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Intelligent Task Scheduling Approach for IoT Integrated Healthcare Cyber Physical Systems

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Abstract—Cyber-physical systems (CPS) based on cloud computing provides resources over the Internet and allow a variety of applications to be deployed to provide services for various industries. We proposed IoT-based healthcare cyber-physical system that provides effective resource utilization at fog and cloud levels with minimum execution cost. In addition, we also consider data from social media networking and drug review for the analysis. Furthermore, two different feature extraction approaches were applied based on data collection. Homogeneity score-based K-means clustering is used as a feature extraction and selection method for sensor data features, while text mining and sentiment analysis approach is used for social media networking and drug review data feature extraction. We proposed efficient resource utilization and cost-effective task scheduling at the Fog level and multi-objective heuristic approach Ant colony optimization task scheduling (MOHACO-TS) at cloud level. Both task scheduling algorithms focus on executing maximum task tasks in minimum time with effective resource utilization. We consider five different datasets and existing task scheduling and classification approaches for performance evaluation of the proposed IoT-HCPS framework. From the results, it is evident that the proposed work IoT-HCPS outperformed the exisitng techniques and algorithms.

Index Terms—Task Scheduling, Deep Learning, Internet of Things (IoT), Cloud Computing, Cyber Physical Systems, Healthcare.

1 Introduction

HEALTHCARE organizations are facing numerous challenges such as healthcare services, equipment and professionals; lack of skilled health-care workers [1]. Increasing demand for skilled healthcare chain [2], [3]; complexity and size of healthcare services; the demand for association among healthcare service providers and supporting organizations [4]. These kinds of issues are forcing healthcare vendors towards the inclusion and utilize the unique healthcare framework on the basis of cutting edge and innovative communication methodology. Cyber physical systems and internet of things are been significantly used to take over the existing communication framework. This leads to an era of Industry 4.0 [5]. This aims to improve the operation and minimize the cost along with quality improvement.

Another significant sector to profit from considering the industry 4.0 applications is healthcare. This results in gathering of large data from various industrial sources using intelligent IoT systems. For instance, to provide high end services at minimal expenses, the healthcare workers need to deploy practices based on cyber physical network. Considering the healthcare environment, smart systems of intelligent IoT can able to collect, gather and telecast a wider range of data sources [6], [7]. These systems make sure that the real-time analysis of patients to ensure safety in emergency situation, e.g., severe trauma, asthma and heart disorders. The propagation in communication provides the gap between these devices and the vendors by providing reliable and unified delivery of collected data [8]. The patient-oriented methodology of cyber physical methodology makes the remote analysis of patients with hospital accommodation and, in familiar cases, holding the hospital together. By utilizing the industrial methodology in cyber physical system, we have to involve the patients' feelings and willingness about the methodologies.

The improvements in developing of industrial methodology with cyber physical network facing new risks, problems and vulnerabilities for certain patients and practitioners. Considering the diverse attack, the intelligent IoT and its gathered data need to be protected by the complete healthcare environment [9]. The intelligent IoT systems host the healthcare-based applications which holds the sensitive information, e.g., birth date, vendors, medical background and total patients. These devices remain as a gateway to the incoming connections through internet. This kind of adversary may include compromising systems to fabricate data and from unwanted virus [10]. In this computing period, cyber security is an environmental domain and can provide against similar of these unknown threats. The present cyber-security based answers consist cryptographic methodology, protected protocols and protection-based privacy [11], [12]. Certain devices are associated to the internet for initial time and it is very challenging to analyze the environment of threat put forward by these devices. To protect the system, integrity of data, confidentiality of data, availability of data, authenticity need to be in region [13].

Intelligent cyber physical network aided healthcare application

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of resources sensors nodes and need low cost-based measures. To handle with the aforementioned problems, data-gram based security system is proposed as a security methodology [14]. In the literature, various transportation-based methodology were discussed for securing the transmission of data and patients' privacy in healthcare-based applications. Electronic based database can handle large data and transmit through cloud servers for various applications. The advantage of incorporating health 4.0 in healthcare environment are large. This helps in enhancing the scalability, flexibility, reliability, cost significant and healthcare quality based on operational methodology [15]. These parameters will improve the healthcare network in different ways such as associating all these parameters to help enhance global and national comments to pandemic like situations [16]. Moreover, forming and delivering healthcare methodologies that follow the health 4.0 concepts is very tedious. Challenges involved, such as enhanced complexity in design, types of architectural options, support services capabilities and consists of security issues and privacy options are some instances. One methodology to address these problems is to utilize an advanced service-based middle-ware methodology. In addition, this model can improve current methods and enable the initialization of unique value-added application related to Health 4.0.

As data which is related to healthcare are significantly explosive, there are various problems for managing data, processing and storage, as follows.

- Large Scale: Taking this enhancement of medical details into account, normally the enhancement of hospital information network, the amount of medical data has been improvised [8]. In addition, the improvement in wearable devices promotes the expansion of healthcare data [17].
- Rapid Formation: various medical components, normally wearable systems, gathers data on continuous basis. The enormous amount of collected data need to be promptly analyzed for responding to emergency situations [18].
- Different Structures: clinical investigations, treatment, observations, and various healthcare devices gather complex and heterogeneous data (e.g., image, text, audio) that can be semi-structured or structured formation [19].
- Deep Range: The values taken in a remote source is limited. Moreover, using data fusion technology and based on electronic records, we can enhance the deep range from data that is available from healthcare, like guidance for personalized health and warning for public health [20].

Therefore, to ensure secure and privacy based healthcare framework we need to make an improvement in the scalability and resource efficiency of the models. Ensuring processing time, computational cost, and relative balance as per the user needs. For this reason, the contribution of this research work includes:

1) An IoT-based healthcare cyber physical system is proposed in order to provide resource utilization efficiently at fog and cloud level by having minimum execution cost.
2) Two different feature extraction techniques were used to extract certain features from the collected dataset.
3) Furthermore, an adaptive neural network based deep learning model is proposed for the detecting condition of health.

2 LITERATURE REVIEW

The ideas of healthcare 4.0 and its basic goals have been incorporated in various ways in certain situations which could form a lot of misconceptions out of it. We formulate certain background details about healthcare 4.0 to create a base overview of the formed concept. We elaborate a brief conceptual information about the technologies that persists for healthcare applications. High-level based smart cyber physical model (CPM) uses the pervasive implemented smart systems as sensors [21] to gather information and provide amenities, which is on the basics of large-scale public event observation and energy control to maximize path planning for every individual. Involving both the vital adoption and the environment of participants, it is difficult to control the consumption of energy for the participants in a smart CPM. There are various phases of works studying the issues that persists in the resource consumption for CPM. Authors suggested a novel sensing methodology for vehicles and humans who use the association among the sensing data, effects of hot-spots and chance to facilitate a higher energy effective coverage for a monitored region [22]. The work in [23] stated that the event coverage using sensor system with variety of sensors can attain energy savings. Wang et al [24] illustrates recognition of user activities using physical data. The proposed model uses a minimum total of sensors to identify the state of user while communicating the information to the servers. Cui et al [25] studied energy consumption-based model for communicating data in CPM, where wireless model are the vital information barriers. However, these studies do not involve preservation of privacy for participants.

A powerful methodology for data gathering in smart CPM, has also been widely investigated. There is a strategy focusing on gathering data for crowd sensing. For example, Xiong et al. developed a novel methodology [26] which is deployed on an energy efficient framework, which monitors data gathering tasks based on the users' historical behaviors. Li et al [27] investigated heterogenous based sensing task work which includes the price for collecting data of every participant. Foremski et al [28] developed a methodology which utilized crowd sensing to gather the information about the cellular systems coverage. This methodology is designed to be energy effective by monitoring the batteries for resource consumption. Most of the methods mainly focus on monitoring physical data like information pertaining to location. Micinski et al. [29] investigated that toughen locations do not disturb the systems functionality. They deployed a methodology to gather false location near real one. The work in [30] gathers a fake way for uploading information to conceal crucial participants information.

