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iCrop: An Intelligent Crop Recommendation System for Agriculture 5.0

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***Abstract*—This article proposes a crop yield prediction and recommendation system for agriculture 5.0 based on edge computing, machine learning (ML), and steganography. In comparison with the existing crop yield prediction and recommendation frameworks, for the first time we are integrating steganography with edge computing and ML to provide a secure crop yield prediction and recommendation system. In the proposed system, an edge device is used for data preprocessing, and the private cloud server referred to as agri-server is maintained for data analysis and storage. For protecting data privacy during transmission, modified least significant bit-based image steganography is used. For data analysis, six ML approaches are used and compared based on their performance. The experimental results demonstrate that each ML approach achieves above 90% accuracy in crop yield prediction. The results also present that the proposed framework achieves highest prediction accuracy of 99.9% which is better than the existing crop yield prediction frameworks. The results also demonstrate that the proposed framework reduces the latency and energy consumption by ∼10% compared to the remote cloud-based crop yield prediction framework.**

***Index Terms*—Data analysis, edge computing, latency, steganography.**

I. Introduction

INDUSTRY 5.0 leverages technologies, such as artificial intelligence (AI), robotics, Internet of Things (IoTs), and advanced data analytics to transform traditional manufacturing processes [1]. Agriculture 5.0 refers to the use of AI for autonomous decision support and unmanned operations in precision agriculture. An IoT-based crop recommendation system is a technology-driven solution that uses sensors, data analytics, and machine learning (ML) to recommend the most suitable crop and fertilizers for land under particular soil and climate conditions. An accurate crop yield prediction can aid farmers in determining which crops to grow and the optimal time for growing them [2]. By collecting and analyzing data on soil and environmental factors, crop recommendation systems can help farmers to take informed decisions about planting, irrigation, and fertilization. The soil attribute information includes Nitrogen (N), Potassium (K), Phosphorous (P), and pH levels, etc., and the ambient data contain temperature, humidity, etc. The sensors send the collected data to the microcontroller that stores the data temporarily, and provides the facility to even access the data offline. Finally, the data storage and analysis take place inside the cloud servers, and the user can access the data anytime, anywhere. However, the remote cloud-based frameworks suffer from the increase in delay, which the edge and fog computing have overcome [2]. Fog computing allows processing of data inside the intermediate nodes, such as switch, router, etc. Edge computing brings the resources to the network edge. Cache-based dew computing provides the facility to access the data in offline mode [2]. The privacy and security in agricultural research area are significant to protect sensitive information like crop yields, financial records, unique farming techniques, etc. Agricultural research and development continuously involve with the creation of new crop varieties, technologies, and unique growing techniques. Maintaining privacy is necessary to ensure that the efforts and investments made are safeguarded. To build up a secure crop recommendation system there is a need to protect sensitive information, such as user's details, from unauthorized access or tampering. Steganography is employed to enhance data security and privacy by concealing sensitive information within image, audio, or video [3]. In image steganography, the information is hidden inside images [4]. Steganography can ensure secure data transmission, and preserve data privacy and integrity.

Data transmission to the cloud for storage and analysis can cause major concerns for data privacy. However, the data storage inside the cloud servers may be required to provide the facility of accessing the data anytime, anywhere. The authors' motivation is to provide a secure system that will offer the facility to the users (farmers/stake-holders/agronomists) to access the data anytime, anywhere but maintaining data privacy. Further, low latency and low energy consumption are significant for real-time and eco-friendly systems. To attain the objectives, the authors' contributions are as follows.

1) An *i*ntelligent *Crop* yield prediction and recommendation system (*iCrop*) is proposed. The modified least significant bit (LSB)-based image steganography is employed to conceal the data while transmitting it to the private cloud server for analysis. As per our knowledge for the first time we integrate steganography with edge computing and ML in this article to provide a secure as well as intelligent crop yield prediction and recommendation system.

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2) For an individual user, a login page is maintained. For registration, the user's details are embedded inside the image of his/her face, the image is encrypted, and sent to the server. After successful registration, the user can login using his/her credentials. After successful login, a user can upload the data of the agricultural field to the private cloud server using the edge device. After receiving the data, the private cloud server analyzes the data using ML and recommends suitable crop for the land.
3) A multiparametric data analysis is performed for crop yield predictions and generating recommendations accordingly. Six ML algorithms logistic regression (LR), support vector machine (SVM), random forest (RF), decision tree (DT), naive Bayes (NB), and extreme gradient boosting (XGBoost) are used for data analysis, and their performances are compared based on accuracy, precision, recall, F-Score, and execution time (ET).
4) The latency for generating recommendations is measured and compared with the conventional cloud-only crop recommendation system to demonstrate the efficacy of the proposed edge-cloud-based system.

The novelty of the proposed work is that for the first time we propose and implement a system that integrates steganography, multiparametric data analysis, and edge computing, for a secure, latency-aware, energy-efficient, and user-friendly crop yield prediction and recommendation framework. The rest of this article is organized as follows: Section II describes the existing research works along with a comparison with the proposed system. Section III presents the proposed crop recommendation system along with a brief description of the ML approaches used for data analysis. Section IV evaluates the performance of the proposed system. Finally, Section V concludes this article.

