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Decentralizing construction AI applications using blockchain technology

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ABSTRACT

Decentralizing the Artificial Intelligence (AI) applications is deemed the next wave of Blockchain Technology (BT) in the construction industry. Most of previous research studies employed the AI and the BT separately with limited efforts providing a conceptual view for possible convergence in real-life applications. Nevertheless, such efforts do not address construction applications. This research introduces a novel tailorable decentralized AI system that utilizes BT as a computing-oriented technology. The proposed system is developed as an inference engine while having a number of interesting features. First, the system validates and audits the decision-making process while sharing and recording the input data and the computed outcomes in a synchronized trusted manner. Second, the system allows the formation of distributed AI repository that can absorb and manage concurrent use-cases while targeting different scopes and covering diverse AI branches. Third, it provides a workable solution for the AI applications' distribution problem, which hinders their wide employment. Fourth, the introduced system guarantees sustainable versioning and evolution over time for AI applications based on their performance or the newly acquired data. A case study of estimating the construction cost for road projects is provided to illustrate the system's workability and demonstrate its performance.

1. Introduction

Blockchain Technology (BT) and Artificial Intelligence (AI) are the most hyped developments in information technology. These technologies deemed as a major engine to revolutionize the construction industry since it bears many misalignments, fragmentation, and low productivity and effectiveness. AI can provide computers and machines with cognitive capabilities to learn, infer and decide based on a collection of data and sometimes, these capabilities can exceed the human ones. Accordingly, a report by McKinsey Global Institute in 2018 stated that AI applications would supply an additional global economic value around USD 13 trillion by 2030. On the other side, BT can provide consensus over a digital distributed ledger in an untrusted environment that may consist of unreachable nodes or stakeholders while securing access control for electronic records and IT systems. Based on that, a study by Research and Markets Store expects that the global BT market size would grow from USD 3.0 billion in 2020 to USD 39.7 billion by 2025 with 67.3% as a compound annual growth rate (Dinh & Thai, 2018; Pandl et al., 2020; Research-and-Markets-Store, 2020; Vyas et al., 2019).

Most of construction research efforts focus on utilizing AI models separately to add value or transform the industry processes depending on a centralized approach starting from model feasibility, data acquisition, and model development to model deployment. Such approach suffers from three major issues (Ekramifard et al., 2020; ElMousalami et al., 2018; Gupta, 2020; Pandl et al., 2020; Salah et al., 2019). Firstly, the provenance and authenticity of data sources are not warranted. As a result, the data becomes questionable, and the outcomes of developed models could be biased or mistaken. Secondly, the centralized ownership of data exposes it to undesirable risks like single-point attacks, tampering, or leakage of sensitive records. Thirdly, the researchers or developers exert repetitive efforts for reproducing same purpose AI models due to the absence of a secure sharing platform/system for the pre-existing ones.

On the other side, recent research efforts have investigated the usage of BT in the construction field. These efforts can be clustered into four major domains; payment management (Elghaish et al., 2020; Ye &

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König, 2020), chaining of quality and building information (Sheng, Ding, et al., 2020; Xue & Lu, 2020), supply chain management (Helo & Shamsuzzoha, 2020; Wang et al., 2020) and decentralized autonomous organizations (Hunhevicz & Hall, 2020; Sreckovic & Windsperger, 2019). The efforts have employed the BT as a transaction-oriented technology for only exchanging and maintaining raw textual and numeric data without conducting real-time analytics or further analysis based on the whole chained data.

The convergence of AI and BT in a single ecosystem is considered a perfect mechanism to overcome the issues mentioned above, leading to what can be called a Trusted Decentralized Artificial Intelligence (TDAI) (Corea, 2019; Gulati et al., 2020; Harris & Waggoner, 2019; Inbaraj & Chaitanya, 2020; Tanwar et al., 2019). TDAI provides a stable distributed medium to secure the AI models' sharing without the need for intermediaries or trusted third parties. TDAI also enables securing, auditing, and validating the learning data to avoid the development of mistaken or biased AI models. Furthermore, TDAI via the utilization of smart contracts or chaincodes in BT allows the outdated AI models to be modified, versioned, and evolved over time based on validating and calibrating their outcomes by the relevant stakeholders. Therefore, if the outcomes are reliable, the models are still shared and embedded in the chaincodes. Otherwise, access to outdated versions is restricted, and new valid versions are re-developed using off-chain or on-chain learning algorithms based on the chained new data.

The research addresses this potential by developing a decentralized AI system that can be tailored to suit various concurrent applications within the construction companies, research centers, or labs. The proposed system answers the research question of how a decentralized BT system can enhance the trust in AI models' decisions, and analytics. The system's scope is to build a private blockchain-based network (BBN) that encloses a digital AI models' library. This library is coded within a chaincode to facilitate data transaction and storage while providing decisions or predictions based on such data via a Command Line based (CLI-based) interface. The CLI-based interface is utilized mainly for prompt implementation and testing at a more controlled and granular level. The proposed study contributes to the body of knowledge since it presents a novel decentralized intelligent system for construction companies and research centers to exchange and analyze information using blockchain and AI in tandem. Also, it provides practical guidelines for the development and the implementation of such a system in the construction industry that is characterized by different parties with numerous communication channels

The remainder of this paper is structured as follows: Section (2) presents theoretical background related to AI and BT. Section (3) clarifies the research methodology for the proposed system. Section (4) focuses on the system implementation. Section (5) is related to the testing stage to verify the system's capabilities. Sections (6) and (7) provide thorough discussion and conclusions.

