Edge computing-based Internet of Things for Crop Productivity Prediction

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Abstract: *Internet of Things (IoT) has become the key component of designing smart systems. In conventional IoT systems, the use of remote cloud servers for data storage and processing increases the service latency. As a solution, this paper focuses on the use of edge computing in IoT. The edge computing-based IoT architecture is illustrated in this paper. The edge device is used for pre-processing the collected sensor data. The pre-processed data is sent to the cloud for further analysis and storage. For data analysis, we use logistic regression in this paper. The simulation results present that the edge computing-based IoT system reduces the latency by approximately 55% than the cloud-only IoT system. As a case study, we have considered crop productivity prediction based on the soil, weather, and crop related dataset. The experimental results demonstrate that the logistic regression achieves the average accuracy of approximately 90%. Using edge computing, the response time is also reduced by approximately 67% than the cloud-only IoT system.*

Keywords: *Edge computing, low latency, logistic regression, data analysis, Internet of Things.*

1. Introduction:

In the world of contemporary wireless telecommunications, Internet of Things (IoT) is gaining ground quickly. IoT combines a number of technologies, including embedded systems, pervasive computing, actuators, ambient intelligence, sensors, communication technologies, etc. [1, 2]. It is an integration of various devices which communicate, sense, and interact with their internal and external states via the embedded system. It has emerged as a trend for next-generation technologies and the entire business spectrum with extended benefits such as increased connection of end devices, systems, and services. IoT provides appropriate solutions for a wide range of real-time applications, including smart health care, smart cities, smart retail, smart transport, and smart agriculture [3]. Along with the facilities of IoT, cloud computing is introduced in the field of modern research. In cloud computing, dynamically scalable and frequently virtualized resources are supplied through the Internet as a service. The enormous storage, processing, and service capabilities of cloud computing, combined with the information collection capability in IoT, create a network between people and objects, and the objects themselves. Edge computing is another developing field in which data processing occurs close to the end nodes. Edge computing makes it possible for computation to be done at the edge of the network, on downstream data on behalf of cloud services and on upstream data on behalf of IoT services [4, 5]. Cloud, Edge, and IoT plays a vital role to develop smart system in everyday life. In conventional IoT system, the response time is higher as the use of long distant cloud servers increases the propagation and communication latencies [6]. Edge computing has brought the resources at the network edge and reduces the latency [7]

IoT has emerged as a crucial element of smart applications. IoT is a principal component of smart agriculture [8]. IoT in agriculture is referred as the Internet of Agricultural Things (IoAT). The majority of the land on Earth is utilised for agriculture, which accounts for around one third of all land use. The rising global population is driving up demand for agricultural products. The seasonal cycles of crop phenology and dependence of crop production on weather, climate, and soil parameters are only a few of the specific challenges, which need to overcome in order to govern agricultural activities. Farmers and agriculture are harmed nationwide because they are unable to produce adequate crops as a result of abrupt changes in the weather. Therefore, weather forecasting largely impacts on the crop productivity. Moreover, soil data also largely effect on the crop production. The manual analysis, however, does not take into account the dynamic behaviour of the attributes, such as the soil parameters or the ambient parameters, etc. The crop productivity highly depends on several soil and weather parameters. In order to increase prediction accuracy and address issues with manual analysis, artificial intelligence needs to be used in crop yield prediction. In our present work, we have used a well-known machine learning algorithm, logistic regression [9] for data analysis.