II. Related Works

The literature review aims to provide an overview of the state-of-the-art approaches in crop yield prediction and recommendation, including the challenges and opportunities in this field. In [5], three ML models multivariate LR, k-Nearest Neighbor, and DT were used for predicting six crops. A multisensor data fusion strategy was introduced in [6] to classify eight crops using DT, Hoeffding tree, and RF. In [7], an AlexNet-spatial pyramid pooling network with a segmentation algorithm based on a mask region-based convolutional neural network was used to classify the grades of mangoes. In [8] and [9], IoT and ML-based crop recommendation systems were proposed. In conventional cloud-based IoT systems, the devices are connected to the Internet and exchange data, and the data storage takes place remotely inside the cloud. Hence, data privacy and integrity are major concerns. For protecting sensitive data from unauthorized access, steganography can be used in the context of data transmission to conceal confidential information inside a media, such as image, audio, video, etc. [3]. Though, steganography is a popular data hiding approach, in IoT-based smart agriculture, the use of steganography has not been explored so much. In this article, we use steganography for user's data transmission as well as agricultural data transmission securely to maintain data privacy. We use private cloud servers for secure data storage and analysis. Table I presents a comparison of the proposed approach with the existing crop yield prediction and recommendation approaches. We can observe that for the first time, we are using steganography in crop yield prediction and recommendation. The use of an edge-cloud framework will help to reduce the latency. The table presents that the proposed system is novel compared to the existing systems.

TABLE I
Comparison of Proposed System With Existing Systems

Work	Multi crop dataset	Multi parametric data analysis	Edge computing	Steganography	Latency is measured
Bera *et al.* [2]	✓	✓	✓	✗	✓
Cedric *et al.* [5]	✓	✓	✗	✗	✗
Reyana *et al.* [6]	✓	✓	✗	✗	✗
Thilakarathne *et al.* [8]	✓	✓	✗	✗	✗
Bakthavatchalam- *et al.* [9]	✓	✓	✗	✗	✗
Srivastava *et al.* [10]	✓	✓	✗	✗	✗
Cruz *et al.* [11]	✓	✓	✗	✗	✗
Patil *et al.* [12]	✓	✓	✗	✗	✗
Kathiria *et al.* [13]	✓	✓	✗	✗	✗
Dey *et al.* [14]	✓	✓	✓	✗	✓
Gopi *et al.* [15]	✓	✓	✗	✗	✗
iCrop (Proposed work)	✓	✓	✓	✓	✓

III. Proposed Crop Recommendation System

This section discusses the working model of the proposed system, the use of steganography for data privacy protection, ML approaches used for data analysis, and the mathematical model of latency calculation for the proposed paradigm.

A. *Working Model of iCrop*

The system architecture of iCrop is pictorially depicted in Fig. 1 along with the recommendation application designed for the users. In our system for storing and analyzing crop-related data, a private cloud server is maintained, and we refer to it as *agri-server*. It is assumed that each user has his/her own electronic gadget as a smart device (such as a smartphone, tablet, etc.) that works as the edge device, and the agri-server contains the rainfall data. Using the crop recommendation application a user can register, login, upload data, and receive advice regarding the suitable crop for the land. The user registration process is presented in Fig. 2 and the flow diagram of the overall system is presented in Fig. 3.

The steps of the registration process are stated as follows.
1) The user opens the registration page using his/her device.
2) The user provides his/her details, such as name, address, email id, identity number, phone number, etc. The image of the user's face is captured using camera, and the provided details are embedded inside the image using Algorithm 1.
3) The generated image is then encrypted using the advanced encryption standard (AES) system [16], and uploaded to the agri-server.

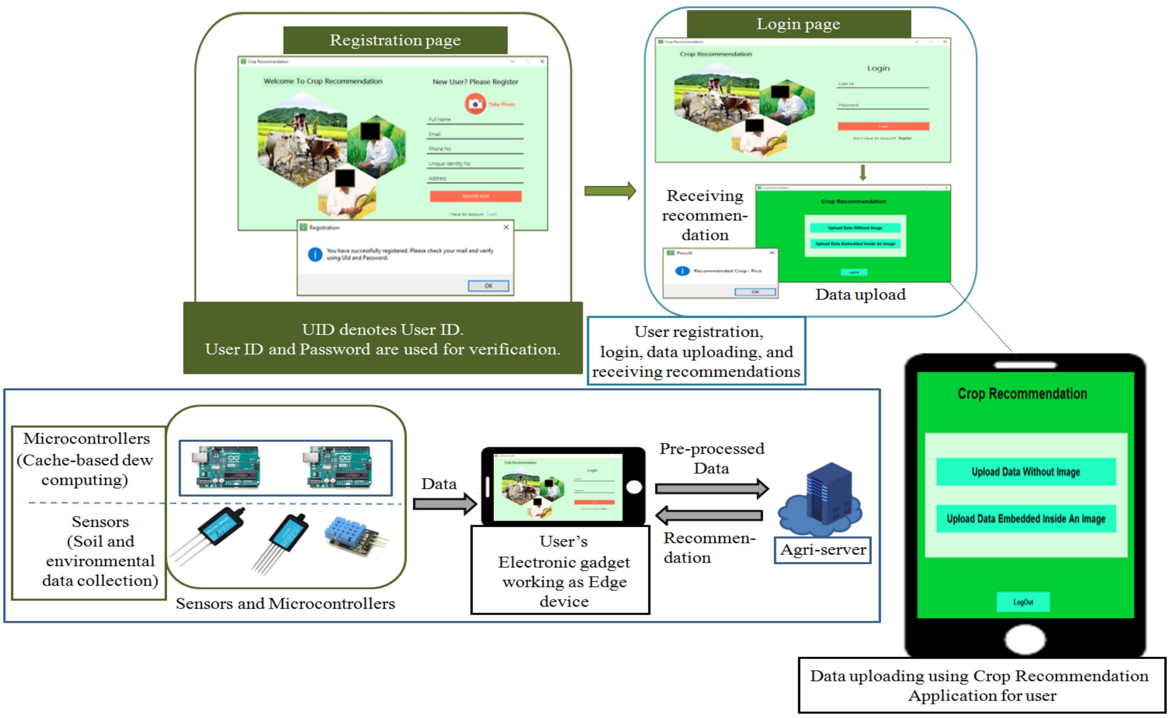

Fig. 1. System architecture of iCrop and the designed recommendation application.