2. Theoretical background

2.1. Artificial Intelligence

AI is an advanced computational discipline that enables machines and computers to perform complex tasks based on a knowledge database to make decisions, predictions, or classification (Krittanawong et al., 2020). It can be sorted into Artificial General Intelligence and Narrow Artificial Intelligence. Artificial General Intelligence refers to self-control computers that able to solve tasks in a wide range of different domains. In contrast, Narrow Artificial Intelligence refers to AI-based applications that are built to solve a particular task in a specific narrow domain. Most of existing AI applications and systems rely on Narrow Artificial Intelligence (Pandl et al., 2020). The divisions of Narrow Artificial Intelligence include but are not limited to Expert Systems, Machine Learning, Deep Learning, Natural Language Processing, and Robotics (Kim & Huh, 2020; Panda & Jena, 2020; Pandl et al., 2020). Machine Learning (ML) is the most exploited AI branch in the construction engineering and management field for diverse purposes. These purposes include cost/price estimating, productivity measurements, assets' inspection and maintenance, construction safety and health management, and risk analysis for construction projects (See Table 1). ML focuses on developing applications and programs that can learn via experience. These applications enclose a model that captures the linkage between input data and output data. Such a model has to be trained using supervised or unsupervised learning algorithms depending on its scope. The ML model's inner working is described as a black box since its functionalities and outcomes are intricate to be explained which reduces the dependability upon it (Nassar et al., 2020).

2.2. Blockchain

BT represents a significant branch of distributed ledger technologies that encloses a digital ledger that scattered and being updated around multiple nodes in a synchronized distributed manner. These nodes form a peer-to-peer network that enables direct interaction and information exchange without the need for any trusted intermediaries while ensuring security and reliability for all nodes (Elghaish et al., 2020). The inner working of BT depends on a list of blocks that are chained together using unique cryptographic hashes. These hashes allow the blockchain transactions to be traceable and impervious against change or tampering (Bamakan et al., 2020; Papakostas et al., 2019; Xu et al., 2019).

2.2.1. Blockchain as a Transaction-Oriented technology

BBN is mainly used as a distributed data structure that able to circulate and maintain diverse types of data with a high degree of encryption and transparency while providing no centralized management since all nodes have the same rights and obligations (Ar et al., 2020; Kim et al., 2020; Penzes et al., 2018; Tang et al., 2019). Thus, it is utilized to minify business frictions, reduce operational costs, settle transactions' vulnerability, and provide a trustworthy information exchange system. BBN is classified into permissioned-less network and permissioned network. The permissioned-less network can be joined by any participant with no restrictions while being secure due to its powerful cryptographic algorithms. On the other side, the permissioned network is mainly used to build a platform for a specific organization that can be accessed by pre-identified or selected participants (Penzes et al., 2018). According to Chang et al. (2019); Penzes et al. (2018); Perera et al. (2020), the major features of these types are summarized as follows:

- **Security**: BT uses impenetrable encryption mechanisms to assure the validity of stored data and prevent manipulation.
- **Transparency**: BT orders and sends the transactions to all members in an apparent way.
- **Decentralization**: BT allows (Write-Once-Read-Many) characteristics with no localized data storage or directory to reduce delays and avoid a single point of failure.
- **Auditability**: BT time-stamps the on-chain data to be easily traced by different nodes.

Table 1
Recent AI Studies in the CEM Field.

Category	Reference
Construction Safety and Health Management	Baker et al. (2020); Cheng et al. (2020); Choi et al. (2020); Sakhakarmi et al. (2019)
Built Assets' Inspection and Maintenance	Guo et al. (2020); Maeda et al. (2020); Pan and Yang (2020); Yao et al. (2020); Zhu et al. (2020)
Risk Analysis	El-Kholy (2019); Fan (2020); Gondia et al. (2020); Sanni-Anibire et al. (2020)
Cost/Price Estimating	Cao et al. (2018); El-Kholy et al. (2020); Gondia et al. (2020); Matel et al. (2019); Rafiei and Adeli (2018)

Despite these features, some issues like network type and size, block time and size, storage bloating, transaction throughput, and latency still need technical enhancements.

2.2.2. Blockchain as a Computing-Oriented technology

BBN can be utilized as a general computing platform through the assembly with Smart Contracts (SCs) or Chaincodes (CCs) that provide the BBN with the needed computational power and programming logic. Although smart contract or chaincode seems like a new notion, it was proposed in 1994 by Szabo (1994). SC or CC is defined as a self-executing program that can be triggered when specific terms and conditions are fulfilled while minimizing exceptions and intermediaries (Nassar et al., 2020; Tanwar et al., 2019). The evolution of BBN affords a low-budget path for building and deploying CCs. Since CC contains trigger conditions and relevant responses, it can be embedded in the BBN to serve as a state machine that constantly observes data fluctuations in the chain while automatically execute predefined actions. CC can also handle complex programmable scenarios by using sets of rich functions that are available and supported by Turing complete languages, such as Go, JavaScript, and TypeScript for Hyperledger Fabric and Solidity for Ethereum (Perera et al., 2020; Sgantzos & Grigg, 2019).

With such unique capabilities, many researchers are recently exploring BBN-CC integration in domains as diverse as healthcare management, supply chain management, banking and financial services, e-voting, Internet of Things (IoT), distributed access control, and energy supply. However, some challenges like lack of standards and protocols, legal issues, looping issues, and error intolerance are deemed the bottleneck that hinders the technological development and employment of CCs (Hasan & Salah, 2018).

2.2.3. Blockchain applications in construction

Recent research efforts have presented the potential uses of BBNs in the construction field, which is deemed a vital step to suit more detailed applications. These efforts focus on employing the BBNs as a transaction-oriented technology for exchanging raw textual and numeric data. The efforts can be classified into four major categories as listed in Table 2. The first category is payment management in which BBN has utilized to control, secure, and direct the financial invoices for ongoing construction projects in an automated approach. The second category is the chaining of quality and building information, which can be a perfect solution for the information fragmentation issues via providing a single source of truth platform for the construction industry while ensuring transparency and auditability. The third category considers the use of BBNs to upgrade supply chain management by ensuring the origin and the timing for procurements and submittals in a verified effective approach for all parties. Finally, BBNs can fully manage and direct construction enterprises without any human mediation via CCs that hold the governing rules and conditions, which leads to decentralized autonomous organizations.

