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RBCA: Context-Aware Yield Forecasting in Agriculture

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Abstract

Most of the developing countries rely on agriculture for their annual growth, a greater section of GDP contribution is affected by its agriculture. Alongside this, major industries rely upon the agricultural to derive their profit. The farmers of many countries are still dependent on classical methods as they are not aware of various technologies and lack significant knowledge in the sector. Consequently, the loss in the agricultural domain accounts for poor quality seed and delayed sowing, environmental hazards, attacks by insects, irrelevant harvesting etc. However, these factors cannot be controlled but can be monitored and an effective strategy can be adopted with the help of the Internet of Things (IoT). IoT-assisted agriculture can help to monitor the conditions and predict the yield which can be useful in taking decision about crops. However, there are no concurrent real-time forecasting strategies that can avail the inputs from different sensors and give parameter-specific or complete forecasting of the yields. To overcome this issue, a Rule-Based Context-Aware (RBCA) framework is proposed that considers a specialized IoT setup to help yield-forecasting of different crops by using available parameters as input. The proposed model uses a probabilistic mapping theory with residual analysis. The model can help to analyze if the given conditions of agriculture-setup are good enough for the growth of a particular crop by using the standard growing environment as matching criteria. Both numerical and real-test data for various crops between the years 1981 and 2012 are used for evaluating the performance of the model.

Keywords: Agriculture, Iot, Rule-Based Framework, Smart-Agriculture, Yield-Forecasting.

Introduction

Nowadays, we are probing for a unique utilization of the Internet, communication and computing technologies in various fields like commerce, business, regime, health, defense, and scholastic applications. Advances in software technology, computing contrivances and the incrementing volume of digital cognizance, offer the opportunity for more refined and utilize-cordial digital services (1–3). Computation is now performed through a variety of devices which include smaller and lighter devices (powerful as conventional desktop computers) that free us from the confines of the single desk. Portable handheld de- vices such as personal organizers, mobile phones are available with us all the time and relate to the electronic world through Wireless technology. Additionally, computation is also moving beyond personal devices. Various astronomically immense and diminutive interconnected computing devices, along with certain sensing technologies from the simple sensor to electronic tags are being used to make offices and buildings "intelligent". Ubiquitous computing, in combination with mobile and distributed computing, wearable computers, and human-computer interaction is other technology that works collectively to make this possible.

Internet of Things (IoT) can be defined as a combination of ubiquitous computing, distributed computing, and mobile computing paradigms. In simple terms which can say that it is a seamless integration between us and the "things" around us. The basic concept is the combination of every device with the existence of human beings as well as nearby devices. It is the state wherein the devices become part of our experience that is no distinguishable difference between the operation of devices surrounding us and our actions. There is a minimal human intervention for the operation of devices and they communicate intelligently with one another to execute daily operations. Every device is connected to every other device, communication with each other, transferring data, retrieving data, intelligently responding and thus triggering actions (4). Generally, IoT is based on intelligent and self- configuring nodes that are

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interconnected in a dynamic and global network infrastructure. It includes the combination of the physical object embedded with software and sensors that maintains a connectivity bridge between the physical world and networks. In current trends, IoT has been suggested as a backbone for many applications. IoT conveyances including smart devices and sensors, gateway, cloud, and analytics are the major components of IoT (5). It further includes a wide variety of objects like smart phones, tablets, digital cameras, sensors, etc. (6). It is also to be considered that such a large number of devices connected through the Internet produce a large amount of data and information, which require efficient solutions for gathering and processing of the collected data. The data collection components can be configured based on the user-defined flow of data. Once a configuration is applied to an IoT-device, the specific devices can gain access to the information (7).

IoT potentially assists a wide range of applications, including smart home systems, smart street lighting, traffic congestion detection, and control, noise monitoring, city-wide waste management, real-time vehicle networks, and smart city frame-works. For assistance, the IoT devices generate biometric and environmental data for either feedback or comprise processors allowing smart decisions to be made based on accumulated information (8). IoT facilitates energy optimization with devices like smart heating systems, refrigerators, connected security cameras, and lighting in the smart city and smart homes (9, 10). In the industry and manufacturing sectors, smart sensors and machine learning methods are used for adjustments to the process. Furthermore, IoT opens new paradigms for smart agriculture by smart sensors to remotely monitor and control pumps and equipment, as well as environmental monitoring of chemical levels, soil profiles, and air quality (6, 9).

Agriculture is the main occupation in our country with almost 60% population directly dependent on agricultural revenue for their livelihood. Though several advancements have been made over the years in improving crop yield still agricultural yield is highly dependent on external and sometimes uncontrollable elements like weather, rainfall, pest onslaught, etc. (11). Even today the farmers are mainly dependent on manual monitoring and conventional techniques to asses analyze these elements and use traditional methods for taking preventive measures. IoT-assistance can help to overcome these issues; however, the complexity of operations is a crucial factor to consider with IoT-assisted agriculture. An approach especially based on the generation of rules needs to fit in the requirements of the low cost of operations. Moreover, it should not cause an additional burden in terms of overheads, cost, and high computational requirements. The approach needs to be light weight with high convergence. All these factors raise a desideratum for a rule- predicated solution, which can take into account the contextual requisites of the crops and provide support for taking efficient control and decision in IoT-assisted agriculture.

