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Q-learning based forecasting early landslide detection in internet of thing wireless sensor network

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ABSTRACT

The issue of climate modification and human actions terminates in a chain of hazardous developments, comprehensive of landslides. The traditional approaches of observing the environmental attributes that is actually obtaining rainfall data from places can be cruel and suppressing supervising necessitated for careful infliction. Thus, landslide forecasting and early notice is a significant application via wireless sensor networks (WSN) to reduce loss of life and property. Because of the heavy preparation of sensors in landslide prostrate regions, clustering is a resourceful method to minimize unnecessary transmission. In this article we introduce Q-learning based forecasting early landslide detection (Q-LFD) in internet of things (IoT) WSN. The Q-LFD mechanism utilizes a dingo optimization algorithm (DOA) to choose the best cluster head (CH). Furthermore, the Q-learning algorithm forecast the landslide by soil water capacity, soil layer, soil temperature, Seismic vibrations, and rainfall. Experimental results illustrate the Q-LFD mechanism raises the landslide detection accuracy. In addition, it minimizes the false positive, false negative ratio.

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1. INTRODUCTION

The motion of soil, rock, and other substance downward a sloping region of land is mentioned as the landslide. Heavy Rain, quakes, volcanoes, and additional natural and synthetic processes that provide a slope unbalanced might all the activates for landslides [1]. The internet of things (IoT) acts a significant function in deciding the landslide issues [2], [3]. It presents a severe threat to humans and the world's several classes of poverty and surface surroundings. Landslides principally happen because of climate change in the surroundings [4]. There are several causes for launching such as surroundings for disaster reduction, in that the sensor notices the element and instantly forwards the data, and special machine learning algorithms are applied to offer data to the people about the disaster. It is an inexpensive and easy to install, and it might be employed via a semi-skilled individual [5].

Landslides are an importance determined movement of a bulk of rock, soil and dust down a slope, and they can origin important human death and economical losing. The enhancing number of usual tragedies because of climate change is of vital anxiety [6]. Landslides are one of the predominant geologic hazards that result in massive human and economic losses. The described analysis has been executed in several nations throughout the world as illustrated in Figure 1.

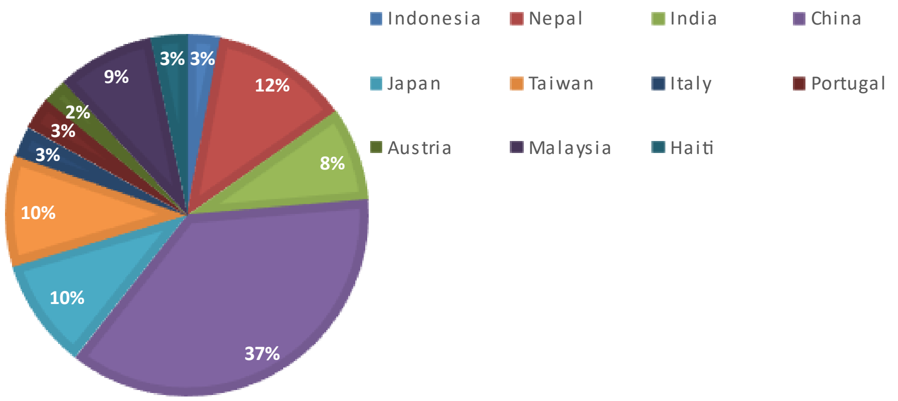

Figure 1. Landslide detection among different countries

Thus, before occurring the landslide, landslide forecasting is a significant issue in wireless sensor networks (WSN). Traditional mechanisms-based landslides prediction analysis not adequate for forecasting exact position and time for bulk motions [7]. Nowadays, the quick growth of machine learning (ML) algorithm disseminate throughout several investigators have initiated searching into disciplinary [8]. Artificial intelligence (AI), and remote sensing to detecting landslide hazard evaluation. IoT with ML to observe the geological landslide actions to protect the creatures from the landslides [9]. The incorporation of a deep learning model with rule-based object-based image analysis (OBIA) to notice landslides. The value of every pixel in the heatmap indicates to the possibility that the pixel belongs to moreover landslide or non-landslide module. However, it cannot able to forecast before occurring [10]. To solve these issues, Q-learning based forecasting early landslide detection in IoT WSN. Several landslide techniques capable of detecting the landslide efficiently; though, it does not forecasting the landslide. The significant aim of this article is to introduce a Q-learning algorithm to recognize landslides well. The section 2 explains Q-learning based forecasting early landslide detection in IoT wireless sensor network. Section 3 describes experimental results. Finally, section 4 presents conclusion and future work.