Table 2
Recent BT Studies in the CEM Field.

Category	Reference
Payment Management	Ahmadisheykhsarmast and Sonmez (2020); Chong and Diamantopoulos (2020); Das, Luo, et al. (2020); Elghaish et al. (2020); Ye and König (2020)
Chaining Quality and Building Information	Cerić (2019); Das, Tao, et al. (2020); Hijazi et al. (2019); Li et al. (2020); Nawari and Ravindran (2019); Sheng, Ding, et al. (2020); Sheng, Luo, et al. (2020); Xue and Lu (2020); Yang et al. (2020); Zhang et al. (2020); Zhong et al. (2020)
Supply Chain Management	Helo and Shamsuzzoha (2020); Wang et al. (2020)
Decentralized Autonomous Organizations	Hunhevicz and Hall (2020); Li et al. (2019); Shi et al. (2019); Sreckovic and Windsperger (2019)

2.3. BT and AI convergence

BT can amplify the conventional AI systems' capabilities by enabling a decentralized digital ledger that performs consensus and provides agreed-upon decisions. These decisions are stored on blocks to be later on traced back and audit. It also allows AI systems to act as autonomously driven-based systems that can collect, store and analyze data. According to Dinh and Thai (2018); Ekramifard et al. (2020); Gulati et al. (2020); Harris and Waggoner (2019); Inbaraj and Chaitanya (2020); Mamoshina et al. (2018); Nassar et al. (2020); Pandl et al. (2020); Salah et al. (2019); Sarpatwar et al. (2019); Sgantzos and Grigg (2019); Tanwar et al. (2019); Vyas et al. (2019), the benefits of utilizing the BT for AI can be summarized as follows:

- BT can provide a digital diskless environment to process AI models/ architectures
- BT can ensure data provenance, authenticity for the training algorithms to learn, infer and make credible outcomes or decisions.
- BT can enhance the transparency and the trust to understand and audit the AI models/architectures outcomes without the need for third-party auditors.
- In AI Multi-user processes that involve various parties such as business firms and governmental authorities, BT can automate and accelerate the decision-making and the data validation between these parties.
- Since AI models/architectures subtend some reasoning issues due to their black-box behavior, BT can help to better explain those models/ architectures by providing a clear route to trace back the development pattern during their life cycle and AI decision-making process.
- BT and CCs can make AI models/architectures perform more smartly by making near-instantaneous engagements "real-time analytics" or business value engagements "analysis based on historical data".
- BT can lower the market barriers for newly developed AI models/ architectures entry since they are developed based on tamper-proof data while using a decentralized direction.
- BT can restrict or minimize risky scenarios since on-chain AI models/ architectures only process specific actions and nothing more.

The emerging research trend is directed toward using BT as a computing-oriented technology for decentralizing AI operations, especially model data storage and management, model development, and model deployment.

2.3.1. Data storage and management

The current centralized storage mechanisms are considered highly susceptible to privacy and security issues and inefficient with regard to massive data transfers or retrievals. As a result, Blockchain-based storage mechanisms can secure the sensitive data and minimize the latency of AI processes via enabling parallel data access from different geographical network nodes (Corea, 2019; Dinh & Thai, 2018; Ekramifard et al., 2020; Gupta, 2020; Inbaraj & Chaitanya, 2020; Pandl et al., 2020; Salah et al., 2019; Tanwar et al., 2019).

2.3.2. Model development

Model development refers to the training, testing, and validation of AI models. Traditionally, it is performed using a centralized approach before real-world deployment. This approach is considered inefficient since it blocks the continuous evolution of models themselves and may provide outcomes based on old data. Decentralizing the model development is a feasible solution that would lead to highly customized learning models for each client or purpose and leverage the continuously evolving data streams. Moreover, it allows periodical or incremental models' building or tuning since it avoids starting the training process from scratch. This can be done by shielding and scaling the computational capabilities of smart contracts to effectively train, test, and validate the AI models on-chain (Dinh & Thai, 2018; Ekramifard et al., 2020;

Gulati et al., 2020; Harris & Waggoner, 2019; Nassar et al., 2020; Pandl et al., 2020; Salah et al., 2019; Tanwar et al., 2019; Wang et al., 2018).

2.3.3. Model deployment

The model deployment or inference refers to the iterative execution of a trained AI model, which requires less computational resources than the model development (Tanwar et al., 2019). In the context of BT, decentralized model deployment refers to embed or share the models as on-chain digital AI assets within the smart contracts. This approach can ensure the models' provenance and authenticity while permanently recording and tracking their changes and versions. Moreover, on-chain models can be accessible and browsable, which forms a new channel for distribution and discoverability problems of new ones with the possibility to utilize them via Pay per Use option or Pay on Demand option (Bagchi et al., 2019; Pandl et al., 2020; Salah et al., 2019; Sgantzos & Grigg, 2019; Tanwar et al., 2019).

3. Research methodology

This study introduces a novel decentralized AI system that performs as an inference engine for construction companies, research centers, and labs. The system is tailorable to absorb concurrent ML models for diverse use-cases. The architecture for such system is operated in a framework that consists of three major layers: (1) Intelligent Chaincode Layer, (2) Permissioned Blockchain Network Layer, and (3) Frontend Access Layer as shown in Fig. 1. The intelligent chaincode layer is the key layer in which computational operations and input-data processing are conducted. The layer serves as a digital library that encloses off-chain trained ML models for obtaining decentralized agreed-upon outcomes while being responsible for storing the input data and such outcomes within the blockchain network and reporting them back via the frontend access layer. The permissioned blockchain network layer includes the key actors' definitions, the transaction validation, and recording policies. Each actor involved in the network represents a peer node with predefined privileges regarding write/read processes while holding its own ledger. The validation policy specifies the endorsement method for a transaction that is proposed from one peer node to the other actors. The recording policy specifies the recording procedure of each validated transaction, including by which actor and through which channel. Such policy should be designed to succeed the actual relationships between the actors. The frontend access layer is proposed in the form of an interactive CLI-based interface. This interface allows data feeding and accessibility for authorized actors and outcomes' traceability of AI operations. It can be directly linked with the blockchain layer by using REST HTTP, which is an approach for communication with cloud data centers.

