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A Novel Blockchain-Based Integrity and Reliable Veterinary Clinic Information Management System Using Predictive Analytics for Provisioning of Quality Health Services

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ABSTRACT The recent advances in information management systems coupled with machine learning algorithms paved the way for a significant revolution in animal healthcare industries. However, the data in such systems suffer from various challenges such as security, reliability, and convenience, to name a few. Traditional systems are not useful to meet these critical issues because these systems have not a consistent structure for data security and reliability policies. Therefore, a new solution is required to enhance data accessibility and should regulate government security policies to ensure the accountability of the usage of the medical records system. Moreover, it is also required to analyze historical data of veterinary clinic using data mining and machine learning techniques to predict the future appointments scheduling requests, which is essential for veterinary management to drive better future decisions, for instance, future demands of medical supplies and to plan veterinary medical staff, etc. This paper aims to fill the gap by proposing a novel blockchain-based reliable and intelligent veterinary information management system (RIVIMS) using smart contract and machine learning techniques. The proposed RIVIMS consists of two main modules; blockchain-based secured veterinary information management, data and predictive analytics modules. First, a blockchain-based secure and reliable veterinary clinic information management system is developed using Hyperledger Fabric. Second, a smart contract enabled data, and predictive analytics modules are developed using permissioned blockchain framework. The data and predictive modules aim to analyze veterinary clinic patients appointments data in order to discover underlying patterns and build a robust prediction model using machine learning algorithms. The data and predictive helps veterinary management to drive better future business decisions to provide better healthcare services to veterinary patients. Hyperledger Caliper is used as a benchmark tool to evaluate the performance of the developed blockchain-based system in terms of transaction per second, transaction success rate, transaction throughput, and transaction latency. Furthermore, machine learning performance measures have utilized, such as MAE, RMSE, and R2 score to evaluate the overall performance of the prediction model. The experimental results demonstrate the effectiveness and robustness of the proposed RIVIMS.

INDEX TERMS Information management system, blockchain technology, machine learning, smart contract, predictive analysis.

I. INTRODUCTION

Electronic health (e-Health) is one of the most promising technologies that has gained more importance over time, which is varying from remote access to healthcare data or exchanging medical records of the patients electronically [1], [2]. e-health technology enables information technology and computer networks to improve healthcare quality and safety of the patient's sensitive data, which enables patients and the healthcare industry to drive effective

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health decisions [3]. The usage of electronic medical records (EMR) has drastically increased from 9% to 96% over the period from 2009 to 2015 [4]. EMR is a digital version of the medical records related to patient's medical history data. It also helps healthcare organizations to track patient's data and ensure preventive screenings for patients. However, the existing EMR systems cause an issue of data interoperability in the case of cross-border EMR sharing, which disabled sharing of healthcare data across different healthcares, health providers, and other social organizations. The lack of effective management and sharing leads the personal medical data of the patients to be fragmented rather than unitive [4]. Furthermore, there are many cases reported related to unauthorized access of the medical data and leaking of personal medical data from the existing EMR systems [5]. Therefore, it is required to develop a close private network to enhance data security, data consistency and reliability of personal healthcare data.

However, healthcare for the human as well as for the pets consists of the following essential requirements, such as data sharing, data reliability, security and consistency of the data, and convenience [6]. These are the most critical requirements of healthcare data in order to interact with EMR systems. The existing EMR systems are not useful to meet these critical issues for an effective process because these systems have not a consistent and reliable structure for data security and reliability policies. Therefore, it is required a secured and reliable platform to enhance data security and authoritative access to medical information under the privacy of government regulations to monitor the usage of the veterinary clinic data. Blockchain technology seems to enhance the traditional healthcare industry by integrating its unique and robust features related to data security, data reliability and consistency [7], [8].

Blockchain technology is a secured and distributed ledger that stores and manages records of online financial transactions that cannot be manipulated. It is also referred to as Distributed Ledger Technology (DLT) because it uses decentralization and cryptographic hashing mechanisms to record signed transactions between two parties [9], [10]. In the blockchain network, each online transaction is digitally signed by both parties to ensure its security and authenticity. The distributed ledger operates and accesses based on a smart contract. Both participants agree at the consensus to put each financial transaction into a block that contains data and information related to that transaction. Furthermore, each block validates using the smart contract in order to add it to the chain. Finally, cryptographic hashing algorithms are used to encrypt and protect the chain of blocks. The most important feature of blockchain technology is to ensure security and restrict users from the manipulation of transaction data because of its stores most of the data resources in a distributed way [11]. Today, data resources stored in centralized servers are not secured from cyber attackers, while the blockchain platform ensures security and privacy of the transaction data using decentralization and cryptographic hashing. Blockchain technology is more reliable and trusted as compared to the traditional records keeping systems. It increases efficiency and operational cost to automate the traditional processes using a smart contract. In contrast, one of the main disadvantages of blockchain technology is the high power consumption in order to keep a real-time distributed ledger [12]. However, blockchain technology is a great impact on the data science field to control and manipulate the raw data [13]. With the help of blockchain technology, such as consensus and cryptography techniques are used to validate data to make it possible for the data analytics.

Data analytics techniques are used to discover hidden insights from the historical data of the veterinary clinic that are most important for veterinary clinic management to formulate better future plans, such as future demands of medical supplies and advance planning of medical staff, etc [14]. However, it is a vital challenge for different business organizations because traditional systems are not able to process and investigate a large scale data having different data format and distributed over different geographic locations. Therefore, business organizations required a platform, which can process and extract useful knowledge and underlying patterns from a massive amount of data to formulate business plans effectively. In this way, business organizations can plan additional business strategies to gain market advantages over their competitors. There are different machine learning (ML) algorithms available to investigate the discover knowledge from the historical data veterinary clinic, such as predictive analytics and classification, to name of few.

Advancement in machine learning models, it is quite possible to build a robust and effective prediction model based on discovered knowledge to predict future outcome [15], [16]. The prediction techniques are the essential modules of every ML-based system, which use to provide a platform for the business organizations to predict future demands based on the inferred knowledge. Nowadays, deep learning (DL) techniques have become one of the demanding research topics in the field of information technology. It has demonstrated the most promising performance in various fields [17]–[19], such as healthcare industry, education, computer vision, natural language processing, to the name of few. Nowadays, deep neural network (DNN) is an emerging algorithm of DL research, which is used to develop intelligent applications in different areas [20]. It is one of the most robust models of the DL, which aims to automate features representation process of the learning model in order to replace the manual process of the traditional models [21], [22]. Similarly, a well-known support vector regressor (SVR) algorithm has been used for the regression problems in order to predict the future outcome based on features of the historical data [23]. The main objective of the SVR model is to guarantee optimal output and accurately fit a regression function.

The main contributions of the proposed RIVIMS are followed as:

- The main contribution of this research study is to integrate real-time data and predictive analytics with permissioned blockchain to process, analyze and store veterinary clinic data securely and reliably.
- Our proposed RIVIMS is developed based on smart contract enabled data and predictive analytics modules using permissioned blockchain framework known as Hyperledger Fabric, which allows only authenticated set of participants to interact and communicate with each other. This will lead to improve the transaction efficiency in terms of throughput and also reduce transaction latency of the entire blockchain network.
- The aim of smart contract enabled data analytics module is to investigate veterinary clinic data stored on the blockchain to extract underlying patterns and hidden knowledge, that is important for veterinary management to plan veterinary clinic resources effectively.
- The aim of smart contract enabled predictive analytics module is to utilized discovered knowledge to build a robust ML-based prediction model, that is used to predict appointments scheduling frequency of veterinary patients on daily basis. The predictive analytics model helps veterinary clinic management to formulate future business strategies, such as future demands of medical supplies and planning of medical staff, etc.
- The proposed RIVIMS is secure because it does not allow unauthorized users to access data of transaction history log and other information related to digital transactions.
- The secured RIVIMS is lightweight because front-end application communicates with the developed blockchain system through the RESTful API. The use of the REST API server leads to offloads the computation.
- Furthermore, a standard tool known as Hyperledger Caliper is used to demonstrate the effectiveness and robustness of the proposed RIVIMS. Moreover, different performance measures, such as MAE, RMSE, and R2 score, are utilized to evaluate the performance of the predictive analytics model.

The remaining paper is structured as follows. Section II presents the related works and background information related to the proposed blockchain-based RIVIMS. Section III presents the methodology of the proposed RIVIMS. Section IV presents the methodology of the proposed RIVIMS. Section V discusses the implementation environment of the proposed RIVIMS. Section VI discusses the experimental results of the proposed RIVIMS. Section VII presents the prediction results of the proposed RIVIMS. Section IX concludes the proposed RIVIMS and possible future directions are also discussed.

II. LITERATURE REVIEW

This section presents existing studies related to the proposed RIVIMS and comparative analysis of the blockchain-based frameworks in order to choose an appropriate blockchain framework for healthcare applications development.

A. BLOCKCHAIN AND MACHINE LEARNING IN VETERIANRY HEALTHCARE

This subsection discusses related work and background studies for the proposed RIVIMS. Today, there are different challenges faced by veterinary clinic management to provide efficient healthcare services and analyze veterinary clinic data to formulates future better future plans. The most fundamental challenge for the veterinary clinic is the security of veterinary clinic data, data interoperability, and ineffective record management, which can enhance the healthcare services of the veterinary clinic. The second challenge is to analyze veterinary clinic data to unearth hidden insights and knowledge, which is important to drive better future decisions and show the effectiveness of data analytics in healthcare for animals. The third challenge is appointment scheduling because sometimes, the veterinary doctor is not available to provide healthcare services to patients due to time constraints. To overcome these existing challenges, different researchers strive to develop reliable and intelligent applications for the healthcare industry to provide efficient services. Recent advancement in blockchain technology paves a revolution to handle healthcare data securely and reliably over the distributed network. In the existing studies, there are many efforts put for improving healthcare service for human beings using blockchain technology. For instance, there are following blockchain-based applications are developed, such as electronic medical record (EMR) [24], [25], MEDIBLOC [26], MEDREC [27], MediLedger [28], blockchain-based drug supply management [29]–[31], Healthcoin [32], to name of few.

L. Hang *et al.* [1] proposed a blockchain-based medical platform to secure the electronic medical record (EMR) management system. MEDIBLOC [26] used an open-source protocol and developed a blockchain-based decentralized healthcare information ecosystem. MEDREC [27] is another blockchain-based distributed and secured record management platform to handle EMRs. MediLedger [28] is another attempt to established a secured peer-to-peer network for the healthcare industry to exchange medical information among different organizations. In [33], the authors proposed a connecting care system (CAS), which used to share healthcare records among different cities of the United Kingdom. A comprehensive review of the healthcare applications using blockchain technology is presented and discussed [34]. For instance, in [35], the authors proposed a blockchain-based framework, which is specified for resource-constraint of the IoT devices. In [36], the authors proposed a smart contract-based system for sharing data related to the healthcare industry in standard Fast Healthcare Interoperability Resources (FHIR). In [37], [38], the authors suggested a user-driven approach for sharing healthcare data over the permissioned blockchain network. In [39], the authors used a permissioned chain of the network to allow only authenticated healthcare professionals to share EMR data of patients. In [29], [30], the authors proposed a blockchain-based drug supply management for secure and authentic drug supply to improve healthcare services. F. Jamil *et al.* [10] suggested a blockchain-based platform to monitor patient vital signs using different healthcare devices equipped with patients.

Recently, data mining techniques have gained more interest in various research fields, such as healthcare, academic, financial services, to name of few. In [40], the authors suggested a prediction model, which is used to predict the risks in animal by-products based on limited rough sets of resources. According to the study presented in [41], the authors applied DM techniques to automatically extract hidden knowledge and patterns from a massive volume of data. In [42], the authors presented a model for veterinary hospitals based on different clustering-based algorithms to find medical records efficiently. Anticipating the hidden insights and useful information from veterinary clinic data may help the management to improve their services to veterinary patients.

There are various ML-based prediction algorithms available to investigate mined knowledge from the raw data to predict the future outcome or event [43], [44]. In [45], the authors investigated a dataset of fifty thousand appointments collected from healthcare to predict future day appointments for human beings based on the characteristics of the individual appointment. In [46], the authors presented a data-driven study to predict the radiotherapy treatment schedule for the patients based on ML techniques. The authors achieved an accuracy of 84%, which is still improvable. In [47], the authors suggested a predictive analytics model, which used to predict hospital attendance using ML models. The authors proposed an ANN-based prediction model, which used to predicts no-shows for individual appointments based on the historical dataset of the patients [48].

To the best of authors knowledge, all the aforementioned blockchain-based systems are either not open source or they facilitate EMRs for the healthcare industry related to human beings. Moreover, most of the existing systems used cryptocurrency to perform costly mining, which increases energy consumptions and decrease the efficiency of the developed systems in terms of transaction throughput. This work aims to presents a novel and robust blockchain-based information management system using smart contracts and machine learning approaches to facilitate knowledge discovery and predictions regarding veterinary clinic patient's data. This work aims to integrate data mining and machine learning techniques with permissioned blockchain in order to process, investigate, and store veterinary patients and other veterinary clinic data securely and reliably. The novelty of this work is to integrate a smart contract enabled data and predictive analytics module with permissioned blockchain in order to process, investigate, and store veterinary patients and other veterinary clinic data securely and reliably. Nonetheless, none of the existing systems used smart contract enabled data and predictive analytics engines to process and analyze veterinary clinic data to unearth underlying patterns using Hyperledger Fabric. To the best of our knowledge, it is first-ever attempt to use a smart contract enabled data and predictive analytics functionalities using Hyperledger Fabric to extract underlying patterns from the veterinary clinic data, drive effective future decisions, and store processed data securely.

B. BLOCKCHAIN-BASED PLATFORMS FOR HEALTHCARE APPLICATIONS DEVELOPMENT

Blockchain technology is one of the most revolutionizing technologies, which uses a distributed ledger in order to record a large number of data transactions securely and reliably. Over the years, there are different blockchain-based frameworks have been developed. These blockchain-based frameworks are classified into three categories, such as public, private, and consortium blockchains. The public blockchain is an open-source, not permissioned and based on Proof-of-work consensus algorithms [49]–[54]. The private blockchain is based on permissioned chain of network and centralized to only one organization [55]–[58]. A consortium or federated blockchain is a permissioned blockchain that associated with enterprise use, with the group of companies work together to leverage blockchain technology for improved business process [59]–[61].

However, our proposed study aims to analyze and choose blockchain-based platforms for the healthcare industry. According to the recent review study [62], It is found that the following blockchain-based platforms are widely used to develop enterprise applications for healthcare industries, such as Ethereum [53] and Hyperledger Fabric [63] frameworks. To select an appropriate blockchain-based development platform, we also consider the working flow of the first blockchain framework known as Bitcoin to understand the core features of general-purpose frameworks for healthcare applications. The following Table 1 presents a detailed summary of analyzing blockchain platforms based on technical factors for developing healthcare applications. It is found that Hyperledger Fabric enables core features of blockchain technology, such as robust privacy and security of data, access control policy, private transaction channels and zero-knowledge proofs, etc. The European General Data Protection Regulation (GDPR) imposes strict rules for processing patients medical data in the healthcare domain [64]. The Hyperledger Fabric is used to develop enterprise applications based on permissioned and private chain of network to ensures the privacy and security. It supports extensive modular architecture to deliver high degrees of privacy, flexibility, and scalability. The modular architecture also enables consensus and membership services provided by a membership service provider (MSP) to be plug-and-play. It does not use cryptocurrency mechanism to perform costly mining as compared to Bitcoin and Ethereum. It supports and implements a smart contract using high level programming languages to enhance the core functionality of the blockchain network. These robust features make Hyperleder Fabric is a reliable and stable blockchain platform for developing health-

TABLE 1. Comparison analysis of blockchain-based platforms for healthcare applications development.

Technical Features	Bitcoin	Ethereum	Hyperledger Fabric
Data Privacy	No private and transparent transactions	Support private transactions	private channels and transactions, and zero-knowledge proofs
Data Security	Public and more security breaches as anyone can access to the network data	Public or private	Permissioned or private, access control policy
Consensus Mechanism	PoW	PoW	Multiple approaches, such as PBFT and RAFT,etc.
Incentive Mining	Cryptocurrency based costly mining	Cryptocurrency based costly mining	No Cryptocurrency-based approach required
Scalability in terms of TT	Low	Low	High
Transaction Cost	High because it uses PoW approach to validate transactions	High due to PoW consensus mechanism	Low due to Pluggable PBFT
State Db	It uses transaction data.	It uses account data.	It uses key-value state database.
Smart Contract	It does not support a smart contact	Smart contract implementation based on solidity programming	Smart contract implementation based on higher level programming languages

care applications. Therefore, our proposed RIVIMS uses Hyperledge Fabric framework to develop a blockchain-based secure and reliable veterinary clinic information management system.