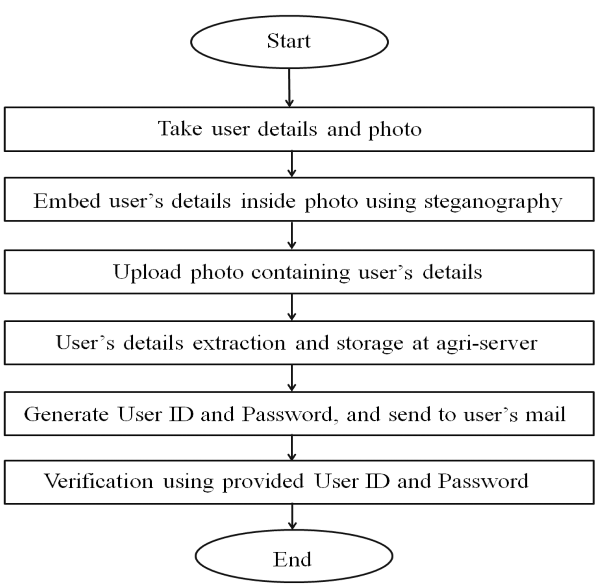

Fig. 2. User registration process.

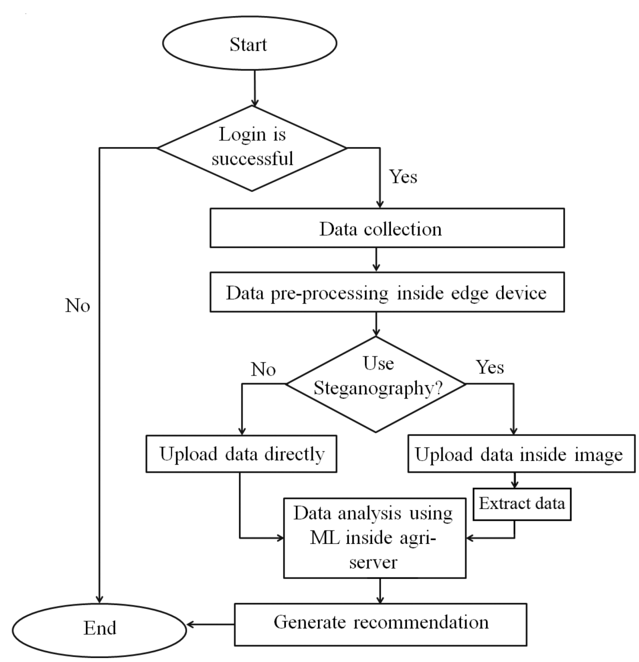

Fig. 3. Flow-diagram of the system.

4) At the agri-server the image is decrypted, and then the user's details are extracted from the image.
5) After extracting user's details the records are stored, and the login credentials (such as user ID and password) are sent to the user's email address. Using the credentials, the user can login to the system.

The use of steganography for data protection is illustrated in Section III-B, and the associated process is presented in Algorithm 1. After successful login, a user can upload the collected soil and environmental parameters' values. The data are preprocessed inside the edge device and then sent to the agri-server for analysis. The data analysis in iCrop is discussed in Section III-C. The steps of crop yield prediction and recommendation generation are stated as follows.

1) The login page is opened, and the user inputs his/her login credentials (user ID and password).
2) After successful login, the user inputs the soil and environmental parameters' data. Here, two options are provided to

the user: a) upload the data directly, or b) upload the data by hiding inside an image. If the user selects the first option, the data are directly uploaded to the agri-server. Otherwise, the data are embedded inside an image selected by the user and then the image is uploaded to the agri-server. For data embedding inside an image, Algorithm 1 is used.

3) If the data are directly uploaded by the user, the agri-server reads the data and merges it with the rainfall data, and generates the CSV file. Otherwise, if the image is uploaded by the user, the agri-server extracts the data from the image, reads the data, merges it with the rainfall data, and generates the CSV file.
4) The agri-server performs data analysis using ML. The server has ML models trained with a global dataset. In iCrop, we have used six ML approaches LR, SVM, RF, DT, NB, and XGBoost, which are discussed in Section III-C, and their performance are evaluated in Section IV.
5) After data analysis, crop yield prediction results are obtained for the generated CSV file, respective recommendations are generated, and displayed to the user. Here, the recommendations are generated in terms of the suitable crops for the land, that the user can harvest in his/her land for better production.

B. *Use of Steganography in iCrop*

To protect data privacy, we use steganography and cryptography in our system. We use modified LSB-based image steganography, which is illustrated in Algorithm 1. The user's details are embedded inside the user's face's image. The user's image is considered in our framework for identification purpose. By user's identity number, we refer to the unique identity number of a citizen of a country. After embedding the user's details inside the image, AES [16] is used to encrypt the image. As the face image is used, to protect privacy the image is encrypted. AES is a symmetric encryption algorithm that uses three types of key lengths: 1) 128 b, 2) 192 b, and 3) 256 b. The AES algorithm operates on the principles of symmetric key cryptography, wherein the same key is utilized for both encryption and decryption. However, the key for individual user is unique for security purpose. The longer key size of AES makes it more resistant and increases security. Further, the time consumption is low in AES [16]. Thus, AES is used in iCrop for image encryption. The encrypted image is sent to the agri-server. At the agri-server the image is decrypted. In Fig. 4, a user's details are hidden inside his face's image, and then the image is encrypted.

