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UbeHealth: A Personalized Ubiquitous Cloud and Edge-Enabled Networked Healthcare System for Smart Cities

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ABSTRACT Smart city advancements are driving massive transformations of healthcare, the largest global industry. The drivers include increasing demands for ubiquitous, preventive, and personalized healthcare, to be provided to the public at reduced risks and costs. Mobile cloud computing could potentially meet the future healthcare demands by enabling anytime, anywhere capture and analyses of patients' data. However, network latency, bandwidth, and reliability are among the many challenges hindering the realization of next-generation healthcare. This paper proposes a ubiquitous healthcare framework, UbeHealth, that leverages edge computing, deep learning, big data, high-performance computing (HPC), and the Internet of Things (IoT) to address the aforementioned challenges. The framework enables an enhanced network quality of service using its three main components and four layers. Deep learning, big data, and HPC are used to predict network traffic, which in turn are used by the Cloudlet and network layers to optimize data rates, data caching, and routing decisions. Application protocols of the traffic flows are classified, enabling the network layer to meet applications' communication requirements better and to detect malicious traffic and anomalous data. Clustering is used to identify the different kinds of data originating from the same application protocols. A proof of concept UbeHealth system has been developed based on the framework. A detailed literature review is used to capture the design requirements for the proposed system. The system is described in detail including the algorithmic implementation of the three components and four layers. Three widely used data sets are used to evaluate the UbeHealth system.

INDEX TERMS Cloudlets, deep learning, Internet of Things (IoT), mobile edge computing, mobile healthcare, preventive healthcare, traffic classification, traffic prediction, survey, fog computing, cloud computing, multimedia applications, smart cities.

I. INTRODUCTION

Healthcare is undergoing a fundamental, extensive, and far-reaching shift due to the technological developments in the past few years [1]. Advancements in Information and Communication Technologies (ICT) such as cloud computing [2], [3], Internet of Things (IoT) [4], [5], wireless communications (WSN, WBAN) [6], [7], big data [8], [9], robotics [10], [11], and artificial intelligence [12]–[14], have played a major role in changing the healthcare landscape. Advances in mobile and wireless communication technologies (4G/5G) have provided us anywhere, anytime connectivity, and this has given birth to new healthcare paradigms and services.

Smart cities are considered a major driver for the transformation of healthcare and many other industries [15], [16]. This is due to the fact that smart cities are driven by, or involve, integration of multiple city systems such as transport, healthcare, and operations research [17]–[20], with the aim to provide its citizens a high quality of life. See [21], for instance, for motivations of smart cities and societies.

Delivering high quality healthcare to the citizens has been a prime challenge for all governments throughout the world due to the increasing health issues among the populations, and falling budgets, and this has been another major driver of the ongoing renewal of the healthcare industry.

Networked healthcare aims to deliver healthcare services without any geographical or temporal constraints. It is supposed to provide anytime anywhere services regardless of the location of patients and without any constraints on patients' mobility. Networked healthcare enables remote care for the patients with chronic and lifestyle diseases requiring constant monitoring such as diabetes, heart disease, arthritis, and lupus [22], [23]. Networked mobile healthcare systems have evolved depending upon the advancements in communication technologies progressing through 2G, 3G, WLAN, 4G and recently 5G networks. Networked healthcare faces a great deal of networking challenges including reliability, service availability, dearth of radio resources, communication delay, energy consumption, and network congestion.

Another major technology that has influenced networked healthcare is cloud computing, which enables anytime anywhere access to the data stored in a cloud. This signifies the ubiquitous and on-demand access to computational, storage, and network resources from a large group of resources via resource virtualization [24]. The users can lease required resources and are billed according to the resources used. This apparent infinite on-demand resource availability has resulted in the provision of infrastructure, platform, and software as services [25]. Cloud computing can considerably reduce the cost of creating a networked healthcare system and efficiently use the resources provided by the cloud. The need for convenient computational power, storage, and networking resources without large operational and maintained costs has led to the adoption of cloud computing for networked healthcare [26]. Easy integration of IoTs with cloud is also another factor that has driven cloud computing forward [21], [27].

Mobile devices are vital in real-time monitoring of patients that (geographically) move around a networked healthcare environment. The traditional cloud architecture did not have provision to accommodate mobility of devices. Hence, a new architecture was introduced called Mobile Cloud Computing (MCC) [28], which enables the mobility of patients without restrictions in availing the medical services. User mobile devices are used as an extra layer of the cloud medical cloud networks to provide unrestricted service to the user. MCC healthcare applications monitor the vitals of a patient in real time, as well as several other activities of patients, in order, for instance, to calculate the calories burnt [29], [30]. The real time data captured by the sensors and IoT devices is analyzed at the central cloud. The user can view the data and the results of these analyses on the various interfaces, e.g. on mobile devices, provided by the healthcare service provider. A survey on the requirements and challenges of MCC can be found in [31].

MCC has a number of advantages: (1) it enables unlimited usage of resources for mobile devices without any energy or memory constraints [32], (2) A centralized resource management results in lower costs as it is easier to maintain and operate without any overheads, and (3) It supports multiple device platforms since the main computation and storage is done in the cloud. However, when it comes to real-time monitoring and analysis required by the mobile applications within a networked healthcare cloud environment, it inevitably suffers from poor performance due to the typical geographic distances between the mobile devices and the backend clouds. Therefore, performance issues such as high latency and bandwidth limitations restrain the use of low-latency or high-bandwidth multimedia healthcare applications using traditional cloud or MCC [26], [33]. To alleviate these issues, a variation of MCC called Mobile Edge Computing (MEC) was proposed for cloud based networked healthcare applications [34], [35].

Unlike MCC, MEC provides lower latencies, higher bandwidths, proximity to the patient, and location awareness. European 5G PPP (5G Infrastructure Public Private Partnership) has recognized MEC as a vital technology in enabling next generation 5G networks [36]. 5G networks are vital in improving the performance of future networked mobile healthcare applications. Three classes of MEC have been discussed in the literature, (1) Mobile Edge Computing, (2) Fog Computing, and (3) Cloudlets. Fog computing was introduced by Cisco [37] and has the capability to leverage future IoT healthcare applications [37]. Fog computing uses edge routers situated near the user to perform a majority of computations. Computations are transferred to the edge network near the user to reduce network latency. The major difference between edge and fog computing is that fog computing identifies itself more in an IoT perspective [38]. Fog and edge computing may also differ in the specific location within the network where the functionality of these technologies are placed.

Fog computing has a number of challenges that need addressing such as network security, authentication, resource management, and privacy. A recent class of edge architecture is known as cloudlets, developed at Carnegie Mellon University [39]. Cloudlets are data centers in a box and can be easily deployed. Cloudlets improve the latency and bandwidth of the network. Healthcare applications involving real-time video streaming, virtual and augmented reality, and content delivery shall greatly benefit from the use of cloudlets. Cloudlets improve the quality of service (QoS) of a networked healthcare system by reducing the latency, improving the capacity, improving the connectivity, and fault tolerance of the network. We will see later that cloudlets that are used in our framework are effective in reducing network latency and energy consumption [40]. The cloudlet architecture is discussed in detail in Section II.

Network traffic modeling and analysis play a vital role in understanding and optimizing network traffic performance [41]. Prediction of future network traffic, based on the historical network traffic is important for maintaining the QoS of a networked healthcare system. Measurement based network control enables us to predict the required bandwidth, probable latency, and jitter in the network [42]. Higher prediction accuracy is required for achieving the optimal utilization of the network resources. Various time series models such as ARIMA, ARMA, and MMPP models have been used in various studies to predict general network traffic [43]. For instance, the distance learning framework UTiLearn [21] has a component that enhances the network quality of service of the UTiLearn teaching and learning system using AI based prediction. However, modeling and analysis of networked healthcare systems from QoS perspectives is sparse in the literature. We will see later in this paper that deep learning based traffic prediction will help in regulating networks and enhancing QoS.

Similarly, network traffic classification is another fundamental aspect to comprehend and enhance network QoS. These classification techniques prioritize the applications when the availability of the bandwidth is limited [44]. Traffic classification also helps in identifying the various protocols and applications passing through the network and can enhance the security by identifying and blocking malicious packages. Three different kinds of classification techniques exist in the literature: (1) port based, (2) payload based, and (3) statistics based. Port-based techniques are ineffective due to the usage of a standard port by multiple applications and protocols. Due to the expansion in protocols, a large number of applications either share the same port or do not use the standard port. The payload based techniques cannot be used if the traffic is encrypted. Healthcare data of the patients are highly confidential and are generally encrypted hence analyzing the payload is not an option. Moreover, it might breach the confidentiality of the patient. We will use classification to improve network QoS and security.

This paper proposes a ubiquitous healthcare framework, UbeHealth, that leverages edge computing, deep learning, big data, high-performance computing (HPC), and the Internet of Things (IoT), to address the challenges that we have discussed earlier in this section. The letters "Ub" in UbeHealth represent the networked and ubiquitous nature of the proposed framework. The next letter "e" represents "edge-enablement". The next word "Health" represents health and healthcare.

The particular focus of this paper is at the network layer. We address the networking challenges such as latency, bandwidth, energy consumption and other QoS parameters faced by networked healthcare systems. The framework enables an enhanced network quality of service using its four layers (Mobile, Cloudlet, Network, and Cloud layers) and three components.

The Network Traffic Analysis and Prediction (DLNTAP) Component uses deep learning, big data, and HPC technologies to predict network traffic for the future. The Cloudlets and the network layers use the predicted traffic to optimize data rates, data caching and routing decisions. The Deep Learning Network Traffic Classification (DLNTC) Component is responsible for classifying the application protocols of the traffic flows. This enables the Network Layer to better meet the communication requirements of applications in order to maintain a high QoS and to detect malicious traffic and anomalous data. The Flow Clustering and Analysis (FCA) Component clusters the data to identify the different kinds of data originating from the same application protocols. IoT forms a part of the digital infrastructure in our proposed framework and is required to collect and monitor the patient's biomedical signals and activity for enabling preventive healthcare. See Section V for further details on the framework components and layers.

We develop a proof of concept UbeHealth system based on the proposed framework. A detailed literature review is used to capture the design requirements for the proposed system. The system is described in detail including the algorithmic implementation of the three components and four layers. A nationwide networked healthcare system case study and three widely used datasets are used to evaluate the UbeHealth system, demonstrating promising results including a 50% reduction in latency. To the best of our knowledge, this is the first work that extensively addresses the various network-related issues in next-generation healthcare systems using adaptive deep learning and data mining techniques to enhance QoS.

The rest of this paper is organized as follows. Section II gives a background on the main technologies used in this work. A review of the related literature is given in III. Section IV identifies the requirements for, and the challenges facing the networked healthcare systems. Section V discusses the proposed network framework that integrates cloudlets, deep learning based traffic prediction system, and DL based traffic classification system. An evaluation of the various components of the proposed framework is provided in Section VI. The entire proposed framework is evaluated in Section VII. Section VIII concludes the article.

II. BACKGROUND

This section briefly introduces the technologies related to this work.

A. CLOUDLETS

Cloudlets were introduced by Satyanarayanan *et al.* [39] for alleviating network issues such as latency and jitter. It is a mobile edge based technology and can be regarded as an extension of the central cloud. It is technically a "data center in a box," which is self-managing, simple to deploy & integrate to Wi-Fi access points or mobile base stations. Cloudlets are highly energy efficient. Cloudlet mainly consists of cache copies of data available elsewhere and hence destruction of cloudlets is not calamitous.

It has a three-tier architecture [39], consisting of (1) Devices, (2) Cloudlets, and (3) Cloud. WiFi access points and mobile base stations can be used to deploy the cloudlets [45]. Multimedia healthcare applications require low network latencies hence the use of cloudlets will enable this. Introduction of 5G base stations along with cloudlets

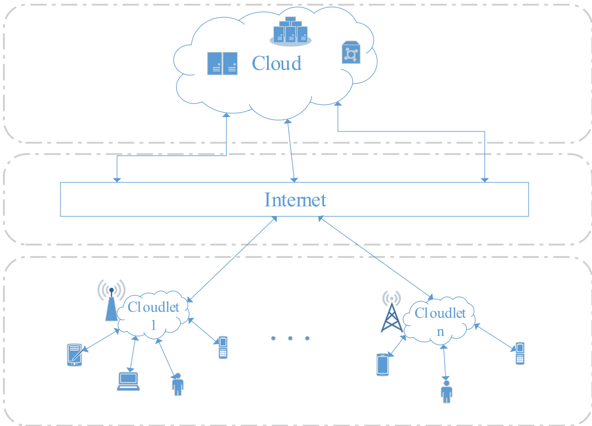


FIGURE 1. The architecture of cloudlets.

will reduce the latency less than 1 ms [46]. The cloudlets will cooperate and communicate with each other to recover from faults as well as meet user demands [47]. A detailed discussion on the mobile edge can be found in [48]. A discussion on mobile cloud computing model and big data analysis for healthcare applications can be seen in [49]. Cloudlets enable reduced latency and improved privacy, energy efficiency, bandwidth, scalability, and reliability.

B. DEEP NEURAL NETWORKS (DNN)

Deep Learning (DL) can learn various representations of data with multiple levels of abstraction with the help of computational models. These computational models consist of multiple processing layers for learning and recognition of these representations. Deep learning discovers complex structures in large data sets by using the backpropagation algorithm to indicate how a machine should change its internal parameters that are used to compute the representation in each layer from the representation in the previous layer. A considerable amount of skill and domain knowledge is required for the design and selection of features. A major advantage of deep learning is that it can discover complex features in between the layers. A thorough discussion of deep learning is covered in [50]–[52].

In this work, we use two kinds of Deep Learning Architecture, (1) Multi-Layer Perceptron (MLP), and (2) Recurrent Neural Network (RNN), more specifically Long Short-Term Memory (LSTM). These are discussed in the subsection below.

1) MULTI LAYER PERCEPTRONS (MLP)

Multi-Layer Perceptrons (MLP) is a type of deep neural network which consists of neurons connected to form an acyclic graph. The neurons are generally arranged in a number of layers. Full connections exist between the layers of the MLP. The output of a neuron in a layer is passed as input to the neurons in the next layer. An MLP should have at least three layers of hidden layers to be classified as a deep neural network. All MLPs have an input layer, an output layer, and multiple hidden layers. The higher the number of the hidden layer the deeper is the network. Each neuron uses various non-linear activation functions to enable learning of features. Fig. 2 illustrates a simple MLP. The common activation functions are sigmoid, tanh, ReLU, Leaky ReLU, and Maxout.

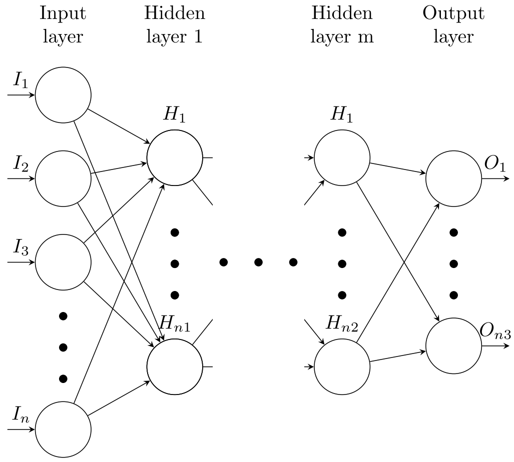


FIGURE 2. The architecture of a Multi Layer Perceptron.

The process of finding the activations is called as the Forward Propagation. After forward propagation, the loss is computed, and the loss function is optimized, which is also known as Backward Propagation.

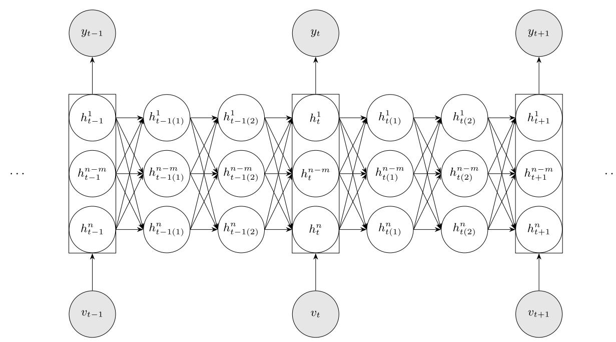


FIGURE 3. The architecture of a recurrent neural network.

2) RECURRENT NEURAL NETWORKS (RNN)

Unlike MLP, RNN is a type of artificial deep neural network in which the connected neurons form a directed cyclic graph, which enables RNN to have a dynamic temporal behavior. An arbitrary sequence of inputs can be processed by the RNN using its internal memory. RNNs show excellent performance in predicting time series tasks [53]. In RNN, the hidden layers of one neural network are connected to the hidden layers of the next neural network in time sequence, i.e., the current state as well the previous state is taken into account. Since RNN is trained with backpropagation through time, it can be considered as a feed-forward neural network that has been unfolded with multiple layers. This is illustrated in Fig. 3. Hence, this can result in issues such as vanishing or exploding gradients as it is passed back through many time steps during the back-propagation [54].

Long Short-term Memory (LSTM) was introduced to solve the vanishing gradient problem of vanilla RNN. It mainly consists of three layers, (1) Input layer, (2) Output layer, and (3) Recurrent hidden layer. The recurrent hidden layer consists of a memory block, which is the fundamental unit instead of neurons. Memory blocks consist of subnets that are recurrently connected. Each block consists of one or more memory cells and three gates [54]. The gates are: (1) Input gate, (2) Output gate, and (3) Forget gate. These gates are used to control the flow of information and enable the blocks to store and retain the information for larger periods of time to solve the vanishing gradient problem. Fig. 4 depicts the general architecture of an LSTM cell block.

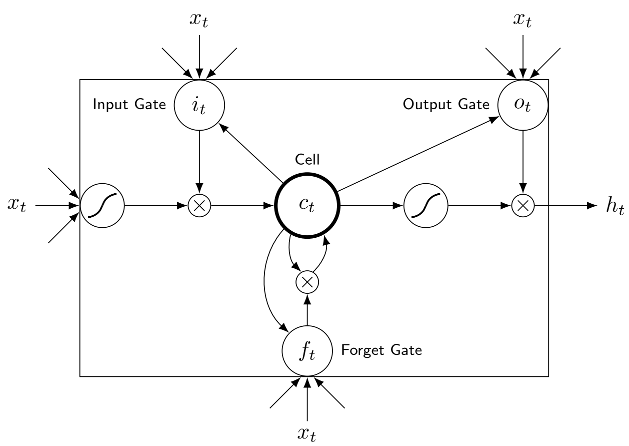


FIGURE 4. The architecture of a single long short-term memory cell block.

III. LITERATURE SURVEY

In this section, we survey the recent advances in ubiquitous healthcare. We discuss advances related to the use of IoT and Big data for mobile healthcare networks and state of the art regarding mobile cloud healthcare and mobile cloud healthcare at the edge. We also discuss recent healthcare applications that are a part of mobile healthcare. A detailed survey on the role of information and communication technologies in healthcare can be found in [55].

A. IoT AND BIG DATA BASED MOBILE HEALTHCARE

Fast-paced developments in the Internet of Things (IoT) and big data has resulted in new opportunities in healthcare such as wearable sensors, personalized e-health, and mobile healthcare. Discussions on the concerns, requirements, safety, and reliability of mobile healthcare networks based on cloud computing and IoT is discussed in [56]. Pag á n *et al.* [57] discuss an energy efficient workload balancing technique for mobile cloud computing for healthcare scenarios. They optimize the energy and balance the load of a Wireless Body Area network for predicting migraines in patients across Europe by developing a set of radio & network policies and load balancing policies.