III. PROPOSED BLOCKCHAIN-BASED RELIABLE AND INTELLIGENT VETERINARY INFORMATION MANAGEMENT SYSTEM

This section presents proposed methodology of the blockchain-based RIVIMS. The subsection III-A presents proposed system overview. The proposed scenario is presented in subsection III-B. In subsection III-C, we present a proposed architecture for a blockchain-based RIVIMS. The interaction model of proposed blockchain-based RIVIMS is presented in subsection III-D. The smart contact definition and transaction process are presented in subsections III-E and III-F, respectively.

A. PROPOSED RIVIMS OVERVIEW

E-health technology comprises of various computer networks to hold sensitive data of patients and also exchange healthcare data electronically. It also enables information technology to provide sensitive data of patients to the healthcare industry and professionals to devise effective decisions. Therefore, a blockchain-based RIVIMS has been introduced to safeguard veterinary clinic data in a distributed way. This system also utilizes data and predictive analytics techniques to unearth hidden insights of veterinary data, which helps veterinary management to formulate effective business decisions to plan and manage future resources, adequately. To design a block diagram of the proposed RIVIMS, we considered work presented in [65], [66] as a foundation to design a block diagram for proposed blockchain-based RIVIMS. The proposed research studies presented in [65], [66] are used to developed a blockchain-based systems to guarantee integrity and privacy of data in internet of things (IoT) environment. Therefore, the aforementioned studies can be considered as a basis to design a block diagram of the proposed blockchain-based RIVIMS. Figure 1 represents a block diagram for the proposed RIVIMS, which combine the overall structure of the blockchain-based reliable veterinary clinic management, data and predictive analytics. The proposed RIVIMS is developed based on the permissioned chain of the network, where each participant required registration and authentication to participate in the blockchain network. In the permissioned blockchain network, a user identity manager is responsible for allowing only authenticated users to participate in the blockchain network. It also provides enrollment and authentication certificates for valid participants. This is a novel and unique feature of the developed blockchain-based system in order to differentiate it from other developed systems. The proposed blockchain-based system aims to store veterinary clinic data in a distributed ledger, which is secure and reliable. The developed system uses smart contract to verify and validate user transactions based on predefined conditions. The smart contract is deployed on the blockchain network and allows to exchange assets (anything of value) reliably and transparently without involving third-parties. The designed blockchain-based RIVIMS contains multiple user groups that determine the role of the user (participant) in the proposed system. These user groups include admin, veterinary doctor, nurse, pharmacist and pet owner, where the admin is responsible for managing all the resources within the veterinary clinic. The veterinarian is the one who examines the pet and defines medical dose in the form of a computerized medical prescription. Then, a doctor sends the computerized medical prescription to the pharmacist (pharmacy personnel), who authenticates and verifies prescription and prepare medicine cart. After the verification process, a pharmacist sends prescription along with prepared medicine cart to in-charge nurse, who performs cross verification and updates the distributed ledger and requests to the veterinarian nurse to follow the veterinarian doctor prescription and provide treatment accordingly. Lastly, the pet owner can access the medical record of their pets through any network peer of their relevant information. The user groups are allowed to communicate with the developed blockchain system through a REST API serve. The complete, up-to-date history of the

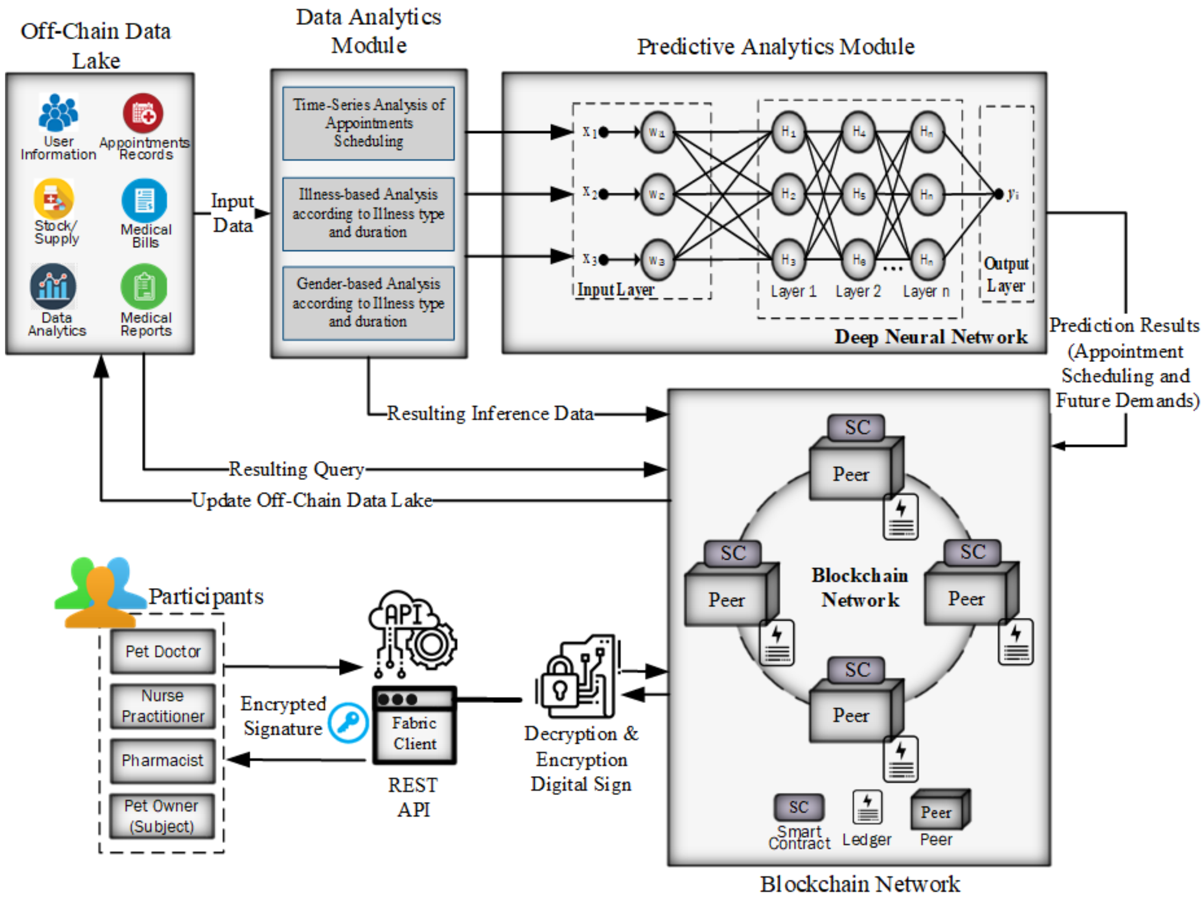


FIGURE 1. **Block diagram of the proposed blockchain-based RIVIMS.**

veterinary patient medical record, including profile management, billing management, appointment module, and medical records history, and data analytics. The veterinary medical record lake is a self-regulated data repository, which use to hold the immutable history of veterinary data including profile management, appointment scheduling, pharmaceutical management, medical records management, data analytics, predictive analytics, to name of few. The blockchain ledger is used to store the immutable list of transactions in blocks, whereas the data lake is responsible for preserving and maintaining data related to RIVIMS. Furthermore, data analytics module acquire validated veterinary clinic data from blockchain ledger and investigates acquired data in order to discover useful hidden insights and knowledge, which helps veterinary management in effective decision making. The discovered knowledge from veterinary clinic data is stored in a distributed and secured blockchain ledger. Moreover, a predictive analytic module uses mined knowledge in order to build a robust and reliable prediction model to predict future appointments scheduling requests. The predictive analytics model aims to facilitate veterinary management to formulate effective future decisions in order to gain market advantages over their competitors.

B. PROPOSED SCENARIO OF BLOCKCHAIN-BASED RIVIMS

This subsection presents the proposed scenario for reliable and secure veterinary clinic management based on blockchain-based technology. Figure 2 presents the proposed scenario for the RIVIMS using Blockchain technology based on a similar concept presented regarding drug supply management in [29]. The proposed work consists of the following participants, such as admin, veterinary doctor, nurse practitioners, pharmacist, and pet owner (patient). The admin is responsible for managing and controlling the overall process of the developed blockchain-based RIVIMS. Admin is also responsible for issuing user identity and transaction certificates to allows only authenticated users to participate in the entire blockchain network and sign the transaction with a private key generated by the Transaction Certificate Authority (CA).

The CA manages and issues different type of certificates, which are essential to run a permissioned chain of network. The veterinary doctor management comprises of various activities including veterinarian profile management, appointment scheduling management, computerized prescription, patient medical records and medical bill

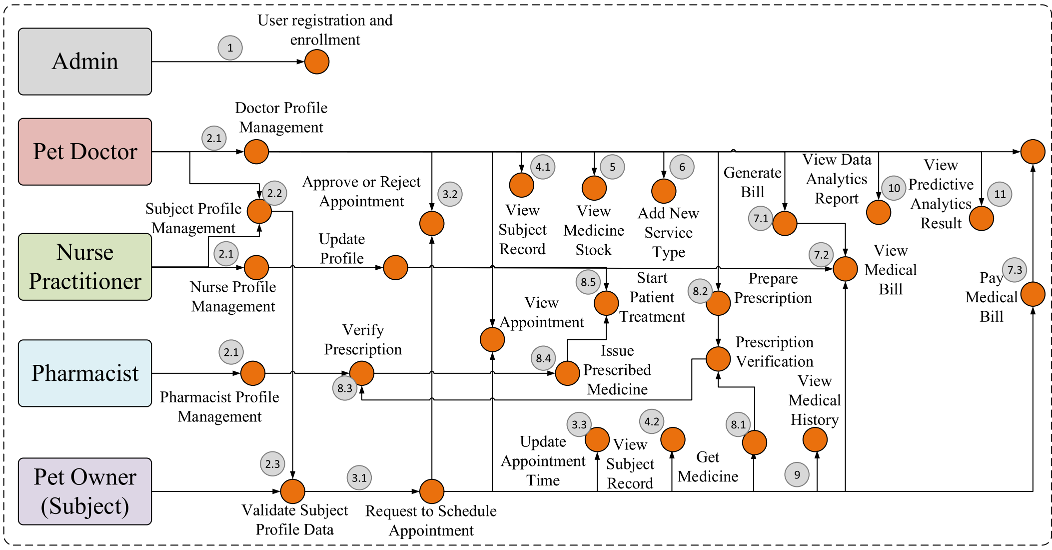


FIGURE 2. Proposed Scenario of the proposed blockchain-based RIVIMS.

management, data and predictive analytics, to name of few. Similarly, veterinary nurse management comprises of the nurse profile management, view appointment scheduling list, and follow the doctor prescription to start patients treatment accordingly. The pharmacist performs the following activities, such as profile management, verify prescription prepared by the doctor and issue medical dose to veterinary nurse in order to start veterinary patient treatment. The veterinary patient can perform the following activities, such as patient profile management, appointment scheduling, medical records history, to the name of few.

Furthermore, an access control policy is defined to allow participants to access only specific contents. The pet owner (patient) can request to schedule an appointment in order to examine his/her pet. The pet owner can perform CURD operations on the patient profile and can also view the pet medical history. The pet owner is also able to update the appointment time and pay a bill to the veterinary clinic. The staff (e.g., doctor) have the privileged to approve or cancel appointment scheduling request, view patient medical history data, view the data and predictive analytics report, and check medicine supply/stock. The veterinary doctor can also add and update professional services. The veterinarian also generates a medical bill and sends to veterinary patients owner. The data form the participants are then stored in the distributed ledger, which is secured and decentralized. The blockchain is a distributed ledger technology consist of Peer-to-Peer (P2P) network. In P2P network, several peers are connected together to share a replica of the distributed ledger and also enable to validate and execute transactions through consensus mechanisms. Furthermore, any modification to the real-time ledger synchronized in all identical copies shared among blockchain peers. Moreover, a smart contract is deployed on each network peer in order to perform CURD operations on ledger using consensus algorithms. Finally, a web application is used to visualize meaningful information using the REST API server from the blockchain system.

C. PROPOSED ARCHITECTURE OF BLOCKCHAIN-BASED RIVIMS

This subsection presents the proposed architecture of blockchain-based RIVIMS. The proposed RIVIMS aims to store veterinary clinic data in the distributed blockchain ledger to overcome fundamental challenges faced by the traditional systems, such as data security and consistency, and accountability of the medical data, to name of few. The second objective of the proposed RIVIMS is to integrate DM and ML techniques with a blockchain-based secure and reliable veterinary clinic in order to investigate veterinary clinic data and build a robust prediction model. In [67], the authors designed an architecture diagram to integrate IoT with permission blockchain platform to guarantee integrity of sensing data. The work presented in [67] is closer to our proposed work. It can be considered as a basis to design proposed architecture diagram, which uses to propose an integrated blockchain platform using smart contract and machine learning to ensure the privacy of veterinary clinic data and build a robust predictive analytics model. Figure 3 presents the proposed architecture of the blockchain-based RIVIMS. The proposed architecture consists of the following layers; system participants, RESTful APIs, blockchain network, data analytics (inference engine) and predictive analytics. The proposed blockchain-based RIVIMS consists of the following participants, such as a veterinary doctor, nurse, pharmacist, veterinary patient, and system admin.

The REST API server layer is used to establish a connection between front-end client application and backend

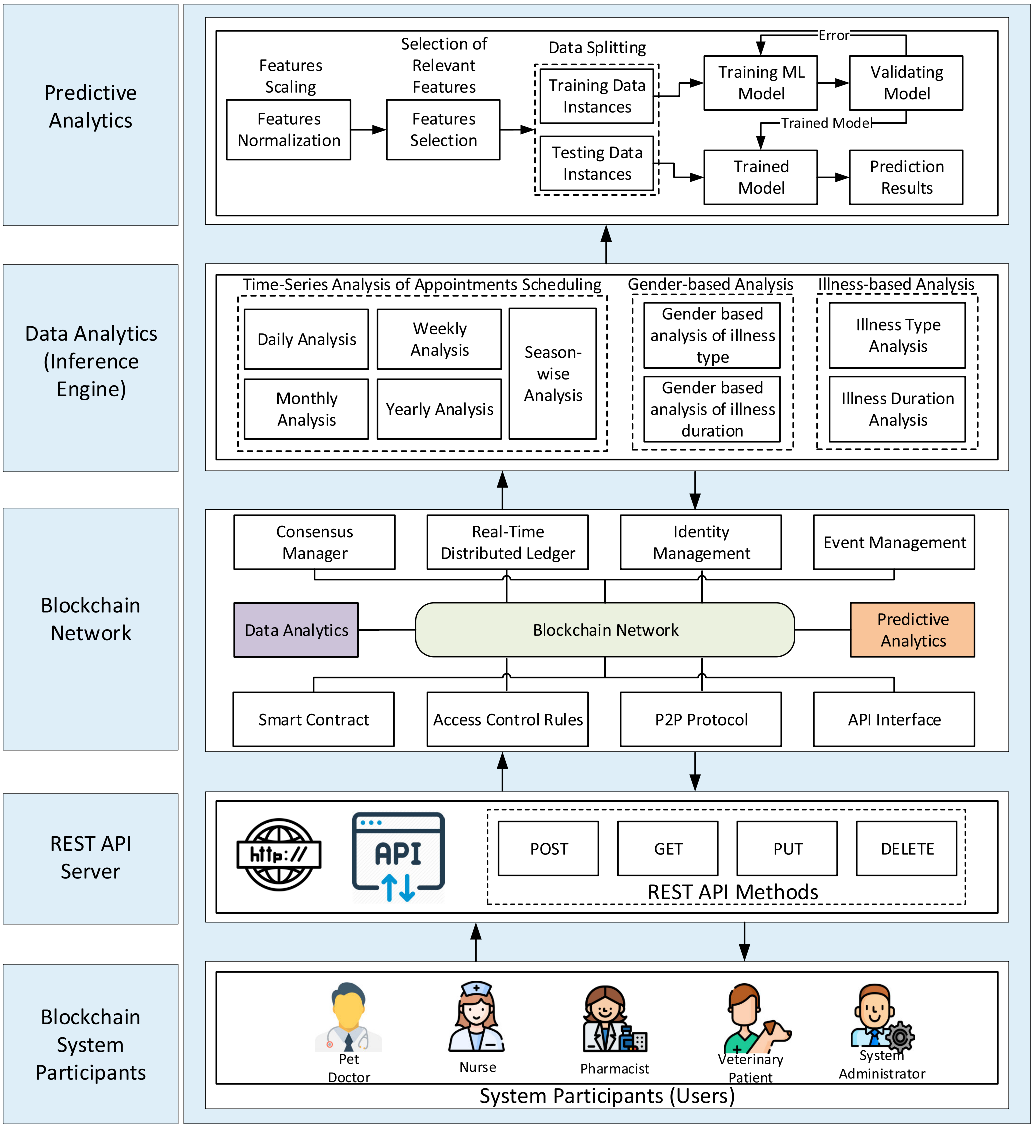


FIGURE 3. Proposed architecture of the blockchain-based RIVIMS.

blockchain system. There are different methods used to retrieve resources, for instance, POST, GET, PUT, and DELETE, etc.