Landslides pose a recurring threat in the Himalayan region, leading to devastating consequences in terms of human casualties and property damage. A groundbreaking mechanism is used to observing and forecasting landslides. This system applies sensor nodes to incessantly observe a surrounding situation and collect pertinent data. This mechanism utilizes a support vector machine (SVM), k-nearest neighbor (K-NN), and decision tree (DT), algorithms measured the gained data [11]. The landslides prediction system utilizing the radio frequency (RF) amplifier and rectifier designed and invented. Next, an boundary among the sensor signal output as well as cloud computing using long range (LoRa) picked out as a IoT end device correspondingly [12]. Landslide displacement predict artificial intelligence algorithms rainfall and displacement data purpose to allow a reliable early warning which can forecast landslide disaster as well as provide early warning [13]. A Gaussian process to forecast the landslide in WSN. This mechanism minimizes the miss with wrong alarm ratio of landslide [14]. The growth of WSN is a cost-efficient solution for observing partly stable slopes to forecast landslides in Pune and Maharashtra. An energy efficient WSN applying low power sensor nodes to observe the moisture of soil, rushing, angle of tilt and rainfall intensity [15]. Landslides are repeating incessantly when causing direct effect on human life. The major reason following raise in landslide happening is crash of change in climate as well as raising human action. Landslide observing system utilizes a several types of sensors that can be applied to uninterrupted landslide risk observing hazard [16]. Deep learning algorithm is utilized to avoid landslides. This mechanism applies a long short-term memory (LSTM) to reveal IoT-based usual hazard observing and forecasting analytics in the hills [17]. The enhancement of forecasting landslides and early alert by applying ML with IoT techniques using features like moisture of soil, soil of fleece strength, rain severity, and terrain slope [18].

Wireless sensor nodes are provided a high sensitivity with huge reporting region. The sensor element discovers the shaking of natural disastrous from earth after that it will forward data to observing location through radio frequency identification (RFID). Moisture, weight as well as tilt meter is applied to observes glib reply from the modifying geo-technical situation. Thus, detects the landslide well [19]. The landslide strain data and subsequent distributed decision algorithm imitate pressure variation on rock tries out and calculate the equivalent strain. The variable mean Gaussian process is modeled the strain data. The distributed scalar based recognition offers as better outcomes regarding feasibility of missed detection, smallest energy utilization and false alarm [20].

Landslide prediction and early warning system is an important application where sensor networks can be deployed to minimize loss of life and property. Due to the dense deployment of sensors in landslide prone areas, clustering is an efficient approach to reduce redundant communication from co-located sensors. In this paper we propose two distributed clustering and multi-hop routing protocols, cluster aided multipath routing (CAMP) and hybrid beacon vector routing (HBVR), for this problem. While CAMP is a new clustering and routing protocol, HBVR is an enhancement of BVR with hybrid energy-efficient distributed (HEED). We further enhance CAMP and HBVR with threshold sensitive energy efficient sensor network (TEEN), a threshold-based event driven protocol. TEEN is most suitable protocol for this application since different rock types can have different thresholds for stress values. Simulation results show that CAMP-TEEN gives the best performance with respect to network life time and energy consumption [15]. The observing and forecasting events for detecting Landslides. An optimal location for sink assignment to enhance the features for example delay, obtained ratio, and jitter [21].