IoTs are regularly used for monitoring the motion and activities of the patients. Real-time information about the activity, motion, and associated health parameters will enable the health practitioners to monitor the patients efficiently and respond to emergencies. Continuous monitoring of patients' physiological signals has an impact on the architecture of the network. Adame *et al.* [58] have developed a monitoring system with Wireless Sensor Networks (WSNs) and Radio Frequency Identification (RFIDs) named CUIDATS, which tracks the location and the health of the patients. Wearable technology is used to detect a patient's vitals such as blood pressure, temperature, heart rate, and movement. Ammae *et al.* [59] have developed another motion detector that detects motion during sleep with the help of WiFi signal fluctuations of the moving patients. Different signal values and associated movements are collected to train a linear regression model for prediction of movements. Another monitoring system using WSNs have been developed in [60]. The signals from multiple patients are collected using sensors and are sent to the base station for monitoring and processing. Mora *et al.* [61] propose an IoT based distributed framework for monitoring the medical signals for human activities involving physical efforts. They use off-the-shelf devices inside existing Wireless Body Area Networks (WBAN) of the patient. They use chest strap sensors and wearable sensors to monitor the health of football players in real time. The communication between the sensors uses Bluetooth, whereas communication with remote devices takes place through wireless access points. The information for further processing is sent through LAN.

LPWAN (Low Power Wide Area Network) is a set of protocols and technologies that belongs to long-range communication standard and fulfills the communication requirements for IoT applications. Unlike traditional IoT communication protocols such as Bluetooth and WiFi which has communication range in orders of meters, LPWAN has a communication range in orders of kilometers which requires setting up of larger networks for efficient healthcare applications [62]. The significant advantage of LPWAN over other communication protocols are a longer lifetime of the sensor nodes, more extended communication range, and inexpensive hardware [63], [64]. Moreover, LPWAN protocols do not require to send more than a few bytes at a time and hence has been designed to support intermittent short bursts of data. The communication can be initiated by both the sensor or an external entity that wishes to communicate with the sensor. These features make LPWAN a suitable candidate for a large number of healthcare applications that do not require significant data rate and low latency [65]. Healthcare use cases such as general monitoring of the patient's vitals and periodic updates and rehabilitation where updates are only required infrequently (once a day) are good examples of LPWAN scenarios. The lower power consumption ensures that the medical sensors would operate for a longer time without recharging or changing of batteries. Low power, long-range communications is achieved at the cost of higher latency and lower bit-rates. Hence, LPWAN is not suitable for safety-critical healthcare applications that require a latency between

1-10 ms [65]. The primary well-established standards for LPWAN include LoRa, LoRaWAN, Sigfox, and NB-IOT. Other standards proposed by various researchers can be found in [62], [65], and [66].

Petäjäjärvi et al [63], [67] evaluates the performance of the LPWAN technology, LoRa, employing real-life measurements for remote health monitoring. Buyukakkaslar *et al.* [68] evaluate the performance of LoRaWAN as a communication protocol for electronic healthcare systems. Catherwood *et al.* [69] designed an IoT based bio-fluid analyzer consisting of an electronic reader for biomedical strip-based diagnostics system for personalized monitoring with LoRa/Bluetooth communication technology. A detailed overview of LPWAN technology, the challenges, and opportunities for implementing LPWAN for smart healthcare can be seen in [62].

A survey on the use of IoT for healthcare can be found in [70]. They discuss various architectures, platforms, and applications of healthcare using IoT. They also propose a security model for the protection of classified patient data from threats including communication and network attacks. A survey on the use of WSNs for healthcare can be seen in [6]. This survey discusses the design issues and challenges of using WSN for healthcare applications. Moreover, they review various healthcare applications and prototypes that exist in the literature.

Many works that discuss the use and role of big data in healthcare have appeared recently. See, for instance, [49].

B. CLOUDS, CLOUDLETS, FOG AND EDGE COMPUTING IN MOBILE HEALTHCARE

A discussion regarding the use of mobile cloud computing for healthcare services can be found in [71]. Hassan *et al.* [72] propose a cloud-based healthcare data sharing network that combines both the cloud and wireless body area network. They combine Zigbee with TCP/IP to enable a reliable interaction. They use Content-Centric Networking (CNN) [73] to enable an adaptive flow of data. They aim to improve the lifetime and efficiency of the proposed network.

Hoang and Chen [74] propose an infrastructure for mobile cloud named Mobile Cloud for Assistive Healthcare (MoCAsH). The proposed healthcare cloud consists of mobile sensing, context-aware middlewares, deployment of agents, and protocol collaboration for resource utilization and sharing. Federated P2P clouds are used to enhance the security and privacy of the patients. Miah *et al.* [75] propose a cloud-based network for healthcare consultancy for remote communities in developing countries which enable interaction between patients, doctors, and healthcare practitioners.

Preventive mobile healthcare requires high data rate and very low latencies for optimal functioning in order to fully benefit from highly interactive, bandwidth-hungry technologies including virtual reality, multimedia applications, and the Internet of Things (IoT). Traditional mobile communication and cloud infrastructures which are base station centric cannot easily cope with the requirements of mobile healthcare infrastructure. Some of the major challenges include difficulty in offloading large data, high latency, redundant transmission of data, and service availability. This has resulted in the development of edge networks. As mentioned in Section I, three types of edge networks have been developed, mobile edge computing (MEC), fog computing, and cloudlets.

Rahmani *et al.* [76] discuss the usage of a gateway based fog architecture to enable local storing and processing of data for a healthcare network using internet of things. The authors try to address issues such as reliability, energy consumption, and scalability to improve the performance of healthcare networks. A prototype of an early warning health monitoring system is developed to analyze the performance of the proposed fog based gateway. Farahani *et al.* [77] discuss the challenges faced in mobile cloud architectures and propose the use of fog computing to enable a faster network for healthcare applications. Negash *et al.* [78] propose a healthcare architecture that uses fog computing layer. The proposed architecture consists of medical sensors, environmental sensors, and activity sensors at the first layer. The second layer is the fog layer which interacts with the sensors to store, compress, and transmit data. The third layer is the primary cloud server which processes and sends/receives a response to/from the fog layer. A discussion on mobile big data fogs and edge computing to enable smarter cities can be seen in [15].

Kraemer *et al.* [79] review and discuss the usage of fog computing in healthcare. They review different healthcare application use cases and determine the suitability of using fog computing for these applications. They list out the various number of applications and computing tasks in healthcare that can be improved using fog computing. They also discuss the privacy concerns related to cloud computing.

Real-time processing, sharing, and processing of big healthcare data require strong wireless and mobile communication infrastructure. For providing a good quality of service for the mobile end users, the resources need to be migrated to different cloudlets as the user moves from one area to another, which can be accomplished using VM migration. Islam *et al.* [80] propose a new VM migration model based on the ant colony optimization techniques for a mobile cloud computing based healthcare system in a smart city environment, improving the response time for the end user. The proposed model is based on both the user mobility as well as the resource utilization load of the cloudlets. Tawalbeh *et al.* [81] propose a master cloudlet based model for mobile cloud healthcare applications. A master cloudlet is utilized to connect other distributed cloudlets. The master cloudlet is connected directly to the central cloud and is in charge of the other cloudlets under it. The cloudlets and master cloudlets are only used if the user is in the range of the cloudlets, else the user is directly connected to the main cloud. The importance of mobile cloud computing in a networked healthcare is discussed in [49]. They discuss the use of cloudlets in mobile cloud computing infrastructure for healthcare big data applications. A review of the tools and technique for big data analysis is also discussed.

C. MULTIMEDIA HEALTHCARE APPLICATIONS

Mobile applications for preventive healthcare is rapidly improving and evolving. A large number of mobile healthcare applications have been developed by the research community with regards to chronic diseases [82], [83], diabetes [84], [85], cardiology [29], [86], [87], obesity [30], and mental health and behaviour [88].

Lv *et al.* [89] introduce two mobile healthcare applications that use Big Data for creating electronic medical records (EMR). The first application is for improving the user experience in oxygen chambers by using virtual glasses and immersive technology and the second application is voice interactive game for providing rehabilitation assistance to therapists.

Deep learning based applications have become a central part of mobile healthcare infrastructure. Deep learning enables prediction as well as detection of various chronic diseases. Deepr [90] is a healthcare application using convolution neural networks to determine unplanned readmission after discharge. This application analyzes the electronic medical records using convolutional neural networks determine the gap of admission to hospital due to various diseases. Doctor AI [91] uses the history of patients to determine the diagnosis and required medications in the next visit. Sathyanarayana *et al.* [92] discuss an application that can estimate the sleep quality from wearable device data with the help of deep learning. A detailed survey of various healthcare applications can be found in [22] and survey on healthcare applications that utilize deep learning can be found in [93].

D. PERFORMANCE MODELING AND QoS OF HEALTHCARE NETWORKS

Complex network analysis is an area of great significance. It uses many diverse methods and have found applications in many areas [94], [95]. Modeling and analysis of complex communication networks and applications is no exception. A great deal of studies exists that discuss and analyze the performance of healthcare applications over various networks [26], and distributed systems, such as computational grids [96], and computational clouds [26], [97]. The traffic on emerging networks that support healthcare systems would include many multimedia and analytics applications requiring a range of interaction frequencies, and communication latencies and bandwidths.

A study conducted to determine the requirements of healthcare applications measured the network performance between three hospitals in the Ontario region (Canada) [98]. Another such study can be seen in [26] where the end-to-end network performance between twelve hospitals in four cities (Birmingham, Washington D.C, Abaha, and Riyadh) is measured for requirement analysis. Both these studies use OPNET modeler to model HTTP, FTP, database, and email transactions to measure the network delay and queuing time for the network components. Quality of Service (QoS) is crucial for the transmission of real-time healthcare data across various networks. Modeling of multimedia services over (infrastructure and ad-hoc) wireless and hybrid networks is discussed in [99] and [100]. Moreover, they discuss modeling of multimedia services over Voice over IP (VoIP) protocol networks within metropolitan area networks in [101]. Mehmood *et al.* [102] and Mehmood and Alturki [103] have proposed a scalable provisioning and routing scheme for multimedia QoS in ad-hoc networks. They also propose a cross-layered QoS over ad-hoc networks for multimedia applications such as (audio, video, and text) [104]. Another work on QoS for multimedia communications over ad-hoc networks and wireless networks is discussed in [105]. Chung and Park [106] proposes a mobile healthcare network based on cloud computing with guaranteed Quality of service. They propose special mobile cloud services and a mobility cloud control software that manages the communication of the network. The proposed system uses the distributed-object group framework and uses a cluster based mobile object based distributed system for the development of the cloud platform. Eucalyptus API [107] is used by the proposed framework for providing user services to the end user.

IV. FUTURE HEALTHCARE SYSTEMS: MOTIVATIONS, CHALLENGES AND REQUIREMENTS

This section discusses the challenges faced in implementation of the mobile cloud-based healthcare systems from networking perspective. The requirements for implementing such a healthcare system are also discussed. The challenges and requirements are discussed both from global perspectives as well as specific to the Kingdom of Saudi Arabia (KSA).

A. NEED FOR MOBILE CLOUD HEALTHCARE IN KSA

Chronic diseases are recognized a predominant challenge to global health [108]. The world health organization in its report has noted that two-thirds of the worlds death occur due to non-communicable chronic ailments such as cardiovascular disease, cancers, diabetes, and respiratory diseases [109]. In KSA, due to increased life expectancy and less fertility rate the demographic composition has changed. By 2050, 20% of the population is predicted to be older adults [110]. A survey conducted by Saudi Ministry of Health (SMOH) reports the occurrence of the chronic diseases such as diabetes, asthma, ulcer, hypertension, and cancer in KSA as 27.3%, 9.7%, 8.9%, 71.3%, and 2% respectively [110]. More than quarter of the population was reported to be obese [111]. Increase in rapidly aging population and chronic diseases all around the world has burdened the traditional healthcare systems. Chronic diseases require frequent visits to the hospital for periodic checkups. The dearth of healthcare practitioners and nurses affects the care provided to the patients in traditional healthcare. Hence implementation of an information-centric mobile cloud-based healthcare system is necessary [112]. Such a network would enable remote monitoring of the patient's vitals, which leads to a ubiquitous, personal, preventive, reliable, and continuous healthcare to the patients. This would provide patients with economic healthcare as compared to the astronomical charges of traditional healthcare [113].

Pre-appointment administrative paperwork including measuring the vital signals, transferring files to different departments are usually done manually and hence wastes the time of the patient. Whereas, healthcare networks would enable remote monitoring which would free up both the healthcare practitioners as well as the patients. Integration with IoT will enable to get a holistic status of person's health with the help of sensors. Analysis of continuously captured biological parameters would help in predicting and preventing sickness or ailments such as cardiac arrests. Hence there is a need to converge home, hospital, and other sources of healthcare with the help of mobile computing networks, IoT, and other technologies specifically in KSA.

B. CHALLENGES AND REQUIREMENTS

In this subsection, we shall discuss the challenges as well as the requirements for mobile cloud healthcare applications that were identified from the literature.

1) LATENCY

The latency requirement varies with the nature of healthcare applications. It varies with the type of application and the context in which the application is being used. Some healthcare applications have stricter requirements than others. Some applications are tolerant to delays while others are not. For example, transmission of ECG signals can tolerate delays up to 2 to 4 seconds [114]. Whereas, real-time applications within the domains of multimedia telemedicine [115] and Tactile Internet [116] require a much lower delay. Multimedia applications in the context of remote diagnosis and surgery require interactive audio and video transmission. The latency for both audio and video should not exceed more than 300 ms [117], [118]. Live remote surgeries would require jitter less than 1 ms along with guaranteed network QoS [119]. Fluctuations in the QoS will result in the loss of lives. Hence these safety-critical applications demand a highly stable, reliable network with QoS.

2) BANDWIDTH

Mobile cloud health services require large transmission bandwidth for transmitting high-quality medical images (MRI, CT-Scan), video and audio for remote VoIP connections, and other biomedical signals that are captured from the patients. Depending upon the context of the usage sometimes high bitrates are required and at times lower bit rates are enough. The required bandwidth for body temperature sensor is just 2.4 bps [120]. A five lead ECG would require a bit rate around 200 kbps. The bit rates for physiological signals based on a number of factors such as the sampling frequency, number of leads being used and step size of analog to digital converter [121]. An EEG with 200 lead can take around 950 kbps. A VoIP based application would require at least 80 Kbps whereas high-resolution videos would require bit rates from 5 Mbps to 12 Mbps.

3) ENERGY EFFICIENCY

The rate of energy consumption of the mobile devices is a concern. Depletion of the battery will pause the monitoring, and the system will only resume once the batteries are replaced. Battery levels need to be constantly monitored so that it does not deplete during a surgery or other safety-critical process. The applications, as well as the network, needs to be optimized such that the mobile devices consume minimum energy [122]. A study on the relationship between power consumption and global positioning system (GPS) of mobile user devices can be found in [123].

4) RELIABILITY

Depending upon the application context the reliability of the network plays an important role. The repercussions of network failure range from minor disruption to major life-threatening scenarios. Hence, fault-tolerant techniques should be incorporated into the network to recover from any faults or errors instantaneously. Analysis of fault tolerant sensor networks can be seen in [124]. Furthermore, security also plays a major factor in facilitating reliable networks.

5) SECURITY

The patient's health records and other data are highly confidential [125]. Tampering or leakage of data caused by hacked infrastructure has severe repercussions due to which security in mobile healthcare network is of paramount importance. Since the network consists of a large number of devices, software, and healthcare applications, each running on different platforms with different device drivers, it can lead to multiple security vulnerabilities that have not yet been identified. These vulnerabilities need to be diagnosed and fixed. Data manipulation and hijacking IoT healthcare devices in the network may even be life threating. Hence security policies should be developed and maintained from the manufacturer of various devices, organizations developing the software, and regulators that check the standard and safety of the proposed mobile healthcare network [126].

V. UbeHealth: THE PROPOSED FRAMEWORK

In this section we introduce our proposed networking framework for mobile healthcare services, give an overview and present its algorithmic refinement. The proposed framework adaptively enhances the network performance and dynamically maintain Quality of Service(QoS) throughout for mobile healthcare applications, especially mobile multimedia applications which shall be fundamental to the next generation smart and intelligent preventive healthcare. Fig. 5 introduces the general layered overview of our proposed architecture and Fig. 6 illustrates the functional components of our proposed framework.

As observed in Fig. 5 the proposed architecture has four layers, (1) Mobile Layer, (2) Cloudlet layer, (3) Network

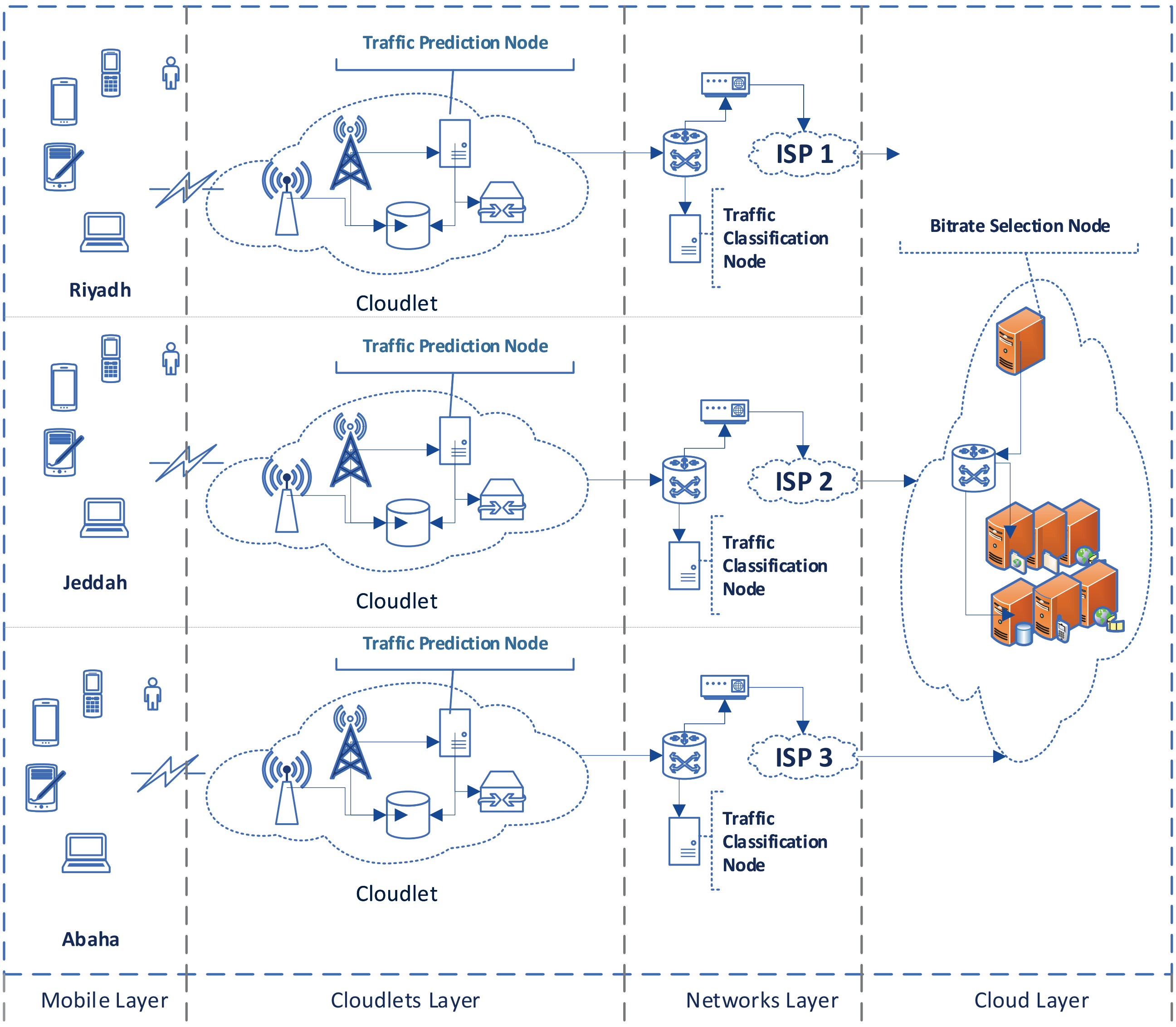


FIGURE 5. **The network and architectural overview of the proposed framework.**

layer, and (4) Cloud layer. Our proposed framework mainly consists of three major components which are distributed among these four layers (Fig. 6). The three major components are:

1) Deep Learning Network Traffic Analysis and Prediction (DLNTAP) Component
2) Deep Learning Network Traffic Classification (DLNTC) Component
3) Flow Clustering and Analysis (FCA) Component

The Mobile layer comprises of all mobile users (mostly doctors and healthcare practitioners) and devices at various places providing multimedia healthcare services such as health monitoring, disease monitoring, and remote supervision of surgery. Fig. 5, depicts users and devices from three different regions in the Kingdom of Saudi Arabia (KSA), namely Riyadh, Jeddah, and Abaha. Any mobile device or user that has network connectivity is included in this layer.