Problem Statement and Motivation

A lot of researchers have focused on resolving the problems of farmers by incorporating technology in the field of agriculture. Various solutions, such as the use of a microcontroller, IoT-sensors, have been used in the same direction with a common objective of increasing the overall crop productivity and reduce human intervention. However, no core framework can lay down their utilization in an accurate yield forecasting. Alongside, no system model fixates on the utilization of existing network layouts and provides an abstracted discussion on it. Several aspects of learning, which is a key requirement of any intelligent framework, irrespective of its deployment, need to consider the situational awareness of the system. The availability of recent technologies can help lower the residuals from the prediction model. However, there are no efficient mechanisms available that can show how and what components are to be used for learning and minimizing the residuals. To add, a common framework which not only considers the related parameters but also provides a strategic solution to forecasting it required.

The motivation is driven by the requirement of reducing crop failure by letting the farmers know what environmental conditions such as temperature, humidity, light, soil moisture are most suitable for the crop and the effects of the used fertilizers through a rule-based mechanism. The key reasons for developing such an approach are eliminating the delays of the non-real time support for yield prediction and decision making, reducing the high cost of operations and additional system-overheads in evaluating the given model, providing better supervisory and control methodology, reducing the complexity of operations and enabling technologies like IoT to govern the overall forecasting results.

The key contributions of the work are listed below:

- A generalized setup is considered for providing IoT- assisted agriculture.
- A rule-based context-aware (RBCA) framework (Hybrid Framework) is proposed that considers the IoT setup to help yield-forecasting of different crops by using available parameters as input.
- Performance evaluation of the model is presented to help understand the convergence and applicability of the proposed model to forecasting.
- Real test-data from Govind Ballabh Pant University of Agriculture & Technology, Uttrakhand, India is used to show how the proposed model allows forecasting by using temperature as a key parameter for wheat, rice, maize and sugarcane crops between the years 1981 and 2012.
- The proposed model can be applied to real-time data as well as can be operated as an offline setup depending on the number of available parameters and complexity of parameters in terms of inter-dependencies and combinations.

In Literature, certain articles have focused on forecasting and prediction of metrics related to agriculture.

A proposal stated agriculture to be based on cloud computing. The desired architecture was based on IoT and also cloud computing. The information about agriculture was combined with IoT to achieve a significant distribution of the concerned resources as well as balancing the load (5).

Another study based on the applications of IoT on agriculture developed a system that would monitor agriculture based on network sensors and the internet (6). A system was developed by authors to monitor the agricultural field along with the acquisition of data, processing the models, and also the configuration of system modules. The resulting application gave immense control for greenhouse monitoring. The expected application in the near future and the various challenges that would be faced by the internet of things were discussed in previous studies (9). Several challenges included: privacy, standards, security, identification, authentication, integration, ownership, trust and regulations. They also suggested that using WSN and RFID along with the technologies related to mobile communication would largely eliminate the gap between the practical and theoretical applications of the Internet of Things.

IoT based digital agriculture has been segregated into two steps, first is the data related to wind, temperature, and contents of soil, gathered by various sensors and second being the information transfer by Zigbee. EPC code is the label given to products of the agricultural domain (10). IoT is influenced by the application of sensor-based networks; a discussion pertaining to the implications of IoT is based on WSN, Wi-Fi and smart grid. Smart Grid is responsible for providing an application for the integration of smart data, thereby improving its reliability and giving exact information. IoT also provides an application that can effectively monitor the environment; data related to water and air, gathered using sensors and then passed for processing. They laid a proposal related to agricultural precision. Also, they concluded that the new technology of WSN is comparatively better than Zigbee (12).

Another application of IoT in the field related to agriculture is the management of the stock chain of the animal using RFID technology. One can effectively use RFID technology to identify objects when every individual object is identified with a unique EPC code. They also suggested using technology to maintain records related to livestock management (13). An Expert system in the diagnosis of mango disorder, pets and insects was developed in which the initial step was the acquisition of knowledge, followed by a diagnosis of ailments through given inputs pertaining to the diseases of mango along with suggestions to control the same was given (11). A proposal for an expert system for diagnosing diseases for rice plants was developed, the main aim behind devising such a system was to help the farmers come up with solutions was developed starting with laying knowledge base pertaining to rules. It is easy to use the system proposed and would be highly effective for people who are not able to drive the support of experts in the agricultural sector (14). A review for the use of artificial intelligence in smart farming, precisely in crop selection, yield prediction, and demand forecasting. Machine learning and deep learning algorithms are used for these processes, with the goal of improving agricultural sustainability and addressing food insufficiency due to population growth. Time series analysis is also discussed as a crucial tool in predicting future crop production (15).

An Expert System named Agpest was formed for examining the disease in CLIPs. It comprises the IF then else rules for finding diseases for preventing diseases of pests in wheat and rice crops. Rules were formulated from several sources (16). A discussion about the use of machine learning techniques to predict crop yields and aid decision making for farmers. Taking into account different soil and environmental factors, the model assists farmers in selecting the optimal crops to cultivate and boosting their production, ultimately reducing crop wastage and maximizing income (17). An expert system to protect Egypt's wheat field works in two sections, the first to identify the domain and then provide information. The system was developed in MATLAB. It was effective in leveraging the quality of the crop and also helps the farmer in rural areas to detect the disease or leaves in several kinds of cereal (18). A review on how IoT technologies are employed in agriculture for improving production and sustainability. The article talks about how sensors, controllers, and communication protocols are combined, along with emphasizing the significance of data analytics (19). The results can help in choosing the right IoT technologies for farming purposes which seems to be very difficult in detecting the leaf disease by farmers without the intervention of an expert. Have techniques such as detecting edges or affine transmutation for comparing images were used to identify diseases. The system was devised to be web-based so that the same can be easily used by any web driven system (20).