For uploading environmental and soil parameters' data, the user is given two choices: 1) user can directly upload the data to the agri-server, or 2) can upload an image containing the data inside. For the second choice, Algorithm 1 is used to embed the data inside an image selected by the user. The data are converted into binary form, and then divided into blocks of 8 b (steps 1 to 3). Sequence numbers are assigned to the blocks (step 4). If the sequence number is odd, one's complement is performed (steps 5 to 7). The XOR operation is performed between each block and the key to generate the encoded block (step 8). All encoded blocks are appended to generate the encoded bit stream (step 9). The cover image is converted into gray scale, resized, and the output image is initialized to it (steps 10 to 12). Each pixel

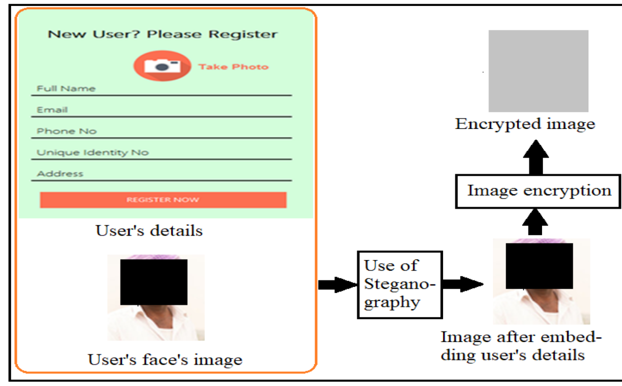

Fig. 4. Hiding user's details using steganography and cryptography.

value of the image is transformed to binary form, each encoded bit is XOR-ed with LSB of the pixel, and the pixel value of the output image is set to the pixel value of the input image plus the generated value (steps 13 to 19). All bits of the encoded stream are embedded to generate the output image. For extracting the data from the image, the number of pixels containing the data is determined, and subsequently one pixel of the image is traversed at a time. To generate the encoded bit stream, the LSB of each pixel is extracted. The encoded bit stream is divided into 8-b blocks, and then decoded using the key. If the block number is odd, one's complement is performed. After that all the blocks are merged sequentially to generate the bit stream, and extra zeros are discarded. The original bit stream is retrieved.

C. *Data Analysis*

It is essential to select the appropriate classification algorithm in crop prediction because of the complex relationships between crop types and environmental variables, which vary. The process of crop prediction necessitates the consideration of the nonlinearity of relationships, the significance of feature importance insights, the model's generalization ability, handling of different data types and missing data, assumptions about data distribution, scalability, and the complexity of the problem. The unique strengths of each ML algorithm can be worked on in response to the specific requirements and characteristics of the crop prediction task. As steganography is used in our framework for security purpose, an additional time consumption is involved for embedding and extracting data to and from the image. Thus, we have to select the ML algorithms which can be able to capture the complex nonlinear relationships between the input variables (environmental and soil parameters) and the output (crop), achieve prediction with high accuracy, but with less computational complexity. Thus, instead of selecting deep learning algorithms we have selected six types ML algorithms to find out the one that performs better for the considered scenario.

1) LR: LR model uses a logistic function to estimate the probability of a binary outcome, such as whether a crop will be produced successfully or not under certain conditions [5]. The LR equation can be written as

$$P(y) = \frac{1}{1 + e^{-(c_0 + c_1 y_1 + c_2 y_2 + \cdots + c_{n_{\mathrm{LR}}} y_{n_{\mathrm{LR}}})}} \tag{1}$$

Algorithm 1: Modified LSB-Based Image Steganography.

Input: data ($Data$), cover image (Cov), key (Key)
Output: output image (OPI)
convert $Data$ into binary form
append '0' at the end if $((numberofbits(Data)\%8)! = 0)$ ▷ append '0' at the end if the number of bits is not multiple of 8
divide the data into 8-bit blocks
assign $Seqno$ to blocks from 1 ▷ assign sequence number ($Seqno$) to blocks starting from 1
if $(Seqno\%2! = 0)$ **then** ▷ if sequence number is odd
  $block_j \leftarrow One'scomplement(block_j)$ where $1 \leq j \leq N$ ▷ perform one's complement of block $block_j$, N is number of blocks
end if
$Eblock_j \leftarrow block_j \oplus Key$ where $1 \leq j \leq N$ ▷ $Eblock$ denotes encoded block
$EStream \leftarrow Appendblocks(Eblock_1, Eblock_2, \ldots, Eblock_N)$ ▷ generate encoded bit stream ($EStream$)
$GrImg \leftarrow Convertgray(Cov)$ ▷ convert cover image into gray scale
IPI $\leftarrow Resize(GrImg)$
OPI $\leftarrow$ IPI
for each pixel in IPI **do**
  transform the pixel value to corresponding binary form
  consider the next bit of $EStream$
  consider a variable v
  $v \leftarrow Ebit \oplus plsb$ ▷ XOR encoded bit ($Ebit$) with LSB of the pixel ($plsb$)
  $\text{OPI}_{\text{pix}} \leftarrow \text{IPI}_{\text{pix}} + v$ ▷ pixel value of OPI is changed to (pixel value of IPI + v)
end for
embed all bits of $EStream$ to generate the output image

where $P(y)$ is the probability of the outcome (i.e., crop recommendation), $\{y_1, y_2, y_3, \ldots, y_{n_{\text{LR}}}\}$ are the input variables, $\{c_1, c_2, c_3, \ldots, c_{n_{\text{LR}}}\}$ are the model coefficients that determine the relationship between the inputs and the output, and n_{LR} is the number of input variables. As LR is suitable for classification tasks, we have used LR in our framework.