The second layer is the Cloudlet layer which hosts the cloudlet infrastructure. Each of these devices and users is connected with the local cloudlets that are nearest to them through access points or mobile networks. The Cloudlet layer contains the Network Traffic Analysis and Prediction (DLNTAP) Component. This component analyzes the current bi-directional traffic and predicts the network traffic for the future. Distributing this component among the cloudlets enhances the prediction since the prediction would be performed for the local network traffic, which results in higher QoS. Based on the predictions of DLNTAP the cloudlet regulates the data transmission rate. Since the prediction is performed after a time interval, the cloudlet adaptively adjusts the data rate to a suitable. The cloudlet layer also

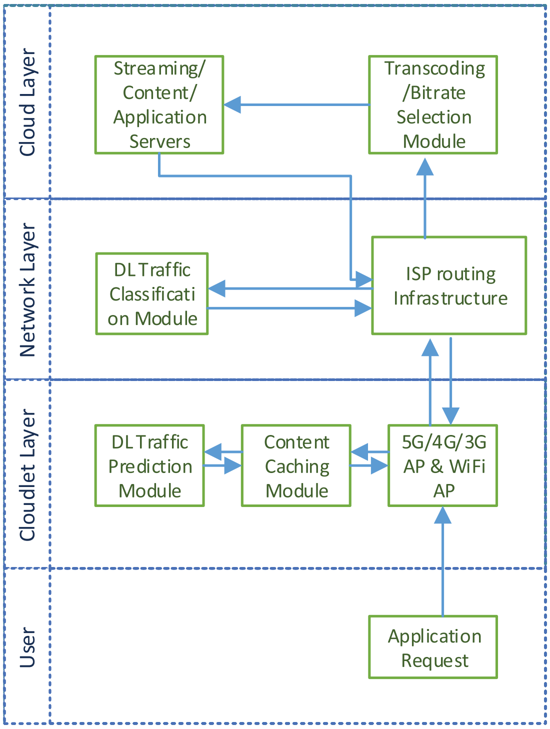


FIGURE 6. The functional architecture of the proposed scheme.

consists of a cache server which is used to cache frequently accessed data. Caching frequency is determined by the predictions from DLNTAP component. This enhances the QoS of the network. The predicted network traffic is also broadcasted to the components in the Network Layer so that they can make informed routing decisions.

The Network layer is responsible for data transmission between the Cloudlet layer and the Cloud Layer. It comprises various local networks connected to the primary Internet Service Provider (ISP) and the gateway. The Deep Learning Network Traffic Classification (DLNTC) Component is implemented in this layer at the ISP network. DLNTC is responsible for classifying the application protocols of the traffic flows. Detecting the application protocol enables the network to understand the application sending the data and adjust the network as per the requirements of the application to maintain the QoS of the network. Moreover, it enables the network to detect malicious traffic and anomalous data and protect the network. Flow Clustering and Analysis (FCA) Component clusters the data of a given application protocol to detect various communication signals, data, and anomalous packets. It helps us in determining the different kinds of data originating from the same application protocol. It is also connected a firewall that blocks unknown data packets.

The Cloud Layer consists of the central cloud infrastructure. The cloud layer stores and manages the data efficiently and process the data for various healthcare applications. The computing at the cloud level is handled by high-performance computers, massive scale accelerators such as GPUs and MICS, and mass storage servers are used for storing the high

Algorithm Main

Input: $T \leftarrow$ Network Traffic
Output: $q \leftarrow QoS$

go to `DLNTAP`
  if *DLSTM* not trained **then**
    feat← features of T
    feat_selected ← Determine from *feat*
    Train the DeepLSTM using *feat_selected*
  else
    Traffic_future← Predict using *feat_selected*
    Update the *data-rate* and *reqd_bandwidth* based on *Traffic_future*
    Update the caching rate and change caching policy at cloudlets
  end if
go to `DLNTC`
  if *DNN* not trained **then**
    feat← features of T
    feat_selected ← Determine from *feat*
    Label *feat_selected* with proper classes
    Train the DNN using *feat_selected*
  else
    app_protocol← Classify using *feat_selected*
    Pass the *app_protocol* to `FCA`
  end if
go to `FCA`
  Cluster *app_protocol* along with other instances of the same protocol using DBSCAN
  Determine if it is anomaly, data, or control signal.
  Pass decision to `Action Module`
go to `Action Module`
  if Decision == Anomaly **then**
    Block the traffic
    Add To blacklist
    Label and send to `DLNTC` for retraining
  else
    Based on `Action Module` decisions Allocate required bandwidth, Prioritize the traffic
    Label and send back response to `DLNTC` for retraining
  end if

FIGURE 7. The main algorithm of the proposed framework.

volume of data. Multimedia is stored in multimedia servers, and web pages are stored in web servers. Large computational infrastructure performs computation and responds to the user request. Distributed and parallel computational techniques have reduced the delay faced by the user. The Adaptive Content Delivery (ACD) module analyzes the traffic predictions and current traffic scenarios to select the appropriate content. For example, a video can be stored in different bit-rates and based on the future traffic predictions and current scenario the Content Delivery Server (CDN) decides whether to deliver a low bit-rate or high bit-rate multimedia content.

The main algorithm of the proposed framework is provided in Fig. 7 and summarizes the proposed framework.

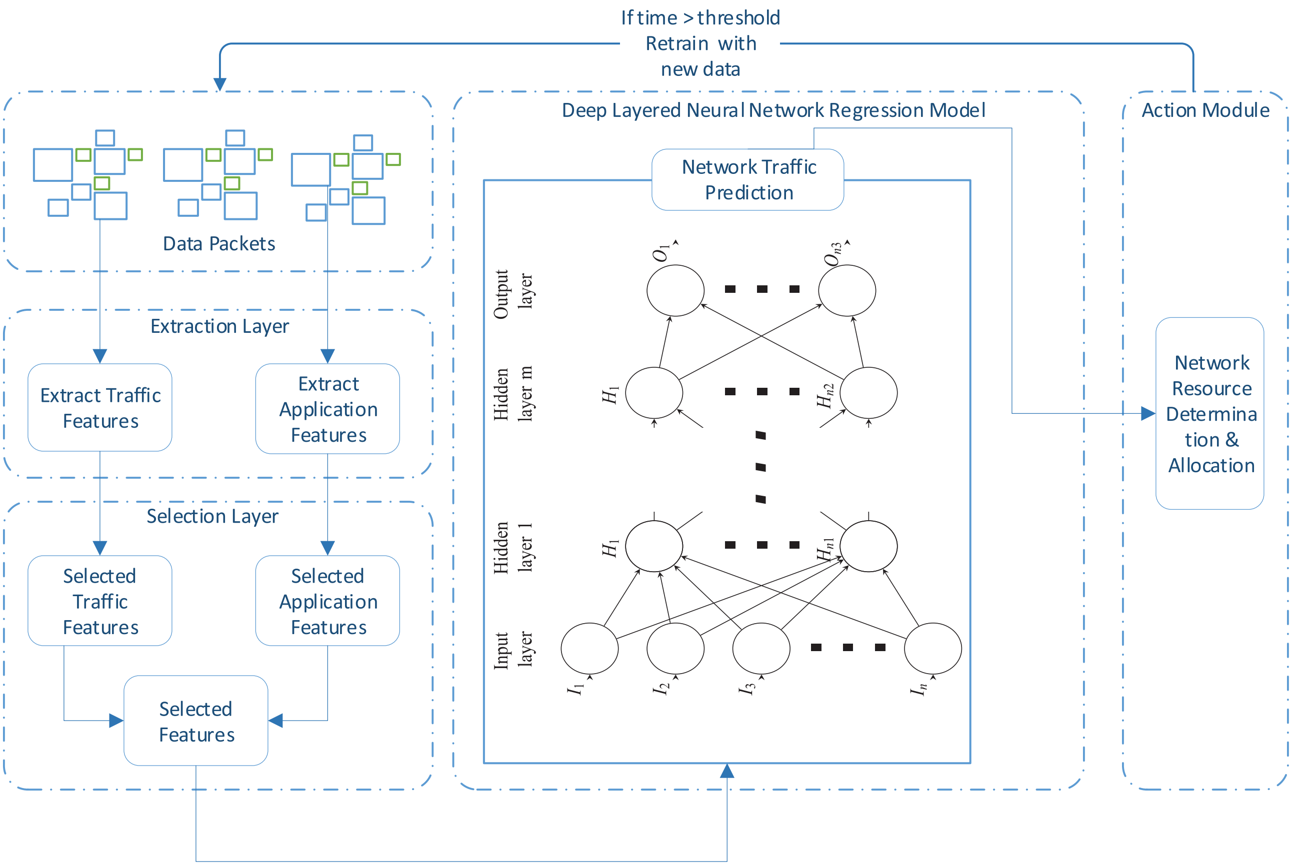


FIGURE 8. The architecture of deep learning network traffic analysis and Prediction (DLNTAP) Component in our proposed framework.

A. DEEP LEARNING NETWORK TRAFFIC ANALYSIS AND PREDICTION (DLNTAP) COMPONENT

With the development of IoT and mobile cloud networks for healthcare, short-term forecasting of network traffic has become of prime importance to reduce the delay and jitter and ensure Quality of Service. To enable this, we have implemented short-term traffic prediction component using Deep learning, specifically Stacked Long Short-Term Memory(LSTM), a variant of Recurrent Neural Network (RNN).

Network traffic prediction requires the capture of temporal and spatial change of network traffic. Unlike Feed forward Neural Network or RNN, LSTMs can capture long-term change with 10-15 mins of lag which was difficult in general RNNs [127]. The model makes predictions based on the current state and knowledge of the previous states.

Fig. 8 illustrates our Deep Learning Network Traffic Analysis and Prediction (DLNTAP) Component. The data packets pass through the extraction layer where both the traffic features and the application features are captured. Traffic features are measured as a time series. The extracted network features, as well as the application features, are further pruned by using dimensionality reduction (PCA) or feature by feature ranking techniques. The selected features are then used to train an LSTM network. After training, we obtain a model that can be used to forecast various network parameters.

We discuss the LSTM network architecture we used as well as the features selected later in Section VI. Once the trained model predicts the future traffic details for a given amount of time, the action module determines the necessary network resources to be allocated and selects appropriate data rates so that the quality of the network is maintained. After a threshold time period, the model is again retrained with new input from the current state to produce a newer accurate model to make predictions.

The algorithm for the Deep Learning Network Traffic Analysis and Prediction (DLNTAP) Component is given in Fig. 9. The selected traffic features are fed into the LSTM model for prediction if a trained model exist. If not the model is trained using the network features. Network features such as the duration of the flow (f_d), the bit-rate of the network (*bps*), the packet rate of the network (*pps*), and the number of bytes per packet (*Bpp*) are predicted. Based on the predicted values the network the traffic is prioritized, resources are allocated for different flows, and the cache policy at the cloudlets are set to improve the *QoS*.

We evaluate the performance of our DLNTAP component and the impact it has on network traffic later in Section. VI

Algorithm Deep Learning Network Traffic Analysis and Prediction (DLNTAP)

Input: $selected\_traffic_{feat}$
Output: $T_{pred} \leftarrow f_d, bps, pps, Bpp$

1: Capture and extract $selected\_traffic_{feat}$
2: **if** *DLSTM* != trained **then**
3: Train LSTM with $selected\_traffic_{feat}$
4: $model_{lstm} \leftarrow$ LSTM *Forward Pass* and *Backward Pass* to get the trained model
5: **else**
6: $T_{pred} \leftarrow model_{lstm}(selected\_traffic_{feat})$ {Predict using the trained model}
7: **end if**
8: **Based on** T_{pred} **:**
9: $Bw_{reqd} \leftarrow$ assign required network bandwidth
10: $Policy_{cache} \leftarrow$ set the cache policy at cloudlet
11: $Traffic_{prior} \leftarrow$ set traffic priority

FIGURE 9. The algorithm for the proposed DLNTAP component.

B. DEEP LEARNING NETWORK TRAFFIC CLASSIFICATION (DLNTC) COMPONENT

Traffic classification is fundamental for any network, especially mobile cloud networks for determining anomalies, for traffic prioritization over a limited bandwidth, to ensure Quality of Service (QoS) [128], [129]. Implementing proper security policies for network firewalls requires a proper understanding of the nature of the network traffic. Hence, we integrate a Deep Learning Network Traffic Classification (DLNTC) Component in our framework using Deep Feed-Forward Neural Networks.

Fig. 10 depicts our proposed DLNTC component along with the FCA component. The first row (two modules) of Fig. 10 illustrates the DLNTC component. Similar to DLNTAP, initially we measure the traffic features and extract application features. Using feature ranking techniques, we rank the extracted features to make the final selection. The selected traffic features are then labeled using the appropriate application protocols. The application protocol indicates the application which generated the packet. For e.g., It can be Youtube, Facebook, Skype, or just a simple SSL used for setting up the network. The Deep Neural Network is then trained using the labeled traffic features from healthcare applications. The trained classifier is then used to predict the application protocol of the incoming traffic. The predicted results are then passed to the Flow Clustering and Analysis (FCA) Component which shall be discussed in the next subsection. The FCA uses the results of the prediction for further analysis to take various actions that improve the QoS of the network.

The algorithm for the Deep Learning Network Traffic Classification (DLNTC) Component is given in Fig. 11

We evaluate the performance of our DLNTC component and the impact it has on network traffic later in Section. VI

C. FLOW CLUSTERING AND ANALYSIS (FCA) COMPONENT

Network traffic originating from a single application protocol will have more than one kind of traffic flow. For e.g., a flow that has been classified as Youtube by our classification module can either be a video streaming flow, browsing flows, or flows generated by redirections between various content servers of Google and Youtube [130], [131]. Hence we integrated Flow Clustering and Analysis (FCA) Component to cluster an analyze the traffic once the DLNTC component predicts the protocol application class.

Fig. 10 (DBSCAN module and action module) depicts the Flow Clustering and Analysis (FCA) Component. Once the DLNTC component classifies the traffic, the FCA component clusters all the traffic with the protocol classified by DLNTC to detect the actual use of the packets. Based on the analysis, the action module allocates the resources, schedules traffic, filters and block malicious traffic. After a certain threshold time, FCA component sends a signal to DLNTC component for retraining the classifier with the latest traffic. We use DBSCAN clustering technique to cluster the group of the application protocol.

The algorithm for the Flow Clustering and Analysis (FCA) Component is illustrated in Fig. 12

We evaluate the performance of our FCA component and the impact it has on network traffic later in Section. VI

VI. UbeHealth: EVALUATION OF THE SYSTEM COMPONENTS

We carried out a large number of experiments using real-world datasets to evaluate the performance of our proposed healthcare architecture, especially the DLNTAP and DLNTC components. In the following subsections, we present and discuss the experiments and the results.

A. DATASET

In this work, we use three real-world network traces for conducting our experiments. Table 1 illustrates some significant properties of these network traces. The three network traces are captured from three different locations of the world and hence are different regarding link type, capacity, and volume. Two of the datasets (ISPDSL-II and Waikato-VIII) is from the year 2013, and Wide-18 is from the year 2018. ISPDSL-II and Waikato-VIII are public traces provided by Waikato Internet Traffic Storage (WITS) Project [132], which is part of the WAND research group at the University of Waikato, Computer Science Department. ISPDSL-II contains entirely contiguous packet headers captured from a New Zealand ISP. This network trace was collected from a switch that relayed traffic to and from the core routers of the ISP. Hence this extensive network trace consists of packets from all the subscribers of the ISP. Waikato-VIII was captured at the border of the Waikato University Network, hence all traffic coming and leaving the university is included in this trace (This trace does not include the

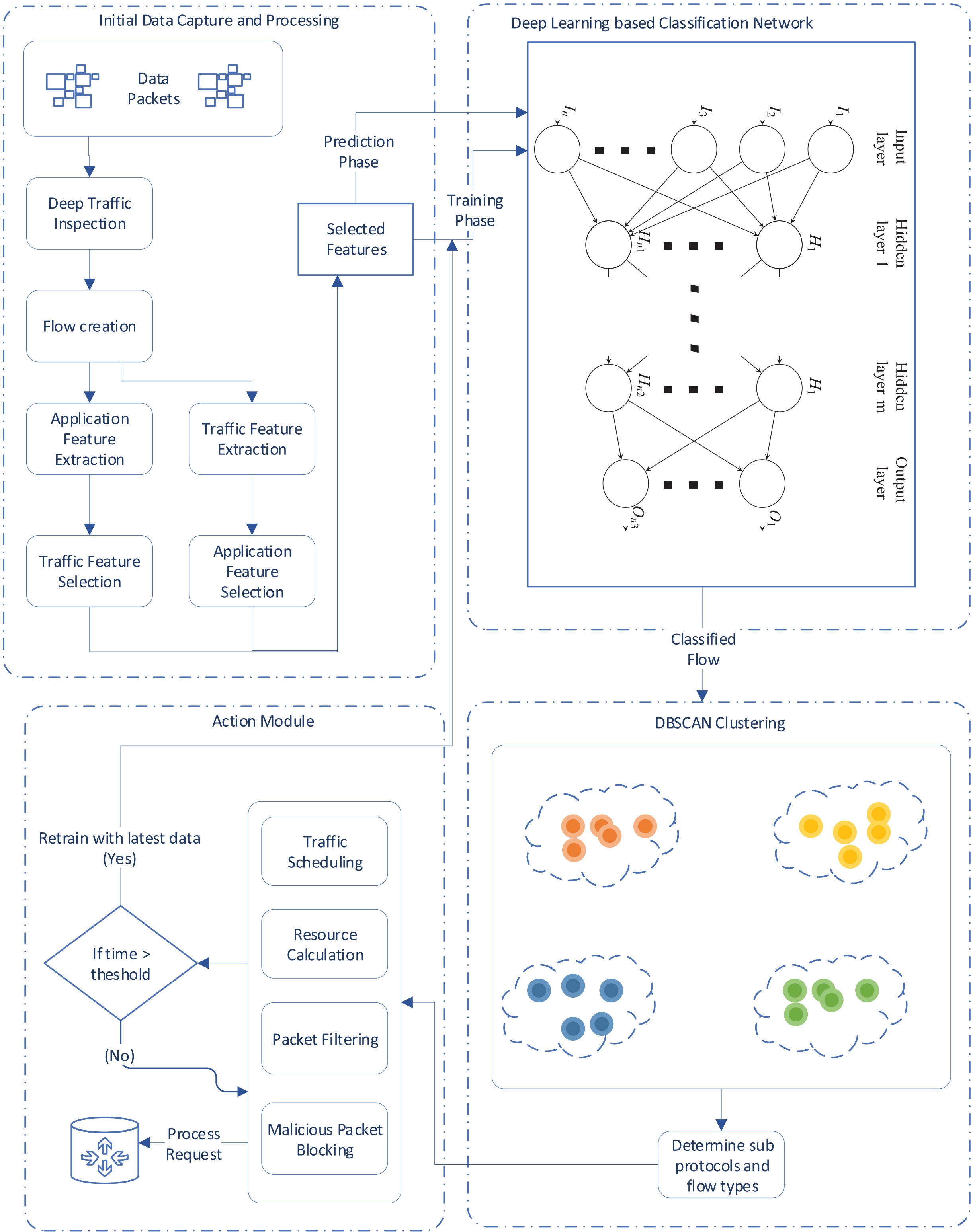


FIGURE 10. **The architecture of DLNTC Component and FCA Component in our proposed framework.**

internal University traffic). The WIDE-18 trace is provided by MAWI working group [133], which is a part of the WIDE project [134]. The WIDE-18 trace is captured at the transit link (1-Gbps Ethernet link) of WIDE to the upstream ISP. All IP addresses are scrambled for maintaining anonymity in the WIDE-18 trace set.

