Figure 5. The metrics of the examination are highlighted as follows: (i) original image (collected via the wireless sensors), (ii) applying cascading (to trace changes), (iii) bits analysis (convert into an encoded array), and (iv) binarization → trace threshold changes and compared.

The performance of the model is described in the tabular structure, which is highlighted as follows (as mentioned in Table 3):

However, on the other end, the proposed model enabled DApp to provide a unique distribution of several generated data points. Schedule individual points of data in terms of their classification values (which is possible with ANN, as shown in Figure 5) for transmission. For this purpose, each point loads in the node of fixed memory size up to 4 MB and then transmits it over the distributed consortium network. The simulation results of the average relationship between the number of data points generation and management are illustrated in Figure 6. The metrics of calculation are as follows: x-axis → the number of data points generation and y-axis → schedule and load data in the node/s.

After scheduling remote sensing data, the path selection for node transmission is described. In this manner, the system integrates with PSO to estimate the best position by calculating local and global searches in the original population.

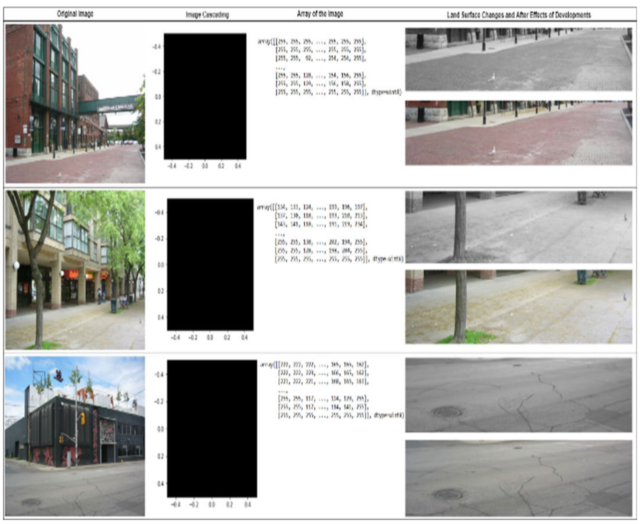

FIGURE 5. Evaluation metrics of land surface changes and after effects of development in smart cities.

However, the proposed model is tested to analyze the average relationship between the number of data scheduled in the node and the shortest path in terms of time deliverance. Figure 7 illustrates that the collaboration of PSO with ANN in the distributed environment reduces the cost of network

TABLE 2. Chaincode implementation.

Assumptions: A Land-Surface Manager is Assigned that manages the overall process of B-DApp
Three communication channels are designed: (i) implicit, (ii) explicit, and (iii) middleware
A cloud-enabled cost-efficient local distributed storage are deployed
Consortium chain are constructed
Data: File[X].a -> .txt
int main():
device enrolment,
dEnroll();
collect data,
dCollect();
schedule data,
dSchedule();
examine data,
dExamine();
store data,
dStore();
organize data,
dOrganize();
optimize data,
dOptimize();
maintain ledger,
MLedger();
add new transations,
ANTran();
fix-size node,
FSNode();
update transactional logs,
UTLogs();
Blockchain timestamp,
[run];
Process: if device != dEnroll(),
then, examine request of registry,
and, add in ledger == ANTran();
if transaction != initiate according to MLedger(),
then, request passes through dCollect(), dSchedule(), dExamine(), dStore(), dOrganize(), dOptimize(),
individual transcation == FSNode(),
private chain = stakeholders,
public chain = user dedicated,
private chain = consortium chain,
public chain = consortium chain,
records preserve = cloud=enabled DLT;
else re-track, state change, exchange, store logs,
terminate,
stop chain transactions;
else re-track, state change, exchange, store logs,
terminate,
stop chain transactions;
Consensus Protocols:
Miner = Max Stakes,
Sub-miner = Number of Stakes,
Verify and validate = Request execution,

TABLE 2. *(Continued.)* Chaincode implementation.

Update transaction = calculate 51% votes,
Digital signature = true,
Transaction encryption = NuCypher threshold proxy re-encryption,
Immutable ledger = Cloud DLT;
Results: dEnroll(); MLedger(); ANTran(); UTLogs();

TABLE 3. Performance metrics.