A magnetic induction established localization that precisely and proficiently positioned arbitrarily distributed sensors by leverage the multipath fading. A two-step positioning method for getting rapid and precise localization outcomes: primary, formulating the fast-initial locating during an tacking direction increased Lagrangian process for uneven sensor positions inside a small processing time, and next suggesting fine-grained positioning for executing great exploration for optimal position evaluation through the coupled gradient algorithm [22]. Landslides can be discovered by studying the environment data through sensor nodes. Hence, forecasted the landslides. Artificial neural networks (ANN) provide precise forecasting and reveal high learning capability. Conversely, the ANN algorithm to unbalanced data allocation. A switching policy which can decide between dissimilar predictors along with ecological states [23]. The fall detection method that utilizes an IoT have several restrictions; for example, latency, energy utilization, and lesser function. This method detecting falls applying a wearable accelerometer [24]. A flexible and proficient for discovering rainfall- caused landslides. The WSN-altered architecture for rainfall observing method to broadcast and gather real time data utilizing general pocket radio service (GPRS). The SVM algorithm to forecasting the rainfall; thus, it detects the landslide [25].

2. METHOD

In WSN, several sensors together occasionally observe the surrounding situation and gather correlated details, next, it forwards it to a base station (BS). Then the BS evaluates a landslide established on the gathered data and forwards an alarm for a feasible landslide to a cloud server on the off chance the landslide outperforms a preset threshold for early landslide avoidance. Forecasting landslide is a vital component of functional early notice systems with IoT technology. Thus, it is applied to expand a landslide forecasting model. WSN contains number of self-governing mobile sensor nodes, which utilizes to observe environmental situation. The BS is acts the owner of the WSN and all mobile sensor nodes are registered with the BS. The proposed system utilizes the sensor nodes like Dielectric moisture sensor to measure the water capacity in the soil, temperature sensor observes the soil temperature, Tilt sensor assessed layer of soil, Seismic vibrations are evaluated by applying accelerometer and Rain gauge sensor notice the rain fall. The proposed system observes a significant indicator via global navigation satellite system (GNSS) equipment with IoT sensors. The distortion and devastation development of the landslide, to determine and predict dangerous conditions in time for extenuating evaluates to avoid the lifespan failure induced by unexpected disasters. A whole landslide detecting system admits data noticing, acquisition, transmission, receiving, processing, decision, early alert, and reaction. Figure 2 explains components of Q-learning based forecasting early landslide detection (Q-LFD) mechanism.

Initially, the sensor nodes are positioned in a landslide region, and these nodes observes then forward to the BS. The number of sensor nodes are grouped into clusters [26] by received strength signal indication (RSSI) then selects the GH based on the dingo optimization algorithm (DOA). The formation of cluster based on three levels: lesser, midway and higher. The lower level RSSI nodes not able to connect the group, thus; it leaves the group. The value of RSSI is middle, the sensor node consider chances a group member (GM). The value of RSSI great that highly chances a GM.

This approach utilizes a DOA to pick out an efficient GH based on DOA process like circumferential, chasing and attacking the object. Dingo is capable to determine the location of the object. Afterward searching the location, the group followed by alpha circles the object. It is recognized that the reachable a better agent is the object, which is related to the optimal since the chasing area is not recognized a priori.

a. Circumferential: Along with the circumstances of the object (R*, S*), a dingo can restore its location at the location of (R, S). Each executable locations are noted around the best agent, considering the present location via modifying the vectors value. It is evidently demonstrated how arbitrary vectors $a1$ as well as $a2$ allocate dingoes to participate every location among the points. The dingoes to adapt their locations within the hunt area about the object in any random location is exposed in (4) and (5).

$$\vec{D}_n = \left|\vec{U}.\vec{R}_R(x) - \vec{R}(j)\right| \tag{1}$$

$$\vec{R}(j+1) = \vec{R}_R(j) - \vec{V}.\vec{D}(n) \tag{2}$$

where,

$$\vec{U} = 2 \cdot \vec{u_1}$$
$$\vec{V} = 2 \cdot \vec{v} \cdot \vec{u_2} - \vec{v}$$
$$\vec{b} = 3 - \left(I * \left(\frac{3}{I_{max}}\right)\right)$$

b. Chasing: In this part, all GM resembling alpha as well as beta have an improved awareness regarding the object location. The alpha dingo everlastingly operates the exploring. On the other hand, occasionally beta dingoes also donate in exploring. As per the location of the best search agent, other dingoes require to notify their location. It announces that alpha and beta dingoes adapt their locations randomly and calculate the location of the object in the search space. After that we work out every dingo intensity (I) is specified in (6), (7) and (8).