Authors in [31] proposed SHM model which includes five modules such as mobile sensor recruitment, privacy with data sharing phases, sensor advertisements, transmission guarantee, and load balancing. Authors confirmed secure communication using mathematical modeling and validated the proposed model with the accurate testing method which includes hardware and software tools. Trade-off between quality-of-service (QoS) and energy efficiency is provided by the proposed model and the performance in compared with other known protocols. Authors in [32] provided security in healthcare from various types of attacks by developing lightweight remote user authentication and key establishing scheme. Authors used lightweight cryptographic operations and conducted security analysis to prove the robustness of the proposed model performing against various possible attacks.

The performance of the proposed model is compared with other existing models based on communication cost, functionality features, offered security, and computation cost. Authors in [33] introduced secure authenticated and cost-effective scheme to protect from cyber threats and reduce computation and communication costs for the cloud-assisted remote health monitoring system. The proposed systems security strength is showed by the proof of informal security against various threats.

Fawaz et al. [34] investigated the issues of gathering mobility scenario instead of unique locations while uploading sensitive information. Wang et al [35] mainly focused on the pattern which holds the sensitive information that contain spatial and temporal association. Moreover, these studies mainly focus on the aspects of privacy, and does not deploy by smart CMPs because to their minimal consideration for utility. Finally, the privacy-based issues have been considered in cyber physical model. Some of the study depicts about the task allocation where the participants would not indicate the task association to their sensitive details. They mainly vary in the privacy definition and the incentive methodology for participants. Various privacy is used in crowd sensing to hold the sensitive details for providing types of applications. These methods mainly involve the identification and competition between various tasks considering cost.

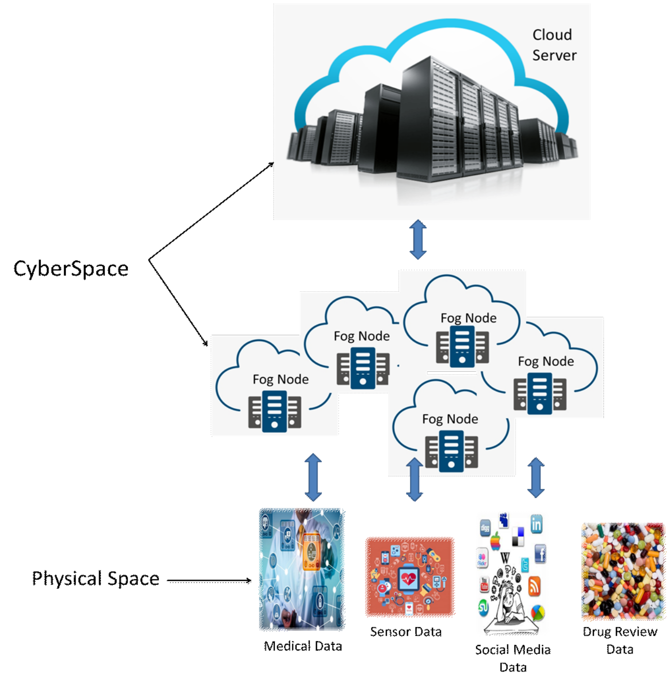

Figure 1: Proposed System Model

3 Proposed IoT-HCPS Model

In this work, we presented a cyber-physical system (CPS) for healthcare in which remote monitoring of patients have been considered. The main objective of this work is to minimize task execution cost, effective utilization of resources at fog and cloud server, and prioritization of critical tasks. Firstly, we proposed a task scheduling algorithm at Fog level based on critical health conditions and loads on fog nodes. Second, we proposed task scheduling at cloud level for effective resource utilization and load balancing in cloud nodes. After the task scheduling, health condition classification based on sensor data, medical records, social networking data, drug review and medication side effects were performed. We used deep learning algorithm at each fog and cloud node for classification process. We also proposed a prioritization method for scheduling critical tasks.

3.1 System Model

This system architecture of the proposed methodology is shown in Fig. 1. There are two phases included in the proposed system model such as physical and cyber space. There is static, incremental with fixed contours, and static in the physical space whereas the undefined, exponential, and dynamic environment is given in cyber space.

Figure 1 demonstrates the Fog-Cloud computing architecture. This framework is developed by deploying a processing unit for Fog and Cloud nodes, in which both have the same CPU processing rate, CPU use charge, memory-utilization cost, and bandwidth utilization price. Cloud nodes, on the other hand, are usually more efficient than Fog nodes, but their use is more expensive. The end user submitted their queries to the Fog node and these are split into individual and small tasks ant then executed via the Fog-Cloud infrastructure. Every task includes the following characteristics: the number of operations, the memory space needed, and the length of input and output file. Let each task be denoted as T_{s_k} and signifies the k^{th} task. Each time a set of n separate tasks is submitted to the system which is mathematically expressed in Eqn. 1.

$$T_{s_n} = T_{s_1}, T_{s_2}, ..., T_{s_n} \tag{1}$$

Each of these tasks is either executed on the fog node or cloud node having the same functional characteristics such as CPU rate, usage fees of CPU, memory and bandwidth. However, processing nodes at cloud are usually more powerful than the nodes at Fog, but the cloud nodes have a higher cost utilization. There are n set of processing nodes including Cloud nodes (Cn) and Fog nodes (Fn) in the system such that $P = Cn \cup Fn$ and P is expressed in Eqn. 2.

$$P = P_1, P_2, ..., P_m \tag{2}$$

Where, P_i represent i^{th} processing node.

3.2 Analysis Model

In this analysis model, we demonstrated pre-processing, resource utilization and optimization based on task scheduling analysis, classification and prediction based deep learning technique. Figure 2 shows the analysis model and resource utilization at Cloud-Fog architecture.

The data will be collected from the physical space by the proposed system which includes sensor readings data, medical information, and social media data. Real-world data, on the other hand, is particularly challenging to deal with because of its irregularities, incompleteness, distortion, multiple formats, inconsistencies, vast size, missing values, and high dimensionality. These findings produce a poor quality and noisy data. Before model analysis and processing, we first perform data pre-processing for all the collected data. Pre-processing step saves the processing time and increases the quality of data. Data pre-processing is performed in cyberspace. Cyberspace is divided into two levels: Fog level

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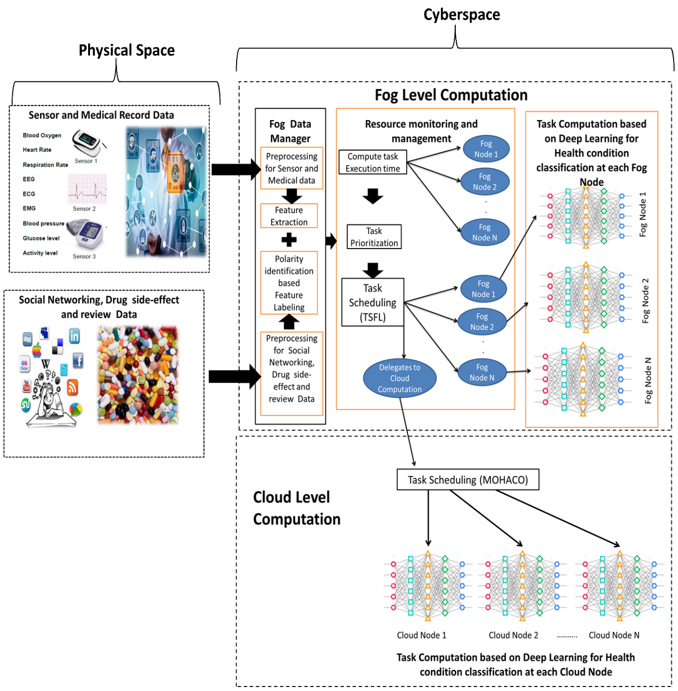

Figure 2: Analysis and Resource Utilization at Cloud-Fog Architecture

computation and cloud level computation. At Fog level, various components are used for performing different computational tasks including pre-processing, feature extraction, resource monitoring and management and deep learning based task computation for health condition prediction. Three modules are used to perform all tasks: Fog data managers, resource utilization management, and task computation. Fog data managers perform pre-processing and feature extraction; resource utilization management performs task prioritization and scheduling; and task computation perform analysis and processing based on deep learning techniques.