Algorithm Deep Learning Network Traffic Classification (DLNTC) Component

Input: $labeled\_traffic_{feat}$
Output: $App_{prot} \leftarrow$ Application protocol name

Capture and extract $selected\_traffic_{feat}$
Label the $selected\_traffic_{feat}$ based on previous knowledge
if DNN != trained **then**
  Train DNN with $selected\_traffic_{feat}$
  $classifier_{dnn} \leftarrow$ DNN *Forward Pass* and *Backward Pass* to get the trained classifier
else
  $App_{prot} \leftarrow classifier_{dnn}(selected\_traffic_{feat})$ {Classify using the trained classifier}
end if
if $App_{prot} == Known$ **then**
  Prioritize the packet and compute the resource required
  Assign resources
else
  Send App_{prot} to **`FCA`** component
end if

FIGURE 11. The algorithm for the proposed DLNTC component.

Algorithm Flow Clustering and Analysis (FCA) Component

Input: $\{App_{prot} : App_{prot} \in UniqueApp\ \}$
Output: $Anomaly_{flow}$, $Purpose_{flow}$

if cluster($UniqueApp$) not exist. **then**
  Find optimal ϵ parameter.
  $cluster \leftarrow$ DBSCAN($UniqueApp$, ϵ, $MinPts$)
  Label each cluster based on their functions
else
  $cluster \leftarrow$ DBSCAN($UniqueApp \cup App_{prot}$, ϵ, $MinPts$)
  $label \leftarrow$ The cluster of App_{prot}
end if
goto `Action Module:`
  if $label$ == Anomaly **then**
    Block the packet. Update the firewall rules.
  else if $label$ == (data |control msgs) **then**
    Prioritize flow, allocate bandwidth
  end if
  Send **`DLNTC`** $label$ and decisions for retraining.

FIGURE 12. The algorithm for the proposed FCA component.

To isolate the traffic and generate the labels (determine the protocol) for the trace set we developed a set of functions interfacing the open source Deep Packet Inspection tool, nDPI [135]. nDPI is based on OpenDPI (includes ntop extensions [136]) and libpcap [137] and can detect large number of application protocols. nDPI is frequently updated to improve the detection of the protocols. The nDPI based functions are used to generate the labels (application protocol names) for the all the three datasets. After labeling the trace set with application protocols, we convert all the traces to NetFlow records using the softflowd [138] tool. More than 150 different application protocols were present in the traces. The distribution of the major application protocol for the traces WIDE-18 and ISPDSL-II is illustrated in Fig. 13 and Fig. 14 respectively.

TABLE 1. Network traces used.

	ISPDSL-II	Waikato VIII	Wide-18
Date	10/21/2013	04/26/2013	02/03/2018
Duration	1 hour 20 mins	13 hours	30 mins
Link type	Backbone	Edge	Backbone
Volume	6.84 GB	6.036 GB	12.08 GB
Flows	10 million	12 million	57 million
Packets	93 million	84 million	183 million
Unique Protocols	157	72	115

The NetFlow format produced by softflowd will have only five network features, and can be enumerated as follows: (1) Source IP address, (2) Destination IP address, (3) Source Port, (4) Destination Port, and (5) Protocol of the flow. These five flow features are not quite enough to make good network quality predictions or traffic classification. Hence, for further identification and expansion of the NetFlow traffic features, we use the nfdump [139] utility to correlate bidirectional flows, as by default the transmitted and received flows are not associated with each other. Hence nfdump correlates the flows and determines other traffic flow details such as duration of the flow, the number of packets transmitted and received, the number of bits transferred per second, packet transfer rate, and bytes per packet for each flow. Table 2 illustrates the resultant flow features consisting of 17 features.

B. EVALUATION OF THE DLNTAP COMPONENT

The DLNTAP Component predicts the selected network traffic properties (Bpp, bps, pps, and duration) for the next fifteen minute. After prediction for the next fifteen minutes, new data is collected, and the model is retrained with the new data to produce a new prediction model. The module trains with the incoming data and performs predictions. In our work, the prediction module is implemented using LSTM Network, a kind of deep Recurrent Neural Network (RNN) as discussed in Section II and Section V. The LSTM implementation in this work is done using the Tensorflow framework [140]. We use two metrics for evaluating the performance of the regression, specifically Root Mean Square Error (RMSE) and Mean Absolute Error(MAE). They are calculated as in (1) and (2) respectively, where x_t indicates the actual measurement and y_t is the forecast. For the LSTM model, the data has been normalized between [0, 1].

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - x_t)^2}{n}} \tag{1}$$

$$MAE = \frac{\sum_{t=1}^{n}|x_t - y_t|}{n} \tag{2}$$

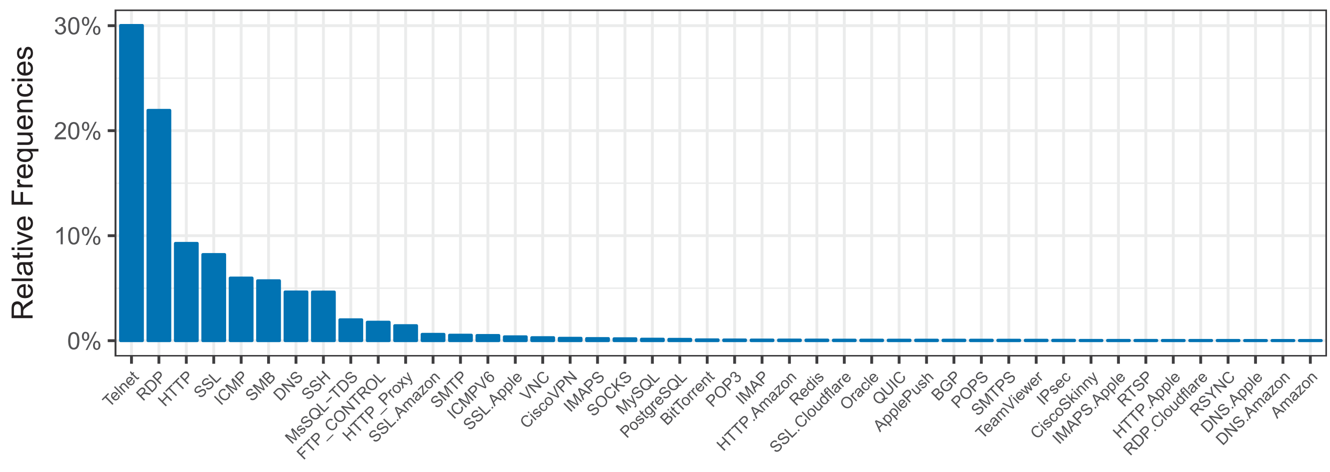


FIGURE 13. The distribution of the application protocols for the trace set WIDE-18.

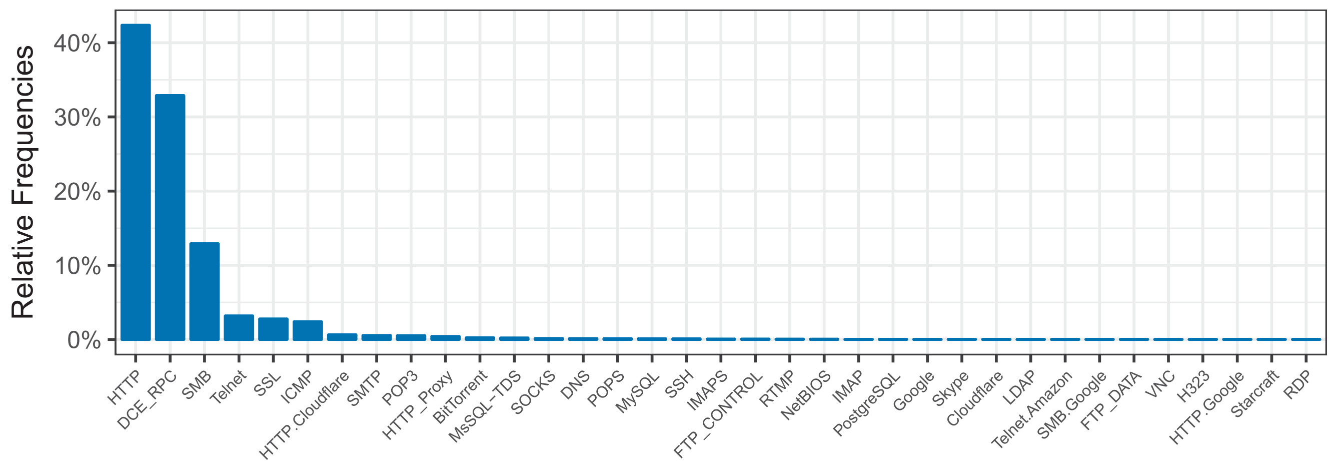


FIGURE 14. The distribution of the application protocols for the trace set ISPDSL-II.

TABLE 2. The extracted flow features from the trace set.

Features	Feature description
srcIP	The source IP addresses
dstIP	The destination IP addresses
srcPort	The source port numbers
dstPort	The destination port numbers
Protocol	The network protocol used to send data (TCP/UDP)
packets_rec	The number of packets received
packets_trans	The number of packets transmitted.
pps_rec	The number of packets per second received
pps_tran	The number of packets per second transmitted
bytes_rec	The number of bytes received
bytes_trans	The number of bytes transmitted
bps_rec	The number of bytes per second received
bps_trans	The number of bytes per second transmitted
time_rec	The duration of received flow
time_trans	The duration of transmitted flow
Bpp_rec	The number of bytes per packet received
Bpp_trans	The number of bytes per packet transmitted

Since there are more than 500 unique source and destination addresses we choose 500 memory units for the LSTM, which implies that there are 500 memory units in the spatial axis of the LSTM network. The designed model was used to predict network traffic at an interval of 15 minutes and 30 minutes. Since a large amount of data is transmitted and received in 15 minutes, the network traffic scenario can change rapidly hence it is advisable to retrain the model every 15 to 30 minutes. The number of layers in the LSTM network was varied in the experiments and was set to 2, 3, 5, and 9. We found from our experiments that three layers of LSTM gave the best performance. Hence, further analysis in later subsections only discusses LSTM with three layers. For training, validation, and testing, we divide the dataset into subsets of size 60%, 20%, and 20% respectively. In the following subsections, we shall discuss the performance of our model using the datasets used in this work.

1) EVALUATION WITH WIDE-18

The WIDE-18 is the biggest dataset we have with more than 183 million packets and 57 million unique flows. Since WIDE-18 is a captured from the network backbone, there are 157 unique application protocols in this dataset.

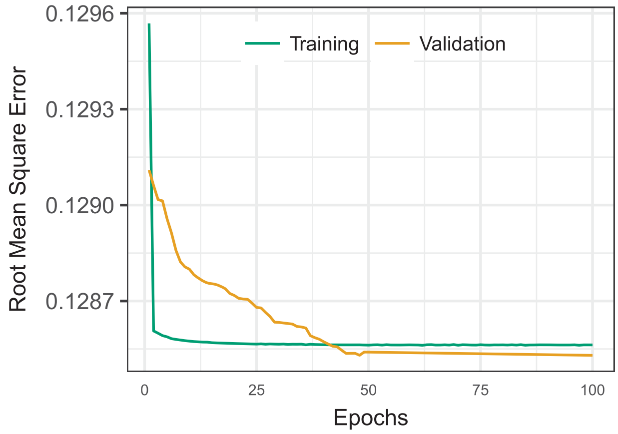


FIGURE 15. **The Root Mean Square Error between the actual value and forecasted value for WIDE-18.**

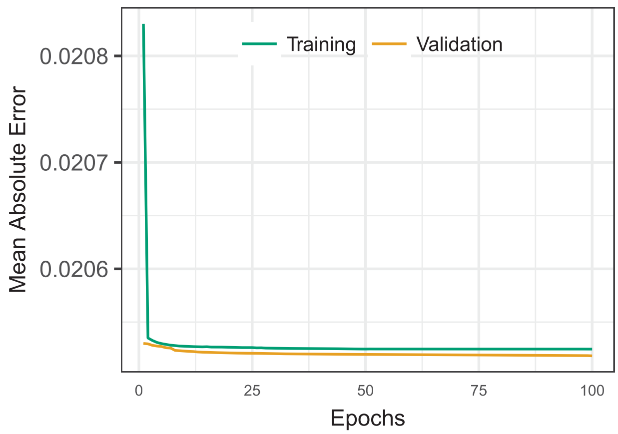


FIGURE 16. **The Mean Absolute Error between the actual value and forecasted value for WIDE-18.**

Fig. 15 illustrates the RMSE for the initial 100 epochs. We can observe that overall RMSE is quite low very close to 0. Initially, there is a difference of 0.0002 between the training and prediction but at later epochs achieves almost the same RMSE. The average RMSE obtained for WIDE-18 for all the four predictions (Bpp, bps, pps, and duration) is 0.128756. Fig. 16 illustrates the Mean Absolute Error for 100 epochs. We observe that Mean Absolute Error is also quite low. The average MAE for all the four predictions (Bpp, bps, pps, and duration) is 0.020534. Low RMSE and MAE indicate that the difference between the actual value and the predictions are quite low. This is further illustrated in Fig. 17, where we compare the actual and predicted values for all the four network traffic parameters.

Fig. 17a shows the comparison of the observed bits per second (bps) against the predicted values for 200 seconds. It is observed that the minimum difference is between both the prediction and observed values are less than 0.00001 units whereas the maximum difference is just 0.00010 bits per second. Fig. 17b illustrates observed and predicted packet rate for 100 seconds. The minimum difference is less than 0.000025 packets per second, and the maximum difference is 0.000125 packets per second. Fig. 17c and Fig. 17d indicates the bytes per packet (Bpp) and the duration of the flows (duration) respectively. We can observe that maximum and minimum difference for both flow duration and Bpp is quite low. The value of Bpp ranges from 40 Bytes per packet to 180 million Bytes per packet. Hence we can observe a slightly larger difference between them. However, the RMSE value is quite low around 0.129. These plots clearly illustrate that the model produces good predictions for the trace set WIDE-18.

2) EVALUATION WITH WAIKATO-VIII

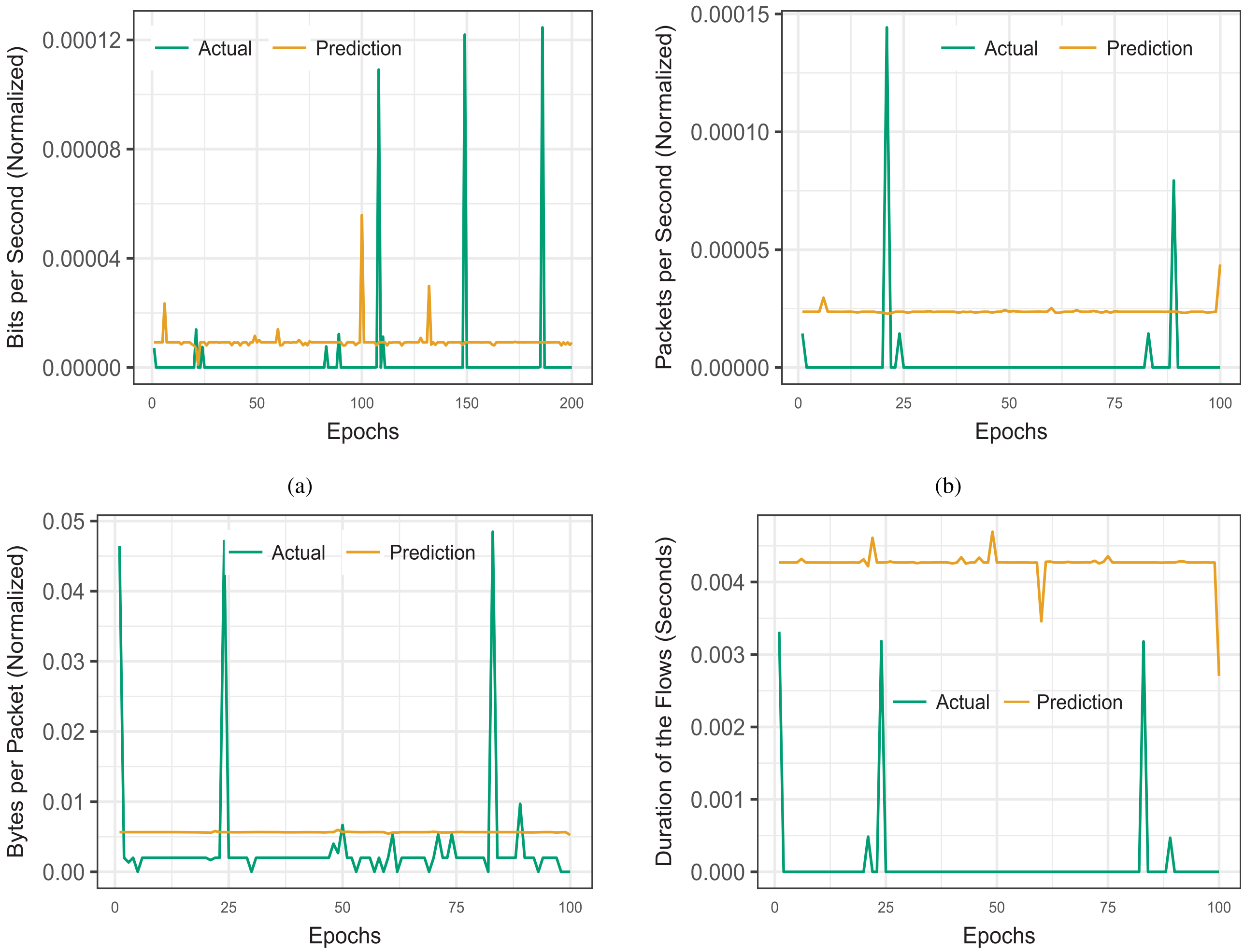
Waikato-VIII has the longest capture time among the three datasets we use in this work. However, since the capture point is at the edge, the traceset is comparable to the other tracesets of smaller durations. Fig. 18 illustrates the RMSE for the initial 100 epochs. The prediction set attains a lower RMSE over the actual values used for training. The average RMSE obtained using Waikato-VIII for all the four predictions (Bpp, bps, pps, and duration) is 0.164734. Fig. 19 illustrates the Mean Absolute Error for 100 epochs. The average MAE for all the four predictions (Bpp, bps, pps, and duration) is 0.029367. Compared to WIDE-18 we observe that the RMSE and MAE of Waikato-VIII is relatively larger.