2) SVM: The SVM algorithm [6], [8], [17] aims to find the optimal hyperplane separating the data points into various classes, and the hyperplane is used to predict the yield of the crop. The equation for SVM in this context can be given as

$$f(x) = \text{sign}(w^t x + b) \tag{2}$$

where x represents the input vector, w denotes the weight vector, b is the bias term, sign is the sign function, and t represents the transpose operation. The objective of SVM is to identify the optimal values of w and b that result in the maximum margin between the different classes. The kernel functions in SVM allows to capture the complex nonlinear relationships between the soil and environmental parameters as the input variables and the crop type as the output. SVM focuses on maximizing the margin between different classes, which often leads to better generalization on unseen data. For these reasons, we use SVM in iCrop.

3) DT: The DT model is constructed as a series of branching nodes, where each node represents a decision based on an input variable. The final outcome or recommendation is obtained by traversing the tree from the root node to a leaf node [5]. The DT model can be represented by a function that takes input variables and returns recommended crop

$$f(z) = \begin{cases} d_1, & \text{if} z_1 < T_1 \\ d_2, & \text{else if} z_2 < T_2 \\ d_{n_{\text{DT}}}, & \text{else} \end{cases} \tag{3}$$

where $\{z_1, z_2, \ldots, z_{n_{\text{DT}}}\}$ are the input variables, $\{T_1, T_2, \ldots, T_{n_{\text{DT}}}\}$ are the thresholds for the input variables, $\{d_1, d_2, \ldots, d_{n_{\text{DT}}}\}$ are the recommended crops for the leaf nodes, and n_{DT} is the number of input variables. DT can handle both categorical and numerical data, which is useful for datasets with a mix of feature types. Hence, we use DT in iCrop so that datasets with a mix of feature types can be dealt with.

4) RF: RF is a type of ensemble learning in which many DTs are built at once during training, with the final output representing the class that is most commonly predicted by the average of the individual trees. By combining the outputs of multiple DTs, this ensemble learning method can generate a more accurate and consistent forecast. Each of the DTs in the forest is trained on a different subset of the data, and the ultimate forecast is obtained by majority vote among the trees [8], [17]. The corresponding equation is written as follows:

$$Q = F(R) + \in . \tag{4}$$

Q is the output variable (crop yield), R is the input variable (soil type, environmental data, etc.), F is the mapping function that predicts Q from R, and $\in$ is the random error term. In RF, F is the sum of the predictions of multiple DTs, which are built from random subsets of the training data. RF can handle missing values and maintain accuracy even when some data points are missing. RF provides estimates of feature importance, helping to understand which environmental factors are most influential in crop classification. By aggregating the results of multiple DTs, RF often achieves higher accuracy compared to a single DT. For these reasons, we use RF in iCrop.

5) NB: NB [18] is a probabilistic algorithm that determines the probability of each class for the provided input features and chooses the class with the highest probability as the predicted output. The NB algorithm assumes that each input feature is independent of all other features, which simplifies the calculation of the probability distribution. Despite its naive assumption, it often performs well in practice and is computationally efficient. The equation of the NB algorithm can be represented as

$$P(g|h) = \frac{P(h_1|g) * P(h_2|g) * \ldots * P(h_{n_{\text{NB}}}|g)}{P(h)} \tag{5}$$

where $P(g|h)$ is the probability of class g given input h, $P(h_i|g)$ is the probability of ith input feature given class g, $P(g)$ is prior probability of class g, $P(h)$ is marginal probability of input h, and n_{NB} is the number of input features. NB classifiers are a good choice for certain types of classification problems, especially those where the features are conditionally independent given the class. For this reason, we use NB in iCrop.

6) XGBoost: XGBoost is another famous ML method that is commonly utilized for classification and regression tasks. It is an implementation of the gradient boosting algorithm. Gradient boosting is a technique in which a group of weak learners (in the form of DTs) are merged to generate a strong learner capable of making accurate predictions. The accuracy of agricultural yield estimation can be enhanced by employing the gradient boosting framework [8], [10]. XGBoost has built-in support for handling missing data, which is common in agricultural datasets. XGBoost provides insights into feature importance, helping to understand which variables are most influential in predicting crop types. For these reasons, we use XGBoost in iCrop.

In Section IV, we use these six ML approaches for analyzing the data, and their performance is compared based on accuracy, precision, recall, F-Score, and ET.

D. Latency of iCrop

To determine the latency of the proposed system iCrop, we consider the user's registration latency, data transmission latency for transmitting the soil and environmental data, computation execution latency for data analysis, and latency in embedding and extracting the soil and environmental data to and from the image using modified LSB-based image steganography. The basic equation of data transmission latency (τ_{tr}) is given as [19] $\tau_{tr} = (1+\eta)\frac{\delta}{\rho}$, where η is the link failure rate, δ is the data amount, and ρ is the data transmission rate. However, in a real-time scenario, the link failure rate, data transmission rate, etc., vary depending on the amount of traffic, signal strength, allocated bandwidth, etc. The basic equation of computation execution latency (τ_{ce}) is given as [19] $\tau_{\text{ce}} = \frac{\zeta}{\sigma}$, where ζ is the amount of computation and σ is the execution speed. However, in a real-time scenario, the execution speed varies based on the present load, configuration of the executing device, etc. If the data transmission latency from IoT devices to the edge device is τ_{tr1} and data transmission latency from edge device to agri-server is τ_{tr2}, the total data transmission latency is given as