3.2.1 Data Pre-processing of Sensor and Medical Data

The information gathered by wearable sensors has a number of drawbacks. Their contents are replete with erroneous and ineffective information. In addition, sensor data is damaged by signal distortions such as interference and inconsistent data, which significantly reduce the classification effectiveness of the sensor data. Pre-processing and filtering of data are performed prior to analysis as a result. We process the data to eliminate errors and interference from the data stream. Data is cleaned up by deleting all of the ASCII characters and for removing noise from the data, a well-known pre-processing technique known as Kalman filtering is used. As an additional step, an unsupervised filter named Replace Missing Values is used to replace any missing numeric values in the dataset with means and modes calculated from the data that is currently accessible. The Remove Useless filter method which is an unsupervised filter with a maximum variance of 90 percent is used to eliminate useless characters with a maximum variance of 90 percent. Afterwards, the numerical values are normalized with the use of a Normalize filter which limits them between 0 and 1 for any categorization. After completing these procedures, the Em Editor is used to partition the dataset into n data files, which are then uploaded for analysis in a Hadoop based cloud environment.

The Medical Records (MR) includes complete health information of patients. These are diagnostic lab tests, self-examination results, and medicines used by the patient. Diagnostic lab tests are data obtained from medical devices that may be used to determine the health of a patient. Also, the health status of patients is evaluated differently based on their past illness and medical history of family. Questions are asked to patients for obtaining self-diagnostic data. Questionnaire includes dyspepsia, alcohol, and smoking. Medicine data contains prescription of medications for diagnosis. Some MR features may be utilized to classify patients. For data analysis, each MR property is given an ID and a reference status value (0, 1) where 0 represents healthy and 1 indicates unhealthy. We also employed MR data to address sensor-based data restrictions for replacing missing values with the actual MR feature values in the dataset.

3.2.2 Pre-processing of Social Network Content

Data pre-processing of social media and web content information is performed using text mining steps like: stop word removal, tokenization, POS tagging, stemming and lemmatization.

Stop word removal: To increase the accuracy of classification model, stop words like preposition, articles, symbols and URL are removed from corpus data. The absence of these stop words does not affect the classification process.

Tokenization: It eliminates blank space and line breaks from a large corpus of text, breaking it up into smaller phrases or tokens. In a complicated sentence, blank space and line breaks are almost always present. To remove blank space and line breaks, the n-gram tokenizer is used. These extracted words are then tagged with their part of speech (PoS) and lemmas for further analysis.

PoS tagging: Words in the content are defined using PoS tagging. For POS tagging, we employed Stanford Core Natural Language Processing (CoreNLP) after splitting the corpus text into sentences. Every phrase contains a full clause after tagging, containing a noun, adverb and a verb.

Stemming and lemmatization: Stemming is the process of taking words from a corpus text and rewriting them from the ground up. For stemming, the system uses a suffix-dropping method. The lemma term used in the text is expressed by lemmatization. The system can easily extract the lexicons for each word after lemmatization. Serum glucose, for instance, is linked to blood sugar. As a result, the root and lemma words are put to good use. In social media, patients use unique terms for some words (for instance, happpppppy, saddddd, depressed etc) that influence the output classifiers. As a result, we create a generic term from a string of letters that occur more than twice (e.g., saddddd becomes sad, happy converts happy, distressed become depressed).

Polarity identification of features: The proposed method analyses social media network posts to determine whether or not a patient is depressed or stressed. Drug reviews are also used by the system to find out how people feel about the effectiveness and possible negative effects of steroidal anti - inflammatory drugs. For the two aforementioned tasks, we rely on sentiment analysis. Sentiment categorization relies on finding the feature polarization and document labeling. We utilize SentiWordNet (SWN) to detect the polarity of opinion terms in social media data and website contents after pre-processing. The feature polarity findings are then added together to get the document's overall polarity. WordNet synsets are linked to three numerical values: positive, negative, and neutral. However, SWN is used to find a word is an noun, adjective, adverb, or verb. Word Sense Disambiguation (WSD) solves this problem by retrieving the words meaning for each word. It also gives value 0 to a word in the corpus if SWN has no meaning for it. After WSD, we extract the SentiWordNet (SWN) scores for the same senses of the opinion words, and then use the following equations to determine the polarity of each feature:

$$Pos_{+score}(X_i) = \sum_{\omega\varepsilon\omega x_i}^{n} Pos_{+score}S_{\omega} \tag{3}$$

$$Neg_{+score}(X_i) = \sum_{\omega\varepsilon\omega x_i}^{n} Neg_{+score}S_{\omega} \tag{4}$$

$$Neu_{+score}(X_i) = \sum_{\omega\varepsilon\omega x_i}^{n} Neu_{+score}S_{\omega} \tag{5}$$

Where, $Pos_{+score}(X_i)$, $Neg_{+score}(X_i)$, and $Neu_{+score}(X_i)$ represent a feature score of positive, negative and neutral sentiments. The score of each sentiment word ω is computed using the arithmetic mean of SentiWordNet. Polarity of Feature (FP)is computed based on following Eqn. 6:

$$\begin{aligned} FP(X_i) = positive, Pos_{+score}(X_i) > Neg_{+score}(X_i) \\ and\ Neu_{+score}(X_i)\ Negative, \\ Neg_{+score}(X_i) > Pos_{+score}(X_i) \\ and\ Neu_{+score}(X_i)\ neutral, \\ Neu_{+score}(X_i) > Pos_{+score}(X_i) \\ and\ Neg_{+score}(X_i) \end{aligned} \tag{6}$$

3.3 Pre-processing of Sensor Data

Feature extraction and selection of sensor data: Feature extraction is performed using K-means clustering. After performing clustering using K-means, each extracted feature is selected using entropy based homogeneity metric score (HMS). After the clusters have been created, the homogeneity score is computed and utilized as a ranking score for the clustering characteristic. Higher the rating, better the classification would be, whereas lower the ranking, less the important for elements present in the classification. When each feature's rank homogeneity is calculated, then features are sorted from the highest to lowest rank that is in decreasing order. With a rank value ranging from 0 to 1, low homogeneity indicates that the data points for the feature extraction in the clusters are dispersed, while high homogeneity indicates that the feature is well-represented. In light of the growing number of heterogeneous data collected from many sources, finding a unique characteristic that belongs to a single class is likely to be more successful than depending on common features in the classification process. We will calculate the HMS of each feature w.r.t to every cluster class using following Eqn. 7.

$$HMS = \frac{H(Y_t|Y_p)}{H(Y_t)} \tag{7}$$

Where, $H(Y_t|Y_p)$ represent conditional entropy for true (Y_t) class and predicted (Y_p) class. $H(Y_t|Y_p)$ is calculated using following Eqn. 8:

$$H(Y_t|Y_p) = -\sum_{ct=1}^{|CT|}\sum_{cs=1}^{|CS}\frac{y_{ct,cs}}{y}log\frac{y_[ct,cs]}{y_{cs}} \tag{8}$$

Class entropy (Y_t) is computed using following Eqn. 9:

$$H(Y_t) = -\sum_{ct=1}^{|CT|}\frac{y_{ct}}{y}log\frac{y_{ct}}{y} \tag{9}$$

Where, ct represents number of cluster, cs denotes number of class (cs=2), y indicates number of features extracted from sensor reading, y_{cs} represent number of feature belonging to class cs, y_{ct} represent number of feature belonging to cluster ct and $y_{ct,cs}$ represent number of feature assign to cluster ct from class cs.