1.1. Motivations and Contribution:

In cloud-only IoT system, the entire sensor data is sent, stored, and analysed inside the cloud. When a user generates a query, the cloud server after analysing the respective data, responds to the user. The use of remote cloud for entire data storage, analysis, and access, results in increase in response time, huge overhead on cloud servers, and concerns in data privacy. The motivation of this work is to provide a solution towards these problems. The contributions of this paper are:

- The architecture of an edge computing-based IoT system (EC-IoT) is presented and the working model is discussed. The sensors after collecting the data send to the edge device that pre-processes the data, and then forwards to the cloud. The cloud performs further analysis on the data and stores the data. A case study on crop productivity prediction using the edge-based IoT system is performed.
- Logistic regression is used for data analysis. We take several crop classes in the input dataset and consider soil characteristics, climate, and weather parameters (temperature, humidity, pH, rainfall, nitrogen (N), potassium (K), and phosphorus (P) levels of soil) as the input features. Logistic regression is used for classifying the input dataset, and finally achieved high level recognition accuracy.

The rest of the paper is organized as: Section 2 presents the existing literatures on IoT and data analytics. Section 3 presents the edge computing-based IoT architecture. Section 4 presents the logistic regression-based data analysis. Section 5 presents the simulation and experimental results. Finally, we conclude in Section 6.

2. **Related Work:**

The IoT has a lot of possibilities leading to a huge number of applications. After a thorough study, it is noted that the wings of IoT has already spread in various areas like home, office, transport, agriculture, medical science, etc. In order to address the fundamental concerns and requirements of the IoT, the authors in [10] provided a concise description of its defining characteristics, focusing on data collection and data fusion. IoT was applied with cloud to develop a smart healthcare system in [11] to monitor patients' health data gathered from a wide range of wireless sensory healthcare devices. By utilizing Raspberry Pi and Docker containers, the suggested architecture was reasonably priced, scalable, interoperable, and provided lightweight access. In [12], a smart rehabilitation system was developed to represent the automating design methodology based on ontology. This study established the groundwork for disease detection and resource allocation by creating a rehabilitation system based on IoT technologies, Service Oriented Architecture (SOA), and multidisciplinary optimization methods, and ontology. IoT and ontology played a pivotal part in the development of this system, which allowed for both rapid rehabilitation system development and the efficient exchange of domain-specific expertise. IoT was applied with cloud to build a smart ECG monitoring system in [13] for smart health care. Using a wearable monitoring node, ECG data were collected and wirelessly transferred to the IoT cloud. The IoT cloud employed both the HTTP and MQTT protocols to provide users with visual and fast ECG data. In [14, 15], IoT was used in smart agriculture for fruit growth monitoring.

For data analysis, machine learning (ML) algorithms have gained popularity. For district level, a crop prediction system was built in [16]. A self-created dataset was used that included production information from the previous 10–12 years as well as a number of soil and climate parameters. With the help of proximal sensing data on soil and crop parameters, four ML algorithms: linear regression (LR), elastic net (EN), k-nearest neighbour (k-NN), and support vector regression (SVR), were utilised in [17] to forecast potato (Solanum tuberosum) tuber yield. By analysing the soil data, ML algorithms had been employed in [18] to forecast the mustard crop output. KNN and Artificial Neural Network (ANN) algorithms could be used to forecast the yield of mustard crops. Semi parametric neural network (SNN), a parametric statistical model combined with deep neural network (DNN), improved the predictive performance, as demonstrated in [19]. When applied to agricultural yield prediction, the SNN outperformed all other methods by adding a neural network to a parametric model in order to capture dynamics, which were either not present or were partially represented in the parametric model. To model the effect of climate change together with the effects of varying soil and climate parameters on crop production projections, a multi-parametric DNN was used in [20]. The multi-parametric DNN outperformed the DNN statistically by drawing on prior information about many functional forms associated to the agricultural production field. However, the complexity increased and the quality of the hidden representation might be jeopardised due to the employment of a hierarchy of characteristics. The technique also had the flaw of not providing the best possible representation for medium-sized datasets. In [21] a crop yield recommendation system was developed by using Random Forest algorithm. Different weather parameters such as temperature, rainfall, were analysed. A greenhouse crop yield prediction system was developed in [22] by combining Temporal Convolution Network (TCN) and Recurrent Neural Network (RNN). The suggested method was rigorously tested on several datasets collected from various authentic greenhouse settings for tomato cultivation. In [23], a crop yield prediction system was developed by using Random Forest algorithm. Different parameters i.e. temperature, pH, humidity, rainfall were classified to provide farmers with a better understanding of the demand and cost of various crops. Farmers could use this information to better decide what to grow in their fields. In this paper, we discuss the edge-based IoT framework and its use in crop productivity prediction using logistic regression. The existing works on IoT systems for different applications are summarized in Table 1.