$$\vec{D}_\alpha = \left|\vec{U}_1.\vec{R}_\alpha - \vec{R}\right| \tag{3}$$

$$\vec{D}_\beta = \left|\vec{V}_1.\vec{R}_\beta - \vec{R}\right| \tag{4}$$

$$\vec{I}_\alpha = log\left(\frac{1}{F_\alpha - (1E-100)} + 1\right) \tag{5}$$

$$\vec{I}_\beta = log\left(\frac{1}{F_\beta - (1E-100)} + 1\right) \tag{6}$$

c. Attacking object: If there are no circumstances modify, it acts dingo finished the chase via attacking the object. Dingoes chase for the object usually together with the group location. They forever travel proceed to path for and strike predators. Accordingly, it is applied for random values (RV), if the RV<-1, it announces object is travel left from the search agent, though if the RV > 1, it denotes group nears the object. This intervention helps the dingoes to observe the objects globally.

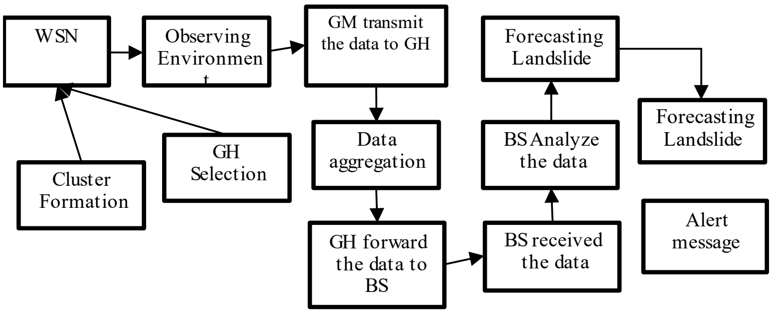

Figure 2. Components of Q-LFD mechanism

2.1. Q-learning based landslide forecasting

Landslide detecting established on IoT and WSN provides real time detection, with accurateness and lacking any person mistake. In addition, the WSN catches an important IoT data of landslide prone regions. WSN is a promising, reliable, and cheap equipment that provides real-time monitoring more extensive distances and hostile terrains. IoT with WSN utilize advanced communicating approach and examine compound sensor data. It is able to not merely notice landslides but can also forecast them. All of these data are approachable to the government referred by the mobile application. Related authorities like administration agencies, and tragedy management on a real time basis. Even local people can also obtain landslide alarms on their mobile by this system. Administration agencies can also distribute Rescue plans with landslide impressed peoples. IoT based forecast landslide recognition and observing systems give a whole transmission channel.

This mechanism utilizes a BS acts a central agent and each node plays an agent, and they considerately distribute the data between neighbor nodes to create which each sensor distinguishes the state transmission behavior. Q-Learning determines optimal function aims to forecast the landslide. The QL objectives to forecast the reward (RW) like landslide of an agent by actions. The agent route collection is employed to landslide or normal the concerned decision. Therefore, the better decision is selected by reward. The Q-L value is applied to obtain an optimal action process predict the future landslide. We observed the landslide region, in that forecast the landslide via RW, and lesser RW results are eliminated. Here S acts the States, and A comprises the action. The conclusion to decide the specified state's actions is to improve the RW of present and future RW.

This mechanism factor as follows {SA, AC, RW, PO}. Where, SA indicates the state, AC represents the action, RW indicates the reward, as well as PO corresponds the feasibility of landslide. Allow current state plays the sc, future state indicates the sf, and t refers the time of waiting for gathered data. The QL-table helps to detecting a better action for each state, The value $Q(sa,\ ac)$ offers the RW of current and future while action a is performed at sa. We consider that the agent selects an action ac in sa, determines RW and extends into future state sa'. Next, the QL, $Q(sa,\ ac)$ is formed as (7),

$$QL(sa, ac) - (1 - \tau)QL(sa, ac) + \tau\{RW + \delta. QL(sa', ac)\} \tag{7}$$

where, τ refers the Q-learning rate and δ depicts the forthcoming RW discount aspect.