An overview of recent research on the use of deep learning and Internet of Things in precision agriculture was studied previously (21). It discusses various applications, challenges, and proposed solutions, including a new model for pest detection that outperforms other models with an accuracy of 96.58. A discussion on how smart agriculture and digital twins can enhance food security, cut resource use, and boosts farm profits. It suggests a theoretical structure for deploying these technologies and showcases a case study on fertilizing crops. The article also discusses obstacles and potential future out- comes, especially in rural agricultural regions (22). A proposal for an irrigation control scheme which is based on the structural similarity (SSIM) - based water valve management mechanism. The author's emphasized to design a precise irrigation monitoring and control mechanism for the real-time farm information through multi- point measurements (23). An IoT-based technologies and applications in the agriculture supply chain context in developing countries. The authors discussed the applicability of IoT based Agri-Food technologies to minimize the wastage of foods which is helpful for the fulfillment of the requirements of users in a most sustained way (24). A work focusing on the opportunities and challenges for smart farming. The authors discussed the existing technologies and possibilities to cope up with the farming requirements. The agricultural domains have been analyzed in this work along with the most relevant communication requirements providing a mapping between the presented use cases and enabling technologies (25). The authors presented an overview of some of the existing supervised and unsupervised machine learning models associated with the crop yield in literature. The authors presented a detailed taxonomy of the machine learning classification and algorithms. The authors discussed the advantages of machine learning methods in agriculture that helps in the analysis of crops using image processing and deep learning especially for the identification of pests, weeds, and diseases (26).

Methodology

This section discusses our new RBCA framework which utilizes the user-end as well as network-facilitated instructions to forecast the agricultural yield. The details of the observational framework, decision-rules, and context-aware prediction performed using RBCA are discussed in this part.

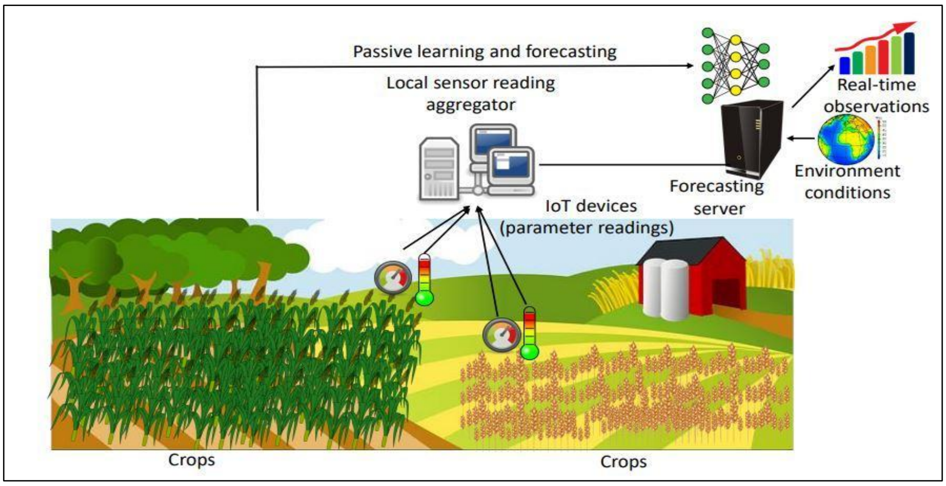

Figure 1: Exemplary Illustration of the Setup for Yield Forecasting in Iot-Assisted Agriculture

System Model

The system comprises a field denoted by area $|A|$ having a set $|C|$ of crops each represented by a set $|S|$ of parameters. Each element in the set $|S|$ denotes the function which is composed of different metrics that affect the yield of the particular crop in the set $|C|$. Alongside this, the field is equipped with a set $|D|$ denoting the IoT devices which are capable of measuring values to support the forecasting and take the decision of recommendations. A centralized server is used to accumulate the current situation of the field and record the readings from the deployed IoT devices. The forecasting framework is deployed at the centralized server and it can provide a detailed report of estimations whenever certain changes are observed in the readings or new rules are fed into the model. An exemplary illustration of the considered setup is shown in Figure 1.

To help understand the model, a setup is considered where the metrics available for evaluations are accumulated such as temperature, soil type, humidity, rainfall, sunlight, wind speed, plant age, water-level, precipitation. These metrics can be dynamically changed, removed or added to get accurate facilitation from the proposed RBCA framework. Let ϵ_k denote the residual for k number of metrics and I_k be their importance level in the measurement. Both these metrics are crucial for deciding the observations of our model and altering one can help understand the impact and performance on the other components. These two values are driven by the rules, which are made by the plant/crop provider and includes set of special conditions which are required for enhanced yield. Let Δ be the range of error permissible for each metric and is used as error-detection in the readings of the proposed model. All these system settings help to form the observation framework and model the rule-based prediction for yield forecasting. For evaluations, $\epsilon_k \leq \Delta_k$.