Feature Fusion: Feature from sensor reading, medical records, social media and drug review are fused using following Eqn. 10:

$$ff_{X,Y} = X_i \cup Y_i \tag{10}$$

Where, feature fusion of the input X for the output Y is defined as $ff_{X,Y}$. Furthermore, X_i and Y_i is the input of first word union with the first word of output variable. In equation 21, ♯oog ants is the number of nodes considered for the global phenomenon.

3.4 Task Scheduling and Cost Optimization at Fog Level

In this section, we presented a cost optimization problem based on task execution and scheduling. There are T_s task such that $T_s = Ts_1, Ts_2, ...Ts_n$ and each task has $wl_i(i = 1,2,3,...W)$ workload and ld_i latency deadline. In the cloud-fog environment, there are fs_g fog server such that $fs_g = fs_1, fs_2, ..., fs_g$ and each fog server has different cost $C_j = C_1, C_2, ..., C_j$ and processing speed $\rho_j; j = 1,2,\ldots,S$. For cost minimization of offloading task, we assign low-cost fog server to each task that is able to satisfy the constraints of deadline dl_i. Assignment of task Ts_i, to fog server fs_j is represented by binary variable $v_{i,j}\varepsilon 0,1$. Each task cost is determined by $\varsigma_j = \frac{\rho_j}{C_i}$ and task execution time Ts_i^{ext}.

The cost minimization problem for task scheduling at fog level computation is defined as per below Equations:

$$C_{mini} = \mathbb{Z} = \sum_{i=1}^{W}\sum_{j=1}^{s} v_{i,j} times \varsigma_j \times Ts_j^{ext} \tag{11}$$

$$Ts_{j,0} = 0 \tag{12}$$

$$Ts_{j,k} = Ts_{j,k-1} + \sum_{k=1}^{W} v_{k,j}Ts_k^{ext} \tag{13}$$

$$Ts_i^{ext} = \sum_{j=1}^{s} v_{i,j} \times \frac{Wl_i}{\rho_j} \tag{14}$$

$$ft_i = \sum_{k=1}^{W}\sum_{j=1}^{s} Ts_{j,k}v_{k,j} \tag{15}$$

$$ft_i \le ld_i \tag{16}$$

$$\sum_{i=1}^{W}\sum_{j=1}^{s} v_{i,j} = 1 \tag{17}$$

Where, $v_{i,j}\varepsilon\{0,1\}$ is the representation of binary variable at fog server.

Task scheduling at fog level computation is shown in Fig. 3. We proposed efficient resource utilization and cost effective task scheduling (RUCE-TS) at Fog level. During this task scheduling, we divide the task into two stages: critical task and non-critical task. All the critical task (e.g., high heartbeat, high blood pressure, deadline oriented, low workload, negative feature polarity etc.) are assigned to fog server while all the non critical task were assigned to cloud sever. Algorithm 1 represents the pseudo code for task scheduling at fog level computation.

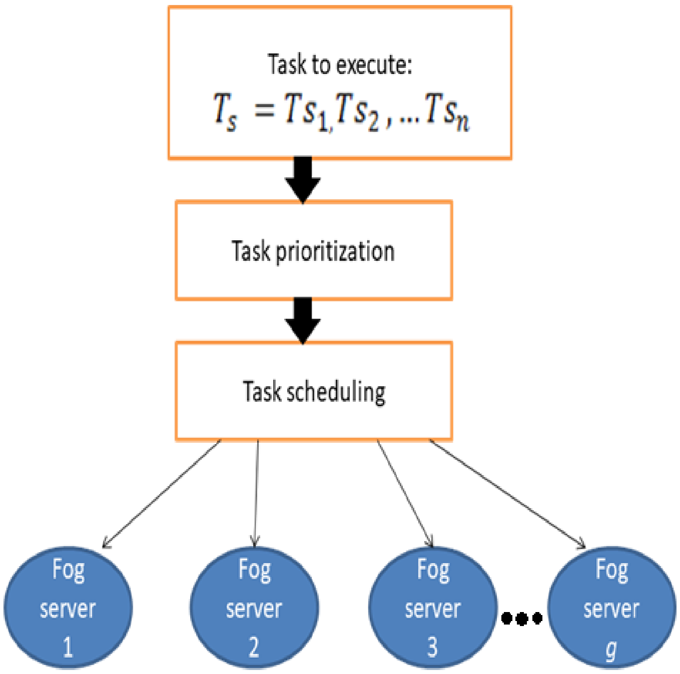

Figure 3: Flowchart of Task Scheduling

Algorithm 1 Task scheduling at Fog level: RUCE-TS

Input: List of tasks Q_{T_s},
Deadline for each task Q_{ld},
Fog server list $Q_{fs_g} = \{fs_1, fs_2, ..., fs_g\}$,
Cloud server list $Q_{cls_g} = \{cls_1, cls_2, ..., cls_g\}$
Output: Relevant resource mapping of the tasks

Begin
Let cost minimization be $\mathbb{Z} = 0$
for Each task Q_{T_s} **do**
  Compute task cost using following equation: $\varsigma_j = \frac{\rho_j}{C_j}$
  Arrange the task based on ς_j in descending order and store it in fog server queue list Q_{fsl}
Set fs=NULL
for each $fs_j \varepsilon Q_{fsl}$ **do**
  $Ts_{j,0} = 0$
  compute Ts_i^{ext} of fs_j using 14.
if $(Ts_{j,i-1} + Ts_i^{ext}) \&\& (Ts_{y_i > \tau_i} \&\& (FP(X_i) = negative))$ **then**
  τ_i represent threshold value for sensor reading
  Assign TS_i to fs_j and compute $Ts_{j,i}$ of fs_j using Eqn. 13
  Compute cost minimization $\mathbb{Z}$ using Eqn. 11
else
  Assign TS_i to cls_j

3.5 Task Scheduling and Cost Optimization at Cloud Level Computation

As mentioned earlier, we have used two-level task scheduling, one at Fog level and other at cloud level. In cloud-level, we proposed a Multi-objective heuristic approach based on ant colony optimization with Global pheromone computation for task scheduling (MOHACO-TS) at cloud machines, which was then refined by a greedy optimum assignment strategy to provide even better solutions. Thus, after an ant has developed a solution, it optimizes the proposed solution by localized greedy search and leading to an improved and best assignment solution (IBAS). So the scenario information is updated during the operation and allocation is determined by the pheromone matrices and verified to the scenario information. The results were then presented as the best of two solutions. When using proposed ACO based task scheduling algorithm, the issue that must be addressed is the allocation of n tasks assigned at cloud which is indicated by Ts_i where the i = 1...n and m VMs (virtual machines) represented by VM_j where j = 1...m and the issue that must be addressed is that every job must be given to one VM. Our goal is to establish a schedule that requires the minimum time over cloud virtual machine systems to accomplish the computing tasks they are assigned. The utilization of the VMs and computer machines were indicated by u_{ij} which is dependent on two factors. First is the computing capability of VM_j, which is measured as MFLOPS (Million Floating point Operations Performed in one Second) and the second factor is length of task Ts_i which is depends on the number of instruction or operation per task that required to complete the task Ts_i. The utilization value of VMs is computed using Eqn. 18:

$$u_{ij} = \frac{Ts_i}{VM_j}(MFLO/MFLOPS) \tag{18}$$

To schedule the task, we employed task scheduling matrix $n \times m$, in which s_{ij} represent entries in the matrix. Assignment of task in VM is represented as Eqn. 19:

$$s_{ij} = f(x) = \begin{cases} 1, & task\ i\ is\ assigned\ to\ VM_j \\ 0, & otherwise \end{cases} \tag{19}$$