Images	PSO	ANN	Blockchain DLT (immutable distributed infrastructure)
	Investigational Parameters		
Image 1	37.3%	17.9%	11.7%
Image 2	21.1%	13.4%	8.5%
Image 3	27.6%	15.8%	9.3%
Average	**28.66%**	**15.70%**	**9.83%**

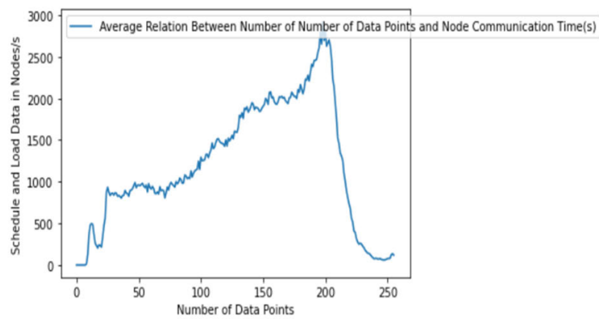

FIGURE 6. Result of average related between the number of data points and node communication time (s).

resources down to 12.73% and increases the data sharing records up to 7.64%.

The average relationship between the number of requests received via the DApp (Land-Surface DApp) and the time consumed for data scheduling, managing, organizing, and optimizing. This evaluation is possible when the system is associated with ML-supervised techniques, such as ANN. However, the criteria of examination are described as follows: x-axis → the number of requests received by the system and y-axis → the average time for schedule data management and optimization (as shown in Figure 8).

In the end, the simulation results are performed on the designed cloud enabled DLT; while calculating the data received by the storage units and optimization, the proposed model decreases a load of resource usage down to 9.11% while increasing the privacy protection of data movement

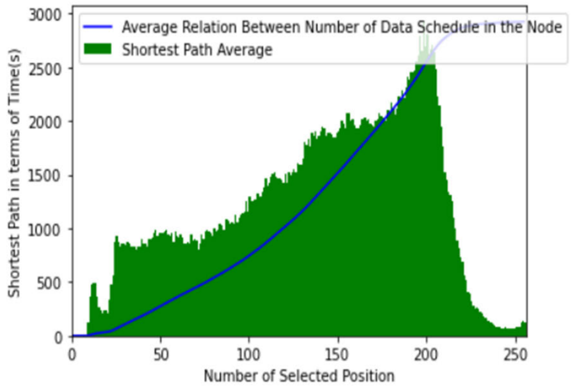

FIGURE 7. Result of average relationship between the number of request received by the land-surface dapp and time for schedule data management (s).

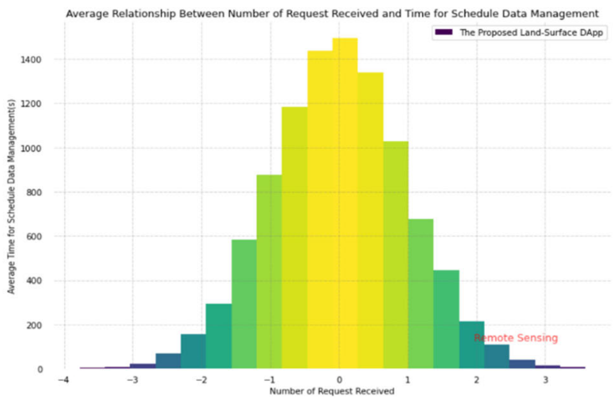

FIGURE 8. Result of average relation between the number of data scheduled in the node and shortest path selection.