The blockchain system layer consists of various services, such as identity management, smart contract, consensus manger, real-time distributed ledger, P2P protocol, event management, access control rules, API interface, data and predictive analytics. Identity management is responsible for providing users enrollment and authentication to allow only authenticated users to participate in the entire permissioned blockchain network. The smart contract is a chain code deployed on the blockchain network, which aims to execute and control events of the distributed ledger-based on pre-defined conditions. The consensus manager is responsible for the digital signing contract among distributed participants using different consensus algorithms, such as proof-of-work (PoW), practical Byzantine fault tolerance (PBFT), and RAFT. The blockchain ledger is a distributed ledger, which shares a replica of the data ledger among the blockchain network peers. The P2P network consists of peers that are connected with each other to hold and share an identical copy of the blockchain ledger. The access control rule (ACR) policy is defined to restrict users to access only specific transactions data. The event management consists of events that are triggered based on the successful execution of the transaction. The API interface enables blockchain services through which front-end application communicate with the developed blockchain network. The smart contract enabled data and predictive analytics modules are used to analyze veterinary clinic data to discover hidden insights and build a prediction model to predict future appointments request frequency.

The fourth layer is a smart contract enabled data analytics module, which is responsible for utilizing DM techniques to analyze veterinary clinic data to unearth hidden patterns and knowledge. There are different data analytics techniques performed, such as time-series pattern analysis of patients appointments scheduling, patient illness type analysis according to illness type and duration, gender-based analysis of illness type and duration. Time-series analyses are useful to track changes of appointments scheduling of the veterinary over time. There are following time-series analyses performed; daily, weekly, monthly, yearly, and seasonally.

The final layer is a predictive analytics model, which aims to build a robust and effective prediction model based on discovered knowledge to predict future appointment scheduling requests of the veterinary patients. The predictive analytics module facilitates management to formulate better future decisions to plan veterinary clinic resources, for instance, staff planning in advance, future demands of medicine, etc.

D. INTERACTION MODEL OF THE PROPOSED BLOCKCHAIN-BASED RIVIMS

This section describes the workflow of the proposed blockchain and ML-based RIVIMS. The developed platform is not just a technical infrastructure but also work as a user service framework that exposes a smart contract and blockchain ledger as a service to the front-end application. Based on the existing flow model of integrated IoT and blockchain [67], a wrokflow diagram of the proposed RIVIMS is depicted in Figure 4. The front-end application provides a user-friendly interface to interact with the blockchain system. The client application also supports intuitive services to submit transactions proposals to the developed blockchain network, for instance, user enrollment and authentication, appointments scheduling, participant profile management, data analytics report, to name of few. The proposed RIVIMS is based on permissioned chain of network. Therefore, users must need to enroll and authenticate his/her identity before submitting a transaction proposal to the blockchain network. The user enrollment and authentication are mandatory in order to generate a private key that is used to sign a digital transaction. The transaction is defined as the process of reading and writing veterinary clinic data from/to the blockchain ledger that executes and validates across the entire blockchain network. The veterinary owner can submit a transaction to schedule an appointment for his/her pet through REST API server to the blockchain network. It can also be observed that veterinarian can submit the following transactions, such as to get appointments scheduling requests data, approve or cancel appointments request, and view data analytics report, etc. Furthermore, an integrated inference engine is used to analyze and discover hidden knowledge from the veterinary clinic data, which is fetched from the ledger and store data analytics results back to the distributed ledger. Moreover, an integrated predictive analytics module is used to build a prediction model based on mined patterns. The predictive analytics module fetches input data from the data analytics module and store prediction results back to the ledger. The off-chain data lake is used as an independent data storage that performs a different set of operations for efficient storage and fetching current values of participants and assets from the blockchain ledger [65]. The off-chain data lake is used to maintains a current set of values of various veterinary clinic data, for instance, the latest medical record of a veterinary patient and data. Finally, an event manager sends a notification alert to the client application to notify the user about the execution of the submitted transaction whether it is completed successfully or not.

E. SMART CONTRACT DEFINITION FOR PROPOSED BLOCKCHAIN-BASED RIVIMS

The smart contract is a program that executes access blockchain blocks, transactions and history; therefore, it is deemed as pivotal to enhance functionality to the blockchain. The distributed database system is used to store the smart contract program. The functionalities, like adding constraints, business logic and validations to transactions, are performed by a smart contract. It holds almost similar characteristics as of database triggers. A smart contract is more than merely a computer program as it serves as an agreement between parties. A smart contract maintains the parts for entering the contract, performing the operations, and then exiting from the contract. The following Figure 5 presents a smart contactbased querying and updating the ledger of the proposed blockchain-based RIVIMS.

Moreover, the execution of transactions is performed by all nodes in a sequence which makes the performance of transaction execution very limited. To address these issues, we believe that transactions must only be executed on a defined group of nodes. To implement this idea, we have defined an appropriate subset of a node and installed small contracts only on those subsets. By doing this, the concurrency and parallelism for the network could be achieved to a greater extent along with an enhanced performance and execution scale of the proposed technique.

In our proposed RIVIMS, a Hyperledger Composer [58] is used to design and implement a smart contract in blockchain application. Hyperledger Composer is an open-source framework, which used to develop blockchain-based secured applications. The smart contract consists of four different components, such as, model file to define participants, assets, and transactions, script file represents definition of smart contract, access control rules in order to define data control policies and query definition. Participants are the authenticated users who interact with the blockchain network. Participants in the blockchain network can also represent the organizations who participate or invest in the digital business network. In our proposed system, there are the following participants, like veterinarian, nurse, pharmacist, and system administrator. Similarly, assets are also modelled, and assets can be defined as anything of value, such as property, goods, and

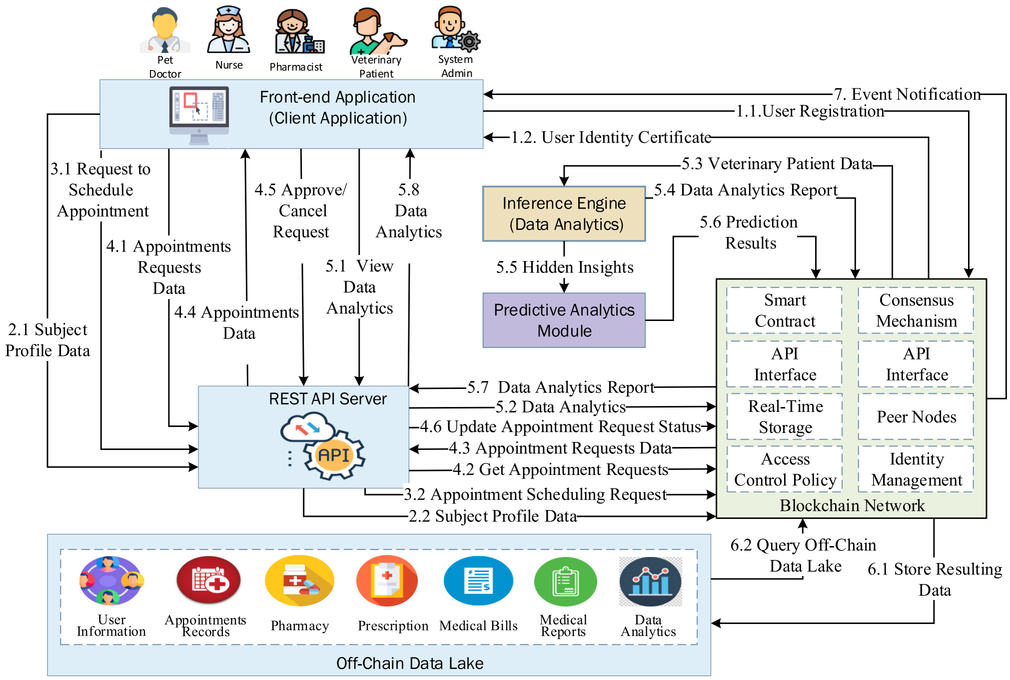


FIGURE 4. Workflow of the proposed blockchain-based RIVIMS.

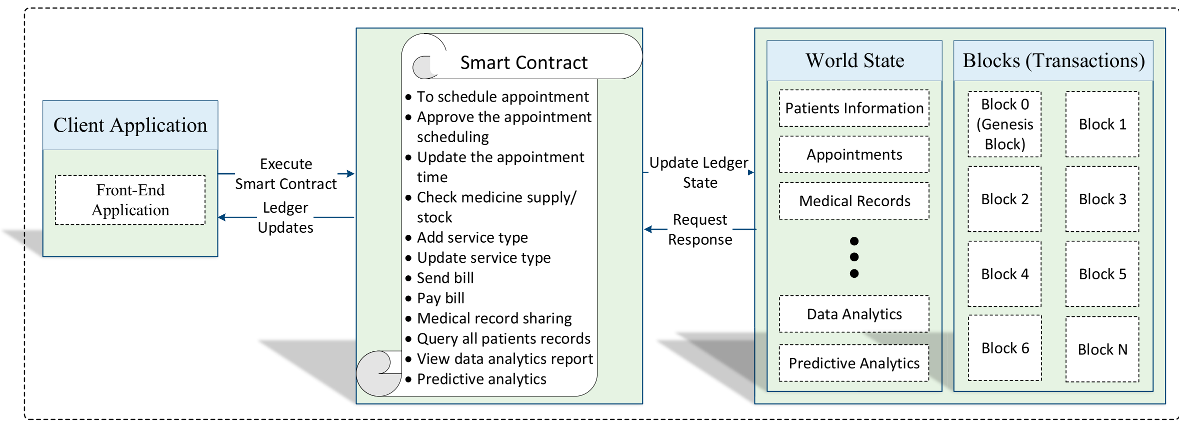


FIGURE 5. Smart contract-based querying and updating a ledger.

services, etc. There are following assets defined, for instance, appointment scheduling, medical record history, pharmacy, data analytics, to name of few. The JSON or binary format can be used to represent assets. Access Controls (ACLs) are a set of access control rules and standards that define the control policy to restrict participants in the permissioned blockchain network. Queries in business network archives are implemented using a bespoke query language and used to construct a smart contract for the business network. The script file contains transaction process functions, which are used to interact with participants and assets in order to perform the following functions, such as CREATE, UPDATE, and DELETE, etc. The summarized veterinary clinic management definition of the blockchain system is listed in Table 2, which contains information related to following like appointment, medicine, services, medical history, prescription, and personal information.

F. TRANSACTION PROCESS MANAGEMENT OF THE PROPOSED RIVIMS

This subsection presents transaction management in a permissioned blockchain network. The blockchain transaction is a process of integrating information into a block. A block consists of various transactions and validated by cryptographic mechanisms to ensure the reliability and consistency of the blockchain ledger. Blockchain technology is based on

TABLE 2. Definition of the proposed RIVIMS in a medical blockchain.

Components	Data Type
petOwnerID	String
petOwnerName	String
petOwnerAddress (e.g. city, street, zip)	String
petOwnerContact (e.g. email, phone)	String
petGender (e.g. male, female)	Enum
petType	String Array
TreatmentType	String Array
VisitedDate	DateTime
AppointmentID	String
DoctorID	String
NurseID	String
AppointmentDescription	String
AppointmentTime	DateTime
ServiceID	String
ServiceType	Enum
PrescriptionID	String
PrescriptionDescription	String

the append-only model, which uses to append a new block to the past data that cannot be altered. Hence, it uses to track all the past data of the recorded transactions, which is important for the organizations to formulate future policies and plans. Blockchain is a decentralized ledger, which means that each authenticated peer of the network holds a replica of all data. When a new transaction invokes in the blockchain network, all the details of the invoked transaction validates using consensus algorithms and updates replica of data across each peer of the entire network. Therefore, it is a transparent and secure way to record transactions permanently, and it does not require any third-party verification to record transactions data. Blockchain technology provides several benefits for transactions management, for example, it reduces costs, decreases settlement times, reducing online fraud, digitization of workflows, to name of few. There are the following transactions listed in Table 3 to interact with the assets registry based on a smart contract.

The following Figure 6 illustrates the overall transaction management of the proposed blockchain-based RIVIMS. The transaction management of the blockchain network divides between two nodes, such as peers and orderers nodes. Every transaction of permissioned chain of the network is executed in peer node using a distributed ledger. Each successful transaction is signed using the peer's certificate. The endorser's nodes are responsible for signing client proposal for transactions whereas committers nodes are used to validates the transaction and writes the all details of the successful transaction into a blockchain ledger. The orderer node is only responsible for ordering the execution of transactions. Both peer and orderer nodes are run independently, so it enables peers to trust all orderers nodes of the entire network. Finally, an asynchronous alert is generated by the committing peer to notify the front-end application whether the submitted transaction is successful or not. Furthermore, transactions are the transfer of the value of the asset among the registered users of the blockchain network. The primary objective of the transactions is to interact with the assets of the blockchain network. Similarly, transactions can interact with participants and events, which are also defined as a part of smart contract modeling and can also interact with all other entities involved in the blockchain network.

TABLE 3. Transaction definition of the proposed blockchain-based RIVIMS.

Transaction	Participant	Description
To Schedule Appointment	Doctor, Pet Owner, Nurse	The Pet owner can schedule an appointment with a doctor
To Approve the Appointment Request	Doctor	The doctor will have privileged to approve or reject the pet owner's appointment.
To Update the Appointment Time	Doctor	The doctor can update the pet owner appointment time
Check Medicine Supply	Doctor	The doctor can view medicine supply details.
Check Medicine Stock	Doctor	The doctor can view medicine stock
Send Bill	Doctor, Pet Owner, Nurse	The doctor will send the bill amount to per Owner.
Pay Bill	Pet Owner	The Pet owner will pay the bill amount to the clinic.
Add New Service Type	Doctor	The doctor can add, update, and delete service type. i.e., Microchipping, Fecal Test, Heartworm Prevention
Update Service Type	Doctor	The doctor will update the service type.

IV. PROPOSED PREDICTIVE ANALYTICS MODEL BASED ON VETERINARY CLINIC APPOINTMENTS SCHEDULING DATA

This section presents the proposed predictive analytics model for predicting appointments scheduling requests of the veterinary patients for veterinary clinic management, which helps veterinary management to formulate business strategies and plans, effectively. The proposed predictive model entails the following steps, including the collection of data, preprocessing data, extraction of underlying patterns using data mining techniques, data normalization to get uniform data, evaluation, and selection of data parameters, training and testing machine learning classifiers. The architecture of the proposed prediction model is presented in Figure 7.

A. COLLECTION OF THE VETERINARY CLINIC DATA

In this paper, we acquired healthcare appointments scheduling data from the veterinary clinic of the veterinary sciences department, Jeju National University, South Korea. The acquired dataset consists of 100,000 healthcare appointment records over a period of 7 years (2012-2018). Table 4 presents the acquired data features and their description.

B. DATA PREPROCESSING

Data Preprocessing is an important step in the data mining and knowledge discovery process to transform raw data

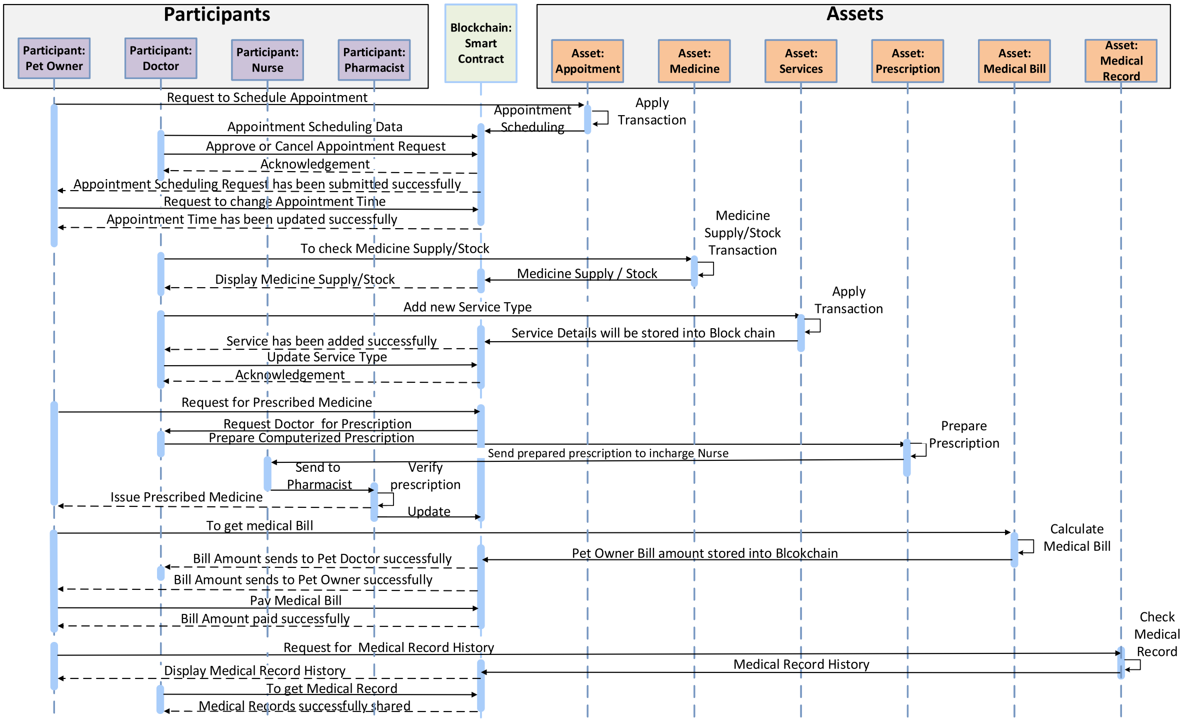


FIGURE 6. Sequence diagram of the proposed blockchain-based RIVIMS.