Take the action indicates the aggregated data is transmit the current state to next state, the RW is determined the current state SA; the action of QV-table for state s is modified. It enhances the quality of service (QoS) and data aggregation; furthermore, it is computed at the future state. The RW rule is utilized to choose a Q-Learning best solution. Then calculate the RW by water capacity (WC), temperature (T), soil layer (SL), seismic vibrations (SV) and rainfall (R) and RW calculation equation is below. Where, the additional discount aspect is applied to the RW, which is needed to evade back warding and discount aspect range involving 0 to 1.

$$RW = \delta^{WC} \times (T + SL + SV + R) \tag{8}$$

3. EXPERIMENTAL RESULTS AND DISCUSSION

The Q-learning based forecasting early landslide detection (Q-LFD) mechanism is executed and examined in laboratory with actual sensors for one-minute. WSN comprise several sensor nodes like temperature and rainfall observing sensor, water capacity observing sensor, vibration observing sensor. Figure 3 explains the hardware for forecasting landslide. This figure contains temperature and rainfall observing sensor, water capacity observing sensor, vibration observing sensor. These sensor nodes observing and early warning platform offers a complete investigation of the observing data that allots visualization of data from all observing locations for the landslide.

Figure 4 demonstrates the OBIA and Q-LFD of the landslide forecasting accuracy ratio against node density. The node density sensitively determines Q-LFD method accuracy. The node size increases the accuracy ratio vaguely increased in the WSN. The Q-LFD mechanism results explain to reach great accuracy. From Figure 4, when raises the sensor nodes the accuracy ratio of OBIA and Q-LFD mechanism is increased. The Q-LFD mechanism accuracy ratio is high since it forecasts the landslide efficiently. But, the Q-LFD cannot able to forecast the landslide efficiently. During landslide detection, the mechanism forecasts the chance of a landslide. But there is no chance of a landslide occurring. From the results, the mechanism is detecting it wrongly, which is called a false alarm. Figure 5 explains the False alarm chances of the OBIA and QLFD against experiments count.