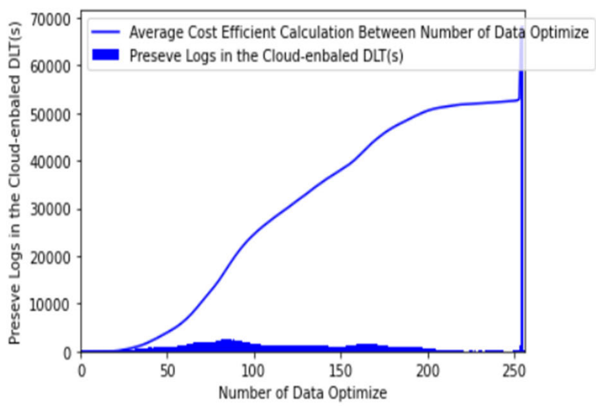

FIGURE 9. Result of average cost of data preservation and optimization.

up to 6.73% using blockchain consortium infrastructure, as shown in Figure 9.

Table 4 presents the comparative results analysis, which is based on the well-known state-of-the-art methods of remote sensing, where the evaluation metrics of this analysis is highlighted as follows:

- ☐ Use of Blockchain DLT
- ☐ Network structure
- ☐ Encryption method
- ☐ Node size
- ☐ Method for data management and optimization
- ☐ Method for data transmission and deliverance
- ☐ Cost of logs preservation
- ☐ System's efficiency
- ☐ System's Accuracy

A. CURRENT INVOLVING IMPLEMENTATION CHALLENGES AND LIMITATIONS

In this context, there are different open research problems are listed and analyzed, where a few of them is addressed with their possible solutions as follows:

1) SCOPE OF DATA PRIVACY PROTECTION

Data privacy protection is a significant objective running throughout the process of remote sensing data; to address such concerns in real-time, proper use of blockchain DLT is required. Especially in smart cities, the personal information of connected nodes needs to protect when joining or before the designed consortium chains, including individual node details, scheduling, and processing hierarchy, gratifying each type of data recorded, and preservation management [35]. In this regard, a cloud-enabling local distributed ledger structure is integrated with blockchain immutable infrastructure and a NuCypher Threshold Proxy Re-Encryption mechanism to prevent records from malicious and preserve all those records in a secure and cost-efficient manner. In addition, the tri-communication channels separate the implicit, explicit, and middleware resource transactions. It helps to examine the list of scheduled transactions effectively and efficiently. However, the explicit transaction from interoperable chains creates a challenging problem, such as a lack of privacy while information exchange among them. To protect such type of issue, NuCypher Re-Encryption with customized PoS consensus is used to integrate the current infrastructure of blockchain technology for land surface applications of smart cities [35], [36].

2) OUTSOURCE COMPUTATION AND REMOTE SENSING DATA

In the recent environment, cloud/fog computing technology is considered a mature concept because it offers storage scalability and computing power in a pay-per-use model. Receiving data from the sensing devices required computation, whereas the current scenario uses cloud/fog-enabling computing systems. These systems are based on the traditional client-server-enabled infrastructure or rely on the third-party environment. It poses a serious issue throughout the process of deliverance [36]. For instance, the existing working hierarchy of outsourced computation is collecting, processing, executing, preserving, and sharing remote sensing data via wireless sensor networks. This unsecure manner increases the rate of integrity, confidentiality, and

TABLE 4. Comparative table.

State-of-th-Art Method (1) [26, 30, 31]	State-of-th-Art Method (2) [32, 33]	State-of-th-Art Method (3) [34]	Proposed Model
The metrics of comparative analysis is mentioned as follows:			
• Use of Blockchain DLT: Public Blockchain • Network structure: Permissionless network structure • Encryption method: hash-encryption (SHA-256) • Node size: Depend on the transactional data • Method for data management and optimization: Not applicable • Method for data transmission and deliverance: • Cost of logs preservation: IPFS Blockchain • System's efficiency: N/A • System's Accuracy: N/A	• Use of Blockchain DLT: Public Blockchain • Network structure: Permissionless network structure • Encryption method: hash-encryption (SHA-256) • Node size: Not applicable • Method for data management and optimization: Deep neural nets • Method for data transmission and deliverance: Not applicable • Cost of logs preservation: IPFS Blockchain • System's efficiency: N/A • System's Accuracy: N/A	• Use of Blockchain DLT: Public Blockchain • Network structure: Permissionless network structure • Encryption method: hash-encryption (SHA-256) • Node size: Depend on the size of transaction • Method for data management and optimization: Computational method • Method for data transmission and deliverance: Not applicable • Cost of logs preservation: IPFS Blockchain • System's efficiency: N/A • System's Accuracy: N/A	• Use of Blockchain DLT: Consortium Blockchain • Network structure: Permissionless network structure • Encryption method: NuCypher Proxy Re-Encryption mechanism • Node size: • Method for data management and optimization: • Method for data transmission and deliverance: • Cost of logs preservation: Cloud-enabled DLT is designed and deployed • System's efficiency: 12.73% and 7.64 • System's Accuracy: 6.73%