Table 1: Existing literatures on IoT systems

Reference	Contribution	Application area
Fan et al. (2014) [12]	Presents an ontology-based automated design methodology (ADM) for smart rehabilitation systems. Ontology assists computers in gaining a deeper understanding of symptoms and medical resources, so facilitating the creation of a rehabilitation strategy and the rapid, automated reconfiguration of medical resources to meet patients' individual needs.	Smart healthcare
Yang et al. (2016) [13]	A novel ECG monitoring methodology based on IoT methods is proposed. A wearable monitoring node collects ECG data, which is then wirelessly sent to the IoT cloud. In order to give consumers visual and timely ECG data, the IoT cloud uses both the HTTP and MQTT protocols.	Smart healthcare
Jaiswal et al. (2018) [11]	Proposed an approach that uses a Raspberry Pi as an edge device and a Docker container to automate the problem of patient data collection, distribution, and processing. This makes it easier for the physician to identify and monitor medical problems.	Smart healthcare
Droesch et al. (2018) [19]	Proposed a method for modelling yields that uses a semiparametric version of DNN. This method can take into account both known parametric structure and unobserved cross-sectional heterogeneity at the same time.	Smart agriculture
Al-Kuwari et	Presented the full architecture of an IoT-based	Smart home

al. (2018) [24]	sensing and monitoring system for automated smart homes. The EmonCMS cloud server platform was utilised in the proposed architecture for data collection, data visualisation, and remote control of household appliances and devices.	system
Lin et al. (2019) [25]	A Secure and Efficient Location-based Service (SELS) scheme for smart transportation was proposed to keep sensitive data private and offer analysis services to users with low computing and communication costs.	Smart transportation
Boukerche. et al. (2019) [26]	Proposed an IoT-based system for traffic control and crowd management to cooperate safer, efficient, eco-friendly, and enjoyable transportation for people and goods in large urban areas.	Smart transportation
Abou-Nassar et al. (2020) [27]	Proposed a blockchain-based system for smart cities to share healthcare resources. A smart contract would ensure the authenticity of budgets, and the Indirect Trust Inference System (ITIS) would reduce semantic gaps and improve the estimation of Trustworthy Factors (TF) through the network's nodes and edges.	Smart healthcare
Abbas et al. (2020) [17]	Proposed a technique for proximal sensing that could be used to study soil and crop variables which affect the crop yield. Precision agriculture technologies could be used to their fullest extent when combined with new ways of processing data, such as ML algorithms, to get useful information to control crop yield.	Smart agriculture
Kelley et al. (2020) [28]	Proposed a vehicular technology adaptation in accordance with the population for various cities.	Smart transportation
Guhr et al.	Data security and privacy issues pertaining to	Smart home

(2020) [29]	healthcare were described for smart home users. The authors analysed potential psychological and behavioural issues with regard to the security of devices and data in smart homes and offered solutions for the issues.	system
Ferraris et al. (2021) [30]	Examined the behaviour of smart home gadgets like the Amazon Echo and Google Home in terms of building trust connections, and suggested a privacy-preserving smart home trust model to strengthen the relationships among all individuals involved.	Smart home system

3. Edge Computing-based Internet of Things (EC-IoT):

In EC-IoT, sensors are attached with the objects for collecting respective data, e.g. soil moisture level, soil temperature level, humidity, temperature, etc., in case of soil health monitoring, blood pressure, body temperature, pulse rate, etc. in health monitoring, etc. The collected object status is sent to the connected edge device that performs data pre-processing. The pre-processed data is sent to the cloud servers for storage and further analysis. Figure 1 presents the three-tier EC-IoT architecture.