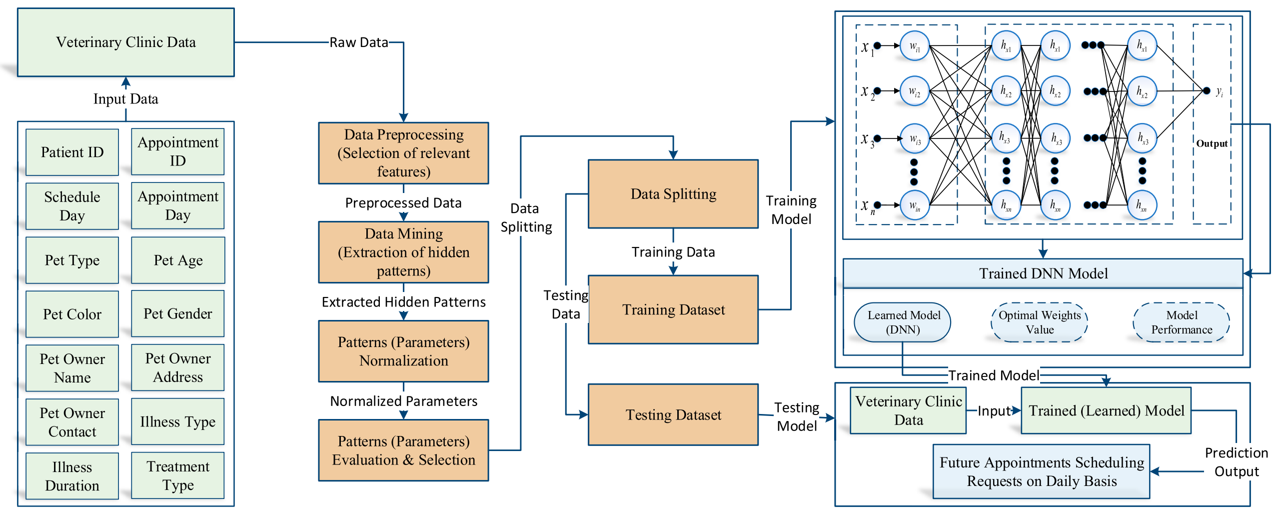


FIGURE 7. Proposed Predictive analytics model for predicting appointments scheduling requests of veterinary patients

into reliable data. The acquired data of the veterinary clinic appointments are not in an efficient and reliable form for discovering hidden knowledge using DM techniques. Therefore, it is required to remove irrelevant information and unreliable data in order to increase the reliability of the veterinary clinic appointments data. The following steps are performed to transform acquired dataset into an efficient format.

- In our proposed RIVIMS, all irrelevant data attributes and redundant records are identified and removed from the given dataset. Thus, it reduces a large set of a dataset, which aims to reduce storage and analysis cost.
- All those medical appointments records are removed that don't have schedule day and appointment day values.

TABLE 4. Dataset features presentation.

#	Data Attribute	Description
1	Patient ID	It represents veterinary patient ID.
2	Appointment ID	It represents appointment ID of the veterinary patient.
3	Schedule Day	It is date and time of the appointment scheduled.
4	Appointment Day	It represents date of the appointment. It includes only date.
5	Gender	It represents gender, e.g., male or female
6	Color	It is gender of the veterinary patients. female
7	Age	It represents age of the veterinary patient
8	Type	It is the type of the veterinary patients
9	Owner Name	Name of the veterinary patient owner
10	Owner Address	Address of the veterinary patient owner
11	Owner Contact	Contact of the veterinary patient owner
12	Illness Type	It is illness type of the veterinary patient.
13	Illness Duration	It is an illness duration of the veterinary patient.
14	Treatment Type	It represents treatment type of the veterinary patient.

- The proposed work also check and handle missing values attributes by central tendency methods, such as the mean.
- The HTML encoded strings, and other outliers are also removed to increase the efficiency and reliability of the dataset.

The following preprocessed data attributes are considered, such as schedule day, appointment day, illness type, illness duration, gender, and treatment type in order to discover hidden knowledge using DM techniques. These are only relevant attributes to extract underlying time-series patterns and other useful knowledge in order to build a robust prediction model to predict the future frequency of the appointments scheduling for a veterinary clinic.

C. PATTERNS ENGINEERING AND ANALYSIS

Patterns engineering is an essential process of discovering hidden features from the preprocessed dataset using DM techniques. The extracted features can be considered effective to improve the training accuracy of the ML-based models. Our proposed RIVIMS considered the following features, such as schedule day, appointment day, illness type, illness duration, gender, and treatment type in order to discover hidden knowledge using DM techniques. Time series features provide a rich source of useful information, which can be used as the input for prediction models. First, our proposed model investigate schedule day attribute to extract the frequency of the medical appointments using the following time series analysis, such as yearly, monthly, and daily, and hourly. Secondly, we analyze appointment day attribute using time series analysis, for instance, yearly, monthly, daily, and hourly, to find the frequency of the veterinary clinic appointments. Figure 8 presents appointment scheduling of veterinary patients on a daily basis. It can be observed that the total number of appointments of veterinary patients is classified into two groups based on a veterinary patients gender. The daily analysis reveals that the average appointment frequency

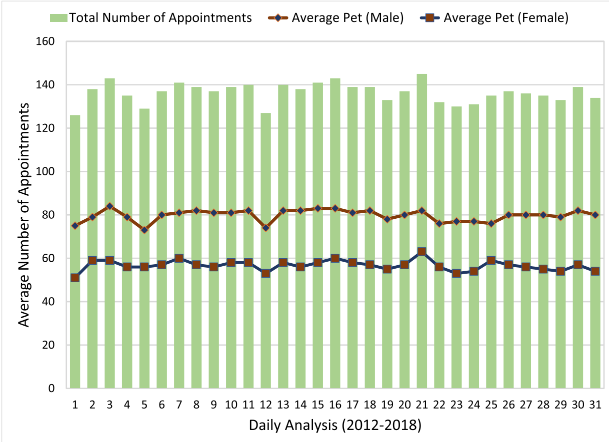


FIGURE 8. Time series analysis of appointment scheduling (Daily Analysis).

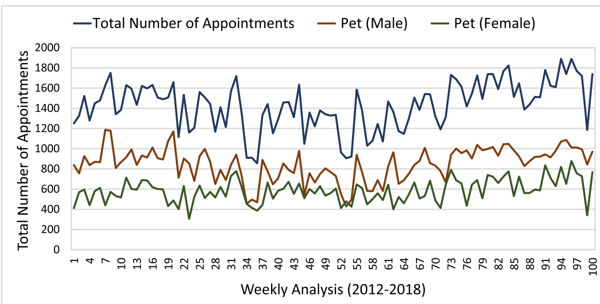


FIGURE 9. Time series analysis of appointment scheduling (Weekly Analysis).

of male patients (veterinary patients) is high as compared to female patients.

Similarly, in Figure 9, veterinary patients appointment scheduling data is analyzed based on a weekly period. It shows that the total number of appointments of veterinary patients on a weekly basis varies between 900 to 1900. It also investigates that appointment scheduling ratio of male patients is high as compared to female patients. Based on data analysis results, it is found that the appointment scheduling frequency of male patients is high as compared to female patients. It reveals that the probability of diseases in male patients has high as compared to female patients. Furthermore, it shows that male patients visited the veterinary clinic more as compared to female patients to get treatment. In other words, it shows the distribution of the appointments scheduling dataset based on veterinary patient gender.

Figure 10 is used to analyze the appointment scheduling trends of veterinary patients on a monthly basis. The monthly analysis represents an average frequency of veterinary clinic appointments day from January to December. The monthly analysis of veterinary clinic appointments scheduling data revealed that a high number of patients visited a veterinary clinic in the month of February and December.

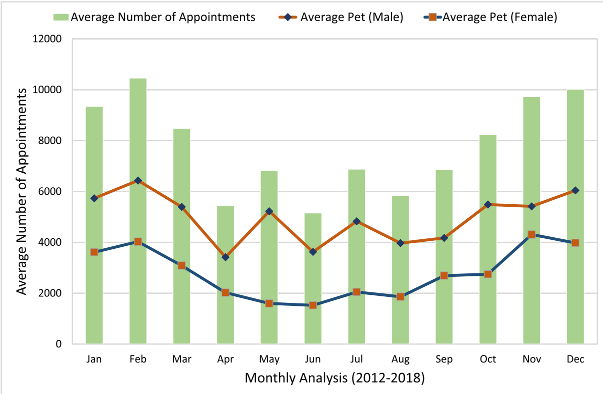


FIGURE 10. **Time series analysis of appointment scheduling (Monthly Analysis).**

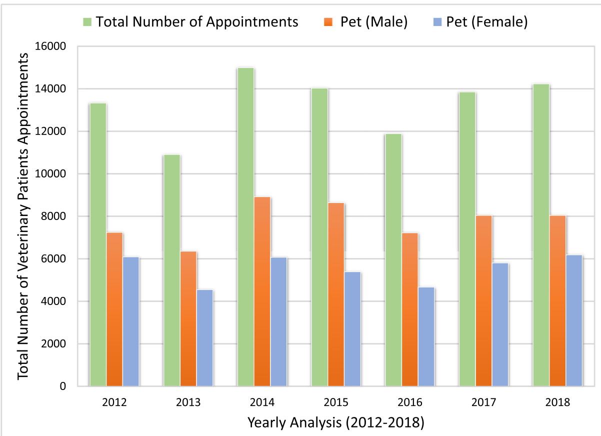


FIGURE 11. **Time series analysis of appointment scheduling (Yearly Analysis).**

Similarly, Figure 11 represents the yearly analysis of the veterinary patient's appointments data. It shows that yearly data of appointments is visualized according to patient gender. The yearly analysis reveals that the yearly appointments of veterinary patients range from 10,000 to 15,000. It is also revealed that the yearly frequency of male patients is high than female patients.

Figure 12 represents seasonally analysis of veterinary appointment data from 2012 to 2018. It is found that the frequency of veterinary patients appointments is high in winter season; whereas summer season is the lowest frequency of veterinary patient appointments.

Figure 13a analyze veterinary patients appointment data based on illness type. The recorded data of veterinary patients indicate that mostly veterinary patients diagnosed with the FeLV virus. The FeLV virus has the highest frequency as compared to the listed illness type; whereas veterinary patients having Aflatoxicosis disease have recorded the lowest frequency. Similarly, Figure 13b visualizes and describes the veterinary patients appointments data in terms of treatment type. It is observed that the highest number of veterinary patients visit the clinic to receive critical care services.

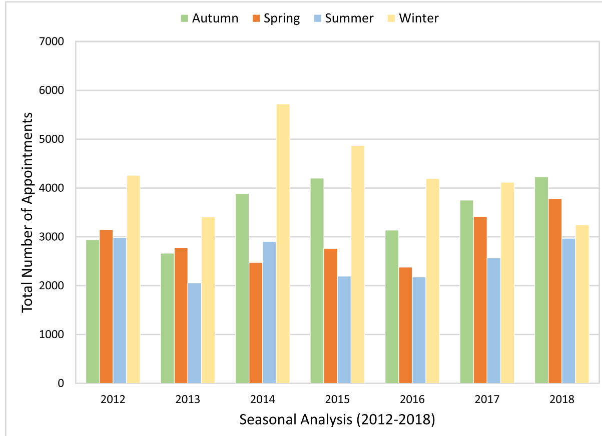


FIGURE 12. **Time series analysis of appointment scheduling (Seasonal Analysis).**

The data analytics helps veterinary management to demonstrate the hidden insights and trends to drive better decisions. Based on mined patterns, an intelligent prediction model is proposed to predict the future frequency of appointments scheduling requests of the veterinary patients for veterinary clinics.

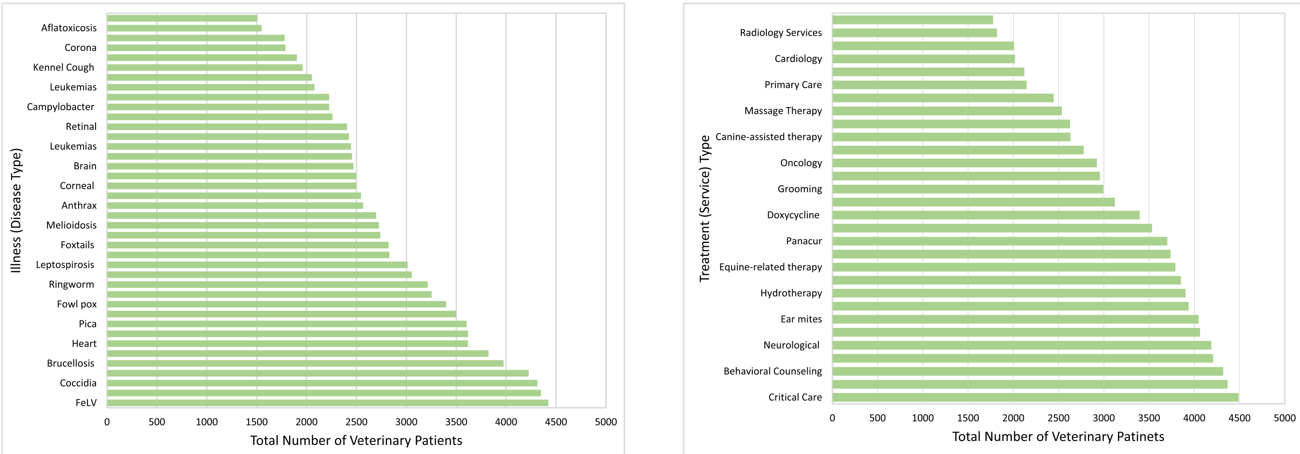
D. DATA NORMALIZATION

In our prepared dataset, it is observed that some of the data features values cause skewness, such as yearly and monthly frequency of the appointments. Therefore, it is required to normalize all these data features in some defined range to get uniform values to avoid skewness. Different data normalization techniques are available such that min-max normalization, z-score normalization, and normalization by scaling decimal, etc. This work uses a min-max normalization technique [68] to normalize all those data features, which cause biases in their values. This technique is used to scale normalized attribute values between 0 and 1 in order to achieve uniformity in data feature values. The following equation (1) is used to normalize data features values in some specified range, such as [0,1].

$$MinMax = \frac{X_i - min(A)}{max(A) - min(A)} \tag{1}$$

E. EVALUATION AND SELECTION OF DATA PARAMETERS

In this paper, we investigate the dataset in order to select only promising and relevant features among a large features set. Because some of the data features may be irrelevant, and other features may be redundant [69]. However, all these irrelevant and redundant features can increase the training time of the model and can have an impact on the performance of the model [70]. These are the following techniques, such as information gain (IG), principle component analysis (PCA),



(a) Veterianry pateints data analysis based on illness (disease) type

(b) Veterianry pateints data analysis based on treatment (service) type

FIGURE 13. Veterinary patient appointment scheduling data analysis based on illness type and treatment type.

correlation matrix with a heat map, etc., used to select the most contributed features of the dataset to reduce training time and improve the performance of the model. This work uses information gain (IG) [71] as a standard technique for the selection of most contributing and promising features from the prepared dataset. It is computed based on the entropy (to measure the impurity) of a system. The IG is a filtering-based approach that aims to rank a subset of features of a large feature space based on high IG in decreasing order. Predictive analytics on a reduced set of features has an extra advantage, improving the accuracy, reducing overfitting, and complexity of the proposed model. The entropy (EN) of the data feature is computed using the following formula given in equation (2).

$$Entropy(EN) = \sum_{i=1}^{m} p_i \log_2(p_i) \tag{2}$$

The IG is calculated based on EN, as defined in equation (3).

$$IG(T, X) = Entropy(T) - Entorpy(T, X) \tag{3}$$

where T represents dataset and X represent features of the dataset.