Fig. 20 depicts the comparison of the actual and predicted values for all the four network traffic parameters. Fig. 20a and Fig. 20b compares the bit-rate as well as the packet rate of the predicted and observed values for 100 seconds. We can observe that the predictions are almost constant and follow a linear pattern. The sudden large peaks in the rate are not predicted but rather an averaged value for a given time period is predicted. Fig. 20b illustrates the comparison of Bytes per packet and Fig. 20c shows the duration of the flow. Unlike WIDE-18 or ISPDSL-II, the Waikato-VIII is not a contiguous traceset. This leads to missing time information hence we can observe the RMSE, and the MAE is larger than WIDE-18 and ISPDSL-II.

3) EVALUATION WITH ISPDSL-II

ISPDSL-II is the second largest traceset that we have used in this work. Fig. 21 depicts the RMSE for the initial 100 epochs. The average RMSE obtained for ISPDSL-II for all the four predictions (Bpp, bps, pps, and duration) is 0.148234. Fig. 19 illustrates the Mean Absolute Error for 100 epochs. The average MAE for all the four predictions (Bpp, bps, pps, and duration) is 0.023517. Compared to Waikato-VIII, we observe that the RMSE and MAE of ISPDSL-II are relatively lower. However, WIDE-18 still has the lowest RMSE and MAE, which can be attributed to its large size which increases the training size. Having large data to train increases the performance of the trained model.

Fig. 23 depicts the actual and predicted values for all the four network traffic parameters. Fig. 23a and Fig. 23b compares the bit-rate as well as the packet rate of the predicted



(a) (b) (c) (d)

FIGURE 17. Comparison between predictions and the actual network values of WIDE-18 dataset for: (a) The bit rate (b) The packet rate (c) The number of bytes per packet (d) Duration of the flow.

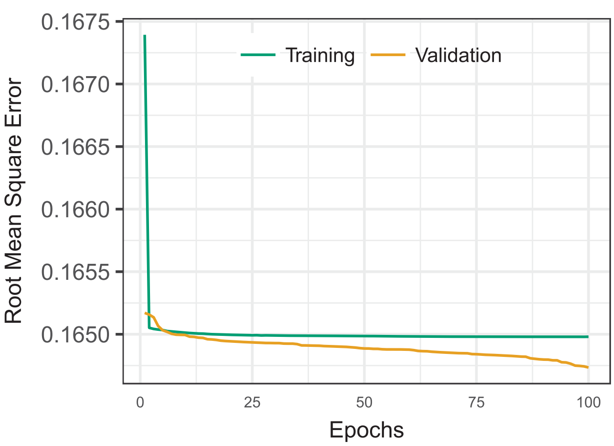


FIGURE 18. The Root Mean Square Error between the actual value and forecasted value for Waikato-VIII.

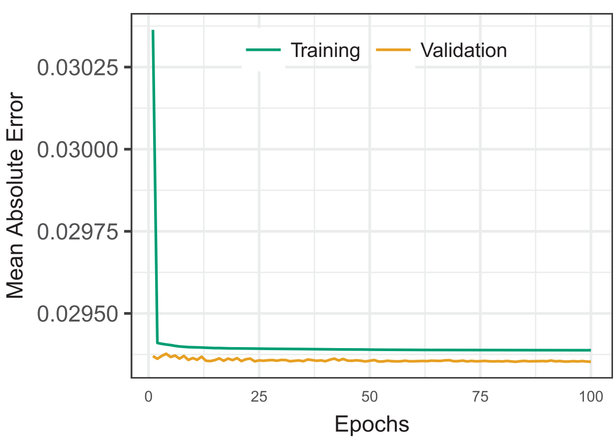


FIGURE 19. The Mean Absolute Error between the actual value and forecasted value for Waikato-VIII.

and observed values for 100 seconds. The maximum difference in the bit-rate is as small as 0.00003, and for packet rate, it is 0.005. Fig. 23b illustrates the comparison of Bytes per packet and Fig. 23c shows the duration of the flow. The observed duration of the flows differs from the actual flow by a maximum of 0.2 unit packets. From the RMSE

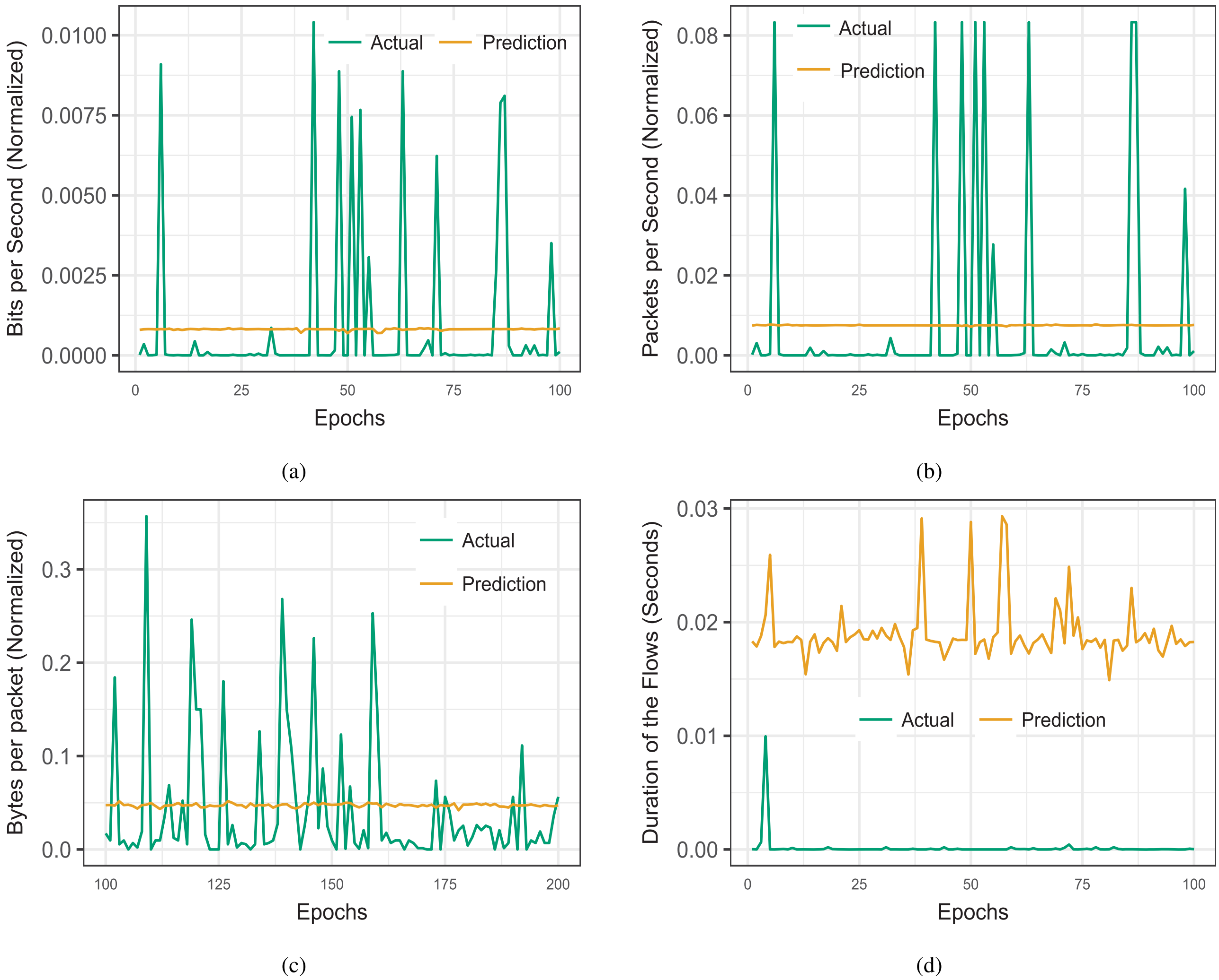


FIGURE 20. Comparison between predictions and the actual network values of Waikato-VIII dataset for: (a) The bit rate (b) The packet rate (c) The number of bytes per packet (d) Duration of the flow.

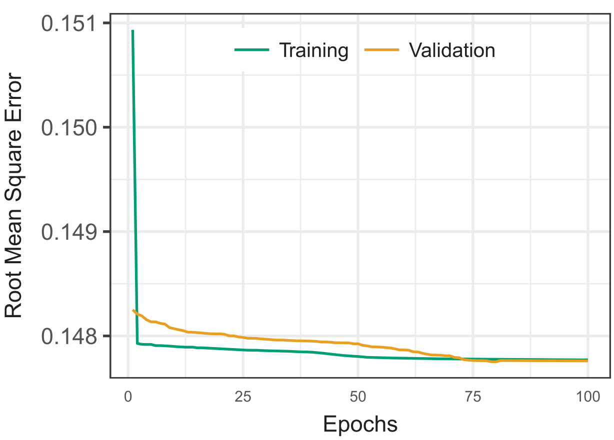


FIGURE 21. The Root Mean Square Error between the actual value and predicted value for ISPDSL-II.

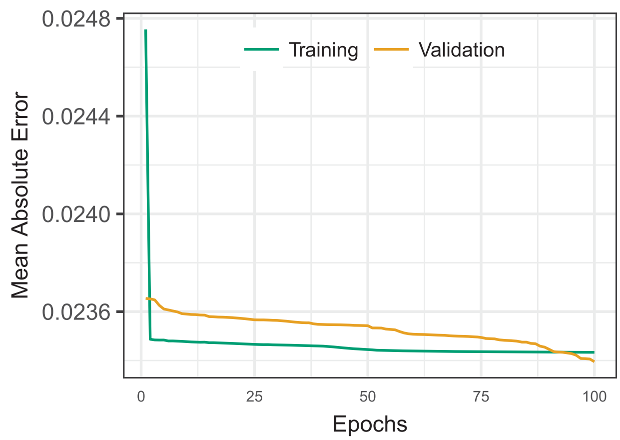


FIGURE 22. The Mean Absolute Error between the actual value and predicted value for ISPDSL-II.

and MAE values, we can infer that the difference between the predicted values and observed values are small and remains deep in the acceptable range.

C. EVALUATION OF THE DLNTC COMPONENT

The DLNTC Component is responsible for identifying the application protocol names of each flow. This enables us

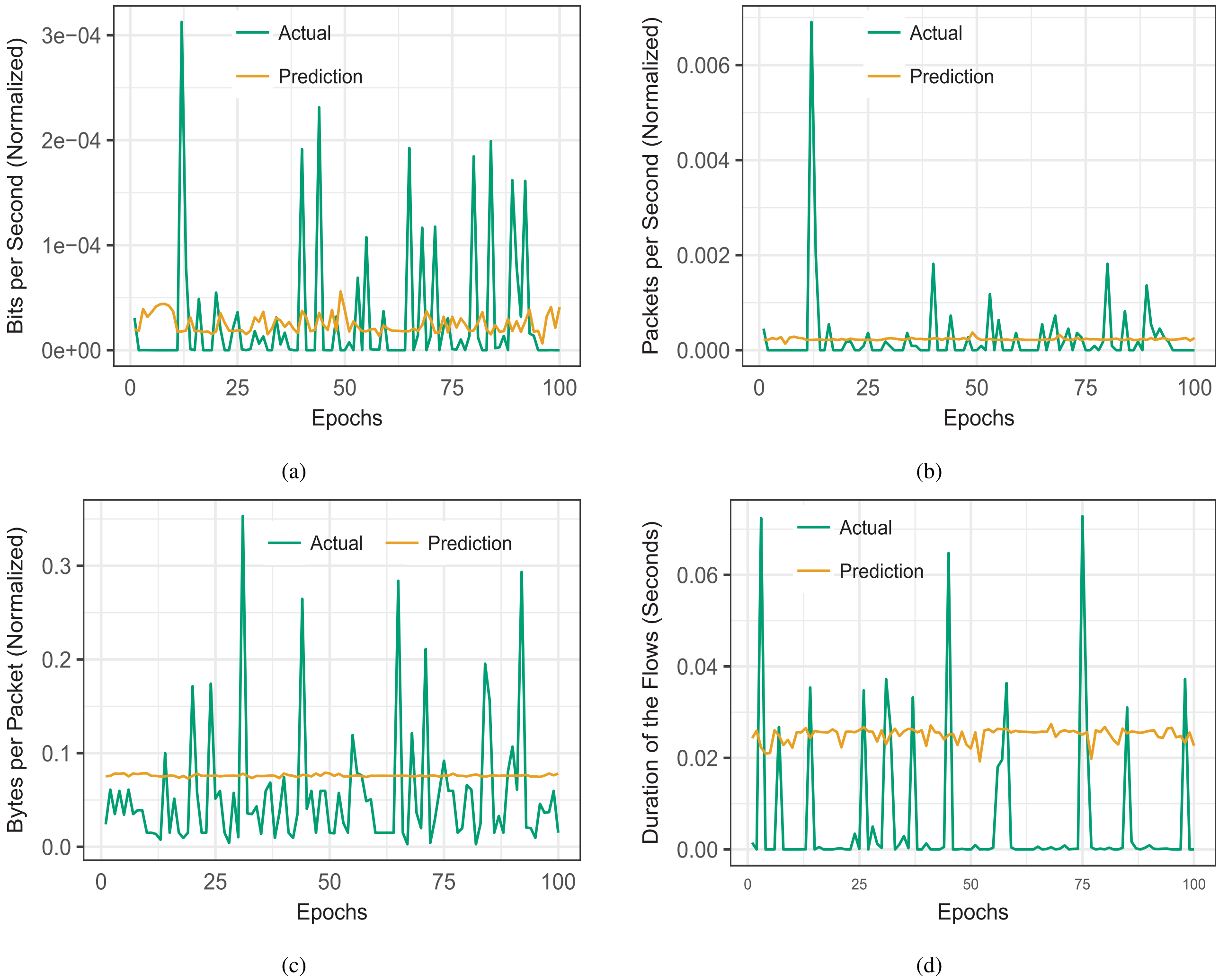


FIGURE 23. Comparison between predictions and the actual network values of ISPDSL-II dataset for: (a) The bit rate (b) The packet rate (c) The number of bytes per packet (d) Duration of the flow.

to calculate the amount of bandwidth and proper routes as per the requirement. Moreover, it enables the detection of malicious packets and malware that negatively affect the quality of the networks as discussed in V. In this module, we use a Deep Neural Network (DNN) to train the deep model using training data. The trained model will be used for classifying incoming flows to various categories. The Classification based Deep Learning Model was implemented using Tensorflow [140].

The implemented model has one input layer of size 17 and one output layer. The size of the output layer is dependent upon the number of unique application protocol in each dataset. We have five hidden layers between the input and output layers. The size of each hidden layer is 200, 175, 150, 100, and 10. The size of hidden layers was chosen after trial and error experiments.

For the training purpose, we divide the data into two splits of 60/40. Sixty percentage of the data is used for training, and the remaining forty percent is used for the prediction (testing).

We assess the performance of our classification model using two metrics, accuracy and kappa(κ). They are defined in as in (3) and (4) respectively.

$$accuracy(\%) = \frac{num\_accurate}{|dataset|} \times 100 \tag{3}$$

The *accuracy* is defined as the ratio of the number of correctly predicted application protocol classes (*num_accurate*) to the total number of application flows in the dataset ($|dataset|$). κ is an index that compares the observed agreement with respect to a baseline agreement called the expected agreement [141]. The κ is defined as follows

$$\kappa = \frac{accuracy_o - accuracy_e}{1 - accuracy_e} | \kappa \in [0, 1] \tag{4}$$

where $accuracy_o$ is the observed accuracy (observed agreement) that we calculated as part of (3). $accuracy_e$ is the expected accuracy or the random accuracy. We can define

$accuracy_e$ as in (5)

$$accuracy_e = \frac{TN(FP+FN)+TP(FN+FP)}{accuracy_o \times accuracy_o} \quad (5)$$

where TN, TP, FP, and FN are the number of true negatives, the number of true positives, the number of false positives, and the number of false negatives respectively.

A universally acceptable interpretation of κ does not exist. However, Landis and Koch provided an interpretation in which, a κ closer to 1 signifies a considerable agreement between the observed and expected observation. The farther κ is from 1, it ranges from slight agreement to no agreement.

TABLE 3. Accuracy and Kappa for the classifiers.

Dataset	Accuracy (%)	κ
ISPDSL-II	97.39	0.86
Waikato-VIII	98.5	0.95
WIDE-18	90.51	0.8607

Table 3 provides the average accuracy and kappa obtained from twenty rounds of the experiment. Waikato-VIII provides the highest accuracy of 98.5% and the highest kappa value (0.95). The total number of unique application protocols in Waikato-VIII was lesser than WIDE=18 and ISPDSL-II as Waikato-VIII was captured at the edge of the network. Moreover, Waikato-VIII had a better distribution of application protocols than WIDE=18 and ISPDSL-II. ISPDSL-II is close behind Waikato-VIII with an accuracy of 97.39% (The difference is just 1%). However, the Kappa value of ISPDSL-II is much lower. This is because the majority of network flows distributed among very few application protocols. This results in the $accuracy_e$ to go down even for few misclassifications of the smaller application protocols. Whereas, WIDE-18 has an accuracy of 90.51%. A large number of unique application protocol(more than 150) results in misclassification of labels with smaller share among the application protocol. However, the overall accuracy and κ value illustrate the high quality of our classifier.

Fig. 24 depicts the variation in the accuracy with respect to the training data size. As the training size increases, we can observe an increase in the classification accuracy for all three datasets. The rate of accuracy increment is higher for the WIDE-18 datasets as the training size increases due to a large number of records in this dataset (183 million packets). Hence, a larger training set is required to produce higher accuracy. However, ISPDSL-II and Waikato-VIII are smaller than WIDE-18. Moreover, Waikato-VIII has lesser number of unique application protocols (labels). This results in Waikato-VIII having the highest accuracy.

Fig. 25 illustrates the variation in the Kappa (κ) with respect to the training size. As the training size increases, we can observe an increase in the κ for all three datasets. ISPDSL-II has the highest rate of increase in κ as the training size increase. Whereas, both WIDE-18 and Waikato-VIII increases gradually as the training size increases. However, we see that all the κ values indicate a good agreement of observed values expected values.

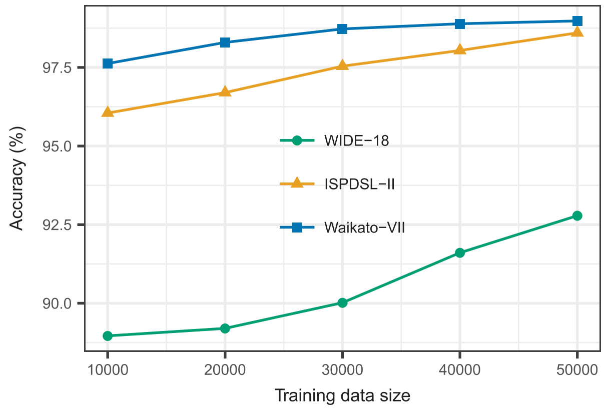


FIGURE 24. Accuracy of the DLNTC component for all the three datasets used against the training size.