Tier 1 contains the sensors attached with the respective objects. A sensor node is represented as a three tuple$S =< S_i, O_i, S_s >$, where S_i presents the ID of the sensor, O_i presents the ID of the object with which it is attached, and S_s presents the status of sensor i.e., active or idle. In tier 1, the sensors collect the object status and send the data to tier 2.

Tier 2 contains the edge device. An edge device is represented as a three tuple $E =< E_i, H_i, E_s >$, where E_i presents the ID of the edge device, H_i presents the hardware and software specification of the device, and E_s presents the status of device i.e., active or idle. The edge device receives data from the sensors present at tier 1, and then pre-processes the received data. After pre-processing, the edge device sends the data to tier 3.

Tier 3 contains the cloud servers. A cloud computing instance is represented as a three tuple $C =< C_i, P_i >$, where C_i presents the cloud computing instance ID, and P_i presents the set consists of the processing unit IDs of the required cloud servers of the instance. The cloud servers store the received data and perform further analysis if required. The edge servers (attached with the base stations) are connected with the cloud, and they contain the cache copies of the frequently accessed data inside the cloud. If a user makes a query, the respective edge server responds to the user. This in turn reduces the response time compared to the cloud-only architecture. As the entire sensor data is not analysed and stored inside the remote cloud servers, the overhead on the cloud is reduced and the data privacy is increased.

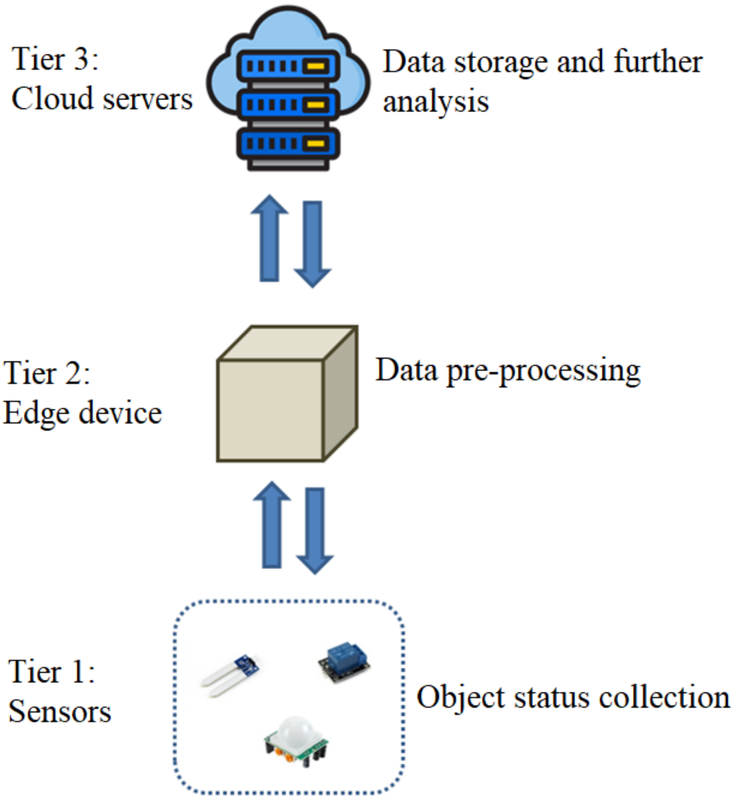

Figure 1: Three-tier architecture of EC-IoT

The latency in the EC-IoT architecture is given as the sum of the data collection latency (L_c), data transmission latency (L_t), and data processing latency (L_p), as follows.