$$\tau_{\text{trp}} = \tau_{\text{tr1}} + \tau_{\text{tr2}}. \tag{6}$$

If the computation execution latency for data preprocessing inside the edge device is τ_{ce1} and the computation execution latency for data analysis inside the agri-server is τ_{ce2}, then the total latency for computation execution is given as

$$\tau_{\text{cep}} = \tau_{\text{ce1}} + \tau_{\text{ce2}}. \tag{7}$$

If the latency for data embedding inside the image is τ_{em} and the latency for data extraction from the image is τ_{ex}, the total latency for data embedding and extracting to and from the image is given as

$$\tau_{\text{emex}} = \tau_{\text{em}} + \tau_{\text{ex}}. \tag{8}$$

The user's registration latency (τ_{reg}) includes the latency for embedding user's details inside the user's image (τ_{emreg}), the latency for encrypting the image (τ_{encr}), the latency for transmitting the encrypted image (τ_{trreg}), the latency to decrypt the image (τ_{decr}), the latency for extracting user's details from the image (τ_{exreg}), the latency for storing the data and image (τ_{str}), and the latency for generating the user's credentials (τ_{ucd}). Thus, the total latency for registration is given as

$$\tau_{\text{reg}} = \tau_{\text{emreg}} + \tau_{\text{encr}} + \tau_{\text{trreg}} + \tau_{\text{decr}} + \tau_{\text{exreg}} + \tau_{\text{str}} + \tau_{\text{ucd}}. \tag{9}$$

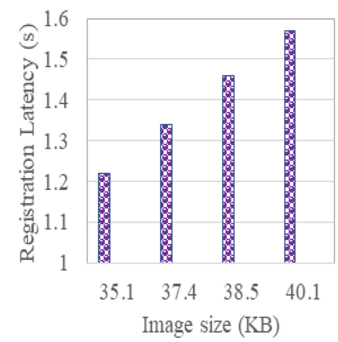

Fig. 5. Latency in user's registration.

Therefore, the total latency in iCrop is determined as the sum of the latency τ_{trp}, τ_{cep}, τ_{emex}, and τ_{reg}, as follows:

$$\tau_{\text{iCrop}} = \tau_{\text{trp}} + \tau_{\text{cep}} + \tau_{\text{emex}} + \tau_{\text{reg}}. \tag{10}$$

In Section IV, the user's registration latency, data transmission latency, computation ET for data analysis, and the latency for soil and environmental data embedding and extracting to and from the image are measured. Finally, the total latency and energy consumption are measured. The energy consumption in iCrop is measured as sum of the energy consumption of the devices used in iCrop during the time period τ_{iCrop}.

IV. Results and Discussion

In this section, we measure the latency for user's registration, the latency for transmitting the soil and environmental data in iCrop, and the latency for data embedding and extraction to and from the image. We also compare the performance of the used ML approaches in terms of accuracy, precision, recall, F-Score, and ET. Finally, the total latency and energy consumption in iCrop are measured.

A. Latency in User's Registration

The latency for user's registration is measured for different size of images inside which the user's details are embedded. The uplink data transmission rate is 5–10 Mbps and downlink data transmission rate is 10–15 Mbps. The latency for user's registration is presented in Fig. 5, and it is demonstrated that the latency for registration is not high. For any type of application, minimal latency is desirable. However, for soft deadline applications, a small increase in latency may not be fatal, whereas for hard deadline applications a small increase in latency can be fatal. Crop recommendation system is a soft deadline application, therefore, a small increase in latency is admissible. On the other hand, maintaining data privacy is more crucial as the user's details are transmitted. We observe that the latency for registration is not very high, but the privacy can be ensured.

B. Soil and Environmental Data Transmission Latency

The soil and environmental data (N, P, K, and pH of soil, temperature, humidity) for 20, 30, 40, and 50 d, are considered. The data are exported into a CSV file. The CSV file sizes for 20, 30, 40, and 50 d data are 1.2, 2.1, 2.97, and 3.8 KB, respectively. The user's mobile device acts as the edge device, and it has 4-GB RAM. The agri-server has 16-GB RAM, 1TB HDD, and Intel(R)

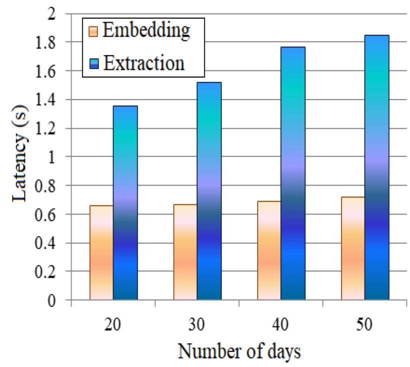

Fig. 6. Latency in data embedding and extracting to and from image in iCrop.

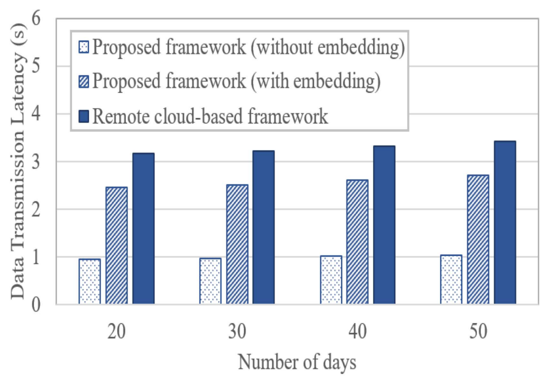

Fig. 7. Data transmission latency in proposed and remote cloud-based frameworks.