F. APPLIED ALGORITHMS

This subsection describes the applied regression models of the proposed predictive analytics model. The following two regression models are implemented, such as a deep neural network (DNN) and support vector regression (SVR).

1) DEEP NEURAL NETWORK

Deep learning (DL) is an emerging area in the field of machine learning. The DL techniques have robust and widely implemented because of deep and self-learning capabilities. Deep neural network (DNN) is an important part of DL techniques, which typically move data in a forward direction from the input layer, through multiple hidden layers, and to the output layer. DNN are typically used feed-forward approach to move data from input nodes to the output layer through multiple hidden layers. In DNN, each neuron of one layer is directly linked with other neurons of the resulting layers. The input layer consists of several numbers of input nodes, which are connected with many hidden neurons. Each neuron consists of 'n' number of optimal weights for each of the input 'x'. The weights for each neuron are optimized using an optimization-based approach to improve the performance of the DNN model. Each weight value is multiplied with each corresponding input node in each neuron and added to forms output using activation function, which moves in the feed-forward direction as an input for the next hidden layer. The basic activation function for the input and hidden layers is given in equation (4).

$$y_1 = activation\_function(W_1 x_0 + b_{c1}) \tag{4}$$

Our proposed RIVIMS uses a ReLU as an activation function between input and hidden layers because it is more effective and can easily be optimized as compared to swish, sigmoid, and tanh [72]. It also enables the regression model to converge quickly and effectively [73]. The following equation (5) is used to define ReLU activation function:

$$y_k = ReLU(W_k x_{k-1} + b_c) \tag{5}$$

where W_k indicates the weights for each neuron x indicates the input matrix for the input layer, and b represents the bias vector for adjusting output to fit the given training data best. In our proposed RIVIMS model, a Softmax method is used as an activation function between hidden and output layers to transform the output results of hidden layers to form and obtain the expected value $\hat{y}$ for the observed value y. The softmax method is given in equation (6) to obtain predicted value.

$$\hat{y} = softmax(W_{output} x_h + b_{output}) \tag{6}$$

where $\hat{y}$ represents the expected value as a predicted value, which is corresponding to the observed value (actual value) y, h represents the total number of deployed hidden layers, x_h is the output of the last hidden layer h, W_{output} indicates the final weight matrix between last hidden and output layers and b_{output} is a constant value to indicate the bias factor to shift the Softmax to the left or right to adjust the output in order to fit the given data best. Finally, different statistical measures are utilized, such as MAE, RMSE, and R2 score, to evaluate the performance of the implemented DNN.

2) SUPPORT VECTOR REGRESSION

Support vector machines (SVMs) are a category of computational intelligence in artificial intelligence. The SVMs techniques are well known in classification as well as regression problems. Support vector regression (SVR) is used as a supervised regression method, which maintains all the decision attributes in the learning model process. The main objective of the regression models is to minimize error (loss) value in the prediction process [74]. It is one of the effective and robust developing strategies in the field of ML because of its excellent capacity for generalization and efficient assembly execution. The main objective of the SVR model is to tries to fit the best line inside a defined threshold, which is form based on error value. It is also an effective approach to minimize the coefficients. In contrast, other regression models based on linear kernels are used to limit the prediction error (loss). The SVR method consists of the following steps:

1) Collection of training samples in order to train or learn the model using SVR algorithm
2) Selection of Kernel function, which is used to transform a lower-dimensional data samples into a higher dimensional data samples. In our proposed model, a linear splines kernel selects as a kernel function, because it is useful to deal with the massive amount of data and give a high performance as compared to other kernel functions, such as polynomial, Gaussian, sigmoid, etc.
3) Training the model using SVMs based strategy to constructs the learned model
4) Testing unseen (new) data on trained SVR model to evaluate the performance of the SVR model by calculating the difference between predicted and actual values. The presented RIVIMS evaluates the performance of the implemented model based on the following performance analysis measures, such as MAE, RMSE, and R2 score.

V. IMPLEMENTATION ENVIRONMENT OF THE PROPOSED BLOCKCHAIN AND ML-BASED RIVIMS

This section presents the implementation environment of the veterinary clinic management using blockchain-based technology and predictive analytics to predict appointments scheduling requests to reduce waiting time for pet owners.

TABLE 5. Development environment for proposed blockchain-based RIVIMS.

System Components	Description
Operating System	Ubuntu Linux 18.04.1 LTS.
CPU	Intel ®Core ™ i3-2130 CPU at 3.40 GHz
Memory	12 GB
IDE	Composer-playground
Hyperledger Fabric	v1.2 and v-2.0
Docker Engine	Version 18.06.1-ce
Docker Composer	v-1.13
Node	Node v8.11.4
CLI Tool	CLI Tool Composer REST server
Python	V2.7.15

The implementation environment is divided into two subcategories, such as the implementation of veterinary clinic management using blockchain technology and the implementation of predictive analytics to predict appointments scheduling requests.

A. IMPLEMENTATION ENVIRONMENT OF THE PROPOSED BLOCKCHAIN-BASED RIVIMS

The development of the proposed blockchain-based system is divided into two parts, i.e., the front end and back-end. The implementation setup for the back-end development for the proposed reliable veterinary clinic management is listed in Table 5. An Ubuntu Linux (i.e., 18.04.1 LTS) is used to implement the proposed system and conduct a series of experiments. In the case of the Docker environment, the Docker engine (i.e., v-18.06.1-ce) with Docker-composer is used for the configuration and setting up the Docker image in the virtual machine. Furthermore, a Hyperledger Fabric is used, which is an open-source framework developed by Linux foundation for the blockchain runtime development.

Moreover, for the designing and development of a business network definition, we have used the composer-web-playground. The composer web-playground is provided support to develop blockchain applications in both localhosts as well as web-based. For the RESTful API, we configure the composer-rest-server in order to fetch data from the developed application using blockchain technology system. The tool and technologies for GUI implementation for veterinary clinic management are mentioned in Table 6. The following technologies are used to develop a web-based application, such as HTML5, CSS3, Bootstrap, and JQuery, to achieve dynamic behavior of the front-end application. The client performs some action on the web application that will trigger the HTTP method like POST, GET, PUT, and DELETE, which, in response, perform according to the client HTTP request.

Table 7 summarizes the REST APIs list, which is generated by the composer-rest-server for establishing a connection between the client machine and the proposed blockchain system. At runtime, CRUD operations can be performed through a REST server to manipulate or modify the state of the distributed ledger. The composer-rest-server API consists of three different parts, such as resource, verb, and action.

TABLE 6. Front-end development environment of the proposed blockchain-based RIVIMS.

System Components	Description
Operating System	Ubuntu Linux 18.04.1 LTS.
Programming Language	HTML5, CSS5, JQuery
Front-end Library	Bootstrap
Client SDK	Google Chrome and Firefox

TABLE 7. RESTFul API of the proposed blockchain-based RIVIMS.

Resource	Verb	Action
/api/petOwner	POST, GET, PUT, DELETE	Veterinary patient management
/api/nursePractitioner	POST, GET, PUT, DELETE	Nurse management
/api/appointmentScheduling	POST, GET, PUT, DELETE	Appointment scheduling
/api/updateAppointmentTime	POST	Update appointment scheduling time
/api/updateAppointmentStatus	POST	Update appointment scheduling status, e.g., approve or reject.
/api/service	POST, GET, PUT, DELETE	Service management
/api/bill	POST, GET, PUT, DELETE	Medical bill management
/api/sendBill	POST	Send bill receipt to PetOwner
/api/payBill	POST	Pay bill to veterinary clinic
/api/shareRecordWithDoctor	POST	Share Pet (patient) record with pet doctor
/api/updatePastVisits	POST	Update veterinary patient history data
/api/medicine/supply	POST, GET, PUT, DELETE	Medicine supply management
/api/medicine/stock	POST, GET, PUT, DELETE	Medicine stock management
/api/dataAnalytics	GET	Data analytics report management

The resource represents the request/response path of the data entity like /api/PetDoctor, and the verb specifies the required action to be performed on a given resource, for example, POST, GET, and DELETE, etc. The POST request is used to create/update a new asset or participant on a particular resource, while the GET request is used to retrieve data of the data entity for a given resource, i.e., /api/PetOwner.

B. IMPLEMENTATION AND EXPERIMENTATION SETUP OF THE PREDICTIVE ANALYTICS MODEL

This subsection presents the implementation setup of the predictive analytics model to predict appointments scheduling requests. Table 8 presents the implementation environment of the proposed ML-based predictive analytics module.

The proposed RIVIMS utilize a one-hot encoding scheme to transform each categorical attribute into a new column and assign binary notations, such as 1 or 0. This approach is more effective and reliable because it eliminates order issues faced by the label encoding scheme. Also, our work uses the following machine learning algorithms, such as DNNs and SVR, to predict the future frequency of appointments scheduling requests of the veterinary patients for a veterinary clinic. Both algorithms consist of two operational steps, such as train the learning model and test the learned model using unseen data. Therefore, it is required to divide the prepared dataset into two subsets; training and testing subsets. There are different techniques available to split data into subsets, such as K-fold and holdout, etc. This work uses a python library known as sklearn to divide the prepared dataset into two different subsets with the ratio of 70-30 split. The following equation (7) is used to define a split data ratio for training and testing purposes.

TABLE 8. Development setup of the proposed ML-based predictive analytics module.

System Components	Description
Operating System	Microsoft Windows 10
CPU	Intel®Core™i3-2130CPUat3.40 GHz
Main Memory	16GB RAM
Core Programming Language	Python
IDE (Platform)	PyCharm Professional 2020

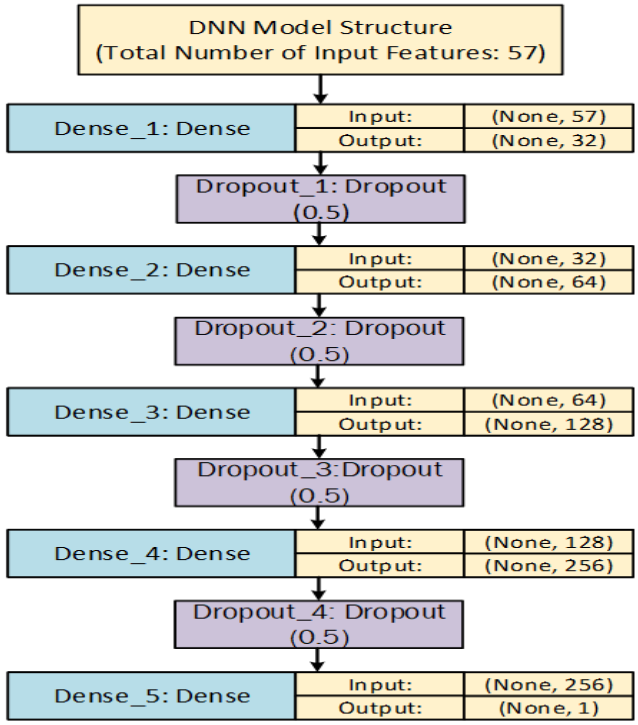


FIGURE 14. Structure of the implemented DNN model.

$$Data\_Split\_Ratio = \begin{Bmatrix} 70, & Training_{instances} \\ 30, & Testing_{instances} \end{Bmatrix} \tag{7}$$

The following Figure 14 presents structure of the implemented DNN model. The structure of the implemented DNN model consists of five dense layers. Initially, our proposed model used the following activation functions; ReLU (between input and hidden layers) and softmax (between last hidden and output layers) in order to obtained prediction results using 100, 200, and 300 training epochs. The implemented DNN model uses Adam optimizer as an optimization algorithm, which is an adaptive learning rate based optimization scheme and commonly used for training of DNN model [75]. Dropout technique is used in the training process, which use to drop out randomly selected nodes in hidden layers. Our proposed model uses 0.5 as a dropout rate, which is a common value in order to retain the output of each node in the hidden layer. Later, we optimize hyperparameters for our proposed DNN model to achieve better prediction results. The following parameters are optimized, such as activation function, learning rate, batch size, and epochs.

Table 9 presents the discovered time series and other veterinary data features using existing domain knowledge.

VI. EXPERIMENTAL RESULTS OF THE BLOCKCHAIN-BASED SECURE AND TRANSPARENT RIVIMS

This section presents experimental results and performance evaluation of the proposed blockchain-based RIVIMS.

A. EXECUTION RESULTS

This subsection presents the execution results of the proposed blockchain-based RIVIMS. The following Figure 15 shows the main dashboard of the proposed blockchain-based RIVIMS using Hyperledger Fabric. The front-end user interface shows the core functionality of the proposed RIVIMS, such as veterinary doctor profile, nurse profile, veterinary patient profile, appointment scheduling, medical record history of the patients, services, medical supply/stock, and data analytics. The veterinary doctor profile management represents personal data of the veterinary doctors. It can also be used to create a new profile, edit and delete the selected doctor profile. The veterinary patient profile management consists of the information related to pet and their owners. The appointment scheduling module presents the appointment information related to the pet owner (user), veterinary doctor, appointment scheduling date, and current status of the appointment. The veterinary doctors have only privileged to modify the current status of the appointment request, and also delete the appointment request from the blockchain ledger. The pet owners (users) have accessed to view information related to their submitted appointment requests. The medicine supply/stock dashboard contains information related to medicine, pet doctor id, and pet owner id, to save a complete and secure record of the medicine supply/stock in the blockchain ledger. Moreover, it allows admin to perform CRUD operations on a selected medicine supply/stock record and also save track changes record in a distributed ledger. Furthermore, data analytics module is used to provide hidden insights and useful knowledge from veterinary patients data, which is essential for veterinary management to plan future strategies in order to gain a significant market value over their competitors.

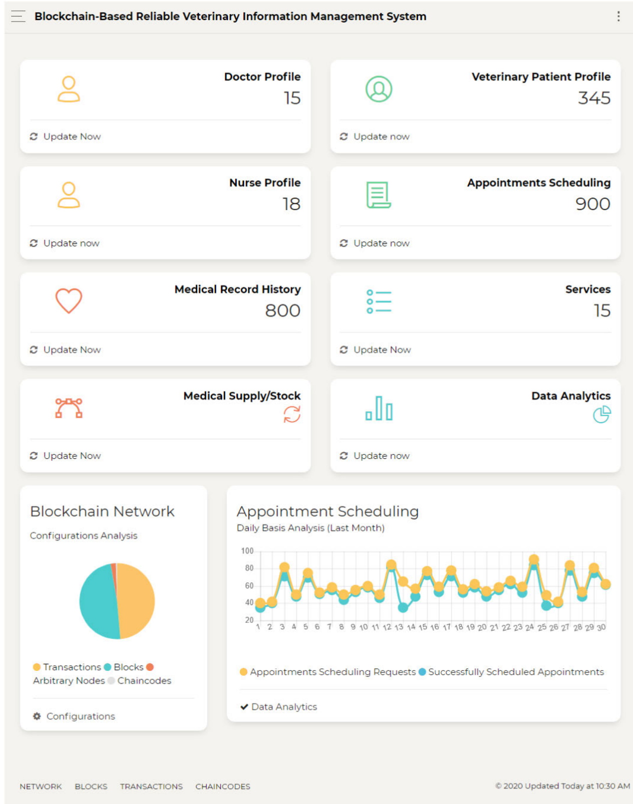


FIGURE 15. Front-end user interface of the proposed Blockchain-based RIVIMS using Hyperledger Fabric.

B. PERFORMANCE EVALUATION

This subsection describes the performance evaluation of the proposed reliable blockchain system for veterinary clinic management. In this paper, we use two different types of consensus algorithms, such as PBFT and RAFT, to evaluate the performance of the proposed RIVIMS. The PBFT algorithm is used to support Byzantine fault tolerance (Bft) and give high transactions throughput and low latency for the limited numbers of nodes in the blockchain network. The bottleneck of the PBFT algorithm is to provide poor scalability due to transmitting a large number of consensus messages as the number of nodes of the entire network increases [76]. The proposed RIVIMS is developed based on permissioned blockchain network. Therefore, we used the PBFT algorithm because it relies on a message-based consensus algorithm as compared to relay on hashing schemes to operate in a trusted environment. Furthermore, PBFT algorithm has been widely used by permissioned blockchain in order to outperform proof of work (PoW) consensus schemes in terms of transactions throughput and latency [77]. In contrast, RAFT is a consistency-based consensus algorithm, which uses log synchronization in order to assure data consistency. It also aims to give high TT and low TL, but it does not support Bft like PBFT algorithm. The RAFT algorithm achieves data consistency by dividing the whole process into four steps: a selection of leadership (leader node), synchronization of the

TABLE 9. Base and discovered features summary.