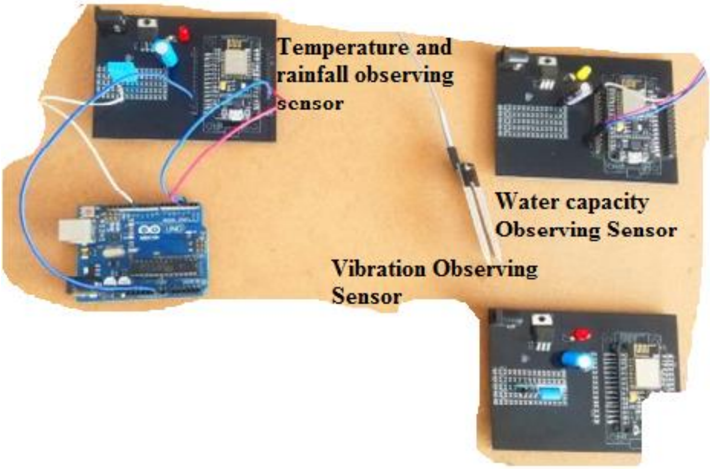

Figure 3. Hardware for landslide prediction

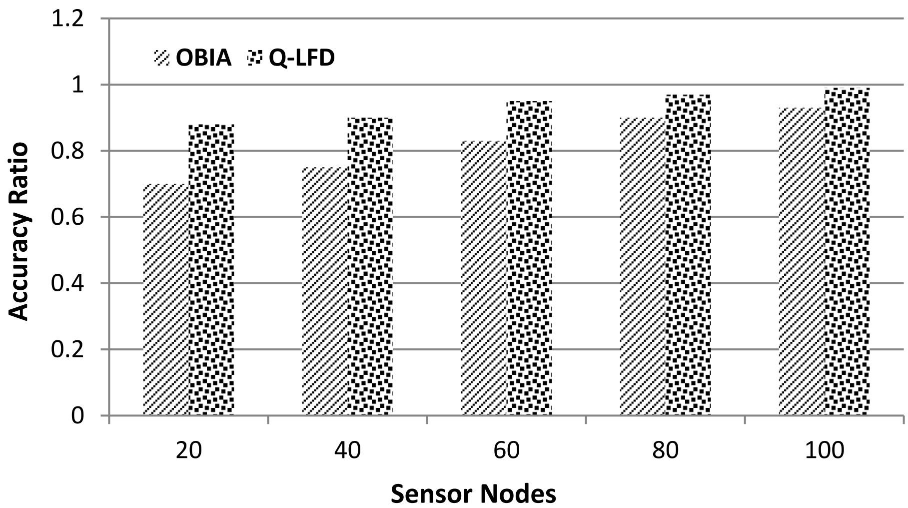

Figure 4. Accuracy of OBIA and Q-LFD against node density

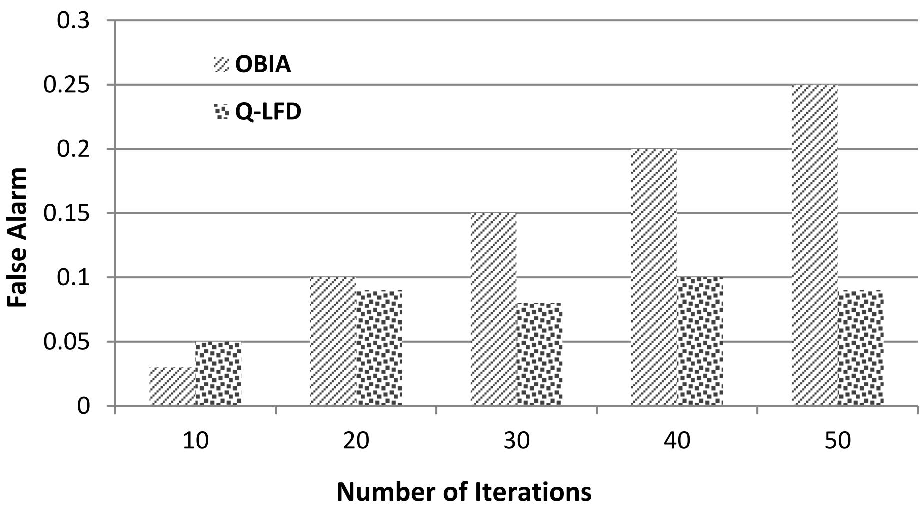

Figure 5. False alarm of OBIA and Q-LFD against iterations

From Figure 5, evaluate the number experiments the Q-LFD mechanism false alarm rate is below 0.1 percentage. Since, the Q-LFD mechanism forecasts the landslide efficiently. It is specified as the correlation among the count of normal time is inappropriately predicting a landslide as well as the total count prediction. But, the existing OBIA mechanism raises the false alarm because, it cannot forecast the landslide efficiently. Figure 6 describes the false positive ratio against iterations.

Figure 6 illustrates the false positive ratio of Q-LFD and OBIA mechanisms. When increases an iteration count, the ratio of false positive is high. The Q-LFD mechanism rate of the highest false positive ratio is 0.11 and the lowest level of false positive rate is 0.01. Because, of the Q-LFD mechanism utilizes a Q-learning to detect the early landslide efficiently. It is specified as the correlation among the count of normal time is inappropriately predicting a landslide as well as the total count iterations. However, the existing OBIA mechanism increases the false positive ratio since it cannot forecast the landslide well. Figure 7 describes the false negative ratio against iterations.

Figure 7 illustrates the false negative ratio of Q-LFD and OBIA mechanisms. When increases an iteration count, the ratio of false negative ratio is high. The rate of the maximum false negative ratio is 0.1 and the lowest level of false negative rate is 0.03. For the reason that, of the Q-LFD mechanism applying a Q-learning to distinguish the early landslide powerfully. But, the existing OBIA mechanism lowest level of false negative rate is 0.07 and the highest false negative rate is 0.21. Since it cannot able to before forecast the landslide.