The element of n∗m matrix represents the global pheromone values which is denoted by t_{ij}. Using pheromone values, we can determine whether or not a certain task should be assigned to an individual machine. In the pheromone matrix, the values of t_{ij} are conditionally modified by a probability of P(i,j). In other words, tasks i that was suggested by a greater number of ants and has a better chance of being completed on machine j than other assignments. Initially, the values of pheromone are equal. Every ant during each iteration of the algorithm updates its matrix of global pheromone. Eqn. 20 and 21 are used for matrix update of global pheromone and assignment of task Ts_i to machine VM_j.

$$p(i,j) = \frac{t(i,j)}{\sum_{j=0}^{m} t(i,j)} \tag{20}$$

$$t_{ij} = 1 + t_{ij} + \frac{p(i,j)}{\natural oogAnts} \tag{21}$$

Additionally, these values are modified by a dissipation factor ρ, which is applied when each ant completes its iterations throughout the course of loop. In other words, the pheromone concentration is lowered in relation with ρ to imitate pheromone dissipation over a period of time. For instance, if the dissipation factor ρ=0.6, then the dissipation rate ρ-1=0.4,. As a result, Eqn. 20 is used for the concentration of all components in the pheromone matrix which is lowered.

$$t_{ij} = (1-\rho) \times t_{ij} \tag{22}$$

For local pheromone update, we presented greedy search approach in which the ant first produces a local schedule (Loc) and initial task-machine allocation is performed randomly. The ant then iterates through a series of updates, assigning each task to a separate machine while leaving other tasks on their initial machines as Loc. The randomly initialized assignment is compared to every new updated Loc. After iteration, if better schedule assignment (BSA) obtained based on maximum execution time of machine then Loc is placed with BSA. The usage (U) of schedule is evaluated by computing total time consumption (TTC) of each VR for executing tasks. The total time consumption (TTC) is evaluated by multiplying usage matrix (UM) with schedule matrix and output of this matrix multiplication is n∗m matrix. Mathematical equation for time consumption and utilization is as represented in Eqn. 23, 24, and 25:

$$TTC = UM \times S \tag{23}$$

$$u = \sum_{i=0}^{n} \sum_{j=0}^{m} TTC(i,j) \tag{24}$$

$$cost(C) = \frac{u \times machine\ cost\ in\ 1\ min}{60} \tag{25}$$

After completion of successful iteration by each ant, the best allocation is achieved by that ant and compared with the best allocation acquired by all preceding ants. Later on, this comparison will be useful for comparing the improved and best assignment solution (IBAS) with the assignment based on the pheromone matrix. After all the ants completed their iterations, the pheromone matrix is ready to extract an allocation that has been agreed upon by the majority of ants. That is, the largest value of each row 'i' implies that the associated VM_j was assigned to task Ts_i by the majority of ants. However, our goal is to get the greatest possible work assignment. As a result, we altered the ACO algorithm slightly and used a basic greedy technique to compare each individual ant's IBAS with the allocation provided by the majority of ants. The algorithm then picks the best of two and uses it as the algorithm's output.

3.6 Deep Learning based Classification

In this work, we deployed adaptive neural network based deep learning (ANNDL) approach in which extracted features $ff_{X,Y} = \{X_1, X_2, ..., X_n, ..Y_1..Y_m\} = ff_k$ where $\{k = 1,2,3,....,N\}$ and N represent total number of feature extracted from all the input source. are applied as input to the NNDL classifier. Weights $w_k = \{w_1, w_2, ..., w_N\}$ are attached to each input link and its values are assigned arbitrarily. The hidden nodes of the succeeding hidden layer executes the function of adding the product of input data and the weight vector for all the input nodes which are connected to it and is represented by the input value multiplied by the weight vector and summation value M is represented using following Eqn. 26:

$$M = \sum_{k=1}^{N} ff_k.w_k \tag{26}$$

The back propagation method is used to get the outcome and it is improved when the weight values are generated randomly. The optimization process is carried out in this manner. The activation function (F_i) is then used and is represented mathematically as Eqn. 27:

$$F_k = A_k\Big(\sum_{k=1}^{N} ff_k.w_k\Big) \tag{27}$$

$$A_k = exp(-G_k^2) \tag{28}$$

Where, G represents the Gaussian function used in this work as activation function. Subsequently, hidden layer for output is computed using following Eqn. 29:

$$Y_k = B_k + \sum A_k w_k \tag{29}$$

Final output layer OL_k is computed using following Eqn. 30:

$$OL_k = B_k + \sum OP_k.w_k \tag{30}$$

Where, OP_k represents the output for preceding output layer. Error rate is denoted as (e_r), relative error defined as (R_e), and weight correction is represented as (Wc) between network and target output which is computed using following equations 31, 32, and 33:

$$e_r = TO_k - OL_k \tag{31}$$

$$R_{e_k} = e_r[f(OL_k)] \tag{32}$$

$$\mathbb{W}c = \gamma R_{e_k}(ff_k) \tag{33}$$

Where, TO_k represent target output, γ represent momentum factor.

4 Result Analysis

This section discusses the findings of proposed healthcare monitoring system. The model is tested using five distinct datasets. Various experiments were performed on these four datasets to obtain the efficiency of proposed approach. Data were collected from the patient's body and social networks through wearable sensors and APIs. The retrieved data then transmitted to the Hadoop cloud environment for big data processing. Hadoop MapReduce used for splitting the dataset into separate mapping. From obtained datasets, we also develop models for diabetes, blood pressure, mental health, and medication side effects categorization. Word embedding is used to represent the social networking data and classification model for medicine evaluations. The dimensionality of word embedding for drug reviews and social networks datasets is described below.

4.1 Dataset Description

Diabetes dataset: UCI machine learning repository provides the Pima Indians Diabetes dataset which is collected from 768 individuals where 268 persons have diabetes and 500 were normal. The dataset has eight input characteristics. However, the diabetes categorization model only uses six variables and it is classified based on age, family, gender, activity, Body Mass Index (BMI), blood pressure, and blood sugar. The Blood Pressure (BP) data for classification model is trained using data from the PhysioNet MIMIC-II database. This dataset includes BP and Heart Rate (HR). However, the BP classification model is trained on just nine characteristics. Type-2 diabetes mellitus is defined as diabetes with a systolic blood pressure of 140/90 or above. We also integrated our new diabetes and blood pressure datasets with the previous dataset. Thus, the total number of diabetes and BP cases is 868 and 550. Researchers at the Gottsegen Hungarian Institute of Cardiology in Hungary and others utilize the Cleveland database to identify heart disease. Therefore, we used 14 variable characteristics to assess patient health.

Drug reviews and social media: This data is collected based on the side effects of medication which is given in UCI repository. It has six variables. However, the suggested approach only considers two features (drug name and patient reviews). We used social media to track patient mental wellness. Section 3.1 goes through the social networking and drug reviews datasets. Both the social networking and medication reviews dataset were represented by a 200-dimensional Word2vec model.

4.2 Performance evaluation

From our proposed RUCE-TS algorithm, we scheduled tasks at Fog server and used MOHACO to schedule tasks at cloud server. Therefore, efficiency of both scheduling algorithm is discussed here with classification performance of adaptive neural network based deep learning (ANNDL) model for different health conditions.

4.2.1 Comparative Analysis for RUCE-TS in Fog–Cloud Environment

To evaluate the performance of proposed RUCE-TS, we used three metric measures and these are: relative percentage deviation (RPD), Bandwidth utilization, and CPU utilization. Proposed RUCE-TS operated over a heterogeneous fog server and we compared our scheduling approach with two different scenarios: scenario 1 which represents the fog-cloud and scenario 2 represents public cloud. Both scenarios have limited resources and operate over homogeneous fog servers during scheduling. A total of 2000 tasks is used in both scenarios with the evident of finding RPD values. The scheduling policy used in the process is named block-scheduling which ir represented as priority in this task scheduling policy. Here, block hierarchy is created as a tow-fold in which one will increase the blocks visibility and second is authorization of decision making based on the given details. The current policy of scheduling algorithm can predispose the inefficiency and inaccuracy using the blocks. The resource time lets user to fully or minimum dependency on effectiveness and decision making steps.