Feature	Description	Total Features	Feature Type
Day-wise frequency of scheduled day	It is used to represents the total frequency of veterinary patients appointments according to the scheduled day.	1	Discovered
Day-wise frequency of appointments day	It represents the total frequency of veterinary patients appointments for the exact day of the appointment.	1	Discovered
Delta Day Interval	It is a day-based time difference between appointment date and the scheduled date.	1	Discovered
Weekly distribution of appointments scheduling	It represents an average frequency of appointments from Monday to Saturday.	6	Discovered
Monthly distribution of appointments scheduling	It represents an average frequency of appointments from January to December.	12	Discovered
Gender-based distribution of appointments scheduling	It represents the gender-based distribution of appointments scheduling on a daily basis.	2	Discovered
Illness Type	It represents veterinary patients appointments based on illness type. It is a categorical feature having 20 unique values. Therefore, we use a one-hot encoding technique to transform into 20 features and assign binary notations to each newly created feature.	20	Base
Illness duration	It represents the illness duration (in terms of days) of veterinary patients.	1	Base
Treatment Type	It represents veterinary patients appointments based on treatment type. It is also a categorical feature, which is transformed into 13 features by using one-hot encoding scheme.	13	Base

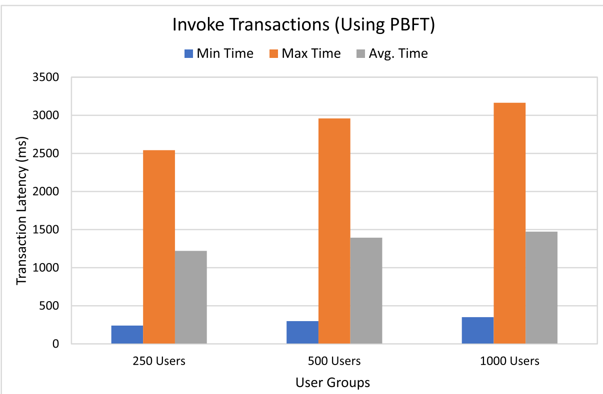


FIGURE 16. Performance evaluation of the invoke transactions in terms of TL (ms).

log, member change, and assurance of security. The RAFT algorithm can perform better in terms of TPS because it does not cause network consensus costs due to leader and other candidate nodes. Furthermore, we use a benchmark framework known as Hyperledger caliper to evaluate the performance of the proposed blockchain-based system [78]. Hyperledger Caliper is an open-source framework, which use to evaluate the performance of the blockchain application with a set of predefined use cases to get a set of evaluation results. Currently, it supports different blockchain-based solutions, such as Hyperledger Fabric, Besu, Ethereum, and Sawtooth, to name of few. The benchmark Hyperledger Caliper framework supports several performance measures, such as transaction per second (TPS), transaction success rate (TSR), transaction throughput (TT), and transaction latency (TL). In our proposed system, the following performance measures are utilized, such as TPS, TSR, TT, and TL, to evaluate the performance of the developed blockchain system.

The following Figure 16 describes the performance of the invoke transaction of the proposed blockchain system in terms of transaction latency (TL). Different user sets were considered by different researchers [1], [10], [29] to demonstrate the efficiency of the proposed blockchain-based systems using Hyperledger Caliper tool. Based on existing blockchain-based studies, three distinct use cases are defined to evaluate the execution of the transactions, such as 250, 500, and 1000 users. The average transaction latency (TL) for the defined user-group of 250 users is 1220 milliseconds (ms). Likewise, in the case of 500 users, the average TL is increased from 1220 to 1393 milliseconds.

However, if the number of users increases from 500 to 1000, then the average TL increased to 1473 milliseconds. It is observed as the number of users increases in the defined use case; the average TL also increases with a slightly different from the previously defined user groups. The minimum TL for all three defined user groups is 240, 298, and 351 milliseconds, respectively. Moreover, the maximum TL for all defined user groups is 2542, 2959, and 3165 milliseconds, respectively. It is analyzed for all three defined user-groups that the increased number of transactions in the blockchain system also slightly increase the TL.

Similarly, in Figure 17, we provided the same number of user-groups to the blockchain system to evaluate the results of executing the query transactions in terms of query latency QL. In the blockchain, it is very time costly and expensive to query for data because it does not support fast query for on-chain data. Therefore, we used an off-chain lake as an independent data storage for storing and fetching participants and assets data efficiently. The following Figure 17 is used to evaluate the performance of data query in terms of QL. In the defined use case of 250 users, the average TL is 154 ms for successfully executing the query transaction. Likewise, the average TL for the specified use cases of defined 500 and 1000 users, is 172 and 429 milliseconds, respectively. The minimum

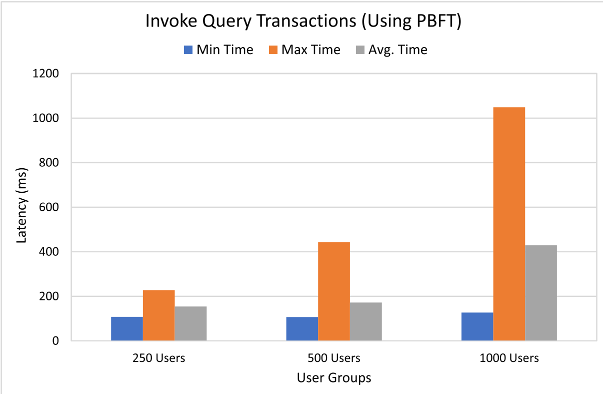


FIGURE 17. Performance evaluation of the invoke query transactions in terms of TL (ms).

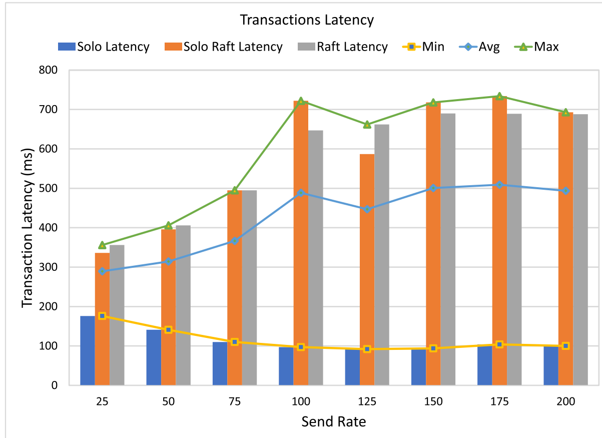


FIGURE 18. Performance evaluation of ordering services in terms of latency.

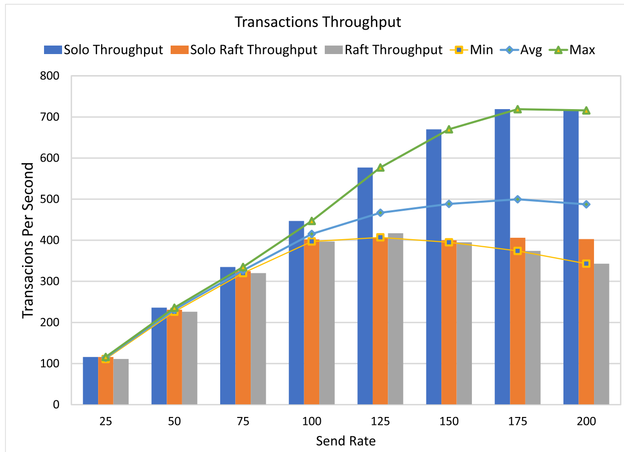


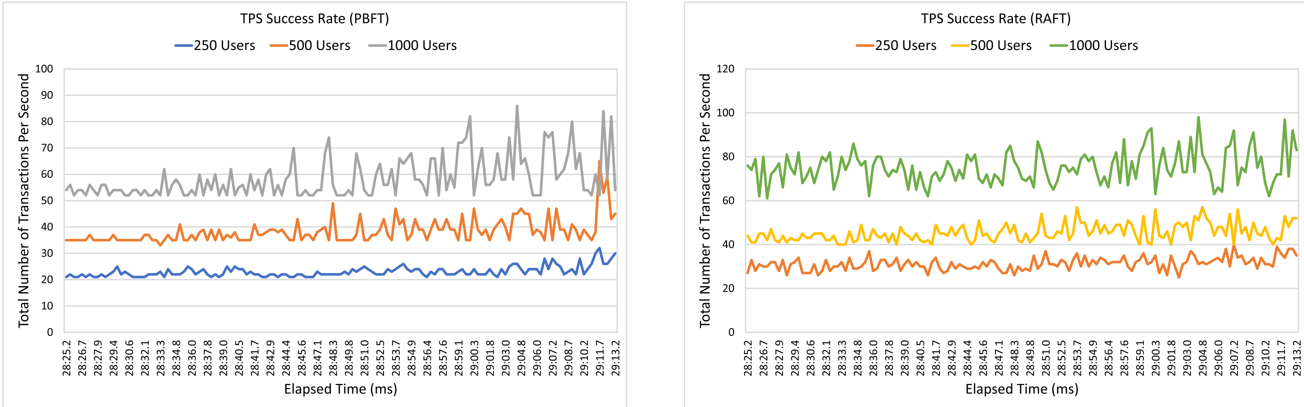
FIGURE 19. Performance evaluation of ordering services in terms of throughput.

TL of the executing query transactions for all three defined user groups is 108, 107, and 127 milliseconds, respectively. Whereas, the maximum TL of executing query transaction with defined user groups is 228, 443, and 1049 milliseconds, respectively.

Hyperledger Fabric provides ordering services, which are used for the ordering of submitted transactions in well-organized sequence using ordering nodes. The ordering nodes are used to perform following operations, such as accept submitted transactions from endorsers nodes, order them into well-defined blocks, and then send the ordered blocks to committing nodes. The performance of the proposed RIVIMS is evaluated using three different types of ordering services, such as Solo (single ordering node), Solo-RAFT (single to multi nodes), and RAFT (multi nodes network). The performance of these services are evaluated in terms of transactions latency, and transactions throughput with different transactions send rate varies from 25 TPS to 200 TPS. The following Figure 18 presents minimum, maximum, and average transactions latency using transaction send rate of 25 TPS to 200 TPS. It is analyzed that the transaction latency of Solo-RAFT and RAFT is higher than the Solo ordering by adding transport layer security (TLS), which increase the security and authentication among blockchain peers.

Similarly, in Figure 19, a transaction throughput of the ordering services are analyzed in terms of minimum, maximum, and average throughput. It can be observed that the transaction throughput of solo ordering is higher because it does not require additional TLS services as compared to other ordering services.

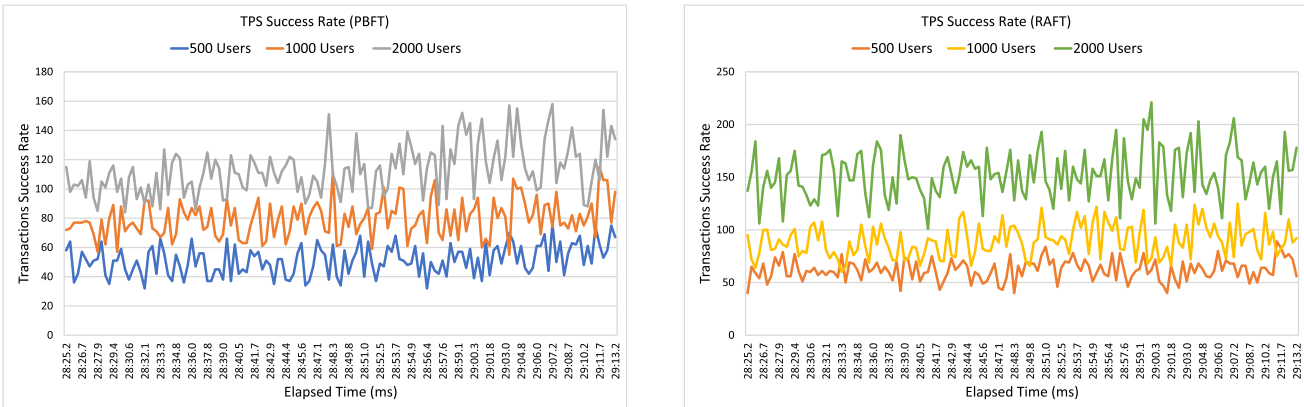
Figures 20 and 21 present comparative analysis of the proposed blockchain-based RIVIMS using PBFT and RAFT in terms of TPS. The following Figure 20 presents a comparative analysis of PBFT and RAFT consensus algorithms in terms of TPS. Different user groups are taken as a set of predefined use cases to evaluate and investigate the performance of developed blockchain-based RIVIMS. For both consensus mechanisms, the predefined set of users is comprised of three distinct user groups, such as 250 users, 500 users, and 1000 users. First, we analyzed the throughput of the proposed system using 250 users. It can be observed that the TPS of the PBFT algorithm fluctuated between 20 and 30; whereas the transactions success rate of the RAFT algorithm varied between 25 to 40. Secondly, we increased the number of users from 250 to 500 to examine the throughput of the proposed RIVIMS using PBFT and RAFT. It is found that the TPS of the PBFT algorithm is increased, but it also increased TL due to transmitting a large number of consensus messages. Besides, the transaction success rate of RAFT algorithm is high for a use case of 500 users as compared to the PBFT algorithm. Lastly, the use case of 1000 users is used to investigate the execution performance of the developed RIVIMS in terms of TPS. It is evident that the TPS of the RAFT varied between 60 to 100; whereas TPS of PBFT algorithm fluctuated between 50 to 85. The comparative analysis reveals that the TPS of the RAFT algorithm has slightly better as compared to the PBFT algorithms.



(a) Performance evaluation in terms of TPS using PBFT

(b) Performance evaluation in terms of TPS using RAFT

FIGURE 20. Comparative analysis of PBFT and RAFT in terms of TPS.



(a) Performance evaluation in terms of TPS using PBFT (Double Send Rate)

(b) Performance evaluation in terms of TPS using RAFT (Double Send Rate)

FIGURE 21. Comparative analysis of PBFT and RAFT in terms of TPS.

Similarly, in Figure 21, we double the send rate in order to evaluate the performance of PBFT and RAFT in terms of TPS. It can be observed that the TPS of PBFT algorithm for 500 users is varied between 38 to 65. In contrast, the TPS of the RAFT algorithm varied between 48 to 75. Likewise, in the case of 1000 users, the TPS of PBFT fluctuated between 58 to 110; whereas the TPS of RAFT increased and fluctuated between 75 to 125. Furthermore, we increased the number of participating users from 1000 to 2000 in order to evaluate the performance of proposed RIVIMS using PBFT and RAFT. It is found that the TPS of PBFT for 2000 users is varied between 85 to 155. In contrast, the TPS of RAFT increased and varied between 110 to 220. Based on comparative analysis, it shows that RAFT is performed well in terms of TPS as compared to PBFT.

VII. PREDICTION RESULTS OF THE PROPOSED RIVIMS

This section presents the experimental results of the proposed predictive module for the appointments scheduling prediction using different regression models.

A. CASE 1: VETERINARY PATIENTS APPOINTMENTS PREDICTION USING TIME-SERIES AND OTHER VETERINARY DATA

This subsection presents veterinary patients appointments prediction results obtained using time series and other veterinary clinic appointments data. In this paper, a well-known python library sklearn is utilized to implement the regression models to predict future appointments scheduling requests of the veterinary patients on a daily basis, that is important for veterinary clinic management to formulate future business plans and strategies plan to manage their demands effectively. Also, we have utilized the following statistical measures, such as mean absolute error (MAE), root mean square error (RMSE), and R2 score to evaluate the prediction performance of the implemented regression models. The following Figure 22 is used to analyze and compare the prediction performance of the proposed DNN with traditional DNN and SVR algorithms using the following performance measures, such as MAE and RMSE. The proposed DNN achieved significant and accurate results in terms of MAE and RMSE

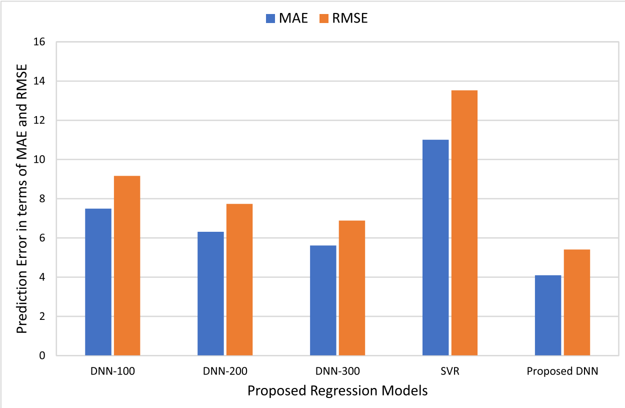


FIGURE 22. Performance evaluation of the regression models in terms of MAE and RMSE.