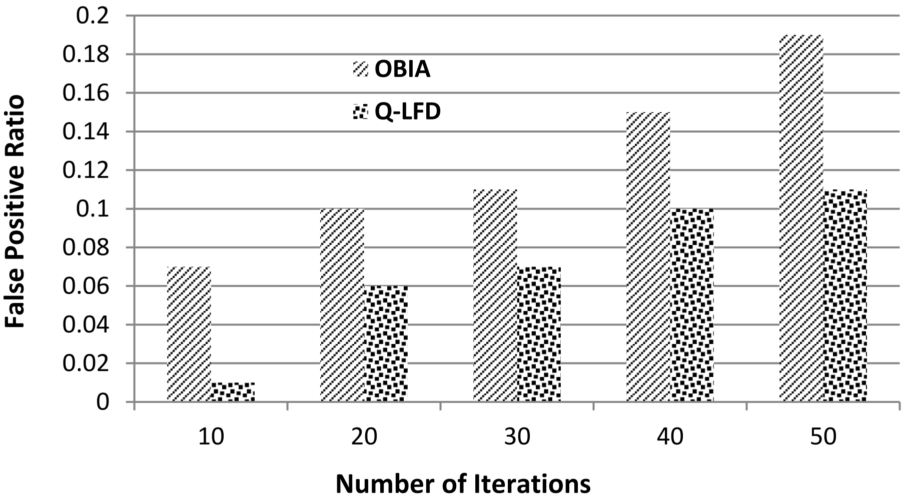

Figure 6. False positive ratio of OBIA and Q-LFD against iterations

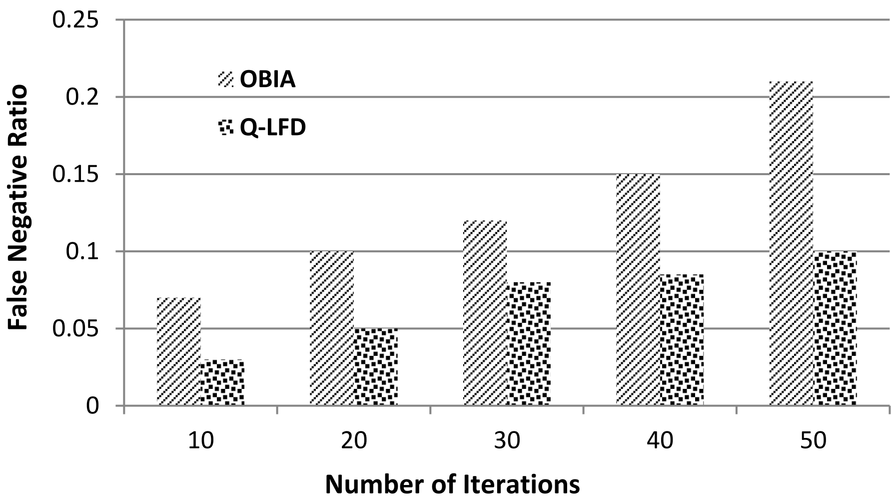

Figure 7. False negative ratio of OBIA and Q-LFD against iterations

4. CONCLUSION

This paper gives the Q-learning based forecasting early landslide detection mechanism design and execution of IoT WSN established on real-time observing of environmental arguments for landslides prediction. Initially, the sensor nodes are form the group then select the group head based on DOA algorithm fitness function. Real time observing of soil parameters and early prediction system applying parameters like soil water capacity, soil layer, soil temperature, seismic vibrations, and rainfall. These parameters values are compared and early warnings are generated by applying-learning algorithm. Then alarm is activated in the region to notify about occurring of Landslide in early. Thus, avoids more dangerous issues due to landslide. The experimental results reveals that the Q-LFD mechanism minimizes the false positive, false negative ratio. Furthermore, it increases the detection accuracy ratio. In future, to provide data security for information gathering in landslide environment.

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