Relative Percentage Deviation (RPD): Firstly, we presented the performance of objective function for RUCE-TS on the basis of relative percentage deviation (RPD) metric. Figure 4 shows the RPD percentage ratio of the objective function of the proposed RUCE-TS method is lower. One of the reasons is that scenario 1 and 2 are operated over homogeneous fog-cloud servers and have restricted resource capabilities. Figure 4 shows that proposed RUCE-TS improves the RPD percent of the target compared to the existing Scenario techniques. The existing scenario heuristics technique does not account job criticality and deadline when assigning tasks to heterogeneous clouds.

Bandwidth Utilization: Figure 5 indicates that the proposed RUCE-TS uses less metric bandwidth than current approaches when compared to the edge of computation. This is because Scenario 1 and 2 used edge based clouds and public clouds for sending and receiving tasks in the system which consumes a lot of bandwidth.

CPU Utilization: By using our proposed RUCE-TS model, critical tasks can be scheduled to obtain low cost cloud servers,

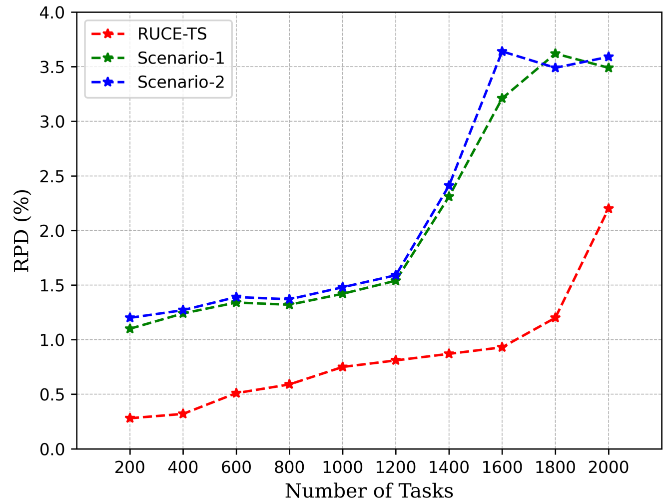

Figure 4: Performance evaluation of RUCE-TS objective function with deadline constraint on the basis of RPD %

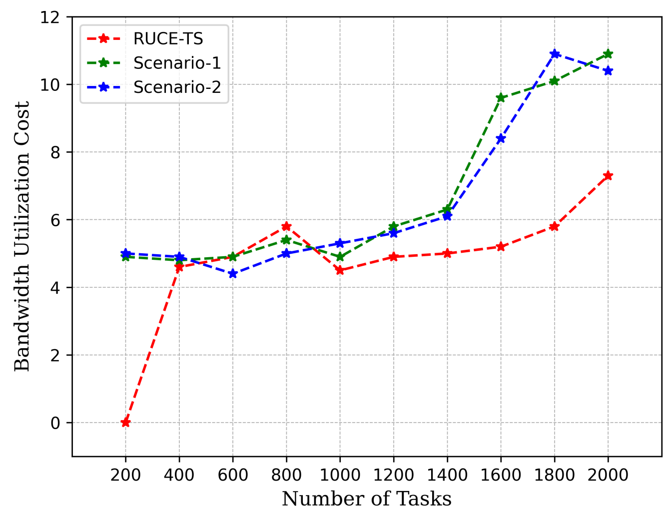

Figure 5: Bandwidth utilization of proposed RUCE-TS and Scenario1 and 2

non-critical tasks, high performance, and high cost fog servers. Figure 6 shows that the RUCE-TS uses less CPU than Scenario 1 and Scenario 2. Scheduling expenses were excessive as Scenario 1 and 2 used homogeneous fog cloud systems with high costs. Figure 7 shows that RUCE-TS is an adaptable approach during a dynamic environment without affecting application performance.

4.3 Comparative Analysis for MOHACO-TS in Fog–Cloud Environment

In this section, we discussed the comparative analysis of proposed MOHACO-TS task scheduling algorithm at cloud with the existing max-min scheduling approach on the basis of optimal scheduling time. We considered three different amount of tasks to schedule in our approach. Case 1 represents scheduling of 40 tasks, Case 2 represents scheduling of 400 tasks and Case 3 represents scheduling of 4000 tasks. We consider 10, 20 and 30 ants for scheduling tasks in MOHACO-TS over different VMs in the cloud. Figures 8 , 9 and 10 represent scheduling of tasks at cloud for Case 1,

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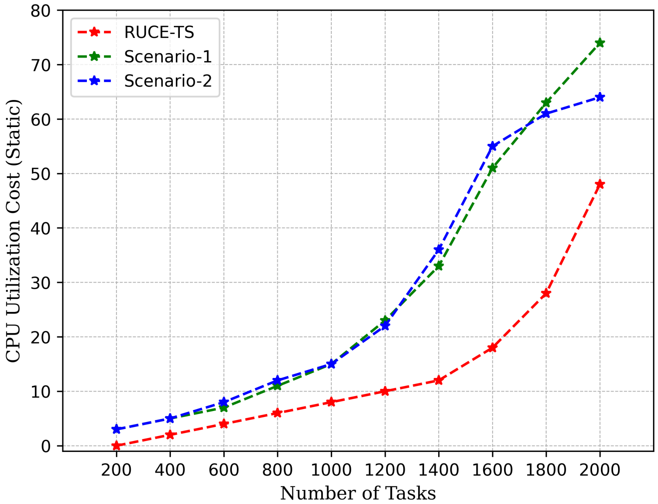

Figure 6: CPU Utilization for Static environment

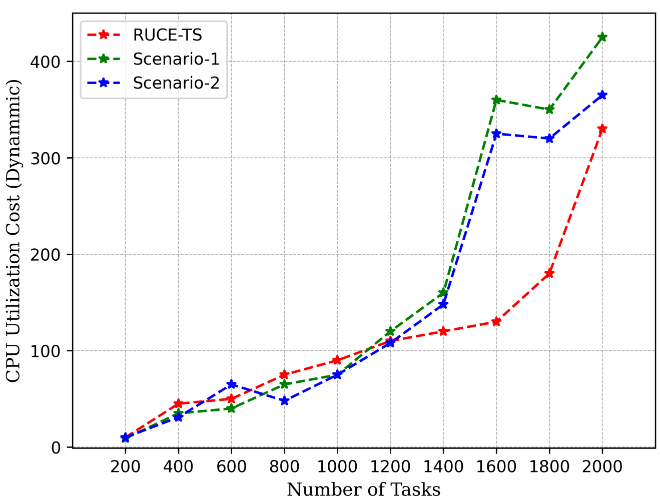

Figure 7: CPU Utilization for Dynamic environment

Case 2 and Case 3 for the proposed MOHACO-TS and max-min algorithm. We can observe that the proposed MOHACO-TS outperformed the Maxi-min algorithm represented by red dotted line and schedule the task in minimum time consumption.

4.4 Comparative Analysis of ANNDL Classification Approach in Fog–Cloud Environment

To evaluate the performance of proposed ANNDL, we considered more than 5000 records from five different dataset and compare it with benchmark techniques including deep learning neural network (DLNN) and logistic regression (LR). Accuracy is considered as a metric measure for performance evaluation. Figure 11 represents comparative analysis between three algorithms for classifying health conditions on five different dataset. From Figure it is evident that proposed ANNDL achieves highest accuracy of 99.2% while other DLNN and LR attain low accuracy of 89.5% and 82.6%. Additionally the proposed ANNDL attains a high performance for the remaining records.