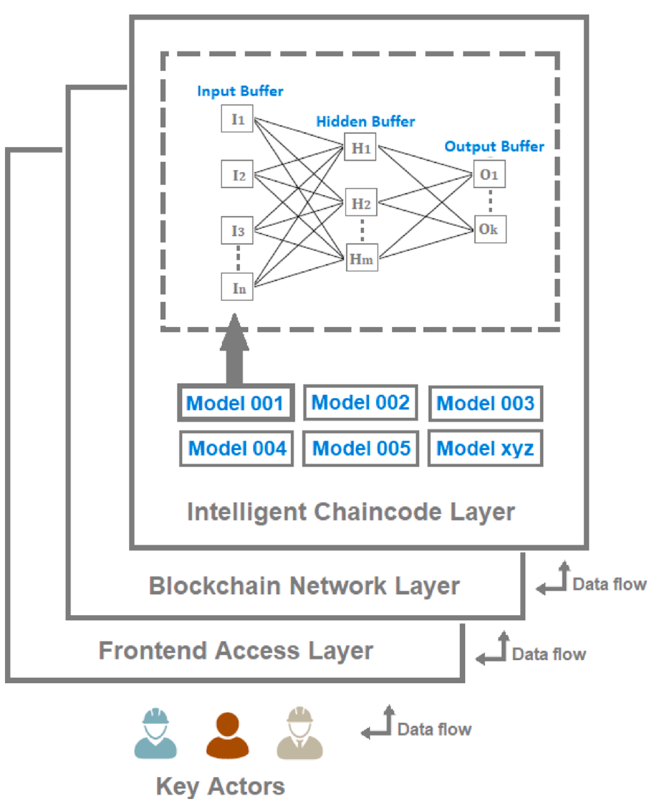

Fig. 1. Proposed Architecture for Decentralized AI System.

The system processes the data transactions in five main steps as shown in Fig. 2. Firstly, an authorized actor uses the frontend interface to submit a transaction proposal for inferring a ML model. Secondly, the interface communicates with BBN to activate the corresponding chaincode to process the proposed inputs via the embedded ML model and provide an outcome. Thirdly, as predefined in the validation policy, the inputs and outcomes are sent for validation to certain peer nodes. Fourthly, once the validation is performed, the transaction data "inputs and outcomes" is time-stamped and stored within a block then broadcasted to the peer nodes to be committed and listed in their digital ledgers according to the recording policy. Fifthly, the same data is returned to the proposing actor via the frontend interface. At each transaction proposal, the same sequence is repeated.

4. System implementation

The proposed system was initially implemented for the case study of estimating the construction cost of road projects. Regarding the case study, the key actors were cost engineer, decision/policy maker, and ML developer. These actors can be scaled at any point of time. The ML developer holds the overall governance to build ML models, configure BBN, technically train other actors and register them within the system. The data exchange's relationships between these actors were mapped as shown in Table 3.

4.1. ML model

The ML model was developed for estimating the construction cost of road projects in the early stages to assist the construction firms' decision-makers in bidding and budgeting decisions. Seven parameters were identified based on an in-depth review of the available database from the General Authority for Roads, Bridges, and Land Transport in Egypt. These parameters are listed as follows:

- Type of work (I_1): The scope to be performed as a new road or a re-pavement of an existing road.
- Grade of Road (I_2): The functional grade of the road.
- Construction Duration (I_3): The project duration in months for completing the construction phase.
- Construction Year (I_4): The difference between the construction year and the base year which is 2002.
- Sector (I_5): The district where the road is constructed.
- Road Length (I_6): The total length of a road in Kilometers.
- Road Width (I_7): The total width of a road in Meters.

The ML model was built as a multi-buffer perceptron artificial neural network using NeuroSolutions Software Version 5.92. The model was composed of processing units distributed among multiple buffers, weights, and activation functions. The processing units represent the computational nodes in which the input data is analyzed. The weights represent the evolved learning embedded within the network. The activation functions refer to the data interpretation functions used inside each computational node (Cirilovic et al., 2014; ElMousalami et al., 2018). The model's topology was designated in three successive buffers

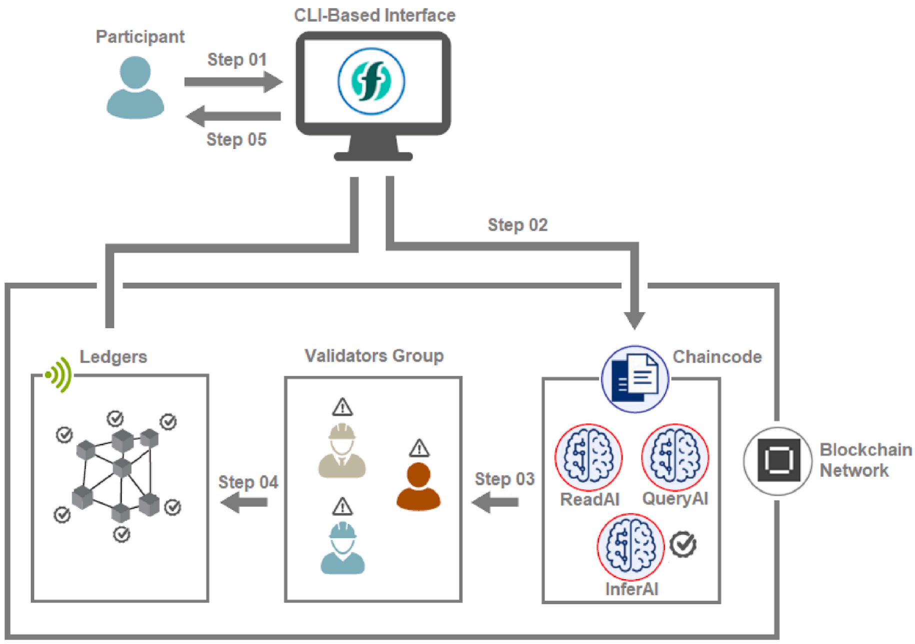

Fig. 2. Dataflow for the System.