Xeon(R) CPU E5-2667 0 @ 2.90GHz (Octa Core) processor. The mobile device sends the CSV file to the agri-server either directly or after embedding into an image. If the agri-server receives the image, it extracts the CSV file from the image. The agri-server has the rainfall data of the region, and it generates a CSV file by merging the rainfall data with the received data regarding soil and environmental parameters. Here, the latency for both the cases are considered: 1) the CSV file containing the data is directly uploaded, and 2) the CSV file is embedded into an image and then uploaded. The latency for both cases are measured. The latency is measured in seconds (s). The sizes of the images containing 20, 30, 40, and 50 d data are 25.1, 26, 26.9, and 27.8 KB, respectively. The latency for embedding the CSV files inside the image and extracting the CSV files from the image are presented in Fig. 6. We observe that the latency in data embedding and extraction are very less. The data transmission latency for the proposed and remote cloud-based frameworks are presented in Fig. 7. The data transmission latency for the CSV file and image containing the CSV file inside both are considered. The CSV file contains the soil and environmental data. We observe that if the CSV file is sent, the latency is reduced by 70% and if the image is sent, the latency is reduced by 20% than the remote cloud-based framework. As in our system, the data preprocessing happens inside the edge device, and the preprocessed data are only sent to the cloud, the latency is reduced.

C. Performance of ML Approaches

To compare the performance of the ML approaches, we have considered accuracy, precision, recall, F-Score, and ET. The soil

TABLE II
STATISTICAL SUMMARY OF DATASET[1]

Parameter	Maximum value	Minimum value	Mean	Standard deviation
Temperature	43.67	8.82	25.62	5.06
Humidity	99.98	14.25	71.48	22.26
pH	9.93	3.5	6.47	0.77
N	140	0	50.55	36.91
P	145	5	53.36	32.98
K	205	5	48.14	50.64
Rainfall	298.56	20.21	103.46	54.95

TABLE III
PERFORMANCE OF ML APPROACHES USED IN ICROP

Performance metrics	LR	SVM	DT	RF	NB	XG-Boost
Accuracy (%)	94.09	97.95	99.09	99.99	99.32	98.86
Precision (%)	94.09	97.95	99.09	99.98	99.31	98.86
Recall (%)	94.09	97.95	99.09	99.99	99.31	98.86
F-Score (%)	94.09	97.95	99.09	99.98	99.31	98.86
ET (ms)	160.6	25.5	13.04	266.12	9.03	1159.9

data (N, P, K, pH) and environmental data including rainfall (temperature, humidity, rainfall) are analyzed. The data used for analysis is in CSV form. For better analysis we have considered the dataset.[1] The statistical summary of the mentioned dataset is provided in Table II. The considered dataset has been partitioned into train and test datasets. The program is guided through the use of training instances in order to deduce valid conclusions. After completion of the training phase, testing instances are utilized to validate the model accuracy. Finally, we have used the 50 days' data contained in the CSV file of size 3.8 KB to get recommendation regarding the crop to harvest. The accuracy, precision, recall, and F-Score for LR, SVM, DT, RF, NB, and XGBoost, are presented in Table III. The accuracy is mathematically defined as (TP+TN)/(TP+FP+TN+FN), where TP is denoted as true positive, FP as false positive, TN as true negative, and FN as false negative, respectively. The precision is mathematically presented as [TP/(TP+FP)]. The recall is mathematically presented as [TP/(TP+FN)]. The F-Score is mathematically presented as [2*Precision*Recall/(Precision+Recall)]. The ET here refers to the time consumption for executing the code to analyze the data and generate result. As observed from the results, for each of the ML approaches, the accuracy, precision, recall, and F-Score are above 90%. We also observe that RF outperforms other approaches with respect to accuracy, precision, recall, and F-Score. The ET of LR, SVM, DT, RF, NB, and XGBoost for crop yield prediction are measured in milliseconds (ms). We observe that the ET of NB is the lowest. We also observe the NB has above 99% accuracy, precision, recall, and F-Score. Though, RF has the highest accuracy, precision, recall, and F-Score, the ET is high. Hence, if accuracy and ET, both are considered NB can be considered as the best performer for the used dataset.

For more validation of the proposed work, we have considered another dataset,[2] and determined the accuracy metrics using that dataset. The second dataset has 1600 samples, and 16 crop classes. We observe that for the second dataset also all the ML approaches used in iCrop have achieved above 90% prediction

[1][Online]. Available: https://www.kaggle.com/datasets/atharvaingle/crop-recommendation-dataset

[2][Online]. Available: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/4GBWFV

TABLE IV
COMPARISON OF iCROP WITH EXISTING FRAMEWORKS BASED ON ACCURACY, PRECISION, RECALL, AND F-SCORE

Work	Classifier	Accuracy	Precision	Recall	F-Score
Bera *et al.* [2]	DT (Highest), K-Nearest Neighbors (KNN), SVM, Linear Discriminant Analysis (LDA)	98%	98%	98%	98%
Thilakarathne *et al.* [8]	RF (Highest), DT, KNN, XGBoost, SVM	97.18%	97%	97%	97%
Bakthavatchalam *et al.* [9]	Multilayer Perceptron (MLP)	98.23%	98.4%	98.23%	98.2%
Cruz *et al.* [11]	KNN	92.62%	96.74%	92.62%	95.46%
Patil *et al.* [12]	LR, SVM, DT, RF (highest), NB, XGBoost, KNN	99.55%	Not determined	Not determined	Not determined
Kathiria *et al.* [13]	DT, Light Gradient Boosting Machine (LGBM), SVM, KNN, and RF (Hightest)	99.24% 99.24%	99.23% 99.23%	99.32% 99.32%	99.27% 99.27%
Dey *et al.* [14]	Bidirectional-Long Short-Term Memory (Bi-LSTM) Network	98.64%	98.68%	98.64%	98.68%
Gopi *et al.* [15]	LSTM, Bi-LSTM, Gated Recurrent Unit (GRU)	98.45%	98.51%	98.45%	98.46%
iCrop (Proposed system)	LR, SVM, DT, RF (highest), NB, XGBoost	99.99%	99.98%	99.99%	99.98%

accuracy, precision, recall, and F-Score. For this dataset, RF, NB, and DT have achieved the highest accuracy of 99.9%. The precision, recall, and F-Score for RF, NB, and DT are above 99.5%. The accuracy of LR, XGB, and SVM are 96%, 99%, and 99%, respectively, for the second dataset. Thus, we observe that for both of the datasets, highest accuracy of 99.9% can be achieved using iCrop.