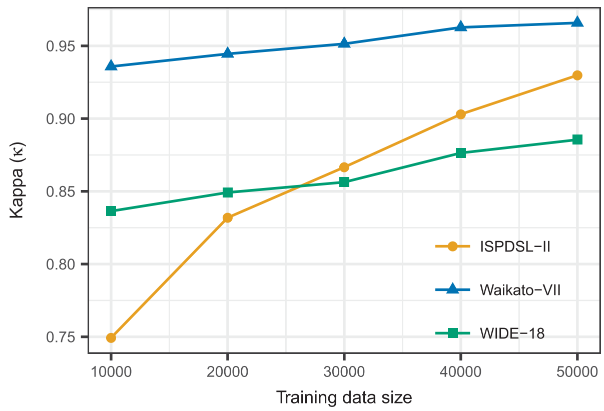


FIGURE 25. Kappa of the DLNTAP component for all the three datasets used against the training size.

D. EVALUATION OF THE FCA COMPONENT

The traffic flows of a given application protocol will have different flow types. For e.g., a flow that has been classified as Youtube by our classification component can either be a video streaming flow, browsing flows, or flows generated by redirections between various content servers of Google and Youtube [130], [131]. An analysis of these flow classes of a single application protocol will give more control on scheduling and better utilizing the network. After the classification component classifies the flows into application protocol classes, we apply DBSCAN clustering to analyze the flows further.

In this experiment we segregated all the flows that have application protocol *Skype* and *Google Drive* into separate datasets. For both of these application protocols, we calculated the three nearest neighbor distance. Fig. 26 and Fig. 27 are the plots of the three nearest neighbor (3-NN) distance with respect to the points sorted by the distance for *Skype* and *Google Drive* respectively.

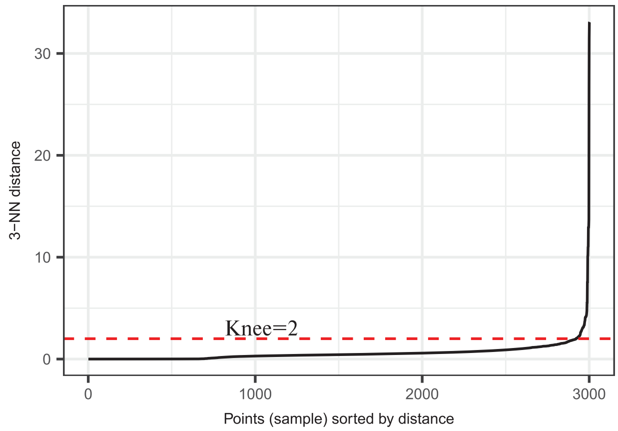


FIGURE 26. The plot of three nearest neighbor against the points sorted by the distance for the application protocol *Skype*.

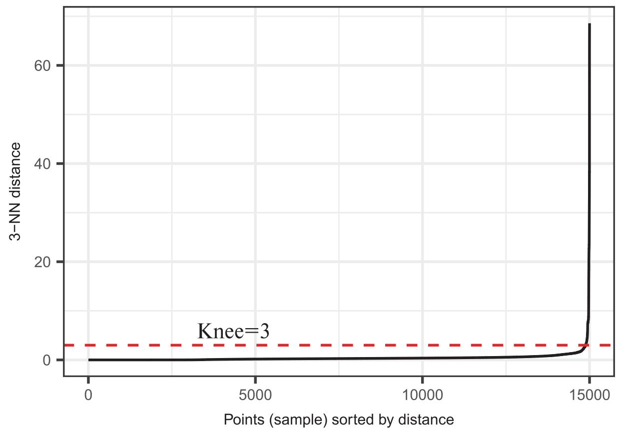


FIGURE 27. The plot of three nearest neighbor against the points sorted by the distance for the application protocol *Google Drive*.

The knee point indicated in the figure helps us in selecting the best ϵ parameter required by the DBSCAN algorithm. The red dashed line indicates the knee values. For *Skype* we select $\epsilon = 2$ and for *Google Drive* we select $\epsilon = 3$ as shown in the figure.

The selected ϵ is used to cluster both *Skype* and *Google Drive* sets. Fig. 28a and Fig. 28b illustrates the results of the clustering. We can observe that in Fig. 28a that *Skype* flow has been clustered into two clusters and in Fig. 28b we observe that *Google Drive* has been divided into three clusters. The flows for each application set were manually analyzed.

Skype has a decentralized architecture in which the clients (host nodes) connect to one of the many supernodes for registering with login servers [142], [143]. They keep exchanging keep-alive messages continuously. Hence, we can infer that one of the clusters corresponds to the control signals that handles connection and authentication between hosts and primary servers. This group would hence have low volume data flow. The second flow cluster is associated with the actual audio and video communication data and hence has a higher volume and packet rate. In the Fig. 28a, the blue cluster is denser and contains more points and hence is associated with the data flow, whereas the second yellow cluster is sparse with few points indicating control signals. The black dots in the figure indicates the anomalous traffic or the unknown traffic that was identified.

Similarly, analyzing the Google Drive flows indicated the presence of three clusters, one for the downloaded data, one for the uploaded data, and the third one was browsing. The download and upload clusters will be denser and bigger due to the larger volume of data whereas the cluster with the control signals will be smaller and of low volume. In Fig. 28b, we observe that the blue and yellow clusters are denser and have more points and hence corresponds to the download and upload flow. Whereas, the grey cluster is smaller and might correspond to the flows generated by browsing Google drive. Similarly, the black dots in the figure indicates the anomalous traffic or the unknown traffic that was identified.

Clustering and identifying the subclasses of the flows will enable to have more control over planning the routes as well as stopping anomaly based attacks.

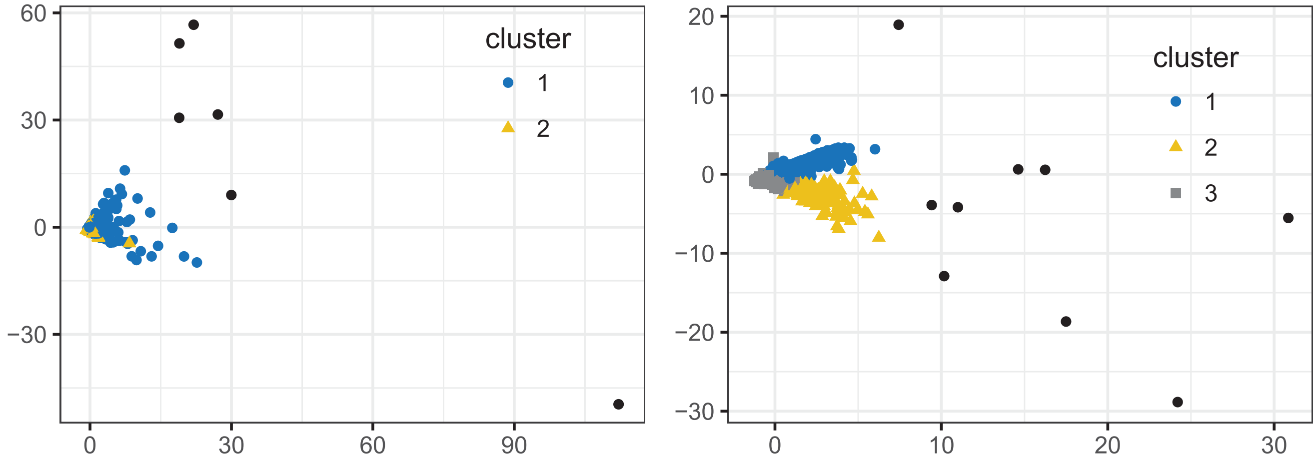
VII. UbeHealth: EVALUATION OF THE WHOLE SYSTEM

In this section, we evaluate the performance of our proposed mobile preventive healthcare cloud architecture using simulation environments. We start by explaining the case study and simulation scenario using the proposed network based on mobile health cloud network between different hospitals in Kingdom of Saudi Arabia. Then we discuss the simulation environment and the parameters used in the simulation. We then evaluate our proposed framework using the simulated cloud healthcare network.

A. CASE STUDY WITH PROTOTYPE

In this case study, we design a scenario in which we implement a mobile healthcare networking framework that we proposed among the various hospitals in Saudi cities. We create two scenarios, one that deals with intra-network and one that deals with inter-network between the cities. In the first scenario, we consider the city of Riyadh, the capital of KSA.

Fig. 29 shows some of the major hospitals in the city of Riyadh. We deploy cloudlets at four of the major hospitals: (1) National hospital, (2) King Faisal Specialist Hospital, (3) King Fahad Medical City, and (4) Riyadh military Hospital as seen in the Fig. 29 (shown with the clouds in the figure). We assume our central server is installed at the King Fahad Medical City as indicated in the figure. We assume that all of the hospitals have the same network and application environment. The number of cloudlets deployed is also assumed to be same at all the hospital and is explained in the next subsection with the simulation parameters. Even though the hospital names used are real, this is a case study with simulation. Hence, the networks, applications, and all related data are generated by the authors with the help of a cloud simulator to evaluate the performance of the proposed preventive mobile healthcare network cloud architecture. Hence, we would like to provide a disclaimer that the hospital names are used for



(a) (b)

FIGURE 28. Clustering of (a) application flows marked as Skype (b) application flows marked as Google Drive.

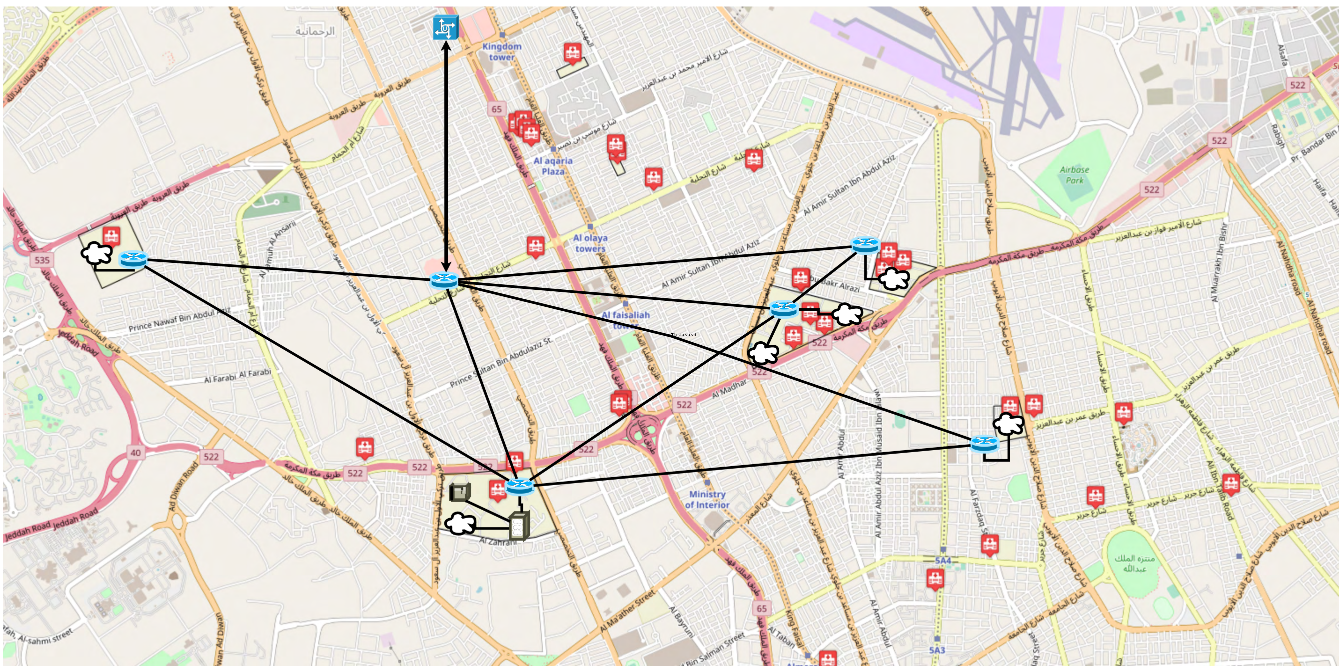


FIGURE 29. Map of Riyadh with Hospitals showing the deployed cloudlets and the cloud server at various hospitals.

a better explanation. Therefore, the hospitals have no liability and will not be held accountable for anything in this article.

In the second scenario, two hospitals in each of the cities Riyadh, Jeddah, Dammam, and Abaha have cloudlets installed, and the central server is at Riyadh. Hence the total number of hospitals involved in this mobile healthcare network is eight. Fig. 30 illustrates this scenario. Users at one hospital in a city have to access the main server situated at Riyadh. In this scenario, we show the performance of our proposed scheme for inter-city data streaming. In our simulation, we compare the performance of our proposed mobile cloud preventive healthcare architecture with the traditional network and cloud infrastructure.

The healthcare practitioners at the hospitals will be using medical applications, monitoring patients health, or performing remote assistance for surgery. We simulate data that represent streaming multimedia applications, FTP access, and HTTP requests to complement with real world scenario. We shall assess the network in terms of latency of the network, and the power consumption of user devices. We compare our work with [26] in which a healthcare network has

FIGURE 30. Map of Saudi Arabia showing the deployed cloudlets and the cloud server at hospitals in major cities around KSA.

been modeled to explore the QoS using a traditional network infrastructure.

B. SIMULATION ENVIRONMENT

We develop our simulations on top of iCanCloud [144], [145] a cloud simulator. iCanCloud can model and simulate cloud computing systems. It can simulate large experiments unlike other existing cloud simulators as it is written C++. It runs on 32 or 64-bit system and can use the entire system memory unlike other simulators developed in Java. Cloud computing scenarios can be developed using set pre-existing components provided by iCanCloud. These pre-existing components represent the working and behavior of real components such as the disk, networks, memory, the file system, the nodes, etc. More components can be added to the existing components of iCanCloud based on the requirements. It also provides a POSIX API which can be used to develop our implementation. We integrate our Deep Learning based components to the simulation environment such that the results from these components are also simulated.

The network parameters that we have used in this work have been illustrated Table 4. For the intra-city scenario, we deploy 15 cloudlets at each hospital, and each cloudlet has five internal servers. The total number of users in each hospital campus was set to 150. The service rate for the cloudlets, as well as the clouds, are set to 15. The Internet delay has been set to 0.8 for inter-city networks and 0.5 for intra-city networks. The task arrival rate changes between 0 to 5.

C. RESULTS

In this subsection, we discuss the results of the simulation using the discussed scenarios.

TABLE 4. The simulation parameters used to simulate the mobile edge based cloud healthcare system using proposed framework.

Parameters (per Hospital)	Values
Total Number of Users	150
Total Number of Access Points	50
Total Number of Cloudlets	15
Task arrival rate	[0,5]
Cloudlet service rate	15
Servers in Each Cloudlet	5
Latency in Internet (inter and intra city)	0.8 & 0.5
Cloudlet Workload (Maximum)	50

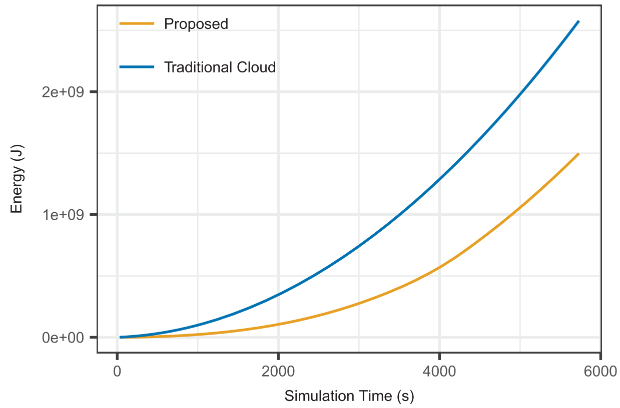


FIGURE 31. The change in total energy as with respect to the simulation time for the proposed model and traditional cloud infrastructure.

Fig. 31 illustrates the total energy that was consumed for the simulation of the intercity scenario for our prosed technique as well as the traditional infrastructure-based health network. As the time increases, we observe that the traditional infrastructure requires a more considerable amount of energy and the rate of increase in energy be far greater than our proposed method. Whereas, our method utilizes a lesser amount of energy. This is mainly due to the caching and fast access provided by the cloudlets as well as network optimizations that are enabled by our deep learning models.

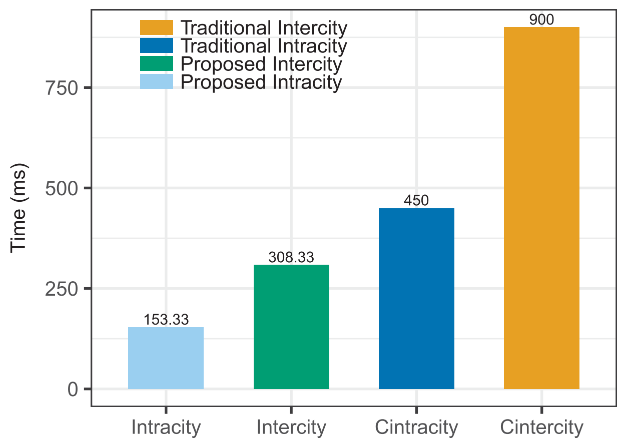


FIGURE 32. The latency of Intercity and Intracity networks for the proposed technique and traditional cloud infrastructure.

Fig. 32 depicts the average latencies of the intercity and intracity networks for both the proposed technique as well as the traditional healthcare infrastructure. We can observe that the average latency of the proposed healthcare technique is lower than the traditional network-based healthcare infrastructure. The proposed technique provides an average latency of 154 milliseconds (ms) and 308.33 ms for intracity and intercity networks respectively. Whereas, traditional networking approach provides a latency of 450 ms and 900 ms for intracity and intercity networks respectively.

The latency of the proposed technique is 37% and 50% less than traditional infrastructure for intracity and intercity healthcare networks. The higher performance of our technique is due to the caching at the cloudlets and adaptively resource management enabled by our deep learning model.

VIII. CONCLUSIONS AND OUTLOOK

Advancements in ICT technologies such as 4G/5G communications, big data, IoT, HPC, robotics, cloud computing, and smart cities are driving a major transformation of the healthcare industry. Another driver for this transformation is the need for governments globally to make high quality healthcare accessible to the citizens, and this has been challenging due to the increasing health issues among the populations, and falling budgets. Networked healthcare aims to deliver anytime anywhere healthcare services, remotely, or otherwise, regardless of the location of patients and their mobilities. Mobile cloud computing could potentially meet the future healthcare demands by enabling anytime, anywhere capture and analyses of data. However, network latency, bandwidth, and reliability are among the many challenges hindering the realization of next-generation healthcare.

In this paper, we proposed UbeHealth, a ubiquitous healthcare framework that leverages edge computing, deep learning, big data, high performance computing (HPC), and the Internet of Things (IoT) to address the very many challenges hindering the networked healthcare domain. We addressed the networking challenges such as latency, bandwidth, energy consumption and other QoS parameters, faced by networked healthcare systems. The framework enabled an enhanced network quality of service using its four layers and three components. The DLNTAP Component used deep learning, big data, and HPC technologies to predict network traffic for the future in order to optimize data rates, data caching and routing decisions. The DLNTC Component provided classification of the application protocols of the traffic flows allowing UbeHealth to better meet the communication requirements of applications in order to maintain a high QoS and to detect malicious traffic and anomalous data. The FCA Component clustered the data to identify the different kinds of data originating from the same application protocols. IoT allowed the collection and monitoring of the patient's biomedical signals and activities.