Rule-Based Modeling

The rule-based modeling suggests that under the given conditions the expected-residual of the system should be minimized allowing better strategic formations for context-aware predictions. To follow this, the conditions can be written as

$$min(\epsilon_k), \quad [1]$$

s.t.

$$(P_k)\ ,\ \forall C \rightarrow S_k\ \exists\ \vartheta_k, \quad [2]$$

Where P_k is the probability of successful mapping of the metric to its importance value. The entire system operates towards minimizing the overall cost of operations (OC), which is related to the updates required to minimize the residuals at maximum mapping. This can be written as:

$$(O_C)\ , \forall k \in S. \quad [3]$$

To model ϵ_k Bayesian stochastic modelling is used as it allows better prediction over the contextual events irrespective of their distribution, which is given as:

$$\epsilon_k = ||E_{exp} - E_{obs}||_k, \quad [4]$$

Where

$$E_{exp,k} = R_k \int_{t_1}^{t_2} f(k, I_k), P_k dt, \quad [5]$$

and

E_{obs} is the observational value obtained from the near-field readings from the sensors. Here, R_k is the associated rule with the governing parameter which is observed from context-aware rule-based framework. In case of prehistoric observations, this is filled with the available range of real-data which is used for making decision on predictions. Here, $f(k, I_k)$ is the mapping function which is considered based on the distribution of the metrics as well as the important factor associated with each metric. In general, the importance value for each metric I_k is aligned w.r.t. some distribution based on the dependability Damongst the metrics in the dependent set D_k. Thus, in the case of known dependence, the mapping function is expressed as:

$$f(k, I_k) = \frac{\sum_{i=1}^{|k|} I_k \cdot \frac{D_i}{|D_k|}}{|S|}. \quad [6]$$

For continuous prediction, I_k should be replaced with the associated distributive function of the importance value for the given set of parameters. The probability of mapping is understood by the dependability of metrics ~\cite{joseph2015probability}, such that

$$P_k = \frac{|D_k|^k e^{-k}}{k!}. \quad [7]$$

This probability helps to derive the expected observation for any parameter which is used in forecasting. The model in Figure 2 considers the formalized rules to check which parameters should be updated based on the error observed as an output from this model.

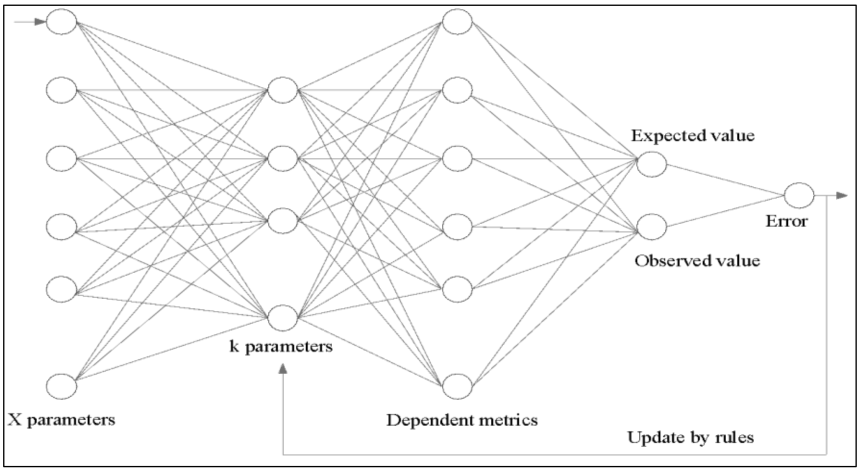

Figure 2: An Illustration of the Neural Setup Used to Update the Model from a Given Set of Parameters

Context-Awareness for Prediction

The prediction in the proposed RBCA model is based on the ANN, shown in Figure 2. The model operates based on the residual attained after each iteration and uses to predict the next closer value. The model helps to forecast a decision whether the given metrics are close enough to give accurate yield during a given season. The model uses a sigmoid function, which allows it to be used for multiple classes with better convergence. In the proposed RBCA model, the context-awareness is included in the form of weights that also govern the mapping rules in the proposed setup. In the given model,

$$\sigma_k = \frac{W_k}{1 - e^{-W_k}}, \quad [8]$$

Where W_k is the associated weight with the given parameter. The model sets a range for $\epsilon_k$and only if, within the conditions, the forecast is marked accurate otherwise checked for errors and the model is updated. The learning can be induced to make the model predictable instead of forecast-able, however, the current work does not form a complete prediction rather it operates only towards forecasting. To have a general feature of prediction along with forecasting, the sigmoid function is converted to cost function O_C. for each iteration,

$$O_c(W_1, W_2, \dots, W_k) = \frac{\frac{1}{k}\sum_{i=1}^{k} W_i}{1 - exp^{-\left(\frac{1}{k}\sum_{i=1}^{k} W_i\right)}} \quad [9]$$

Similarly, the cost function is derived for all possible combinations, such that

$$O_c(W_j) = \frac{\frac{1}{j}\sum_{i=1}^{j} W_i}{1 - exp^{-\left(\frac{1}{j}\sum_{i=1}^{j} W_i\right)}}, j \leq k-1. \quad [10]$$

The combination in $O_c(W_j)$can have 1 to k-1 combinations and the total number of combinations are $\frac{k!}{x!(k-x)!}$, where x varies from 1 to k-1. Now, for the accurate functioning of the model,

$$O_c(W_1, W_2, \dots, W_k) \leq \sum_{x=1}^{k-1} \frac{1}{\frac{k!}{x!\,(k-x)!}} \left(\sum_{j=1}^{k-1} O_c(W_j) \right) \quad [11]$$

The higher deviation refers to more errors in forecasting and the model needs to be re-tuned for accurate functioning with better adjustments to its weights. The target is to minimize the cost as well as the difference when the combinatorial cost is considered over the given model.