$$L = L_c + L_t + L_p \tag{1}$$

The data transmission latency from a sensor j to the edge device is given as,

$$L_{tsej} = \left(1 + f_{sej}\right) \cdot \frac{D_{sej}}{R_{sej}} \tag{2}$$

where D_{sej} is the amount of data transmitted, f_{sej} is the link failure rate, and R_{sej} is the data transmission rate from the sensor j to the edge device. If there are n sensors, then the latency in data transmission from tier 1 to tier 2 is given as,

$$L_{tse} = \max(L_{tse1}, L_{tse2,\dots,} L_{tsen}) \qquad (2)$$

where L_{tsej} is the latency in data transmission from a sensor j to the edge device, and $1 \leq j \leq n$.

The data transmission latency from tier 2 to tier 3 i.e., from the edge device to the cloud is given as,

$$L_{tec} = (1 + f_{ec}) \cdot \frac{D_{ec}}{R_{ec}} \qquad (3)$$

Where, D_{ec} is the amount of data transmitted, f_{ec} is the link failure rate, and R_{ec} is the data transmission rate from the edge device to the cloud.

The total data transmission latency is given as the sum of the data transmission latency from tier 1 to tier 2 and the data transmission latency from tier 2 to tier 3, given as,

$$L_t = L_{tse} + L_{tec} \qquad (4)$$

The data processing latency of the edge device is given as,

$$L_{ep} = \frac{D_{ep}}{S_{ep}} \qquad (5)$$

Where, S_{ep} is the processing speed of the edge device and D_{ep} is the amount of data processed.

The data processing latency of the cloud is given as,

$$L_{cp} = \frac{D_{cp}}{S_{cp}} \qquad (6)$$

Where, S_{cp} is the processing speed of the cloud and D_{cp} is the amount of data processed.

The total data processing latency is given as the sum of data processing latency of the edge device and the data processing latency of the cloud, given as,

$$L_p = L_{ep} + L_{cp} \qquad (7)$$

In Section 5, we compare the latency in edge-based IoT system and cloud-only IoT system. If the user generates a query regarding crop productivity prediction of a land, the latency in query generation and transmission (L_q), latency in accessing respective data (L_a), and latency in receiving the response (L_r), are considered to calculate the response time. The response time is therefore determined as,

$$T = L_q + L_a + L_r \qquad (8)$$

In edge-based system, the edge server responds to the user, whereas in cloud-only system the cloud sends the response. Hence, the total latency in the EC-IoT is lower than the cloud-only IoT system. In Section 5, we compare the response time in edge-based IoT system and cloud-only IoT system.

4. Logistic regression for data analysis in EC-IoT system:

In this work, we use logistic regression for data analysis. Logistic Regression is a well-known ML algorithm that can provide probabilities and classify new data using both continuous and discrete datasets. The categorical dependent variable is predicted using a set of independent variables. Logistic regression is a way to predict the outcome of a categorical dependent variable. The result must be a categorical or discrete value. It can be Yes or No, 0 or 1, true or false, etc., but instead of giving the exact value, it gives the probabilistic values that lie between 0 and 1. Logistic regression can be used to classify observations based on different types of data, and it is easy to find out which variables work best for classification [9].

We use the sigmoid function to map the predicted values to probabilities. The function maps any real value to a number between 0 and 1. In ML, the sigmoid function is used to convert predictions to probabilities. The hypothesis of logistic regression tends to keep the cost function between 0 and 1, presented as follows:

$$0 \leq h_\alpha(\mathrm{x}) \leq 1$$

The equation of straight line is given in eq. (8) as follows:

$$Z = \beta_0 + \beta_1 x \qquad (9)$$

The hypothesis of logistic regression is given in eq. (9) as follows:

$$h_\alpha(\mathrm{x}) = sigmoid(Z) = \frac{1}{1+e^{-(\beta_0+\beta_1 x)}} \qquad (10)$$

In our EC-IoT system, we use logistic regression for analysing the collected sensor data. As a case study, we consider soil, weather, and crop related dataset for crop productivity prediction. The accuracy, precision, recall, and F1-score using the logistic regression are measured for performance evaluation.