A proof of concept UbeHealth system was developed based on the proposed framework. A detailed literature review was used to capture the design requirements for the proposed system. The system was described including the algorithmic implementation of the components and layers. A nationwide networked healthcare system case study and three widely used datasets were used to evaluate the UbeHealth system. The proposed system provided 50% reduction in latency as compared to traditional cloud-based networked healthcare systems. To the best of our knowledge, this is the first work that extensively addresses the various network-related issues in next-generation healthcare systems using adaptive deep learning and data mining techniques to enhance QoS. In future, we plan to work on improving the security, privacy, reliability, and scalability of the networked healthcare systems using deep learning based models.

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REFERENCES

[1] E. J. Topol and D. Hill, *The Creative Destruction of Medicine: How the Digital Revolution Will Create Better Health Care*. New York, NY, USA: Basic Books, Dec. 2012.

[2] T. Ermakova, J. Huenges, K. Erek, and R. Zarnekow, "Cloud computing in healthcare—A literature review on current state of research," in *19th Americas Conference on Information Systems (AMCIS 2013): Hyperconnected World: Anything, Anywhere, Anytime*, J. Shim, Y. Hwang, and S. Petter, Eds. Chicago, IL, USA: Association for Information Systems, 2013. [Online]. Availabe: http://aisel.aisnet.org/amcis2013/HealthInformation/GeneralPresentations/17/

[3] C. Pino and R. Di Salvo, "A survey of cloud computing architecture and applications in health," in *Proc. Int. Conf. Comput. Sci. Electron. Eng.*, 2013, pp. 1649–1653.

[4] A. S. Yeole and D. R. Kalbande, "Use of Internet of Things (IoT) in healthcare: A survey," in *Proc. ACM Symp. Women Res. (WIR)*, New York, NY, USA: ACM, 2016, pp. 71–76. [Online]. Available: http://doi.acm.org/10.1145/2909067.2909079

[5] P. A. Laplante and N. L. Laplante, "A structured approach for describing healthcare applications for the Internet of Things," in *Proc. IEEE 2nd World Forum Internet Things (WF-IoT)*, Dec. 2015, pp. 621–625.

[6] H. Alemdar and C. Ersoy, "Wireless sensor networks for healthcare: A survey," *Comput. Netw.*, vol. 54, no. 15, pp. 2688–2710, Oct. 2010. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1389128610001398

[7] M. Chen, S. Gonzalez, A. Vasilakos, H. Cao, and V. C. M. Leung, "Body area networks: A survey," *Mobile Netw. Appl.*, vol. 16, no. 2, pp. 171–193, 2011. [Online]. Available: https://doi.org/10.1007/s11036-010-0260-8

[8] D. Ramesh, P. Suraj, and L. Saini, "Big data analytics in healthcare: A survey approach," in *Proc. Int. Conf. Microelectron., Comput. Commun. (MicroCom)*, Jan. 2016, pp. 1–6.

[9] J. Sun and C. K. Reddy, "Big data analytics for healthcare," in *Proc. 19th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining (KDD)*, New York, NY, USA: ACM, 2013, p. 1525. [Online]. Available: http://doi.acm.org/10.1145/2487575.2506178

[10] R. H. Taylor, "A perspective on medical robotics," *Proc. IEEE*, vol. 94, no. 9, pp. 1652–1664, Sep. 2006.

[11] R. H. Taylor, A. Menciassi, G. Fichtinger, P. Fiorini, and P. Dario, *Medical Robotics and Computer-Integrated Surgery*. Cham, Switzerland: Springer, 2016, pp. 1657–1684. [Online]. Available: https://doi.org/10.1007/978-3-319-32552-1_63

[12] M. S. Hossain and G. Muhammad, "Cloud-assisted speech and face recognition framework for health monitoring," *Mobile Netw. Appl.*, vol. 20, no. 3, pp. 391–399, Jun. 2015. [Online]. Available: https://doi.org/10.1007/s11036-015-0586-3

[13] G. C. Kagadis *et al.*, "Cloud computing in medical imaging," *Med. Phys.*, vol. 40, no. 7, p. 070901, 2013. [Online]. Available: https://aapm.onlinelibrary.wiley.com/doi/abs/10.1118/1.4811272

[14] F. Alam, R. Mehmood, I. Katib, N. N. Albogami, and A. Albeshri, "Data fusion and IoT for smart ubiquitous environments: A survey," *IEEE Access*, vol. 5, pp. 9533–9554, 2017.
[15] Y. Arfat *et al.*, "Enabling smarter societies through mobile big data fogs and clouds," *Procedia Comput. Sci.*, vol. 109, pp. 1128–1133, Jan. 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1877050917311213
[16] S. Suma, R. Mehmood, N. Albugami, I. Katib, and A. Albeshri, "Enabling next generation logistics and planning for smarter societies," *Procedia Comput. Sci.*, vol. 109, pp. 1122–1127, Jan. 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1877050917311225
[17] J. Schlingensiepen, F. Nemtanu, R. Mehmood, and L. McCluskey, *Autonomic Transport Management Systems—Enabler for Smart Cities, Personalized Medicine, Participation and Industry Grid/Industry 4.0*. Cham, Switzerland: Springer, 2016, pp. 3–35.
[18] R. Mehmood and G. Graham, "Big data logistics: A health-care transport capacity sharing model," *Procedia Comput. Sci.*, vol. 64, pp. 1107–1114, Sep. 2015. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1877050915027015
[19] R. Mehmood, R. Meriton, G. Graham, P. Hennelly, and M. Kumar, "Exploring the influence of big data on city transport operations: A mark Ovian approach," *Int. J. Oper., Prod. Manage.*, vol. 37, no. 1, pp. 75–104, 2017. [Online]. Available: https://doi.org/10.1108/IJOPM-03-2015-0179
[20] R. Mehmood and J. A. Lu, "Computational Markovian analysis of large systems," *J. Manuf. Technol. Manage.*, vol. 22, no. 6, pp. 804–817, Jul. 2011. [Online]. Available: https://doi.org/10.1108/17410381111149657
[21] R. Mehmood, F. Alam, N. N. Albogami, I. Katib, A. Albeshri, and S. M. Altowaijri, "UTiLearn: A personalised ubiquitous teaching and learning system for smart societies," *IEEE Access*, vol. 5, pp. 2615–2635, 2017.
[22] B. M. Silva, J. J. Rodrigues, I. de la Torre Díez, M. López-Coronado, and K. Saleem, "Mobile-health: A review of current state in 2015," *J. Biomed. Informat.*, vol. 56, pp. 265–272, Aug. 2015. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1532046415001136
[23] A. Awad, A. Mohamed, C.-F. Chiasserini, and T. Elfouly, "Distributed in-network processing and resource optimization over mobile-health systems," *J. Netw. Comput. Appl.*, vol. 82, pp. 65–76, Mar. 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S108480451730022X
[24] Q. Zhang, L. Cheng, and R. Boutaba, "Cloud computing: State-of-the-art and research challenges," *J. Internet Services Appl.*, vol. 1, no. 1, pp. 7–18, May 2010. [Online]. Available: https://doi.org/10.1007/s13174-010-0007-6
[25] P. D. Kaur and I. Chana, "Cloud based intelligent system for delivering health care as a service," *Comput. Methods Programs Biomed.*, vol. 113, no. 1, pp. 346–359, 2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0169260713003209
[26] R. Mehmood, M. A. Faisal, and S. Altowaijri, "Future networked healthcare systems: A review and case study," in *Handbook of Research on Redesigning the Future of Internet Architectures*, M. Boucadair and C. Jacquenet, Eds. Hershey, PA, USA: IGI Global, 2015, pp. 531–558. [Online]. Available: http://services.igi-global.com/resolvedoi/resolve.aspx?doi=10.4018/978-1-4666-8371-6.ch022
[27] M. Armbrust *et al.*, "A view of cloud computing," *Commun. ACM*, vol. 53, no. 4, pp. 50–58, 2010. [Online]. Available: http://doi.acm.org/10.1145/1721654.1721672
[28] N. Fernando, S. W. Loke, and W. Rahayu, "Mobile cloud computing: A survey," *Future Generat. Comput. Syst.*, vol. 29, no. 1, pp. 84–106, 2013. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167739X12001318
[29] B. Martínez-Pérez, I. de la Torre-Díez, M. López-Coronado, and J. Herreros-González, "Mobile apps in cardiology: Review," *JMIR Mhealth Uhealth*, vol. 1, no. 2, p. e15, Jul. 2013. [Online]. Available: http://mhealth.jmir.org/2013/2/e15/
[30] H. R. Maamar, A. Boukerche, and E. M. Petriu, "3-D streaming supplying partner protocols for mobile collaborative exergaming for health," *IEEE Trans. Inf. Technol. Biomed.*, vol. 16, no. 6, pp. 1079–1095, Nov. 2012.
[31] H. T. Dinh, C. Lee, D. Niyato, and P. Wang, "A survey of mobile cloud computing: Architecture, applications, and approaches," *Wireless Commun. Mobile Comput.*, vol. 13, no. 18, pp. 1587–1611, Oct. 2011. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/wcm.1203
[32] T. Mastelic, A. Oleksiak, H. Claussen, I. Brandic, J.-M. Pierson, and A. V. Vasilakos, "Cloud computing: Survey on energy efficiency," *ACM Comput. Surv.*, vol. 47, no. 2, pp. 33-1–33-36, Dec. 2014. [Online]. Available: http://doi.acm.org/10.1145/2656204
[33] Y. C. Hu, M. Patel, D. Sabella, N. Sprecher, and V. Young, "Mobile edge computing—A key technology towards 5G," ETSI (European Telecommunications Standards Institute), Sophia Antipolis, France, White Paper 11, Sep. 2015, vol. 11, no. 11.
[34] Y. Yu, "Mobile edge computing towards 5G: Vision, recent progress, and open challenges," *China Commun.*, vol. 13, no. 2, pp. 89–99, 2016.
[35] T. N. Gia, M. Jiang, A.-M. Rahmani, T. Westerlund, P. Liljeberg, and H. Tenhunen, "Fog computing in healthcare Internet of Things: A case study on ECG feature extraction," in *Proc. IEEE Int. Conf. Comput. Inf. Technol., Ubiquitous Comput. Commun. Depend., Auto. Secure Comput. Pervasive Intell. Comput.*, Oct. 2015, pp. 356–363.
[36] 5GPPP. (Oct. 2016). *5G Vision: The Next Generation of Communication Networks and Services*. [Online]. Available: https://5gppp.eu/wp-content/uploads/2015/02/5G-Vision-Brochure-v1.pdf
[37] F. Bonomi, R. Milito, J. Zhu, and S. Addepalli, "Fog computing and its role in the Internet of Things," in *Proc. 1st Ed. MCC Workshop Mobile Cloud Comput. (MCC)*, New York, NY, USA: ACM, 2012, pp. 13–16. [Online]. Available: http://doi.acm.org/10.1145/2342509.2342513
[38] S. Yi, C. Li, and Q. Li, "A survey of fog computing: Concepts, applications and issues," in *Proc. Workshop Mobile Big Data (Mobidata)*, New York, NY, USA: ACM, 2015, pp. 37–42. [Online]. Available: http://doi.acm.org/10.1145/2757384.2757397
[39] M. Satyanarayanan, P. Bahl, R. Caceres, and N. Davies, "The case for VM-based cloudlets in mobile computing," *IEEE Pervasive Comput.*, vol. 8, no. 4, pp. 14–23, Oct. 2009.
[40] A. Md Whaiduzzaman, "Performance enhancement framework for cloudlet in mobile cloud computing," Ph. dissertation, Dept. Faculty Comput. Sci. Inf. Technol., Univ. Malaya, Kuala Lumpur, Malaysia, Mar. 2016. [Online]. Available: http://studentsrepo.um.edu.my/.id/eprint/6246
[41] H. Feng and Y. Shu, "Study on network traffic prediction techniques," in *Proc. Netw. Mobile Wireless Commun.*, vol. 2, Sep. 2005, pp. 1041–1044.
[42] A. Sang and S. Q. Li, "A predictability analysis of network traffic," *Comput. Netw.*, vol. 39, no. 4, pp. 329–345, 2002. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1389128601003048
[43] I. M. Wagner-Muns, I. G. Guardiola, V. A. Samaranayke, and W. I. Kayani, "A functional data analysis approach to traffic vol. forecasting," *IEEE Trans.Intell. Transp. Syst.*, vol. 19, no. 3, pp. 878–888, Mar. 2018.
[44] J. Zhang, X. Chen, Y. Xiang, W. Zhou, and J. Wu, "Robust network traffic classification," *IEEE/ACM Trans. Netw.*, vol. 23, no. 3, pp. 1257–1270, Aug. 2015. [Online]. Available: https://doi.org/10.1109/TNET.2014.2320577
[45] Y. Gao, W. Hu, K. Ha, B. Amos, P. Pillai, and M. Satyanarayanan, "Are cloudlets necessary?," School Comput. Sci., Carnegie Mellon University, Pittsburgh, PA, USA, Tech. Rep. CMU-CS-15-139, 2015.
[46] M. Satyanarayanan *et al.*, "An open ecosystem for mobile-cloud convergence," *IEEE Commun. Mag.*, vol. 53, no. 3, pp. 63–70, Mar. 2015.
[47] Y. Jararweh, A. Doulat, O. AlQudah, E. Ahmed, M. Al-Ayyoub, and E. Benkhelifa, "The future of mobile cloud computing: Integrating cloudlets and mobile edge computing," in *Proc. 23rd Int. Conf. Telecommun. (ICT)*, May 2016, pp. 1–5.
[48] S. Wang, X. Zhang, Y. Zhang, L. Wang, J. Yang, and W. Wang, "A survey on mobile edge networks: Convergence of computing, caching and communications," *IEEE Access*, vol. 5, pp. 6757–6779, 2017.
[49] L. A. Tawalbeh, R. Mehmood, E. Benkhlifa, and H. Song, "Mobile cloud computing model and big data analysis for healthcare applications," *IEEE Access*, vol. 4, pp. 6171–6180, 2016.
[50] Y. Bengio, A. Courville, and P. Vincent, "Representation learning: A review and new perspectives," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 8, pp. 1798–1828, Aug. 2013. [Online]. Available: http://dx.doi.org/10.1109/TPAMI.2013.50
[51] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, May 2015. [Online]. Available: http://dx.doi.org/10.1038/nature14539
[52] J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural Netw.*, vol. 61, pp. 85–117, Jan. 2015. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0893608014002135
[53] R. Jozefowicz, W. Zaremba, and I. Sutskever, "An empirical exploration of recurrent network architectures," *J. Mach. Learn. Res.*, vol. 37, pp. 2342–2350, Jul. 2015. [Online]. Available: http://dl.acm.org/citation.cfm?id=3045118.3045367