Rules for Selecting Weights

The weights in the given model play crucial rules to give high accuracy in forecasting. The weights are allocated based on the importance factor associated with each of the parameters. In the given model, the importance is allocated in terms of priority according to which the forecast decision should be made. Based on this, the weights are normalized by considering the high priority parameter and then obtaining the weighted average for all the available parameters, i.e., $\frac{(I_k) - I_k}{(I_k) - (I_k)}$. Changing the priority will change the normalization, which will also help to understand the impact of one parameter over the over as well as on the final forecasting.

Lemma-1: In the given model, the forecast is governed by the expected value of a parameter, which is tuned between the two ranges of available sets governed by a period denoted by t_1 and t_2 . If the given values of range and mapping importance is known, the expected value can be given by:

$$-\frac{I_k\big((0, -(l(D_k) - 1)t_2) - (0, -(l(D_k) - 1)t_1)\big)D_k k R_k}{|D_k||S|}, \quad [12]$$

s.t.

$$t_2 - t_1 > 0, t_1 > 0, t_2 > 0 \quad [13]$$

From the definition of $E_{exp,k}$,we have

$$R_k \int_{t_1}^{t_2} \frac{I_k D_k^{x+1} k e^{-x}}{|D_k||S|x} dx, \quad [14]$$

Where $k! = e^{log(x)}$is estimated for better convergence. Now, substituting, $D_k = d_1, |\,D_k| = d_2,\ R_k = r, I = i, and S = s$. Now, solving linearity,

$$\frac{id_2kr}{s} \int_{t_1}^{t_2} e^{-x} \frac{d_1^x}{x} dx, \quad [15]$$

and applying exponential integration, we have

$$\frac{id_1krEi\big((ln\,ln\,(d_1) - 1)x\big)}{d_2 s}. \quad [16]$$

On simplification and re-substitution, we obtain

$$-\frac{I_k\big((0, -(ln\,ln\,(D_k) - 1)t_2) - (0, -(ln\,ln\,(D_k) - 1)t_1)\big)D_k k R_k}{|D_k||S|}, \quad [17]$$

which is the desired solution at$t_2 > 0, t_1 > 0 and t_2 - t_1 > 0$.

The above equation will help to make accurate forecasting over the given set of parameters. The equation can be modeled to fit cumulative parameters as well as individual values. However, the cumulative parameters need prior normalized values and the results will be affected by this normalization.

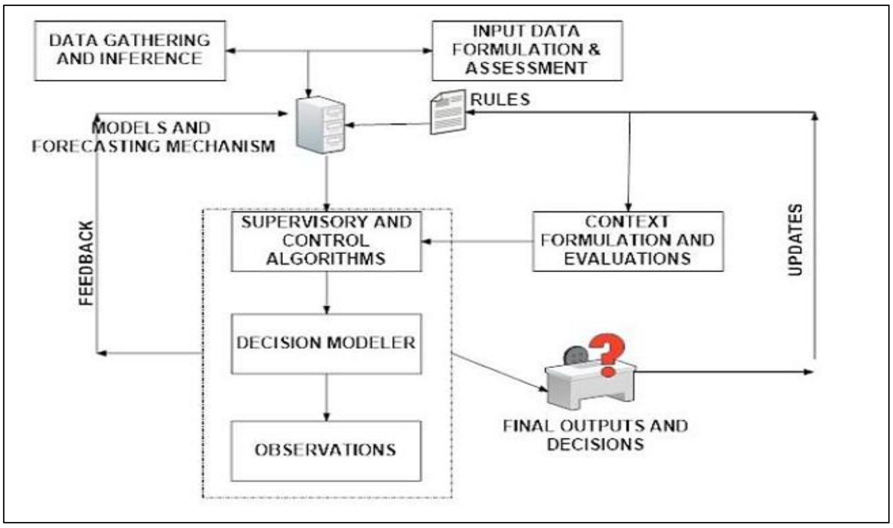

Figure 3: An Illustration of Complete Operational Framework for Implementing Forecasting Yield Using the Given Modular Inputs

Overall Operational Framework: The framework includes the data gathering and inference phase, which is motivated around the setting of the field area and deploying necessary tools to collect as much information as possible. The workflow of the proposed system is depicted in Figure 3. Once initial inputs are observed, the data is reformulated and assessed for the given set of parameters around which the entire model of the application is developed. Next, the rules for modeling (including those to generate weights) are provided and all these are managed by the centralized server, which will be the house of other operations related to forecasting. Next, the operational module, which includes supervisory and control algorithms, decision modeler, and observatory module is initiated. This module is responsible for the neural functioning of the setup and helps to detect the true functioning of the entire mode. This module allows tracking the results as well as give feedback which will be used for updating the rules as well as the general functioning of the system.

Results and Discussion

The evaluation of the proposed RBCA model is done in two parts. The first part helps to understand the operational aspect of the model and allow us to check the importance of different factors on the general workflow. It allows for understanding the impact of variation in parameters on the learning and prediction phases. In the second part, a real-data set is used to check how much time it takes to converge the system towards forecasting and how the system can be adapted to predict the operations based on the given synthetic inputs where the forecasting is done using true (real) data for different crops. The details of parameters used for operational evaluations of the model are given in Table 1. These values are then used to understand the behavior of the model and what parameters cause a major impact on the forecasting.