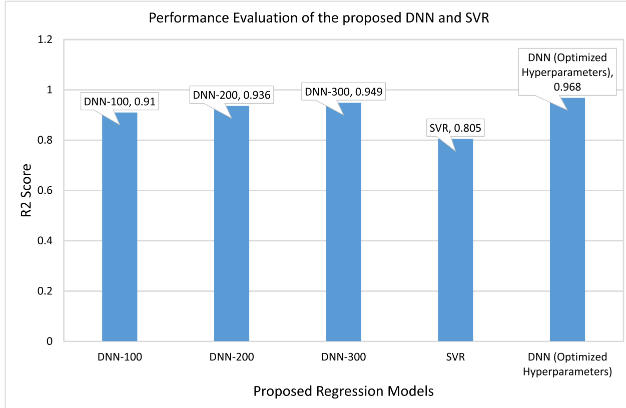


FIGURE 23. Performance evaluation of the regression models in terms of R2 score.

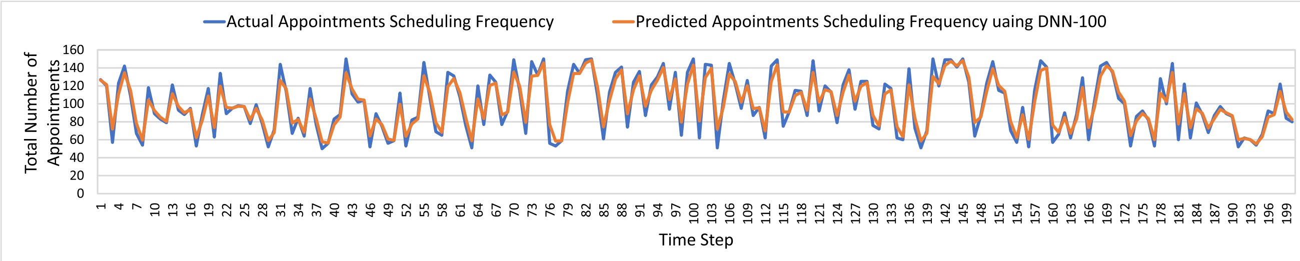
as compared to DNN and SVR. The prediction error of the proposed DNN model in terms of MAE and RMSE is 4.1 and 5.409, respectively. It can be observed that the prediction error decreases as epoch increases, which positively influence the overall performance of the prediction model. Hence, our proposed RIVIMS achieved accurate prediction results using proposed DNN. Furthermore, the DNN model with 100, 200, and 300 training epochs produced the most promising results as compared to the SVR model.

The performance evaluation and comparison of the proposed DNN with other traditional regression models is depicted in Figure 23. The prediction performance is evaluated in terms of R2 score. The prediction performance of the traditional DNN model with 100, 200, and 300 in terms of R2 score is 0.910, 0.936, and 0.949, respectively; whereas the prediction performance of the SVR model in terms of R2 score is 0.805. Furthermore, we optimize the hyperparameters of the DNN model to train the DNN model using an optimized set of the hyperparameters to enhance the prediction accuracy. In contrast, our proposed DNN model produced the most prominent results in terms of R2 score of 0.968, which is significantly high as compared to other baseline models. Hence, our proposed DNN model with optimized hyperparameters outperformed the baseline DNN and SVR models to produce more effective and accurate prediction results.

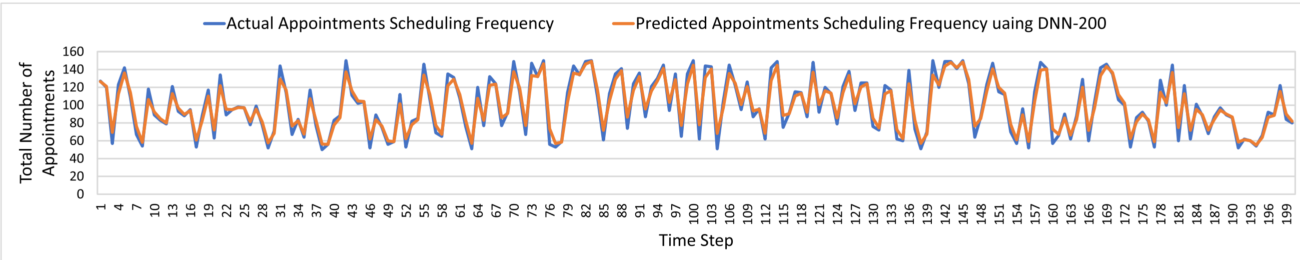
Figure 24 demonstrates the comparison of actual and predicted appointments scheduling requests results using traditional DNN model with 100, 200, and 300 epochs. The traditional DNN model is configured with 100, 200, and 300 epochs timing in order to build a robust predictive model. It is evident that the performance of the proposed model increases as epochs increases. It is also observed that prediction loss decreased due to an increase in the training epochs, which positively influence the performance of the prediction model. It is evident that the traditional DNN model with 100 epochs produced a slightly high prediction error in terms of MAE and RMSE of 7.496 and 9.166, respectively, as compared to the traditional DNN model with 200 and 300 epochs. The traditional DNN model with 200 epochs reduced prediction error slightly and improved the performance of the proposed predictive analytics model in terms of MAE and RMSE as compared to using 100 epochs. Finally, a traditional DNN model with 300 epochs improved the overall performance of the RIVIMS in terms of MAE and RMSE of 5.617 and 6.887, respectively. Hence, a traditional DNN model with 300 epochs produced the most effective and promising results in terms of R2 score of 0.949 as compared to the DNN model with 100 and 200 epochs of 0.910 and 0.936, respectively.

Similarly, Figure 25 presents the prediction results of the traditional SVR model to predict the future frequency of the appointments scheduling requests. The prediction error of this model in terms of MAE and RMSE is 11.01 and 13.526, respectively.The accurate prediction rate of the implemented SVR algorithm in terms of R2 score is 0.805. However, the prediction error rate of the SVR model in terms of MAE and RMSE is high than a baseline DNN model with 100, 200, and 300 epochs.

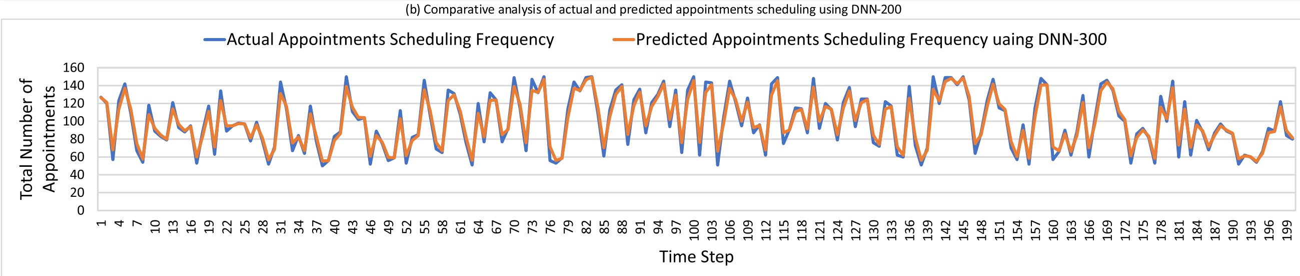
Figure 26 presents prediction results obtained using the proposed DNN model based on optimized hyperparameters. The following parameters are tunned, such as activation function, learning rate, epoch, and batch size, to enhance the overall performance of the DNN model. The proposed DNN model with following hyperparameters (‘learning_rate’: 0.001, ‘epochs’: 200, ‘batch_size’: 32, ‘activation’: ’relu’) produced relatively better prediction results in terms of MAE, RMSE, and R2 score as compared to the traditional DNN with 100, 200, and 300 epochs. It is observed that the hyperparameters tuning process enhances the prediction performance of the proposed DNN model. The DNN with optimized hyperparameters produced the optimal prediction results in terms of MAE and RMSE of 4.1 and 5.409, respectively. Hence, it is evident that the error of the prediction process decreased and the performance of the build model increased. Furthermore, it produced effective prediction results in terms of R2 score of 0.968, which is significantly better as compared to simple DNN and SVR.



(a) Comparative analysis of actual and predicted appointments scheduling using DNN-100



(b) Comparative analysis of actual and predicted appointments scheduling using DNN-200



(c) Comparative analysis of actual and predicted appointments scheduling using DNN-300

FIGURE 24. Comparison of actual and predicted appointments scheduling requests using DNNs 100, 200, 300 epochs.

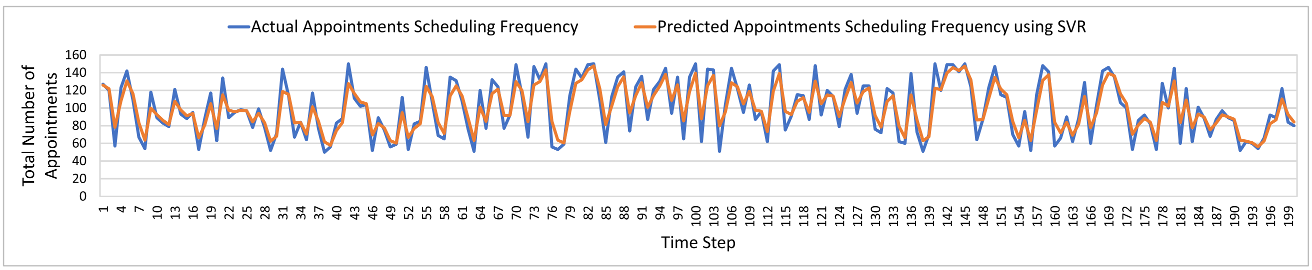


FIGURE 25. Comparative analysis of actual and predicted appointments scheduling requests frequency using SVR.

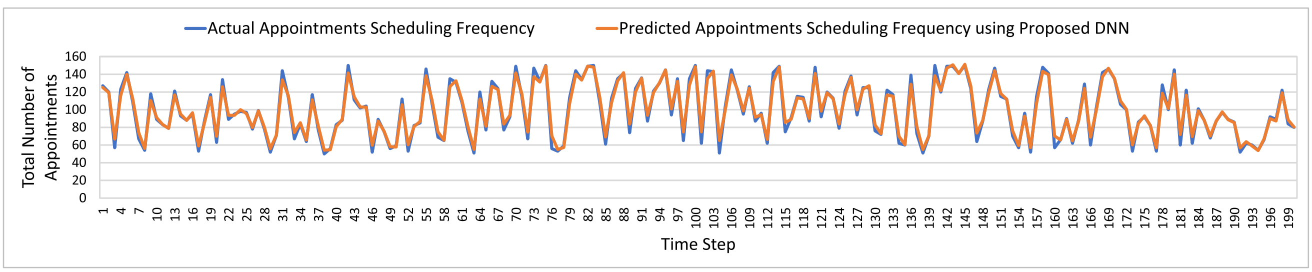


FIGURE 26. Comparative analysis of actual and predicted appointments scheduling requests frequency using DNN (using Optimized Hyperparameters).

B. CASE 2: VETERINARY PATIENTS APPOINTMENTS PREDICTION USING TIME-SERIES DATA

This subsection presents the prediction results of veterinary patients obtained using time-series data. In this work, a multi-directional long short term memory (MD-LSTM) is proposed. The flow of the proposed MD-LSTM model is depicted in Figure 27 to predict the frequency of the appointments scheduling using time series data of the veterinary clinic. The proposed helps veterinary management to formulate their resources effectively to provide QoS services to veterinary patients. The basic flow of the proposed MD-LSTM model is categorized in the following layers, such as

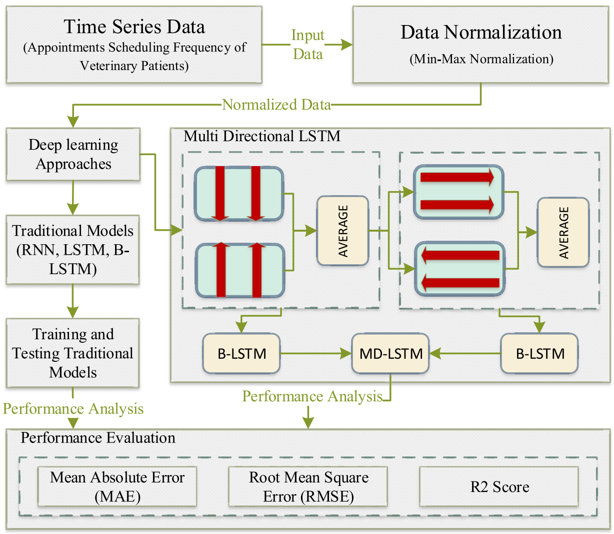


FIGURE 27. **Proposed flow diagram of Multi-Directional LSTM.**

time-series data preparation, normalization of data, training and testing of deep learning approaches including traditional DL models and proposed ML-LSTM model. In this use case, we consider a time series data of veterinary appointments scheduling data, such as the total number of appointments per day as an input feature to train and test DL models. First, a time series data of appointment scheduling requests are prepared to increase the reliability of the given data. Next, a min-max normalization technique is used to normalize data in the specified range [0,1] as defined in equation 1. After normalization of data, a DL-based ML-LSTM model is trained and tested using prepared dataset. In this work, a train-test split ratio is used to divide prepared data into training and testing sets with a ratio of 70-30 split. 70% of data instances are used to train DL models, and the remaining 30% of data is used for testing and evaluation purpose. The performance of the proposed MD-LSTM is evaluated using different performance metrics, such as MAE, RMSE, and R2 score to show the significance of the proposed model. Finally, we compare the performance of the proposed MD-LSTM with the traditional DL models; Recurrent Neural Network (RNN), LSTM, and Bi-directional LSTM (BD-LSTM). These traditional DL models are explained in brief as follow below.

RNN belongs to the family of deep neural networks that can handle dependencies. Recurrent nets possess feedback loops between different blocks in a single layer. As the name suggests, recurrent operations are executed on all elements sequence wise. Hence, it is used to model time series data efficiently. In RNN current output of neurons is calculated based on the previous and present inputs along with their associated weights and can remember and store it. However, RNNs can practically look back a few time steps only, which results in vanishing and exploding gradient over longer periods. That means the distance of information from a specific time step to the point where it is required becomes too large, which makes the process of learning difficult.

Therefore, a new architecture is required to solve the problem of vanishing and exploding gradients in traditional RNN. LSTM units were introduced by [79] as a solution to these problems. LSTM is a special kind of recurrent neural network that has cell states and gated architecture. It comprises of three fully connected gates, namely as input, forget and output to save the useful information in cell states and discard the unnecessary. So basically these gates control what's coming in and update the cell states accordingly and output new cell states based on present input and previous output. This process continues, weights are updated using back-propagation and biases are added until error is minimized. LSTM neural network can model complex nonlinear time series data and scaling inputs which make it an ideal candidate for modelling time series data.

BD-LSTM is an extension of the conventional LSTM developed for performance improvements [80]. It is a sequence processing model comprising of two long short term memory units; the first one is responsible for taking inputs in the forward direction and other for taking it backwards. In this way, two LSTM models are trained on the input sequence, and a large amount of information is available to the network resulting in faster convergence and better training of the model.

To the best of our knowledge, the aforementioned traditional DL models are not well suited for multi-dimensional data [81]. Therefore, an MD-LSTM is required to replace a single recurrent connection with multiple connections or according to the required dimensions of the data. MD-LSTM works across the streams rather within them the reason being the timings is advanced and lagged for input to hidden layers. The proposed MD-LSTM consists of two BD-LSTM models where each BD-LSTM works in a bidirectional fashion. The first BD-LSTM is used for vertically scanning; whereas another BD-LSTM is used for horizontal scanning. The average is used as a standard merge mode to merge the output of the LSTM models in each BD-LSTM. The average merge mode is useful as compared to other merge modes; such as SUM and CONCATENATE, etc. The SUM and CONCATENATE can be used to merge the output feature maps, but these approaches would increase the computational complexity in terms of increasing the number of features [82]. The merged output of the first BD-LSTM is used as an input for the second BD-LSTM to form an MD-LSTM model. The proposed MD-LSTM model significantly improves the prediction accuracy, but it increases the computational complexity of the model because it uses the twice number of gates as compared to other models like traditional LSTM.

Figure 28 presents a comparative analysis of actual and predicted appointments scheduling results obtained using traditional DL models and proposed MD-LSTM. Figure 28-a depicts a comparative analysis of actual and predicted appointment scheduling frequency using traditional RNN.