[54] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997. [Online]. Available: https://doi.org/10.1162/neco.1997.9.8.1735
[55] G. Aceto, V. Persico, and A. Pescapé, "The role of information and communication technologies in healthcare: Taxonomies, perspectives, and challenges," *J. Netw. Comput. Appl.*, vol. 107, pp. 125–154, 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1084804518300456
[56] F. Firouzi *et al.*, "Internet-of-Things and big data for smarter healthcare: From device to architecture, applications and analytics," *Future Gener. Comput. Syst.*, vol. 78, pp. 583–586, Jan. 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167739X17319726
[57] J. Pagán, M. Zapater, and J. L. Ayala, "Power transmission and workload balancing policies in eHealth mobile cloud computing scenarios," *Future Gener. Comput. Syst.*, vol. 78, pp. 587–601, Jan. 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167739X17302133
[58] T. Adame, A. Bel, A. Carreras, and J. Melià-Seguí, M. Oliver, and R. Pous, "CUIDATS: An RFID–WSN hybrid monitoring system for smart health care environments," *Future Gener. Comput. Syst.*, vol. 78, pp. 602–615, 2018.
[59] O. Ammae, J. Korpela, and T. Maekawa, "Unobtrusive detection of body movements during sleep using Wi-Fi received signal strength with model adaptation technique," *Future Gener. Comput. Syst.*, vol. 78, pp. 616–625, Jan. 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167739X17304454
[60] A. Soomro and R. Schmitt, "A framework for mobile healthcare applications over heterogeneous networks," in *Proc. 13th IEEE Int. Conf. e-Health Netw. Appl. Services (Healthcom)*, Jun. 2011, pp. 70–73.
[61] H. Mora, D. Gil, R. M. Terol, and J. Azorín, and J. Szymanski, "An IoT-based computational framework for healthcare monitoring in mobile environments," *Sensors*, vol. 17, no. 10, p. 2302, Oct. 2017. [Online]. Available: http://www.mdpi.com/1424-8220/17/10/2302
[62] S. B. Baker, W. Xiang, and I. Atkinson, "Internet of Things for smart healthcare: Technologies, challenges, and opportunities," *IEEE Access*, vol. 5, pp. 26521–26544, 2017.
[63] J. Petäjäjärvi, K. Mikhaylov, R. Yasmin, M. Hämäläinen, and J. Iinatti, "Evaluation of LoRa LPWAN technology for indoor remote health and wellbeing monitoring," *Int. J. Wireless Inf. Netw.*, vol. 24, no. 2, pp. 153–165, Jun. 2017. [Online]. Available: https://doi.org/10.1007/s10776-017-0341-8
[64] A. Augustin, J. Yi, T. Clausen, and W. M. Townsley, "A study of LoRa: Long range & low power networks for the Internet of Things," *Sensors*, vol. 16, no. 9, p. 1466, 2016. [Online]. Available: http://www.mdpi.com/1424-8220/16/9/1466
[65] U. Raza, P. Kulkarni, and M. Sooriyabandara, "Low power wide area networks: An overview," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 2, pp. 855–873, 2nd Quart., 2017.
[66] A. A. Boulogeorgos, P. D. Diamantoulakis, and G. K. Karagiannidis. (2016). "Low power wide area networks (LPWANs) for Internet of Things (IoT) applications: Research challenges and future trends." [Online]. Available: http://arxiv.org/abs/1611.07449
[67] J. Petäjäjärvi, K. Mikhaylov, M. Hämäläinen, and J. Iinatti, "Evaluation of LoRa LPWAN technology for remote health and wellbeing monitoring," in *Proc. 10th Int. Symp. Med. Inf. Commun. Technol. (ISMICT)*, Mar. 2016, pp. 1–5.
[68] M. T. Buyukakkaslar, M. A. Erturk, M. A. Aydin, and L. Vollero, "Lorawan as an e-health communication technology," in *Proc. IEEE 41st Annu. Comput. Softw. Appl. Conf. (COMPSAC)*, vol. 2, Jul. 2017, pp. 310–313.
[69] P. A. Catherwood, D. Steele, M. Little, S. Mccomb, and J. Mclaughlin, "A community-based IoT personalized wireless healthcare solution trial," *IEEE J. Transl. Eng. Health Med.*, vol. 6, 2018, Art. no. 2800313.
[70] S. M. R. Islam, D. Kwak, M. H. Kabir, M. Hossain, and K.-S. Kwak, "The Internet of Things for health care: A comprehensive survey," *IEEE Access*, vol. 3, pp. 678–708, Jun. 2015.
[71] J. N. Z. Yuan, W. W. Ping, Y. H. Wen, and W. Husain, "Healthcare applications on mobile cloud computing," in *Proc. 3rd Int. Conf. Digit. Inf. Process. Commun.*, 2013, pp. 514–522.
[72] M. M. Hassan, K. Lin, X. Yue, and J. Wan, "A multimedia healthcare data sharing approach through cloud-based body area network," *Future Gen. Comput. Syst.*, vol. 66, pp. 48–58, Jan. 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167739X15004070
[73] V. Jacobson, D. K. Smetters, J. D. Thornton, M. F. Plass, N. H. Briggs, and R. L. Braynard, "Networking named content," in *Proc. 5th Int. Conf. Emerg. Netw. Exp. Technol. (CoNEXT)*, New York, NY, USA: ACM, 2009, pp. 1–12. [Online]. Available: http://doi.acm.org/10.1145/1658939.1658941
[74] D. B. Hoang and L. Chen, "Mobile cloud for assistive healthcare (MoCAsH)," in *Proc. IEEE Asia-Pacific Services Comput. Conf.*, Dec. 2010, pp. 325–332.
[75] S. J. Miah, J. Hasan, and J. G. Gammack, "On-cloud healthcare clinic: An e-health consultancy approach for remote communities in a developing country," *Telematics Informat.*, vol. 34, no. 1, pp. 311–322, 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0736585315300897
[76] A. M. Rahmani *et al.*, "Exploiting smart e-health gateways at the edge of healthcare Internet-of-Things: A fog computing approach," *Future Gener. Comput. Syst.*, vol. 78, pp. 641–658, Jan. 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167739X17302121
[77] B. Farahani, F. Firouzi, V. Chang, M. Badaroglu, N. Constant, and K. Mankodiya, "Towards fog-driven IoT eHealth: Promises and challenges of IoT in medicine and healthcare," *Future Generat. Comput. Syst.*, vol. 78, pp. 659–676, Jan. 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0167739X17307677
[78] B. Negash, T. N. Gia, A. Anzanpour, I. Azimi, M. Jiang, T. Westerlund, A. M. Rahmani, P. Liljeberg, and H. Tenhunen, *Leveraging Fog Computing for Healthcare IoT*. Cham, Switzerland: Springer, 2018, ch. 8, pp. 145–169.
[79] F. A. Kraemer, A. E. Braten, N. Tamkittikhun, and D. Palma, "Fog computing in healthcare—A review and discussion," *IEEE Access*, vol. 5, pp. 9206–9222, 2017.
[80] M. M. Islam, M. A. Razzaque, M. M. Hassan, W. N. Ismail, and B. Song, "Mobile cloud-based big healthcare data processing in smart cities," *IEEE Access*, vol. 5, pp. 11887–11899, 2017.
[81] L. A. Tawalbeh, W. Bakhader, R. Mehmood, and H. Song, "Cloudlet-based mobile cloud computing for healthcare applications," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec. 2016, pp. 1–6.
[82] J. Fontecha, R. Hervás, J. Bravo, and J. F. Navarro, "A mobile and ubiquitous approach for supporting frailty assessment in elderly people," *J. Med. Internet Res.*, vol. 15, no. 9, p. e197, Sep. 2013. [Online]. Available: http://www.jmir.org/2013/9/e197/
[83] G. Chiarini, P. Ray, S. Akter, C. Masella, and A. Ganz, "mhealth technologies for chronic diseases and elders: A systematic review," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 9, pp. 6–18, Sep. 2013.
[84] J. C. Sieverdes, F. Treiber, C. Jenkins, and K. Hermayer, "Improving diabetes management with mobile health technology," *Amer. J. Med. Sci.*, vol. 345, no. 4, pp. 289–295, Apr. 2018. [Online]. Available: http://dx.doi.org/10.1097/MAJ.0b013e3182896cee
[85] M. Kirwan, C. Vandelanotte, A. Fenning, and J. M. Duncan, "Diabetes self-management smartphone application for adults with type 1 diabetes: Randomized controlled trial," *J. Med. Internet Res.*, vol. 15, no. 11, p. e235, Nov. 2013. [Online]. Available: http://www.jmir.org/2013/11/e235/
[86] I. Bisio, F. Lavagetto, M. Marchese, and A. Sciarrone, "A smartphone-centric platform for remote health monitoring of heart failure," *Int. J. Commun. Syst.*, vol. 28, no. 11, pp. 1753–1771, Apr. 2014. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/dac.2778
[87] J. Fayn and P. Rubel, "Toward a personal health society in cardiology," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 2, pp. 401–409, Mar. 2010.
[88] Y. Zhang, M. Qiu, C.-W. Tsai, M. M. Hassan, and A. Alamri, "Health-CPS: Healthcare cyber-physical system assisted by cloud and big data," *IEEE Syst. J.*, vol. 11, no. 1, pp. 88–95, Mar. 2017.
[89] Z. Lv, J. Chirivella, and P. Gagliardo, "Bigdata oriented multimedia mobile health applications," *J. Med. Syst.*, vol. 40, no. 5, p. 120, Mar. 2016. [Online]. Available: https://doi.org/10.1007/s10916-016-0475-8
[90] P. Nguyen, T. Tran, N. Wickramasinghe, and S. Venkatesh, "*mathttDeepr*: A convolutional net for medical records," *IEEE J. Biomed. Health Inform.*, vol. 21, no. 1, pp. 22–30, Jan. 2017.
[91] E. Choi, M. T. Bahadori, A. Schuetz, W. F. Stewart, and J. Sun, "Doctor ai: Predicting clinical events via recurrent neural networks," in *Proc. 1st Mach. Learn. Healthcare Conf.* (Proceedings of Machine Learning Research), F. Doshi-Velez, J. Fackler, D. Kale, B. Wallace, and J. Wiens, Eds., vol. 56. Children's Hospital LA, Los Angeles, CA, USA: PMLR, Aug. 2016, pp. 301–318. [Online]. Available: http://proceedings.mlr.press/v56/Choi16.html

[92] A. Sathyanarayana *et al.*, "Sleep quality prediction from wearable data using deep learning," *JMIR Mhealth Uhealth*, vol. 4, no. 4, p. e125, Nov. 2016. [Online]. Available: http://mhealth.jmir.org/2016/4/e125/

[93] R. Miotto, F. Wang, S. Wang, X. Jiang, and J. T. Dudley, "Deep learning for healthcare: Review, opportunities and challenges," *Briefings Bioinf.*, p. bbx044, 2017. [Online]. Available: http://dx.doi.org/10.1093/bib/bbx044

[94] Z.-K. Gao, M. Small, and J. Kurths, "Complex network analysis of time series," *EPL (Europhys. Lett.)*, vol. 116, no. 5, p. 50001, 2016. [Online]. Available: http://stacks.iop.org/0295-5075/116/i=5/a=50001

[95] Z.-K. Gao, S. Li, W.-D. Dang, Y.-X. Yang, Y. Do, and C. Grebogi, "Wavelet multiresolution complex network for analyzing multivariate nonlinear time series," *Int. J. Bifurcation Chaos*, vol. 27, no. 8, p. 1750123, 2017. [Online]. Available: https://www.worldscientific.com/doi/abs/10.1142/S0218127417501231

[96] S. Altowaijri, R. Mehmood, and J. Williams, "A quantitative model of grid systems performance in healthcare organisations," in *Proc. Int. Conf. Intell. Syst., Modelling Simulation*, Jan. 2010, pp. 431–436.

[97] J. Wan, C. Zou, S. Ullah, C. F. Lai, M. Zhou, and X. Wang, "Cloud-enabled wireless body area networks for pervasive healthcare," *IEEE Netw.*, vol. 27, no. 5, pp. 56–61, Sep. 2013.

[98] A. Assaad and D. Fayek, "General hospitals network models for the support of e-health applications," in *Proc. IEEE/IFIP Netw. Oper. Manage. Symp. (NOMS)*, Apr. 2006, pp. 1–4.

[99] R. Alturki, K. Nwizege, R. Mehmood, and M. Faisal, "End to end wireless multimedia service modelling over a metropolitan area network," in *Proc. 11th Int. Conf. Comput. Modelling Simulation*, Mar. 2009, pp. 532–537.

[100] R. AlTurki and R. Mehmood, "Multimedia ad hoc networks: Performance analysis," in *Proc. 2nd UKSIM Eur. Symp. Comput. Modeling Simulation*, Sep. 2008, pp. 561–566.

[101] R. Mehmood, R. Alturki, and S. Zeadally, "Multimedia applications over metropolitan area networks (MANs)," *J. Netw. Comput. Appl.*, vol. 34, no. 5, pp. 1518–1529, 2011. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1084804510001414

[102] R. Mehmood, R. Alturki, and M. Faisal, "A scalable provisioning and routing scheme for multimedia QoS over ad hoc networks," in *Future Multimedia Networking*, A. Mauthe, S. Zeadally, E. Cerqueira, and M. Curado, Eds. Berlin, Germany: Springer, 2009, pp. 131–142.

[103] R. Mehmood and R. Alturki, "A scalable multimedia QoS architecture for ad hoc networks," *Multimedia Tools Appl.*, vol. 54, no. 3, pp. 551–568, 2011. [Online]. Available: https://doi.org/10.1007/s11042-010-0569-0

[104] R. Alturki and R. Mehmood, "Cross-layer multimedia QoS provisioning over ad hoc networks," in *Using Cross-Layer Techn. Commun. Syst.*, H. F. Rashvand and Y. S. Kavian, Eds. Hershey, PA, USA: IGI Global, 2012, pp. 460–499. [Online]. Available: http://services.igi-global.com/resolvedoi/resolve.aspx?doi=10.4018/978-1-4666-0960-0.ch019

[105] R. Mehmood and R. Alturki, *Video QoS Analysis Over Wi-Fi Networks*, 1st ed. Boca Raton, FL, USA: CRC Press, 2013, ch. 15, pp. 439–480.

[106] K. Chung and R. C. Park, "Cloud based u-healthcare network with QoS guarantee for mobile health service," *Cluster Comput.*, Oct. 2017. [Online]. Available: https://doi.org/10.1007/s10586-017-1120-0

[107] F. Wang, J. Li, J. Zhang, and Q. Huang, "Research on the multitenant placement genetic algorithm based on eucalyptus platform," in *Proc. 12th Int. Conf. Comput. Intell. Secur. (CIS)*, Dec. 2016, pp. 382–385.

[108] D. Yach, C. Hawkes, C. L. Gould, and K. J. Hofman, "The global burden of chronic diseases: Overcoming impediments to prevention and control," *J. Amer. Med. Assoc.*, vol. 291, no. 21, pp. 2616–2622, 2004. [Online]. Available: http://dx.doi.org/10.1001/jama.291.21.2616

[109] *Global Status Report on Non-Communicable Diseases 2010*, World Health Org., Geneva, Switzerland, Jul. 2011. [Online]. Available: http://www.who.int/nmh/publications/ncd_report2010/en/

[110] N. Saquib *et al.*, "Chronic disease prevalence among elderly Saudi men," *Int. J. Health Sci.*, vol. 11, no. 5, pp. 11–16, 2017. [Online]. Available: http://www.ncbi.nlm.nih.gov/pmc/articles/PMC5669504/

[111] Z. A. Memish *et al.*, "Obesity and associated factors—Kingdom of Saudi Arabia, 2013," *Prevent. Chronic Disease*, vol. 11, p. E174, Oct. 2014. [Online]. Available: http://www.ncbi.nlm.nih.gov/pmc/articles/PMC4193060/

[112] L. Catarinucci *et al.*, "An IoT-aware architecture for smart healthcare systems," *IEEE Internet Things J.*, vol. 2, no. 6, pp. 515–526, Dec. 2015.

[113] G. J. Mandellos, G. V. Koutelakis, T. C. Panagiotakopoulos, M. N. Koukias, and D. K. Lymberopoulos, "Requirements and solutions for advanced telemedicine applications," in *Biomedical Engineering*. Rijeka, Croatia: InTech, 2009, pp. 645–658. [Online]. Available: https://mts.intechopen.com/books/biomedical-engineering/requirements-and-solutions-for-advanced-telemedicine-applications

[114] Á. Alesanco and J. García, "Clinical assessment of wireless ecg transmission in real-time cardiac telemonitoring," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 5, pp. 1144–1152, Sep. 2010.

[115] R. Steele and A. Lo, "Telehealth and ubiquitous computing for bandwidth-constrained rural and remote areas," *Pers. Ubiquitous Comput.*, vol. 17, no. 3, pp. 533–543, Mar. 2013. [Online]. Available: https://doi.org/10.1007/s00779-012-0506-5

[116] G. P. Fettweis, "The tactile Internet: Applications and challenges," *IEEE Veh. Technol. Mag.*, vol. 9, no. 1, pp. 64–70, Mar. 2014.

[117] H. P. Sze, S. C. Liew, J. Y. B. Lee, and D. C. S. Yip, "A multiplexing scheme for H.323 voice-over-IP applications," *IEEE J. Sel. Areas Commun.*, vol. 20, no. 7, pp. 1360–1368, Sep. 2002.

[118] S. Feng, Z. Liang, and D. Zhao, "Providing telemedicine services in an infrastructure-based cognitive radio network," *IEEE Wireless Commun.*, vol. 17, no. 1, pp. 96–103, Feb. 2010.

[119] T. Szymanski and D. Gilbert, "Provisioning mission-critical telerobotic control systems over Internet backbone networks with essentially-perfect QoS," *IEEE J. Sel. Areas Commun.*, vol. 28, no. 5, pp. 630–643, Jun. 2010.

[120] M. Paksuniemi, H. Sorvoja, E. Alasaarela, and R. Myllyla, "Wireless sensor and data transmission needs and technologies for patient monitoring in the operating room and intensive care unit," in *Proc. IEEE-EMBS 27th Annu. Int. Conf. Eng. Med. Biol. Soc.*, Jan. 2005, pp. 5182–5185.

[121] M. Raza, M. H. Le, N. Aslam, C. H. Le, N. T. Le, and T. L. Le, "Telehealth technology: Potentials, challenges and research directions for developing countries," in *Proc. 6th Int. Conf. Develop. Biomed. Eng. Vietnam (BME6)*, T. V. Van, T. L. Nguyen, and D. T. Nguyen, Eds. Singapore: Springer, 2018, pp. 523–528.

[122] K. Kumar and Y. H. Lu, "Cloud computing for mobile users: Can offloading computation save energy?" *Computer*, vol. 43, no. 4, pp. 51–56, Apr. 2010.

[123] L. A. Tawalbeh, A. Basalamah, R. Mehmood, and H. Tawalbeh, "Greener and smarter phones for future cities: Characterizing the impact of GPS signal strength on power consumption," *IEEE Access*, vol. 4, pp. 858–868, 2016.

[124] T. Muhammed and R. A. Shaikh, "An analysis of fault detection strategies in wireless sensor networks," *J. Network Comput. Appl.*, vol. 78, pp. 267–287, Jan. 2017. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1084804516302545

[125] S. Nepal, R. Ranjan, and K. K. R. Choo, "Trustworthy processing of healthcare big data in hybrid clouds," *IEEE Cloud Comput.*, vol. 2, no. 2, pp. 78–84, Mar. 2015.

[126] J. Sametinger, J. Rozenblit, R. Lysecky, and P. Ott, "Security challenges for medical devices," *Commun. ACM*, vol. 58, no. 4, pp. 74–82, Mar. 2015. [Online]. Available: http://doi.acm.org/10.1145/2667218

[127] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997. [Online]. Available: http://dx.doi.org/10.1162/neco.1997.9.8.1735

[128] T. T. T. Nguyen and G. Armitage, "A survey of techniques for Internet traffic classification using machine learning," *IEEE Commun. Surveys Tuts.*, vol. 10, no. 4, pp. 56–76, 4th Quart., 2008.

[129] H. Kim, K. Claffy, M. Fomenkov, D. Barman, M. Faloutsos, and K. Lee, "Internet traffic classification demystified: Myths, caveats, and the best practices," in *Proc. ACM CoNEXT Conf. (CoNEXT)*, New York, NY, USA: ACM, 2008, pp. 11-1–11-12. [Online]. Available: http://doi.acm.org/10.1145/1544012.1544023

[130] X. Cheng, J. Liu, and C. Dale, "Understanding the characteristics of Internet short video sharing: A YouTube-based measurement study," *IEEE Trans. Multimedia*, vol. 15, no. 5, pp. 1184–1194, Aug. 2013. [Online]. Available: http://dx.doi.org/10.1109/TMM.2013.2265531

[131] M. Zink, K. Suh, Y. Gu, and J. Kurose, "Characteristics of youtube network traffic at a campus network–measurements, models, and implications," *Comput. Netw.*, vol. 53, no. 4, pp. 501–514, 2009. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1389128608003423

[132] WAND. (Mar. 2018). *WITS: Waikato Internet Traffic Storage*. [Online]. Available: https://wand.net.nz/wits/

[133] C. Sony and K. Cho, "Traffic data repository at the wide project," in *Proc. USENIX Annu. Tech. Conf., FREENIX Track*, 2000, pp. 263–270.

[134] WIDE. (Mar. 2018). *Wide. WAND Network Research Group*. [Online]. Available: http://www.wide.ad.jp/

[135] L. Deri, M. Martinelli, T. Bujlow, and A. Cardigliano, "nDPI: Open-source high-speed deep packet inspection," in *Proc. Int. Wireless Commun. Mobile Comput. Conf. (IWCMC)*, Aug. 2014, pp. 617–622.

[136] L. Deri and S. Suin, "Ntop: Beyond ping and traceroute," in *Active Technologies for Network and Service Management*, R. Stadler and B. Stiller, Eds. Berlin, Germany: Springer, 1999, pp. 271–283.

[137] V. Jacobson and S. McCanne, "Libpcap: Packet capture library," Lawrence Berkeley Lab., Berkeley, CA, USA, 2009.

[138] D. Miller, WAND Network Research Group. (Apr. 2012). *Softflowd: A Flow-Based Network Traffic Analyser*. [Online]. Available: https://github.com/davidediger/softflowd

[139] P. Haag. (2011). *NFDUMP: Netflow Processing Tools*. [Online]. Available: http://nfdump.sourceforge.net

[140] M. Abadi *et al.*, "TensorFlow: A system for large-scale machine learning," in *Proc. 12th USENIX Conf. Oper. Syst. Des. Implement. (OSDI)*, Berkeley, CA, USA: USENIX Association, 2016, pp. 265–283. [Online]. Available: http://dl.acm.org/citation.cfm?id=3026877.3026899

[141] J. R. Landis and G. G. Koch, "The measurement of observer agreement for categorical data," *Biometrics*, vol. 33, no. 1, pp. 159–174, 1977.

[142] S. A. Baset and H. G. Schulzrinne, "An analysis of the skype peer-to-peer internet telephony protocol," in *Proc. IEEE INFOCOM 25TH IEEE Int. Conf. Comput. Commun.*, Apr. 2006, pp. 1–11.

[143] T. Sinam, I. T. Singh, P. Lamabam, and N. Ngasham, "An efficient technique for detecting skype flows in UDP media streams," in *Proc. IEEE Int. Conf. Adv. Netw. Telecommun. Syst. (ANTS)*, Dec. 2013, pp. 1–6.

[144] A. Núñez, J. L. Vázquez-Poletti, A. C. Caminero, G. G. Castañé, J. Carretero, and I. M. Llorente, "iCanCloud: A flexible and scalable cloud infrastructure simulator," *J. Grid Comput.*, vol. 10, no. 1, pp. 185–209, Mar. 2012. [Online]. Available: https://doi.org/10.1007/s10723-012-9208-5

[145] A. Nuñez, J. L. Vázquez-Poletti, A. C. Caminero, J. Carretero, and I. M. Llorente, "Design of a new cloud computing simulation platform," in *Computational Science and Its Applications—ICCSA*, B. Murgante, O. Gervasi, A. Iglesias, D. Taniar, and B. O. Apduhan, Eds. Berlin, Germany: Springer, 2011, pp. 582–593.

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