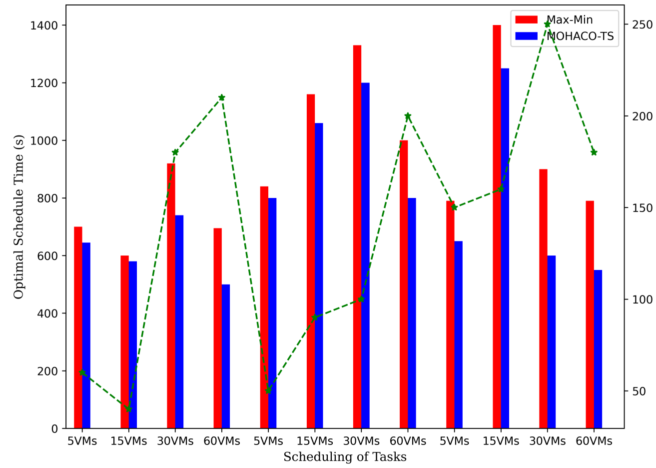

Figure 8: Comparative Analysis of Task Scheduling for Case1: 40 Task

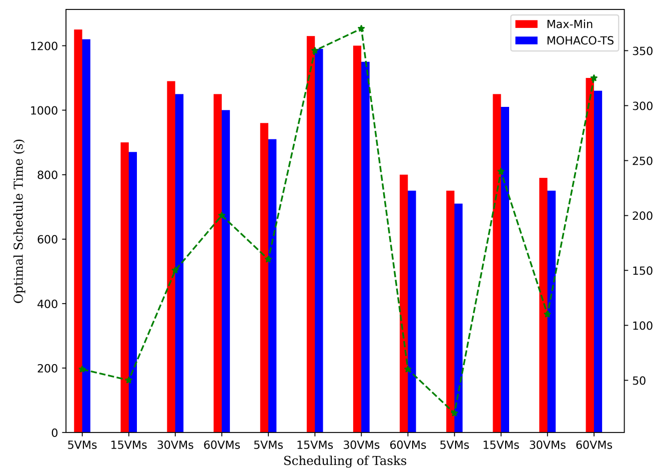

Figure 9: Comparative Analysis of Task Scheduling for Case2: 400 Task

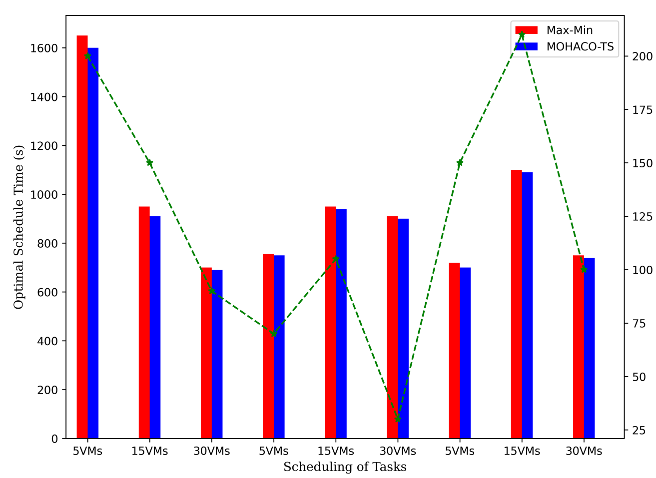

Figure 10: Comparative Analysis of Task Scheduling for Case3: 4000 Task

5 Limitations of the Work

The main limitation of this research work is that the VMs chosen for cases 1, 2, and 3 have not been increased after 60 and also

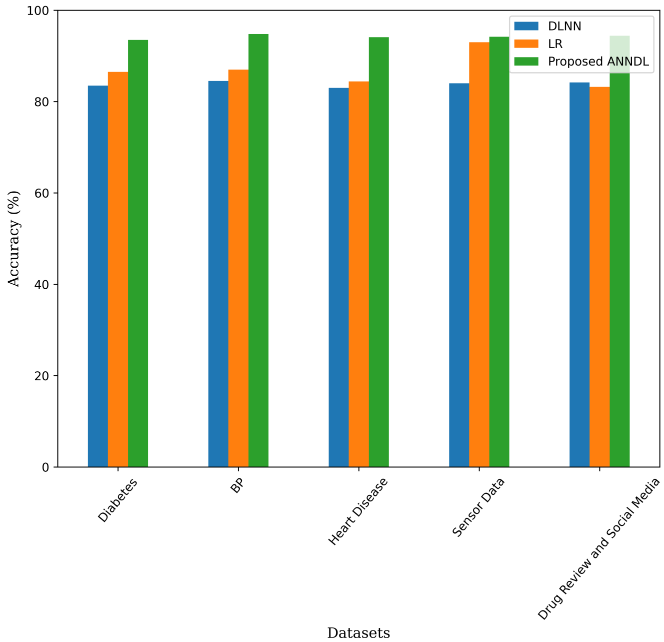

Figure 11: Comparative Analysis of ANNDL classification with DLNN and LR based on Accuracy

the time out performance need to be prioritized by reducing the number of VMs and increase in tasks.

6 Conclusion

Cloud-based cyber physical system gives resources through the Internet and enables diverse applications to be installed at serve in various sectors. The present limitation of these cloud frameworks is the inability to scale and meet the demands of centralized Internet of Things (IoT) computing platforms. Still, current fog models have shortcomings and solely focus on one of two things: accuracy of results or reduced response time. Also Task scheduling is an NP-Hard problem in complex environments like healthcare monitoring when there are many tasks. As a consequence, automatic task scheduling saves time and effort. Fog computing opens up new possibilities like automated task scheduling. We proposed an IoT-based healthcare cyber physical system (IoT-HCPS) architecture with efficient resource utilization and low execution cost. We fuse IoT healthcare data with social media networking and drug review data. We use two data gathering approaches to extract features. Sensor data features are extracted and selected using homogeneity score based K-means clustering, while social media and drug review data features are extracted and selected using text mining and sentiment analysis. The IoT-HCPS framework uses an ANNDL model to identify health conditions in real-time. We proposed efficient resource utilization and cost effective task scheduling (RUCE-TS) for fog and MOHACO-TS-TS (multi-objective heuristic approach Ant colony optimization task scheduling) for cloud. Both task scheduling systems aim to complete tasks quickly and efficiently. The proposed IoT-HCPS architecture is evaluated using five datasets and existing job scheduling and classification methods. The proposed work IoT-HCPS outperformed the benchmark methodologies and algorithms. In the future this work can be extended for the optimization model of task scheduling algorithms. Also proposed ANNDL can further be optimized by suitable optimization techniques.

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References

[1] Z. Pang, G. Yang, R. Khedri, and Y.-T. Zhang, "Introduction to the special section: convergence of automation technology, biomedical engineering, and health informatics toward the healthcare 4.0," *IEEE Reviews in Biomedical Engineering*, vol. 11, pp. 249–259, 2018.

[2] J. Wan, S. Tang, D. Li, M. Imran, C. Zhang, C. Liu, and Z. Pang, "Reconfigurable smart factory for drug packing in healthcare industry 4.0," *IEEE transactions on industrial informatics*, vol. 15, no. 1, pp. 507–516, 2018.

[3] K. Wang, Y. Shao, L. Xie, J. Wu, and S. Guo, "Adaptive and fault-tolerant data processing in healthcare iot based on fog computing," *IEEE Transactions on Network Science and Engineering*, vol. 7, no. 1, pp. 263–273, 2020.

[4] H. Yi, "Secure social internet of things based on post-quantum blockchain," *IEEE Transactions on Network Science and Engineering*, pp. 1–1, 2021.

[5] Z. Pang, L. Zheng, J. Tian, S. Kao-Walter, E. Dubrova, and Q. Chen, "Design of a terminal solution for integration of in-home health care devices and services towards the internet-of-things," *Enterprise Information Systems*, vol. 9, no. 1, pp. 86–116, 2015.