Table 3
Data Exchange's Relationships.

Proposed by	Transaction	Transaction Type	Validated by	Ordered to
Cost Engineer Peer	- Model Inference	Write/ Submit	- Decision Maker Peer - ML Developer Peer	Decision Maker Ledger Cost Engineer Ledger ML Developer Ledger
	- Read Specific Record - Query all Records	Read/ Evaluate	- None	
Decision Maker Peer	- Model Inference	Write/ Submit	- Cost Engineer Peer - ML Developer Peer	
	- Read Specific Record - Query all Records	Read/ Evaluate	- None	
ML Developer Peer	- Model Inference	Write/ Submit	- Decision Maker Peer - Cost Engineer Peer	
	- Read Specific Record - Query all Records	Read/ Evaluate	- None	

as depicted in Fig. 3 (Hegazy et al. (1994) and Gunduz et al. (2011)). These buffers are:

- An input buffer encloses seven processing units reflecting the input parameters.
- A middle buffer consists of a number of processing units representing the hidden buffer.
- An output buffer consists of one processing unit representing the average construction cost per (1 Km length, 1 m width & 1-month Duration).

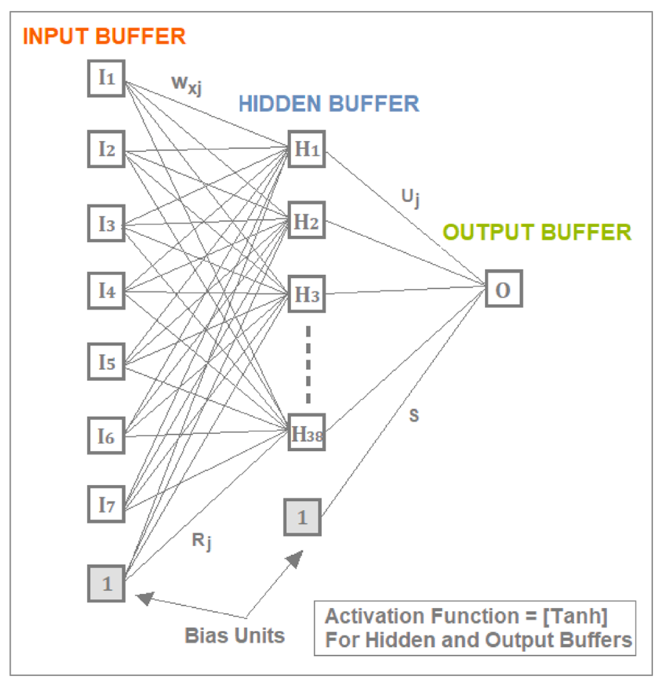

Fig. 3. ML Model Structure.

Concerning the processing units' number in the hidden buffer, NeuroSolutions allows to be varied in a range then uses this range to build, train and cross-validate multiple models and automatically keeps only the one with best results. Such range is determined heuristically based on a trial and error process since there is no generic approach to lean on as stated by Elbeltagi et al. (2014). In this study, the range was set between 2 and 50 and the number of units with preferable results was 38. The model relied on Levenberg Marquardt algorithm as a back-propagation rule for supervised learning while utilized the hyperbolic-tangent function as a nonlinear activation function as recommended by Kim et al. (2004) and Hegazy and Ayed (1998).

The available database was divided into three sets [Training (60 projects), Cross-Validation (5 projects), and Validation (10 projects)]. The size of each set does not rely on standard or acceptable generalized rules as stated by Günaydın and Doğan (2004). However, each set should cover all spectrums and variations of the input parameters. Both training and cross-validation sets were involved in the ML model processing with different functionalities. The training set was utilized to learn and capture the cost relationships between input parameters and output. In contrast, the cross-validation set was utilized for monitoring the model's performance to ensure the best level of generalization and avoid the overtraining issue without affecting the network weights' updating. The validation set was not used during the model processing and was reserved aside to measure the validity and readiness of the processed model to handle new or unseen cases.

It is worth mentioning that the hold-out method was used as the cross-validation scheme as recommended by Adeli and Wu (1998) and employed in previous relevant studies (Cho et al., 2013; Kim et al., 2013; Kim et al., 2005). The model's mathematical formulation and full results are included as Supplementary Data. Table 4 summarizes the results for each set in terms of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Error Percentage (MAEP). As per the table, the model estimates the cost with RMSE of 395.32, 148.53, and 1413.13 EGP for training, cross-validation, and validation sets, respectively. For MAE, the model provides predictions that deviate from actual values by a mean of 240.44, 123.15, and 667.38 EGP for training, cross-validation, and validation sets, respectively. Unlike the MAE, MAEP presents the predictions' deviation from actual values as absolute percentages equal 6.64%, 5.79%, and 9.73% for training, cross-validation, and validation sets, respectively. It is worth noting that the error percentages within the limits of parametric cost estimates set by AACEI (2020).

4.2. Intelligent chaincode layer

The chaincode was coded and packaged using IBM® VSCode extension, including three functions (InferAI, ReadAI, and QueryAI) as detailed in Algorithm 1 and shown in Fig. 4. The InferAI function holds the ML model and is used to calculate and provide an outcome for a specific project/record using a set of predefined parameters. This set can be altered or scaled to accommodate the use-case under consideration. Since the current case study is related to estimating the construction cost for roads projects, nine parameters were defined and listed as follows:

- [RId]: represents record number.
- [I_1, I_2, I_3, I_4, I_5, I_6, and I_7]: represent cost estimating parameters.
- [ER]: represents key actor judgment.