Accuracy: Accuracy (A) is the ratio of the properly predicted values and the total number of predicted values, mathematically presented as follows:

$$A = \frac{\propto + \beta}{\propto + \beta + \delta + \gamma} \quad (11)$$

where, $\propto$, β, δ, and γ presents true positive, true negative, false positive, and false negative predicted values respectively.

Precision: Precision (P) is the ratio of true positive predicted values and the sum of true and false positive predicted values, mathematically presented as follows:

$$P = \frac{\propto}{\propto + \delta} \quad (12)$$

Where, $\propto$ and δ presents true positive and false positive predicted values respectively.

Recall: Recall (R) is the ratio of true positive predicted values and the sum of true positive and false negative predicted values, mathematically presented as follows:

$$R = \frac{\propto}{\propto + \gamma} \quad (13)$$

Where, $\propto$ and γ presents true positive and false negative predicted values respectively.

F-score: F-score is mathematically presented as follows:

$$Fs = \frac{2 \cdot (P \cdot R)}{P + R} \quad (14)$$

Where, P and R presents the precision and recall respectively.

5. Results and Discussion:

We simulate the EC-IoT framework in MATLAB2021a. Figure 2 presents the latency in the EC-IoT and conventional cloud-only IoT systems. The latency is measured in seconds (sec). In cloud-only IoT system, the entire collected sensor data is sent to the cloud instead of using the edge device for pre-processing the data. As a result, the data transmission latency is high compared to the edge-based system. This is observed that the EC-IoT system has approximately 55% lower latency compared to the cloud-only IoT system.

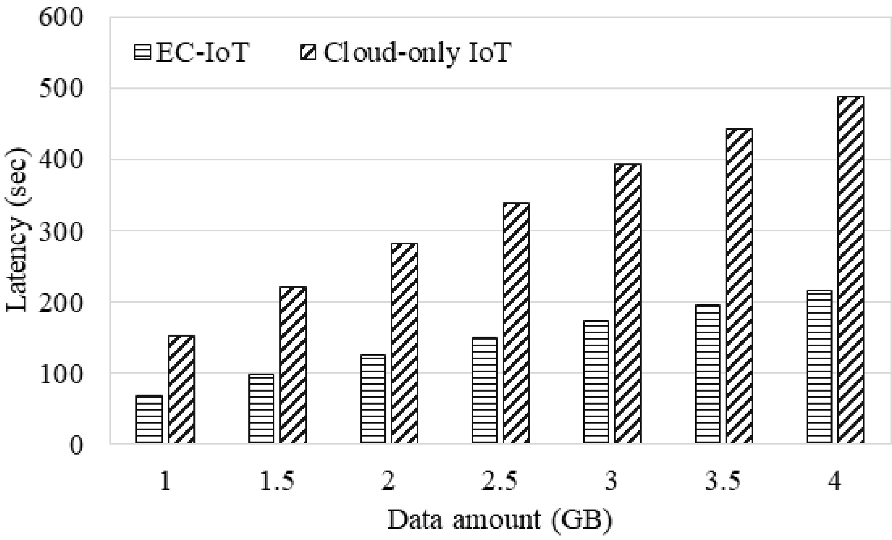

Figure 2: Latency in EC-IoT and cloud-only IoT systems

Case Study: Crop productivity prediction:

In this section, we have applied machine learning methods logistic regression on the input data set [11] to observe their efficacy in agricultural yield prediction. In this experiment, soil, crop, and weather parameters (N, K, P levels of the soil, temperature, humidity, pH, and rainfall) are taken in the input dataset. Among of this dataset, 80% samples are taken as training dataset and 20% samples are taken as testing dataset. According to the classifiers, the obtained prediction accuracy of five different classes (banana, jute, mango, papaya and rice) is represented along with the respected confusion matrix.