[6] P. Kumar, R. Kumar, G. Srivastava, G. P. Gupta, R. Tripathi, T. R. Gadekallu, and N. N. Xiong, "Ppsf: a privacy-preserving and secure framework using blockchain-based machine-learning for iot-driven smart cities," *IEEE Transactions on Network Science and Engineering*, vol. 8, no. 3, pp. 2326–2341, 2021.

[7] Z. Guo, K. Yu, Y. Li, G. Srivastava, and J. C.-W. Lin, "Deep learning-embedded social internet of things for ambiguity-aware social recommendations," *IEEE Transactions on Network Science and Engineering*, 2021.

[8] Y. Han, R. Wang, and J. Wu, "Random caching optimization in large-scale cache-enabled internet of things networks," *IEEE Transactions on Network Science and Engineering*, vol. 7, no. 1, pp. 385–397, 2020.

[9] M. G. Kibria, K. Nguyen, G. P. Villardi, O. Zhao, K. Ishizu, and F. Kojima, "Big data analytics, machine learning, and artificial intelligence in next-generation wireless networks," *IEEE access*, vol. 6, pp. 32 328–32 338, 2018.

[10] H. Tao, M. Z. A. Bhuiyan, A. N. Abdalla, M. M. Hassan, J. M. Zain, and T. Hayajneh, "Secured data collection with hardware-based ciphers for iot-based healthcare," *IEEE Internet of Things Journal*, vol. 6, no. 1, pp. 410–420, 2018.

[11] A. Gupta, M. Tripathi, T. J. Shaikh, and A. Sharma, "A lightweight anonymous user authentication and key establishment scheme for wearable devices," *Computer Networks*, vol. 149, pp. 29–42, 2019.

[12] Y. Liu, M. Ma, X. Liu, N. N. Xiong, A. Liu, and Y. Zhu, "Design and analysis of probing route to defense sink-hole attacks for internet of things security," *IEEE Transactions on Network Science and Engineering*, vol. 7, no. 1, pp. 356–372, 2020.

[13] J. Srinivas, A. K. Das, N. Kumar, and J. J. Rodrigues, "Cloud centric authentication for wearable healthcare monitoring system," *IEEE Transactions on Dependable and Secure Computing*, vol. 17, no. 5, pp. 942–956, 2018.

[14] C.-C. Chang and H.-D. Le, "A provably secure, efficient, and flexible authentication scheme for ad hoc wireless sensor networks," *IEEE Transactions on wireless communications*, vol. 15, no. 1, pp. 357–366, 2015.

[15] S. R. Moosavi, T. N. Gia, E. Nigussie, A. M. Rahmani, S. Virtanen, H. Tenhunen, and J. Isoaho, "End-to-end security scheme for mobility enabled healthcare internet of things," *Future Generation Computer Systems*, vol. 64, pp. 108–124, 2016.

[16] J. Liu, Z. Zhang, X. Chen, and K. S. Kwak, "Certificateless remote anonymous authentication schemes for wirelessbody area networks," *IEEE Transactions on parallel and distributed systems*, vol. 25, no. 2, pp. 332–342, 2013.

[17] M. Chen, Y. Ma, S. Ullah, W. Cai, and E. Song, "Rochas: Robotics and cloud-assisted healthcare system for empty nester," in *Proceedings of the 8th international conference on body area networks*, 2013, pp. 217–220.

[18] M. Chen, "Ndnc-ban: supporting rich media healthcare services via named data networking in cloud-assisted wireless body area networks," *Information Sciences*, vol. 284, pp. 142–156, 2014.

[19] M. Chen, S. Mao, and Y. Liu, "Big data: A survey," *Mobile networks and applications*, vol. 19, no. 2, pp. 171–209, 2014.

[20] X. Ling, J. Gong, R. Li, S. Yu, Q. Ma, and X. Chen, "Dynamic age minimization with real-time information preprocessing for edge-assisted iot devices with energy harvesting," *IEEE Transactions on Network Science and Engineering*, vol. 8, no. 3, pp. 2288–2300, 2021.
[21] J. Wan, H. Yan, H. Suo, and F. Li, "Advances in cyber-physical systems research," *KSII Transactions on Internet and Information Systems (TIIS)*, vol. 5, no. 11, pp. 1891–1908, 2011.
[22] J. Wan, D. Zhang, S. Zhao, L. T. Yang, and J. Lloret, "Context-aware vehicular cyber-physical systems with cloud support: architecture, challenges, and solutions," *IEEE Communications Magazine*, vol. 52, no. 8, pp. 106–113, 2014.
[23] M. Chen, Y. Hao, Y. Li, C.-F. Lai, and D. Wu, "On the computation offloading at ad hoc cloudlet: architecture and service modes," *IEEE Communications Magazine*, vol. 53, no. 6, pp. 18–24, 2015.
[24] Y. Wang, J. Lin, M. Annavaram, Q. A. Jacobson, J. Hong, B. Krishnamachari, and N. Sadeh, "A framework of energy efficient mobile sensing for automatic user state recognition," in *Proceedings of the 7th international conference on Mobile systems, applications, and services*, 2009, pp. 179–192.
[25] Y. Cui, X. Ma, H. Wang, I. Stojmenovic, and J. Liu, "A survey of energy efficient wireless transmission and modeling in mobile cloud computing," *Mobile Networks and Applications*, vol. 18, no. 1, pp. 148–155, 2013.
[26] H. Xiong, D. Zhang, G. Chen, L. Wang, and V. Gauthier, "Crowdtasker: Maximizing coverage quality in piggyback crowdsensing under budget constraint," in *2015 IEEE International Conference on Pervasive Computing and Communications (PerCom)*. IEEE, 2015, pp. 55–62.
[27] H. Li, T. Li, and Y. Wang, "Dynamic participant recruitment of mobile crowd sensing for heterogeneous sensing tasks," in *2015 IEEE 12th International Conference on Mobile Ad Hoc and Sensor Systems*. IEEE, 2015, pp. 136–144.
[28] P. Foremski, M. Gorawski, K. Grochla, and K. Polys, "Energy-efficient crowdsensing of human mobility and signal levels in cellular networks," *Sensors*, vol. 15, no. 9, pp. 22 060–22 088, 2015.
[29] K. Micinski, P. Phelps, and J. S. Foster, "An empirical study of location truncation on android," *Weather*, vol. 2, p. 21, 2013.
[30] R. Chow and P. Golle, "Faking contextual data for fun, profit, and privacy," in *Proceedings of the 8th ACM workshop on Privacy in the electronic society*, 2009, pp. 105–108.
[31] A. Razaque, F. Amsaad, M. Abdulgader, B. Alotaibi, F. Alsolami, D. Gulsezimhas, S. Mohanty, and S. Hariri, "A mobility-aware human-centric cyber-physical system for efficient and secure smart healthcare," *IEEE Internet of Things Journal*, 2022.
[32] M. Wazid, S. Thapliyal, D. P. Singh, A. K. Das, and S. Shetty, "Design and testbed experiments of user authentication and key establishment mechanism for smart healthcare cyber physical systems," *IEEE Transactions on Network Science and Engineering*, 2022.
[33] K. Mahmood, M. Obaidat, Z. Ghaffar, B. A. Alzahrani, S. Shamshad, M. A. Saleem, and S. Hussain, "Cloud-assisted secure and cost-effective authenticated solution for remote wearable health monitoring system," *IEEE Transactions on Network Science and Engineering*, 2022.
[34] K. Fawaz, H. Feng, and K. G. Shin, "Anatomization and protection of mobile apps' location privacy threats," in *24th {USENIX} Security Symposium ({USENIX} Security 15)*, 2015, pp. 753–768.
[35] W. Wang and Q. Zhang, "A stochastic game for privacy preserving context sensing on mobile phone," in *IEEE INFOCOM 2014-IEEE Conference on Computer Communications*. IEEE, 2014, pp. 2328–2336.

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