The ReadAI function calls back a single record based on the [RId] parameter, while the QueryAI function retrieves all on-chain records. The chaincode sequence was configured as a closed-form script to avoid looping issues or any possible logical errors. The next step is to develop the blockchain network to install the chaincode on it.

Algorithm 1. Intelligent Chaincode

InputRId, I_1, I_2, I_3, I_4, I_5, I_6, I_7, ER
ID is the set of all Record's IDs saved on the chain.
Function(InferAI)
  if RId $\in$ ID **then**

(*continued on next column*)

Table 4
Summary of Results.

Set	RMSE (EGP)	MAE (EGP)	MAEP (%)
Training	395.32	240.44	6.64%
Cross-Validation	148.53	123.15	5.79%
Validation	1413.13	667.38	9.73%
*EGP: Egyptian Pound			

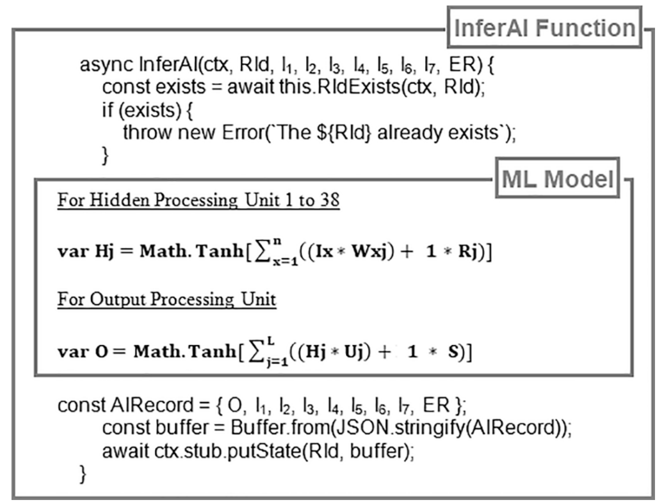

Fig. 4. Sample of Chaincode.

(*continued*)

Algorithm 1. Intelligent Chaincode

    Revert Inputs and Show an error
  end
  else if I_1, I_2, I_3, I_4, I_5, I_6, I_7, ER Exists **then**
    Execute ML Model to Calculate Construction Cost
    Put Inputs and Construction Cost State on Chain
  end
  else
    Revert Inputs and Show an error
  end
end
Function (ReadAI)
  if RId $\notin$ ID **then**
    Revert Inputs and Show an error
  end
  else
    Provide the Transaction with the given RId
  end
end
Function (QueryAI)
  Provide All Transactions
end

4.3. Blockchain network layer

The blockchain network layer was established using IBM Blockchain-as-a-Service solution (BaaS) that relies on Hyperledger Fabric as a hosting platform to leverage the benefits of permissioned BBNs, especially high performance, scalability, and API Support. IBM BaaS allows different users to build, develop, interact and operate a permissioned blockchain network within the context of their environment. Accordingly, the BBN was built via eight main steps as follows:

Step 1: a Kubernetes Service representing the computing cluster was created to manage the IBM BaaS and allow intelligent scheduling, re-allocation, and balancing of computational resources.

Step 2: Certificate Authorities were created to provide the organizations with the required certificates for access and interaction.

- The organizations refer to the participants within the BBN and their numbers can be evolved over time without the need to rebuild the whole network.

Step 3: Membership Service Provider (MSP) for each organization was created to hold its definition and connection profiles.

Step 4: The Peer nodes were created to manage the network ledgers.

Step 5: The Ordering Service was deployed to enroll peer nodes within its consortium.

- The consortium is referenced as a list of the organizations' peer nodes that can build and run the validation and recording channels.

Step 6: Channels were created to allow organizations to propose, validate and record transaction data within specific stream flows with exposing such data to intended organizations only.

- The channel has its ledger that is operated by the enrolled peer nodes.
- The network can consist of several channels that could be built and enrolled by all or particular organizations and be used to run instantiated intelligent chaincodes.

Step 7: Intelligent chaincodes that represent ML models were installed and instantiated within the created channels.

Step 8: The connection profiles and the user identities for each MSP were created and downloaded to provide the CLI-based interface with the required credentials to transact data effectively with the BBN.

4.4. Frontend access layer

The frontend access layer was configured based on the CLI-based interface of IBM Cloud Function through using a serverless action. The action was coded using JavaScript language and operates as a stateless Node.js code snippet. It was designed to interact with the BBN via the MSP connection profiles while acting as a back-engine for the CLI-based interface. The action invocation depends on the chaincode parameters besides two additional parameters representing user identity `[Id]` and chaincode function `[Fcn]` as detailed in Algorithm 2. At this stage, the system was fully developed and ready to be deployed.

Algorithm 2. Serverless Action

InputId, RId, I_1, I_2, I_3, I_4, I_5, I_6, I_7, ER
KAID is the set of Key Actors' IDs that saved in this code.
Credentials are Chaincode-Name, Username, Key, Cert, and Connection Profile that saved in this code.
if Id $\notin$ KAID **then**
  Revert Inputs and Show an error
end
else if Id $\in$ KAID **AND** Fcn = InferAI **then**
  Inherits Credentials
  Execute Function (InferAI) in **Algorithm 1**
end
else if Id $\in$ KAID **AND** Fcn = ReadAI **then**
  Inherits Credentials
  Execute Function (ReadAI) in **Algorithm 1**
end
else if Id $\in$ KAID **AND** Fcn = QueryAI **then**
  Inherits Credentials
  Execute Function (QueryAI) in **Algorithm 1**
end
else
  Revert Inputs and Show an error
end