data redundancy-related problems. To protect data from malicious attacks, a modular architecture of blockchain DLT is used. It provides a decentralized platform where data processes in terms of capturing, scheduling, organizing, managing, optimizing, preserving, and sharing without affecting unknown adversaries. According to this scenario, the current infrastructure of business intelligence is shifting from centralized outsourcing to the newly proposed homomorphic blockchain-based protected outsourcing architecture with cloud/fog computing.

3) DISTRIBUTED PSO AND ANN FOR OPTIMAL DELIVERANCE AND CLASSIFICATION

Various ML algorithms are used to solve complex real-world and combinatorial problems. However, the most successful Artificial Neural Network (ANN) is initiated from scratch, where it takes background knowledge of the problem and then starts consideration [35], [37]. Undoubtedly, the overall execution of ANN consumes significant computational energy, time, and bandwidth-related resources. In this scenario, the integration of PSO with ANN resolves several issues, such as being capable of fast convergence when compared with different evolutionary algorithms for the sake of automating meaningful search of ANN architectures for classifications. A secure encoding channel and a velocity operator are required, where a system can allow optimization facilities and limit computational power with the collaboration of ANN, PSO, and blockchain DLT. The main motive is to propose a good, quick, and secure architectural environment where a system can achieve quality performance.

4) INTEROPERABLE CHAINING LIMITATIONS

Throughout the development of blockchain technology, interoperable chaining raises one of the critical challenging prospects nowadays. It occurs when a single transaction goes from one chain to another, which means remote sensing data delivering, sharing, and exchanging between node to node from chain to chain [36], [37]. For instance, a complete process cycle consumes more time in executions, and most importantly, it uses high computational bandwidth. To lightweight such a scenario, there is a need to provide a protected interconnected node communication facility, which limits the size of blocks for an individual transaction. It can be handling smart production activities, such as a collection of remote sensing big data, organization and management of different values, supply-chain transaction schedules, and a secure real-time monitoring ecosystem. However, the traditional legacy of current industrial architecture also needs improvement, including the lifecycle, service delivery protocols, network structure, intercommunication, and interconnectivity policies for the sake to design a secure remote sensing data hierarchy.

VI. CONCLUSION

This study first addresses current challenges in machine learning techniques and related enabling technologies when using remote sensing data management. The analysis of previously published state-of-the-art techniques makes it feasible. Issues with data transformation, transmission, deliverance, storage, and optimization come up throughout the applicational domain analysis of each item. This report highlights research gaps in open research topics for technological maturity and addresses some of the challenges with potential remedies. That being said, this paper makes three distinct contributions. First, the PSO computational technique handled data from devices that were remotely sensed over the planned dispersed network. Three intercommunication channels are presented in an innovative and secure blockchain-enabled data collecting lifecycle to plan transmission. The second reason that ANN is integrated is that, at first, its main function is to optimize data delivery logs based on data classification. Consequently, arrange logs in the dispersed cloud storage, which is entirely predicated on an unchangeable character. Third, a consortium network is set up to handle different kinds of remote sensing data while encrypting it with the NuCypher Re-Encryption process, PoS, and blockchain architecture. All transactions, whether explicit or tacit, are covered. For example, the proposed model's experimentation achieves minimal resource consumption costs, high privacy protection during data travel, optimal pathway, and quick data exchange capabilities. Because of this, the suggested model is seen as a strong contender for industrial adaption.

CONFLICT OF INTEREST

The author of this paper declares no conflict of interest.

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