Table 2 shows the comparative test accuracy obtained for each of the different classes according to logistic regression classifier.

Table 2: Confusion matrix obtained for the crop-yield dataset

	Banana	**Jute**	**Mango**	**Papaya**	**Rice**
Banana	20	0	0	0	0
Jute	0	15	0	0	5
Mango	0	0	20	0	0

Papaya	0	0	0	18	2
Rice	0	2	0	0	18

The accuracy, precision, recall, and F-score values of the considered dataset for each class are determined and presented in Table 3. Figures 3, 4, 5, and 6 graphically present the respective accuracy, precision, recall, and F-score values.

Table 3: Accuracy, precision, recall, and F-score for the considered dataset

Crop	Accuracy	Precision	Recall	F-score
Banana	0.98	0.98	0.98	0.98
Jute	0.75	0.88	0.75	0.75
Mango	0.98	0.98	0.98	0.98
Papaya	0.9	0.98	0.9	0.9
Rice	0.9	0.72	0.9	0.9

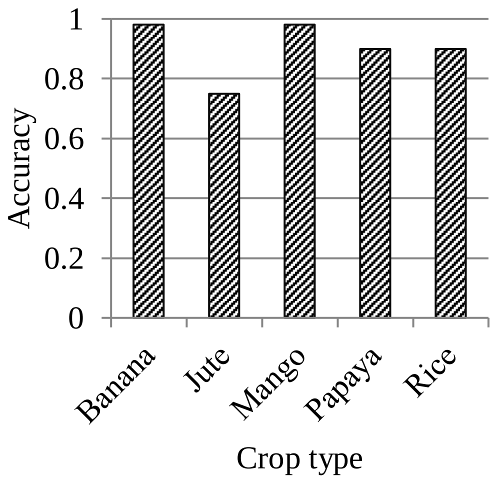

Figure 3: Accuracy in considered set

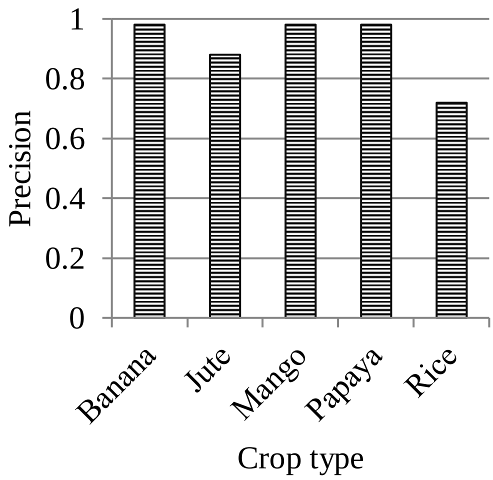

Figure 4: Precision in considered set

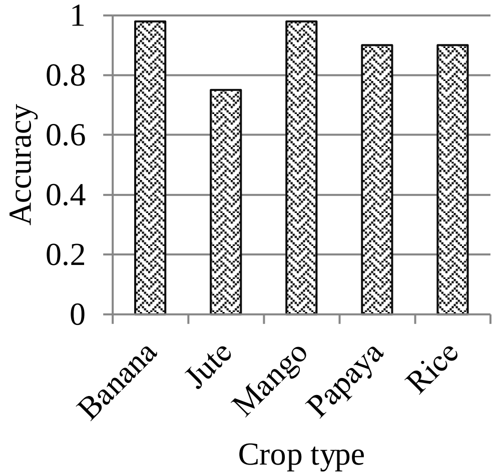

Figure 5: Recall in considered set

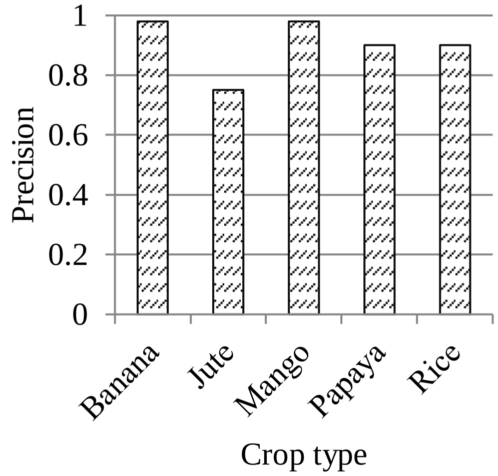

Figure 6: F-score in considered set

From the results we observe that using the logistic regression we achieve the average accuracy, precision, recall, and F-score values of approximately 90% respectively for the considered dataset. The response time for the considered dataset is presented in Figure 7. The response time is measured in milliseconds (msec).

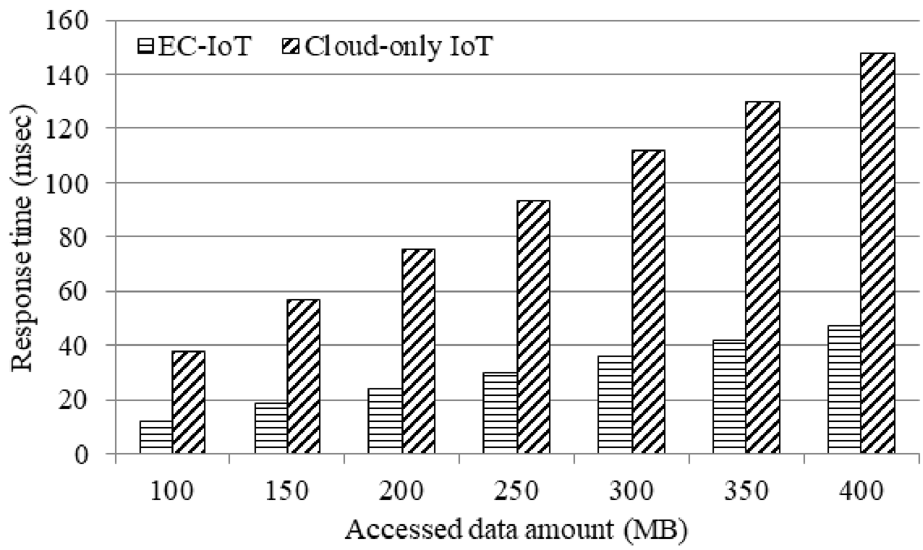

Figure 7: Response time in EC-IoT and cloud-only IoT systems