5. System testing

The system is tested to assess its performance based on the latency of writing and reading, the addition of new participants, and the submission of incomplete data as guided by Almadhoun et al. (2018); Hasan and Salah (2018); Xu et al. (2019). The writing latency for BBNs refers to the inclusion time taken by a transaction to be packaged into a block and stored on the blockchain network. By contrast, reading latency refers to the time spent to retrieve a specific block's data from the BBNs. For the proposed system, the writing latency is less than or equal to 3000 ms, while the reading latency is less than or equal to 500 ms. Both times were calculated using IBM Cloud Function monitoring tools based on 50 successive invocations via the CLI-based interface as shown in Figs. 5 and 6. The result shows acceptable computational speed for both writing and reading operations that nearly similar to conventional centralized systems as guided by Xu et al. (2019). The addition of new participants reflects the system's scalability feature that permits scaling the key actors without rebuilding the whole system. For the proposed system, This process succeeds a simple three-step path that clarified as follows: Creating a Certificate Authority, a MSP and a peer node for the participant and his/her organization, Updating the defined channel to enroll the participant in its consortium, Re-instantiating the intelligent chaincode to take into consideration such participant. The incomplete data submission reflects the system's ability to detect logical or programming errors before deploying the system. Therefore, when a participant attempts to submit incomplete data, the system processes such data via step 01 and step 02 as shown in Fig. 2. At this point, when the corresponding chaincode function tries to handle the proposed input via the embedded ML model, it fails to derive an outcome. As a result, the system provides back a log-error message via the CLI-based interface that the input is incomplete, the computation is not conducted, and the transaction is not recorded on the chain.

6. Discussion

The proposed research is a novel step toward providing a decentralized AI system for the different parties in the construction industry using the BT. The study holds four major theoretical contributions compared to relevant construction studies in expert and intelligent systems. First, transforming the conventional AI systems to act as a persistent decentralized computing platform that automates and validates the decision-making process while sharing and recording the input parameters and the computed outcomes in a synchronized trusted manner. Second, providing and forming a scalable distributed AI repository. This repository is able to encompass concurrent models that target different scopes (e.g., prediction, prioritization, classification and optimization problems) while covering diverse AI branches like expert systems, decision trees, search techniques and evolutionary algorithms unlike the previous studies in Table 1 that provided only non-tailorable single use-case systems. Third, providing a workable solution for the distribution problem of AI models that reduces the dispensable reproduction of similar purpose models. This feature tackles the shortcoming in previous studies' systems since their employment is confined to a closed perimeter of developers or end-users. Fourth, guaranteeing the AI models' versioning and evolution over time which is considered a bottleneck for the related studies' models of Table 1. This can be achievable through reverting to the previously instantiated chaincode and updating the embedded models off-chain based on their performance, the amendment of the existing environment or the new on-chain data.

On the other side, many researchers have provided recent studies with valuable contributions regarding the blockchain features and applications in construction management. For instance, Ar et al. (2020) provided a model to assist the decision-makers in evaluating the feasibility of implementing blockchain in logistics operations. Kiu et al. (2020) investigated the potential areas for utilizing blockchain in the construction industry. Tezel et al. (2020) also investigated the issues associated with using the blockchain for construction supply chains, then provided a conceptual framework to tackle these issues. Elghaish et al. (2020) developed a hyperledger fabric application to automatically execute and process the financial transactions of the ongoing construction projects. Lee et al. (2021) proposed a framework that integrates blockchain with digital twin to exchange and manage information among the construction project stakeholders. Sheng, Ding, et al. (2020) introduced a novel blockchain-based solution to decentralize and manage the quality information in construction projects.

Despite these contributions, there are two notable limitations; the studies are in the exploration and conceptualization phases, or the

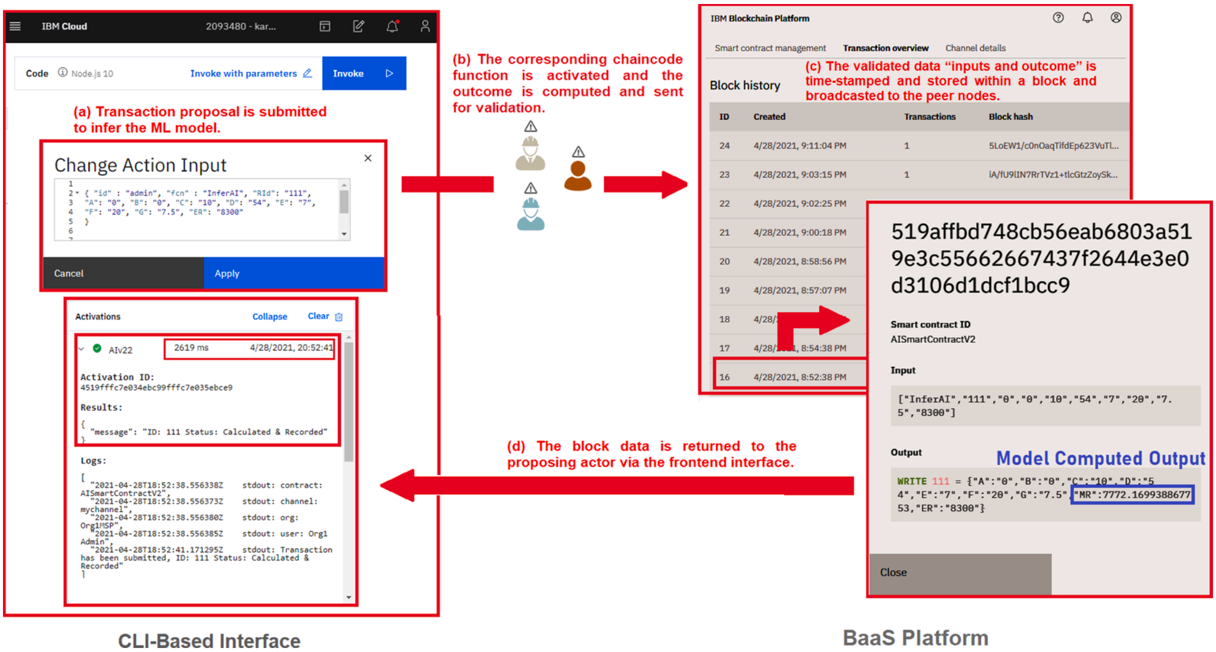

Fig. 5. Writing Process – Invocation of InferAI Function.