Table 1: Parameter Settings

Parameter	Value
$\lvert A \rvert$	5000 x 5000 sq.km
$\lvert S \rvert$	1-10
$\lvert D \rvert$	1-0
I_k	0.1-0.9
k	$\lvert S \rvert$
W_k	$\lvert\lvert I \rvert\rvert$
D	0.1-0.9

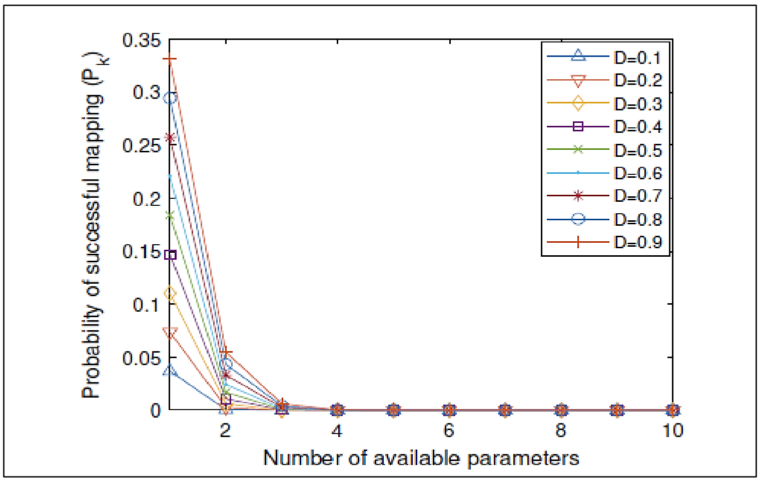

Figure 4: Probability of Successful Mapping vs. Number of Available Parameters with Variation in Dependencies

The model needs to have a clear mapping between the available parameters. The mapping allows a better understanding of the operations and helps to forecast the results. The mapping of parameters is affected by the dependence and the number of parameters associated with each other. As these parameters form the neurons of the ANN model, it is desired to have a strong mapping between them otherwise the probability of obtaining residual and requirement of retraining increases. As shown in Figure 4, the probability of mapping decreases when the dependencies between the variables are too low and also when the number of available parameters with interlinking is high. From the given model, it is understandable that the more the number of dependent variables is there in the input model, the higher are the chances of obtaining better mappings and better will be the observations. However, it is not a serious concern, as the ill-effects of such lesser mappings can be counterfeited by retraining the model and decreasing the residuals. However, it may cause additional overheads of processing and delays. Alongside, common dependency value is far better than having variable dependencies as this allows better convergence of the operating model.

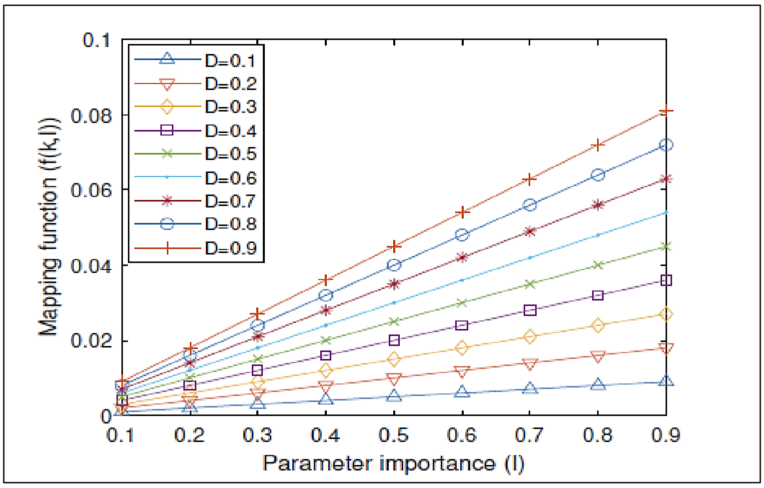

Figure 5: Mapping Function $\boldsymbol{f(k, I_k)}$ vs. Parameter Importance at Difference Dependencies

In continuation of the probability of mapping, $f(k, I_k)$ is another factor that helps to understand as well as control the residuals from the system. This is affected by the importance value associated with each parameter used in the initial configuration of the model. As observed in Figure 5 mapping function gives better results for high importance value as well as for higher dependencies. Thus, the parameters which have a better probability of mappings may give better mapping function and this will affect the convergence of associated sigmoid function positively. However, the selection of optimal value is still an issue as a too optimistic value will cause ideal iterations whereas a too low value will require multiple training and iterations to have a high forecast. The selection of optimal values is not considered at this stage and more work will be presented in our future reports. The residuals are affected by the results of Figure 4 and Figure 5 followed by the rules that are associated with the generation of context that helps to make a prediction and give results of forecasting.