1) Comparison With Existing Approaches: The proposed framework is compared with the existing frameworks for crop yield prediction based on accuracy, precision, recall, and F-Score, in Table IV. For better comparative analysis, we have considered the existing approaches that used the same *dataset*[1] for performance analysis. As we observe, LDA, DT, KNN, and SVM were used in [2], and DT achieved the highest accuracy of 98%. In [8], RF, DT, KNN, XGBoost, and SVM were used, and RF achieved the highest accuracy of 97.18%. In [9], MLP achieved 98.23% accuracy in crop yield prediction. KNN was used as the classifier in [11], and an accuracy of 92.62% was achieved. In [12], the same set of classifiers used in iCrop was used along with KNN, and the highest accuracy of 99.55% was achieved by RF. In [14], Bi-LSTM was used, and an accuracy of 98.64% was achieved in crop yield prediction. A LSTM, Bi-LSTM, and GRU-based system was used in [15], and an accuracy of 98.45% was achieved. In our system, we have used LR, SVM, DT, RF, NB, and XGBoost, where RF has achieved an accuracy of 99.99%, which is higher than the existing frameworks. Further, the precision, recall, and F-Score achieved by RF in iCrop are higher than the existing frameworks. From Table III we observe, NB has also achieved 99.32% accuracy, and the ET is also very less. In our framework, DT also has achieved 99.09% accuracy and has less ET. Hence, finally we conclude that iCrop outperforms the existing crop yield prediction strategies.

D. Total Latency and Energy Consumption

The total latency for iCrop is measured based on (10). The data transmission latency, computation execution latency for data analysis, data embedding and extraction latency to and from the image, and user's registration latency, are added to calculate the total latency in iCrop. The energy consumption of the devices used in iCrop during this period is measured. In Figs. 8 and 9, the latency and energy consumption in iCrop are presented and compared with the cloud-only framework. In the cloud-only framework, edge computing is not used and whole data processing takes place inside the cloud. We observe from

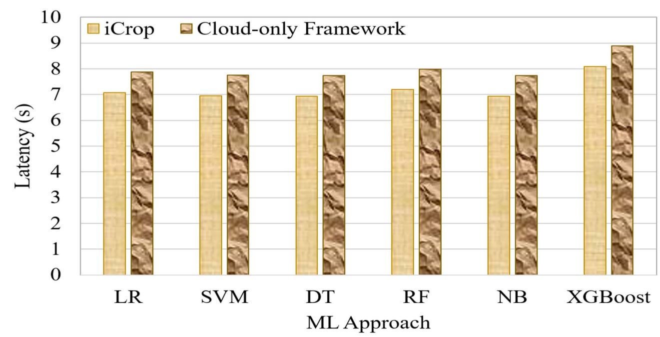

Fig. 8. Total latency in iCrop.

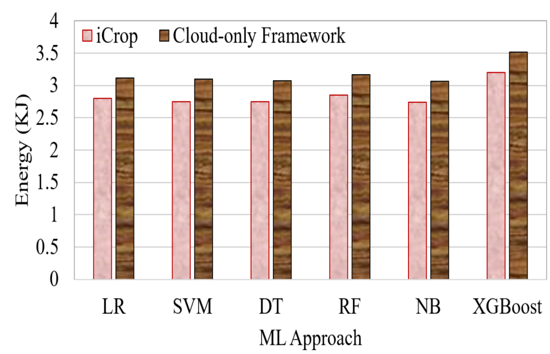

Fig. 9. Energy consumption in iCrop

the results that the use of edge computing in iCrop reduces the latency and energy consumption by $\sim$10% than the cloud-only framework. Eco-friendly and sustainability are two significant factors of Industry 5.0. As energy consumption is reduced in iCrop, eco-friendly framework can be obtained.

V. CONCLUSION

This article has proposed a crop yield prediction and recommendation system referred to as iCrop based on edge computing, ML, and steganography. We have used the private cloud server referred to as agri-server for data analysis and storage. The edge device preprocesses the soil and environmental parameters' data, and sends it to the private cloud server referred to as agri-server. The agri-server stores and analyzes the data using ML. We have used modified LSB-based image steganography for data embedding and extraction to and from the image for securing data transmission. The experimental results illustrate that the suggested system reduces the latency compared to the remote cloud-based architecture. We have used and compared six ML approaches for analyzing the soil and environmental data including rainfall. The experimental results present that each of the ML approaches has achieved above 90% accuracy to predict the crop yield. The results also demonstrate that the proposed framework reduces the latency and energy consumption $\sim$10% than the remote cloud-based crop yield prediction framework. The development of latency-aware and energy-efficient crop yield prediction methods for federated learning-based agriculture 5.0 is a future research goal of this work.

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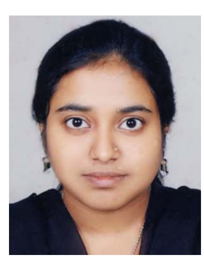

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