This is observed that response time using EC-IoT is approximately 67% lower compared to the cloud-only IoT system. As the edge server provides the service on behalf of the cloud servers, the response time is lower in edge-based system. Hence, from the simulation and experimental results we observe that EC-IoT can provide a latency-aware crop productivity prediction system.

6. Conclusion:

IoT has opened a new era in the field of smart computing. However, in conventional IoT system the use of cloud servers for entire data storage and processing suffers from higher latency. Moreover, storage and processing of the entire sensor data inside the cloud increases the overhead on the cloud and data privacy becomes a concern. Edge computing resolves these problems. This paper discusses the use of edge computing in IoT. The edge computing-based IoT architecture and its working model are demonstrated in this paper. The latency and user response time are calculated. Logistic regression is used for data analysis. In the edge-based IoT model, the collected sensor data are pre-processed inside the edge device, and then for further analysis and storage the cloud servers are used. This is observed that the EC-IoT system has approximately 55% lower latency compared to the cloud-only IoT system. As a case study, we have considered crop productivity prediction based on the N, K, P levels of the soil, temperature, humidity, pH, and rainfall. The experimental analysis presents that logistic regression achieves the average accuracy, precision, recall, and F-score values of approximately 90% respectively. This is observed that response time using EC-IoT is approximately 67% lower compared to the cloud-only IoT system. In future, we wish to introduce block chain and dew computing in the IoT systems for smart agriculture.

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