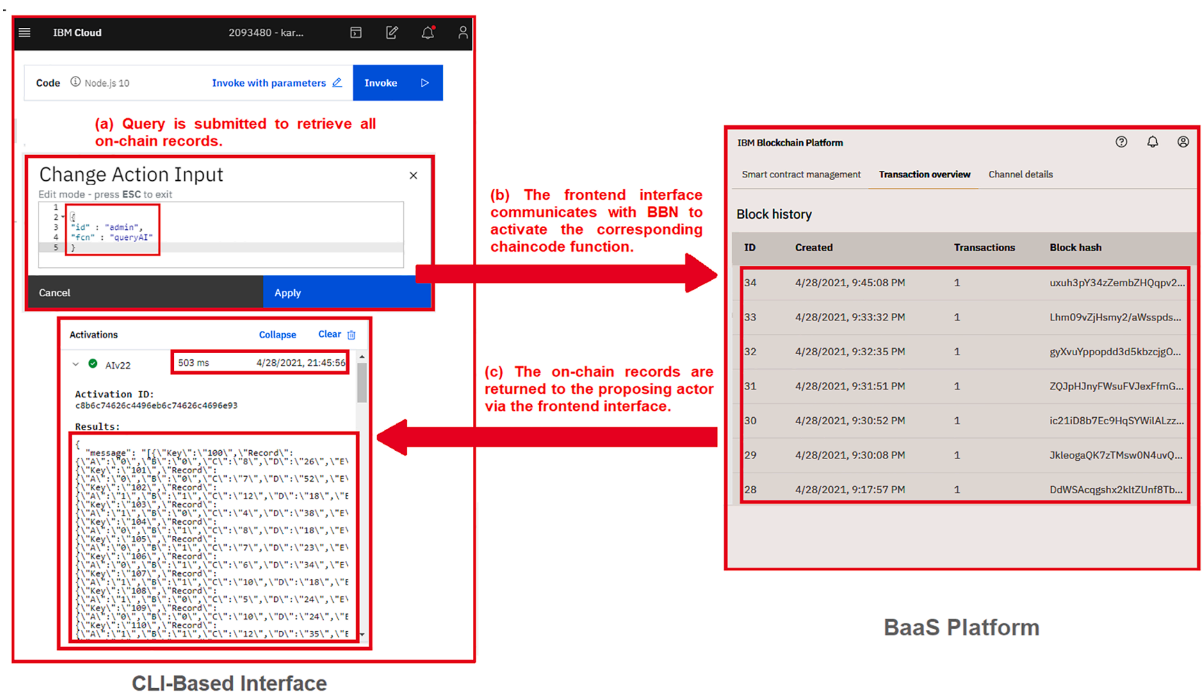

Fig. 6. Reading Process – Invocation of QueryAI Function.

studies present blockchain as a transaction-oriented technology only. This research takes a step forward from the phase of discussing and evaluating the theoretical aspects and the feasibility of blockchain in construction to the design and implementation phases. It focuses on employing the BBN, not only as a decentralized record medium for exchanging raw textual and numeric data but also as a computing-oriented technology to simultaneously process and interpret transactional data by embedding mathematical algorithms and ML models in the chaincodes. Moreover, the study's system provides higher transparency and flexibility for the BBN users to agree upon which information or decisions should be on-chain while diminishing face-to-face consultations, recurring meetings, and administrative workloads. It also ensures the immutability and traceability of on-chain analyzed records that increase the confidence and awareness about the reached decisions or analytics.

The system design has a couple of limitations. First, the system is limited to exchange and analyze textual and numeric data only. As a direct result, the image processing models and visuals' storage are not guaranteed. However, this approach lowers the rate of increasing network storage "storage bloating problem", the computational resources' waste, and the high demand for internet bandwidth as guided by Tanwar et al. (2019). Second, regarding the data feeding, repetitive or ambiguous data may be proposed or submitted, which could congest the system's ledgers, discompose the data's authenticity, and corrupt the models' future evolution. This can be tackled through the BBN's validation policy that allows the key actors to audit and evaluate each fed input and computed outcome before being chained to avoid any possible source of bias or error.

7. Conclusion

Building an AI system within blockchain networks is a novel step towards enabling trusted decentralized artificial intelligence for the construction industry. In this study, a configurable system for data collection and decentralized inference has been introduced to serve as a generic blockchain AI-models repository. The system is designed to guarantee confidential data sharing, AI decisions' verification, and AI models' upgrading and ownership traceability. The proposed system has been implemented via a four-step methodology while aiming to estimate the construction cost of road projects to support the construction firms in bidding and financing alternatives decisions. The first step is building a ML model as a multi-buffer perceptron artificial neural network while employing the Levenberg Marquardt algorithm as a supervised dynamic nonlinear learning rule using NeuroSolution Software Version 5.92. The second step is formulating the model in a chaincode template using JavaScript language. The third step is configuring the blockchain network using IBM BaaS. The fourth step is developing the frontend interface that allows access and interaction with the blockchain network using IBM Cloud Functions. Further, the system performance has been evaluated based on the computing latency through 50 successive invocations, the key actors scaling, and the submission of incomplete data. This research can be extended in the future to provide a completely decentralized AI platform that relies on BT and Inter-Planetary File System to collect, refine, learn from the chained data and produce on-chain trained AI models. As such, it leverages the following features: 1) decentralizing the learning process instead of using conventional off-chain training software packages; 2) upgrading the data acquisition, circulation, and exchange to support image processing models and visuals' storage; 3) avoiding the repetitive records using the content hashing mechanism of Inter-Planetary File System.

CRediT authorship contribution statement

Kareem Adel: Conceptualization, Methodology, Writing – original draft. **Ahmed Elhakeem:** Supervision, Validation, Writing – review & editing. **Mohamed Marzouk:** Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eswa.2022.116548.

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