The rules are controlled by weights, which in turn are affected by the importance levels of the parameters. The initial observations of the model help to understand that continuity in observations is key to give high forecasting. In case of breaks or unavailable data, as in Figure 6 the residual increases which will decrease the performance by generating low-converged forecast data. Such an effect is shown in Figure 7 according to which, the cost function associated with the residual that acts the activation function for the ANN can help to understand whether the system in the current settings will be able to generate a forecast or not. This means that if the cost function has value higher than the aggregated cost of combinations of parameters, the convergence of the system is not possible and the model will not converge towards an output. Thus, the mappings should be done such that the laws in equation [11] are always satisfied. These first parts of evaluations help to understand the workflow of the system and how the performance is affected in terms of different configurations. Furthermore, it also helps to analyze whether or not the system will be able to generate an output or not. Such evaluations can save time as well as and can give forehand observations for correcting the initial settings of the setup.

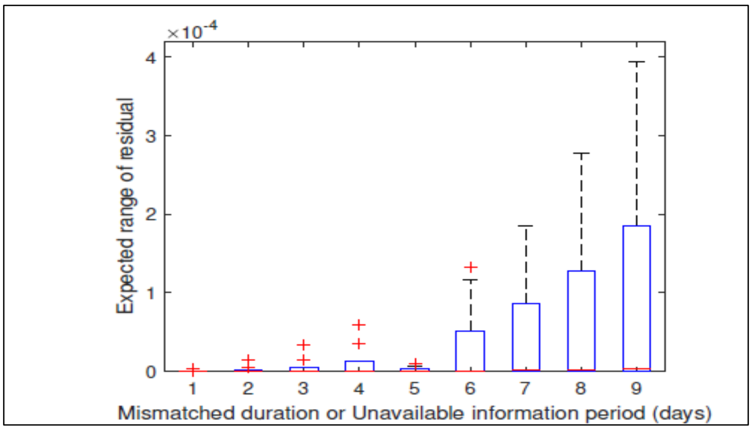

Figure 6: Expected Range of Residual W.R.T $\boldsymbol{E_{exp,k}}$vs. Mismatched Duration in Days

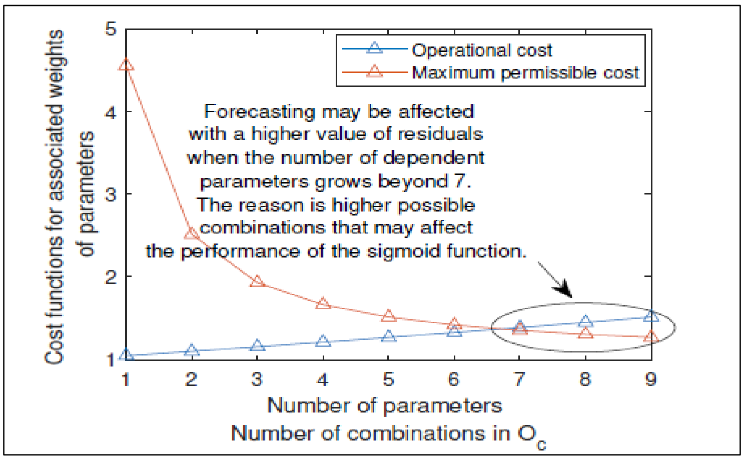

Figure 7: Cost Functions for Associated Weights with Individual Parameters and Dependent Variables vs. Number of Combinations and Parameters

In the next part, we evaluate the model for real-time results by using the data of four crops as shown in Table 2. We also availed the information on some of the parameters such as rain and humidity for different times of year between the years 1981 and 2012. We selected temperature as a dominant entry for evaluation of wheat, rice, and maize and gave it higher precedence in our model. The model was re-formulated to understand the best year for a particular crop based on the residual. The results in Figure 8, 9, 10 helps us to understand years that would have yielded maximum as per the forecast by the proposed RBCA model. However, other factors such as rain and human factors (maintenance) are not observable in these graphs. In Figure 8, it can be noticed that the expected values of temperature lie between the maximum and minimum ranges throughout the available data set. Hence, based on temperature-readings, the years 1981-2012 were fine for the growth of wheat and maize. In Figure 9, it can be noticed that there are major peak points lying outside the expected range of temperature conditions, which denotes that those seasons were unable to give a maximum yield of rice. Such evaluations can also help in future observations and any combination of factors that may cause lesser yield can be predicted in advance. Furthermore, Figure 10 helps to understand the yield for sugarcane between 1981 and 2012.

Table 2: Ideal Conditions for Major Field Crop

Particular/Crop	Wheat	Rice	Maize	Sugarcane
Optimum temp (ºC) for growth	16-22	30-32	30-32	32-35
Sowing Time	1-15 Nov	1st week of July	July	1-15 Oct. and Feb.-March
Soil type	Sandy loam	Clay loam	Sandy loam	Clay loam
Soil pH	7	5-7	6-7	6-7
Sowing Depth (cm)	5-7	3	6-8	12
Seed Rate (kg)	100-125	20-25	18-25	33000 three budded sets
Spacing (cm)	21.5	20	60	90
Irrigation	5-6	2-5	2-3	6-7
Nutrient requirement				
Nitrogen	125	125-150	150	180
Phosphorus	60	60	60	60
Potash	40	40	40	80
Zinc	25	25	25	25
Sulphur	20	20	20	20

From the Figure 10 it is noticeable that expected values are not attained in most of the years, which must have affected the overall yield of the sugarcane in different regions. These results are predicted values for the given data set and may change when more parameters are considered for the study. The results may vary if the precedence of parameters is altered. This gives an interesting utilization of the proposed RBCA model, where different parameters can be tuned at different settings to understand the region-wise yield of crops. Additionally, future predictions can be made by combining different factors or weather conditions and running them against the standard requirements of different crops. The RBCA model can also be transferred at any geographical region and for any crop with only one overhead of retuning the model again for better results. From these evaluations, it can be claimed that the proposed RBCA model not only helps to understand the advantages of IoT-assisted agriculture but also forms the background and layout for using such setup in forecasting. Moreover, the observations from the available data can be re-trained to understand which time and conditions are best suited for particular crops.