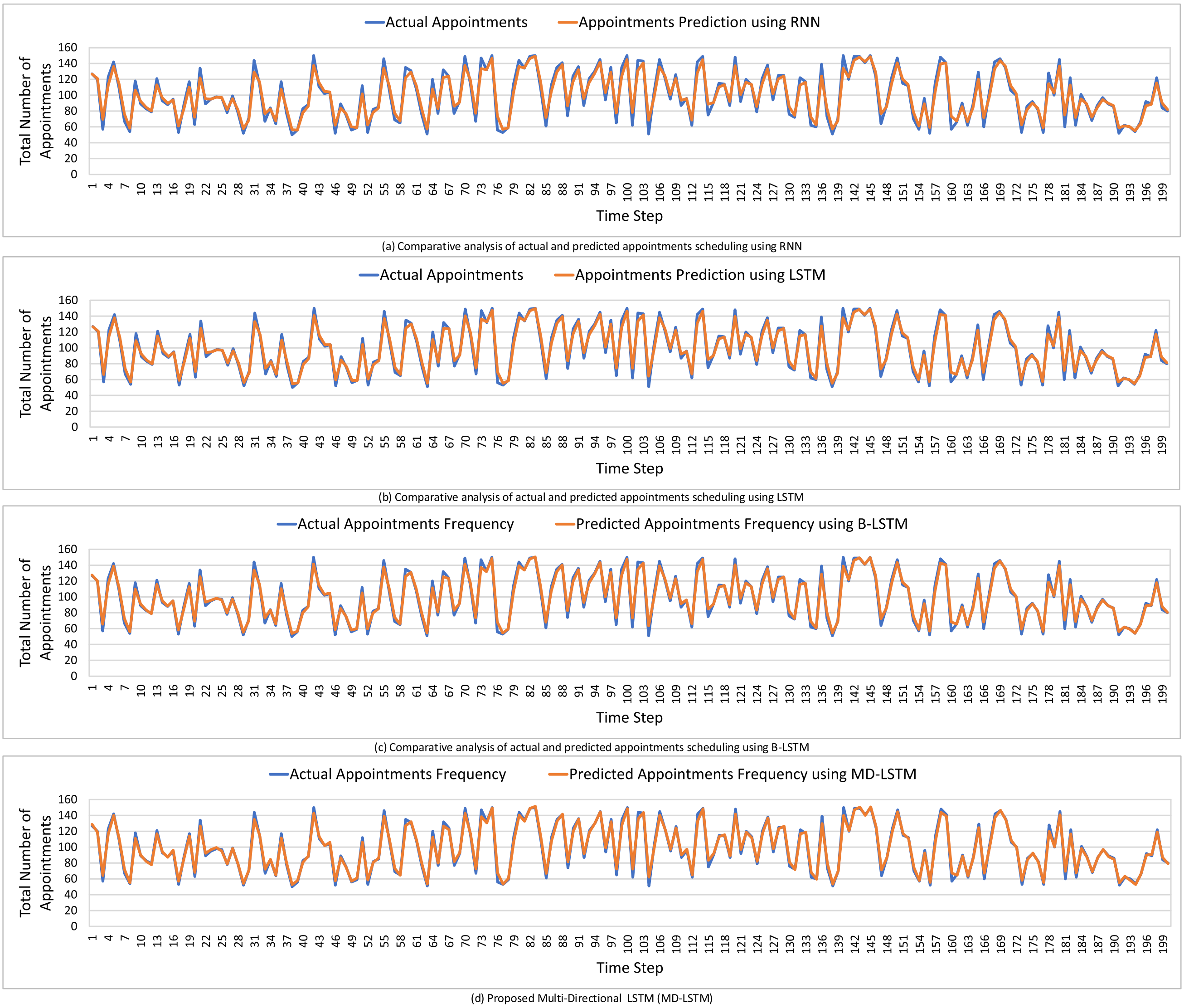


FIGURE 28. Comparison of the proposed MD-LSTM with traditional deep learning models.

It can be observed that the difference between actual and predicted appointments scheduling frequency is high as compared to other models. The difference between actual and predicted values indicate an error in the prediction process. Similarly, it can be observed in Figure 28-b that traditional LSTM produced a low prediction error as compared to the traditional RNN. The traditional LSTM performed significantly better in terms of MAE and RMSE as compared to the traditional RNN. Likewise, Figure 28-c depicts a comparative analysis of actual and predicted appointments scheduling frequency using BD-LSTM. It can be observed that BD-LSTM performed well in the prediction process and produced a low error as compared to traditional RNN and LSTM. The difference between actual and predicted values are low, which shows the significance of the BD-model. Finally, Figure 28-d presents a comparative analysis of actual and predicted appointments scheduling frequency using our proposed MD-LSTM. It is evident that our proposed MD-LSTM produced accurate prediction as compared to other traditional DL models. The proposed MD-LSTM performed significantly better in terms of MAE and RMSE, which demonstrate the effectiveness and robustness of MD-LSTM model for time series data. The comparative analysis reveals that the proposed MD-LSTM is the most promising prediction model to predict veterinary appointment scheduling frequency based on time series data (daily data). Hence, our proposed MD-LSTM model produced a low prediction error, accurate prediction results, and outperformed the other traditional DL models.

C. PERFORMANCE EVALUATION

There are different performance measures available in machine learning to evaluate the performance of the regression models [83]. In this paper, we have utilized following performance measures, such as mean absolute error (MAE), root mean square error (RMSE), and R2 score in order to demonstrate the effectiveness of the regression models.

1) Mean Absolute Error (MAE)
Mean absolute error (MAE) is used to measure the performance of the prediction model by calculating the average of the absolute difference between actual and predicted data instances. It is calculated by equation (8):

$$MAE = \frac{\sum_{i=1}^{n} |Y_i - \hat{Y}_i|}{n} \tag{8}$$

where Y_i represents the actual set of observations and $\hat{Y}_i$ represents the predicted set of observations.

2) Root Mean Square Error (RMSE)
Root mean square error (RMSE) is the square root of the MAE. It is used to evaluate the overall performance of the prediction model by taking the square root of the average of squared difference between actual and predicted data instances. The range of RMSE is from 0 and ∞ whereas '0' indicates that the regression model performed accuratly on unseen data and a large value of RMSE indicates that there is a high error in the prediction process. The following equation (9) is used to calculate RMSE.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)|^2}{n}} \tag{9}$$

3) R^2 Score or R-Squared
It is a statistical measure that indicates the proportion of variance of the two variables (i.e. dependent and independent variables) in a regression model. The range of the R2 score is from 0 to 1. The 0 indicate that the regression model performed worst, whereas 1 indicate that the model performed best over the unseen data samples. The R^2 is calculated using equation (10).

$$R^2 Score = \frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2} \tag{10}$$

where

$$\bar{Y} = \frac{1}{n} \sum_{i=1}^{n} Y_i \tag{11}$$

The following Table 10 summarizes the performance analysis of the implemented ML models. It is evident that the DNN model with optimized hyperparameters performed accurately and efficiently while predicting the future appointment scheduling daily requests of the veterinary patients for veterinary clinic management. The prediction error of the DNN with optimized hyperparameter is significantly low as compared to SVR.

It is also evident that the DNN model with optimized hyperparameters performed significantly better in terms of R2 score as compared to an SVR model. The R2 score of the proposed DNN model with optimized set of hyperparameters is 0.968 whereas the R2 score of the traditional DNN and SVR is 0.805, 0.949. Based on the prediction results, it is observed that the proposed DNN with optimized hyperparameters produced significantly better performance in order to predict appointments scheduling requests of the veterinary patients using time series and other veterinary clinic data, which is important for veterinary management to devise better future business plans and decisions in order to gain market advantages and provide QoS to the veterinary patients.

TABLE 10. Performance evaluation of the implemented regression models using time series and other veterinary data features.

Proposed Models	MAE	RMSE	R2 Score
DNN-100	7.496	9.166	0.910
DNN-200	6.314	7.735	0.936
DNN-300	5.617	6.887	0.949
SVR	11.01	13.526	0.805
Proposed DNN based on Optimized Hyperparameters	**4.1**	**5.409**	**0.968**

TABLE 11. Performance evaluation and comparison of the proposed MD-LSTM with traditional deep learning models.

Proposed Models	MAE	RMSE	R2 Score
RNN	6.315	7.735	0.935
LSTM	4.828	5.922	0.963
BD-LSTM	4.121	5.290	0.97
Proposed MD-LSTM	**3.366**	**4.445**	**0.979**

Table 11 demonstrate the performance evaluation and comparison results of the proposed MD-LSTM with traditional DL models, such as RNN, LSTM, and BD-LSTM. It can be seen that the proposed MD-LSTM model achieved the most promising and significant prediction results as compare to RNN, LSTM, and BD-LSTM. The performance of the proposed MD-LSTM in terms of R2 score is 0.979, whereas the R2 score of RNN, LSTM, and BD-LSTM is 0.935, 0.963, and 0.97, respectively. The prediction error of the proposed MD-LSTM is low as compared to RNN. The performance of proposed MD-LSTM in terms of MAE and RMSE is 3.366 and 4.445, respectively. While, the prediction error of RNN, LSTM, BD-LSTM in terms of MAE and RMSE is 6.315, 4.828, 4.121 and 7.735, 5.922, 5.290, respectively. The time series prediction results reveal that the proposed MD-LSTM produced the most promising results as compared to the traditional DL approaches, which can help veterinary management to formulate future business decisions effectively.

The performance analysis results reveal that the proposed DNN based on an optimized set of hyperparameters and MD-LSTM produced accurate prediction results as compared to the traditional ML models. The proposed DNN model is effective to predict the frequency of the appointments scheduling requests using time series and other veterinary clinic data. The performance of the proposed DNN model in terms of R2 score is 0.968, which is significantly high as compared to the traditional DNN and SVR. Similarly, our

TABLE 12. Comparative analysis of the proposed blockchain-based RIVIMS.

System Name	Crypto. Mechanism	Smart Contract	Consensus Protocol	Consensus Determination	Efficiency	Blockchain Network	Functionality
MEDIBLOC [26]	Yes	Yes	DPoS	All-Nodes	Low	Permissionless	EMR management
MEDREC [27]	Yes	Yes	PoW	All-Nodes	Low	Permissionless	EMR management
MediLedger [28]	No	Yes	PoA	Single-Organization	High	Permissioned	Drug management
DSCMR [30]	No	Yes	-	Arbitrary-Nodes	High	Permissioned	Drug management and recommendation
CAS [33]	Yes	Yes	PoA	Single-Organization	High	Permissioned	EMR management
FHIRChain [36]	Yes	Yes	PoS	Single-Organization	High	Permissioned	EMR management
[37]	No	Yes	PBFT	Selected-Nodes	High	Permissioned	EMR management
[38]	No	Yes	PBFT	Selected-Nodes	High	Permissioned	EMR management
Proposed RIVIMS	**No**	**Yes**	**PBFT and RAFT**	**Arbitrary-Nodes**	**High**	**Permissioned**	**RIVIMS including appointment scheduling, medicine supply chain, billing, etc. , smart contract enabled data and predictive analytics**

proposed MD-LSTM model produced the most promising prediction results using time series data to predict the frequency of appointments scheduling requests. The proposed MD-LSTM model improved the prediction performance and outperformed other traditional DL models, such as RNN, LSTM, and BD-LSTM.

VIII. DISCUSSION

This section presents a comparative analysis of the proposed blockchain-based RIVIMS with state-of-art-techniques. The proposed work carried a benchmark study in order to demonstrate the effectiveness, robustness, and capabilities of the proposed blockchain-based RIVIMS. Table 12 summarizes the evaluation results of the comparative analysis. In our proposed work, we considered only those evaluation factors that affect the overall performance of the blockchain-based systems. The following essential evaluation factors are considered, such as cryptocurrency mechanism, smart contract, consensus protocol, consensus determination, efficiency, type of blockchain network, and the main functionalities of the system. These evaluation factors are used to imply the significance and uniqueness of blockchain-based developed systems. The existing blockchain-based systems, such as MEDIBLOC [26], MEDREC [27], and Healthcoin [32] are developed based on permissionless network, that requires to build consensus mechanisms among all participants, which significantly increase the requirement of energy consumption of the entire network. Furthermore, these systems used cryptocurrency algorithms to perform costly mining, which also increases power computation requirements. In contrast, our proposed RIVIMS is developed based on a permissioned chain of the network, which increases the efficiency and reduces the overall overhead of the entire blockchain network. Some of the existing systems are built based on the permissioned networks, but these systems only focused on EMR management to store personal health medical records data of the patients. However, our proposed RIVIMS is first attempt to store medical records of veterinary clinic patients along with following functionalities, such as appointment scheduling, data analytics, medicine supply chain, billing, which are feasible to the real-world environment. The proposed blockchain-based RIVIMS is a lightweight platform because the client application communicates with blockchain systems through RESTful API to explore the significant services of blockchain technology. Other existing models, such as MediLedger [28], and DSCMR [30] are also developed based on the permissioned chain of the network. However, these systems are used to store drug supply records in a secured and transparent ledger. Moreover, all these existing studies, such as MediLedger [28], DSCMR [30], CAS [33], FHIRChain [36], and models presented in [37], [38] are developed based on permissioned chain of the network to facilitate the healthcare industry related to human beings. Whereas, our proposed work is very first attempt to uses permissioned chain of the network to facilitate veterinary clinic management system in order to store and share veterinary clinic data between veterinary doctors, patients, and other veterinary professionals securely and transparently. Furthermore, our work utilizes DM techniques to investigate appointments scheduling data of the veterinary clinic to unearth hidden insights and useful knowledge. Finally, the ML-based predictive analytics model is developed based on discovered knowledge and integrates predictive analytics module with developed blockchain network to predict the future frequency of the appointments scheduling requests of the veterinary patients on a daily basis. The predictive analytics module helps veterinary clinic management to plan business strategies and drive better future decisions to gain significant market value over their competitors. Moreover, our proposed RIVIMS is based on permissioned blockchain network with low latency, high throughput, user-friendly interface, and ML-based predictive analytics module to predict the total number of future appointments scheduling requests.

IX. CONCLUSION AND FUTURE WORK

The provisioning of health quality services is vital for human as well as for animals. Blockchain technology has paved the revolution to transform the traditional healthcare industry into a secure, reliable, automated, and decentralized healthcare industry. This paper proposed a novel blockchain-based reliable and intelligent veterinary information system using smart contract and machine learning techniques. The proposed RIVIMS consists of two main modules; (i) a blockchain-based reliable and secure veterinary information management system, and (ii) a smart contract enabled data and predictive analytics modules using DM and ML techniques for predicting frequency of appointments scheduling requests. Firstly, a secure and reliable blockchain-based platform is developed using Hyperledger Fabric, which used to keeps track of the medical supply records, patients personal history records, data and predictive analytics appointments result in a decentralized way. It also supports doctors, patients, nurses, pharmacist, to store, access and share information related to personal medical history and veterinary information management in a secure and accountable way. The proposed RIVIMS is based on the permissioned blockchain network, where all nodes of the entire network required authentication to participate in a decentralized blockchain network. A proof of concept is developed based on PBFT and RAFT to addresses the fundamental issues of the traditional veterinary clinics, such as security, transparency, reliability, interoperability, accountability, to the name of few. Besides, a front-end application is developed, which allow users to interact with the blockchain platform through REST server APIs. The experimental results show that the proposed blockchain-based platform significantly increases the overall performance in terms of throughput and minimizes the latency of the proposed permissioned blockchain system. Secondly, a smart contract enabled data, and predictive analytics module is developed based on DM and ML techniques. The data analytics are used to process and analyze veterinary clinic data in order to unearth underlying patterns and useful knowledge, such as time series analysis of appointments scheduling, Illness type-based analysis of veterinary patients, treatment type-based analysis of veterinary patients, gender-based analysis, to name of the few. The predictive analytics aimed to develop a robust prediction model using optimized DNN and traditional ML models based on discovered time series and other veterinary clinic data features to predict an approximate number of appointments scheduling of the veterinary patients. The prediction model helps veterinary clinics to plan and organize resources effectively. The experimental results show that the proposed DNN model with optimized hyperparameters performed better in terms of MAE, RMSE, and R2 as compared to the traditional ML models, such as traditional DNN and SVR. The performance of the proposed DNN model in terms of MAE, RMSE, and R2 is 4.1, 5.409, and 0.968, respectively, which shows that the proposed DNN model produced accurate prediction results as compared to the traditional ML models. Furthermore, an MD-LSTM model is developed to predict appointment scheduling frequency based on the total number of appointments per day. The performance of the proposed model is evaluated and compared with other DL models, such as RNN, LSTM, and BD-LSTM. The performance of the proposed MD-LSTM in terms of R2 score is 0.979, which shows the effectiveness and robustness of the proposed regression model for time-series data. Based on the prediction results, veterinary clinic management formulate future business plans and resources, for example, future demands of medical supplies and planning of medical staff, etc. This will help the veterinary clinic to provide better services, retain loyal customers, and gain market advantages over their competitors. Besides, our proposed RIVIS results empirically demonstrate that blockchain technology and predictive analytics are the most promising solution to manage veterinary clinic resources reliably and intelligently.

The possible future directions of our proposed RIVIMS is to evaluate the interoperability of the developed platform with different ML frameworks. The performance of this work can be enhanced by considering different consensus algorithms and storage technologies to enhance the transaction processing rate and transaction query rate.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests regarding the publication of this paper.

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