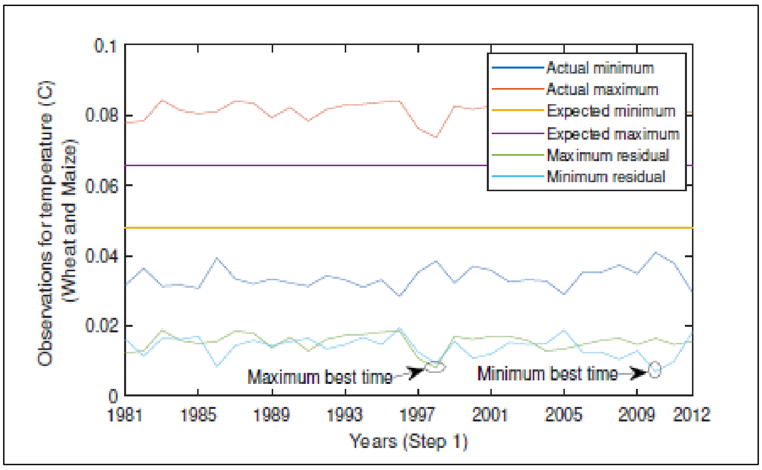

Figure 8: Temperature-Based Yield Forecasting for Wheat and Maize Crops

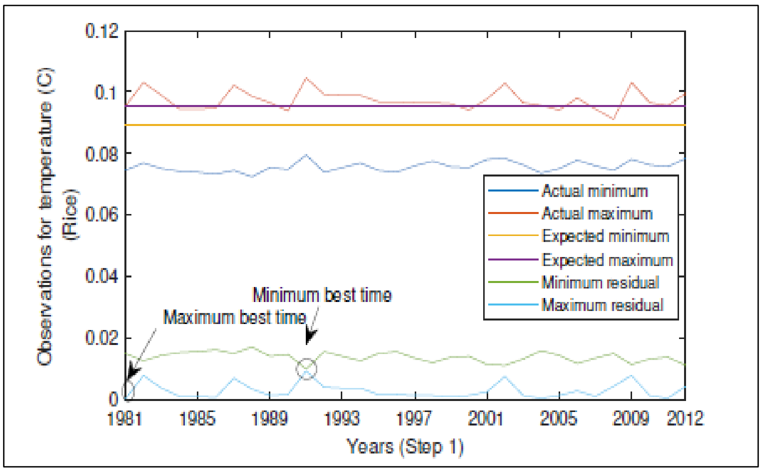

Figure 9: Temperature-Based Yield Forecasting for Rice Crops

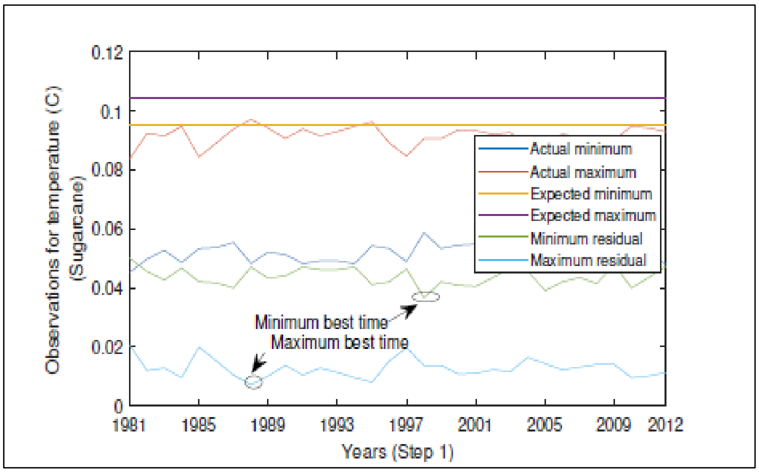

Figure 10: Temperature-Based Yield Forecasting for Sugarcane Crops

Conclusion

IoT-assistance can help understand the growth rate of crops. IoT-based devices can allow to efficiently forecast the yield by considering a different set of parameters recorded by the specialized sensors. In this paper, a rule-based context-aware (RBCA) framework was proposed that considered a specialized IoT setup to help yield-forecasting of different crops by using available parameters as input. The proposed model used a probabilistic mapping theory driven by Bayesian stochastic modeling for residual analysis. Further, the performance evaluation of the model was presented to help understand the convergence and applicability of the proposed model in forecasting. Real test-data was used to show how the proposed model allowed forecasting by using temperature as a key parameter for wheat, rice, maize and sugarcane crops between the years 1981 and 2012. The model helps to understand the impact of different parameters that may include temperature, soil type, rain, humidity, etc on the growth of particular crops by considering the ideal conditions as the final matching criteria.

Abbreviations

IoT: Internet of Things, RBCA: Rule Based Context Aware.

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Author Contributions

Harpreet Singh Chawla: Conceptualization, methodology, data collection, data analysis, original draft preparation, Devendra Singh: Supervision, formal analysis, validation.

Conflict of Interest

None.

Ethics Approval

Not applicable.

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