

## Application of Machine Learning on Crop Yield Prediction in Agriculture Enforcement

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### Abstract

*Yield forecasting is based totally entirely on soil, water and vegetation to be a possible subject. Deep-based depth-based fashions are widely accustomed extract important plant functions for predictive purposes. Although such strategies are necessary to resolve the matter of predicting yields there are the subsequent abnormalities: they can't create an indirect or indirect map between raw facts and yield values; and also the full functionality of this excess is explained within the high satisfaction of the published works. Deep durability provides guidance and motivation for the above-mentioned errors. Combining master intensity and deep mastering, deep reinforcing mastering creates a comprehensive yield prediction framework which will plan the uncooked facts in crop prediction rates. The proposed project creates a version of the Deep Recurrent Q-Network Support Vector Machine deep mastering set of rules over Q-Learning to strengthen the mastering set of rules for predicting yield. Sequential downloads of the Recurrent Neural community are fed by fact parameters. The Q-mastering community creates a predictive yield environment based totally on input criteria. The precise layer displays the discharge values of the Support Vector Machine on the Q values. The reinforcement master component contains a mix of parametric functions on the sting that helps predict the yield. Finally, the agent obtains a measure of the mixture of steps performed by minimizing the error and increasing the accuracy of the forecast. The proposed model successfully predicts this crop yield that's hip by keeping the initial distribution of facts with 93.7% accuracy.*

**Key-words:** Harvest Forecasting, Standard Deep Q-network, In-depth Learning, Intelligent Agricultural Application.

## 1. Introduction

Agriculture is that the most vital area within the community as a part of the food production is manufactured by them. Currently, many countries are still laid low with hunger thanks to shortages or food shortages. Extending food production will be a compulsory process to finish hunger. Improving food security and food depletion by 2030 are the critical goals of the UN. that's why plant protection; soil analysis and crop yield estimates are critical to global food production [1]. The influential person of a rustic relies on a certain forecast, conducting suitable export and import tests to strengthen national food security. Farmers and farmers still enjoy crop forecasts for financial and administrative decisions. Agricultural employment, especially crop monitoring, is critical to achieving food preservation within the region [2]. On the opposite hand, predicting crop yields may be a major challenge due to the various complex factors involved. Yield is very obsessed with climate, soil quality, good soils, pest control, water quality and availability, genotype, harvesting physical exercise to [3] - [5].

The processes and methods of crop production vary over time and are very different in line [6], and thanks to the complexity of the fine-tuning of the corresponding points [7], [8] manifested and littered with non-conflict works with external factors. Often, an outsized a part of the agricultural framework can't be determined between basic step calculations, specifically with complex, incomplete, confusing, and strident data. At present, many studies show that machine learning capabilities are significantly better than standard statistics [9] - [12]. Machine learning is within the field of AI where computers may be taught without a transparent program. These processes solve off-line or off-line agricultural structures with amazing predictive ability [13]. within the mechanized fields of agricultural learning, techniques are found within the training procedure. These processes require the train to perform the chosen function. process, model makes speculation to check information.

In addition, machine learning is sort of a canopy that carries a range of important techniques and techniques. after we take a look at outstanding agricultural models, we are going to monitor the utilization of artificial and deep neural networks [14]. In-depth learning will be alittle group of machine learning that may determine results from different data systems. In-depth studying algorithms, as an example, can build a skill model by taking ten years of field data and giving insight into plant accomplishment under a spread of climates [15]. Data scientists use a range of machine learning techniques to achieve practical insights from available information. Another interesting area of AI is strengthening learning [16]. this can be often thought to be a crucial component of algorithms that may be accustomed redeem the concept of dynamic planning. The consolidation of learning is that the

modification of machine learning models builds decision sequence [17]. The agent learns to accomplish the aim during a mysterious, potentially complex environment. supports the action of the agent, the environment rewards us. this case shows the machine because the agent and also the environment because it's natural.

In recent times the advanced development of the naming process, enhancing in-depth learning (DRL) has deepened into intelligent decision-making in various fields like power administration[18], robotics [19], health care [20], intelligent grid, game vision [21], [22], finance, consolidation opinion [23], language processing [24], interim analysis [25] then integrated a comprehensive combination of reinforcement methods with in-depth learning models [26], [27]. This model has worked well to resolve an honest measure of complex decision-making tasks that were previously beyond the boundaries of the machine. As a result, it's a convincing model that's allowed to develop intelligent agricultural structures. Deep-strengthening learning methods include a deep fan network, in-depth multi-agent learning and an in-depth Q-network.

## **2. Related Work**

The potential growth in AI undoubtedly has potentially lasting effects [33], [34]. By creating new chances, in-depth understanding has advanced the event of knowledge [35]. This latter requires advanced ways to spot, determine and evaluate comprehensive data strategies in agricultural sectors [36], [37]. Yield prediction is usually thought to be a pattern recognition problem during which AI has demonstrated the efficiency of agricultural resources [38]. Abrougui et al. proposed a potato crop forecast and land structure and farming plan by ANN. The ANN model has shown great potential for measuring yields [39]. Haghverdi. Explain the probabilities of cotton fabric from the phenology of plant indices using ANN. The ANN method has been accustomed obtain 61200 models per indicator of individual plants to estimate the sphere of cotton production to be predicted [40]. Byakatonda et al. explain ANN-based man crop forecast supported weather indicators and so the length of the weather. so as to facilitate agricultural planning, yield forecasting was performed using ANN models [41]. within methods as mentioned earlier, ANNs are used for processing, which relies on the discharge of the feature in terms of your time and domain scope. This results in a discount within the actual release of the element mainly by hoping on prior knowledge of pre-harvest information, hence the shallow construction of ANN in studying difficult non-linear relationships within the crop prediction system. With the arrival of in-depth learning, such problems are treated to some extent. Yang et al. have proposed a comprehensive convolution neural net-work model to predict the yield yields of

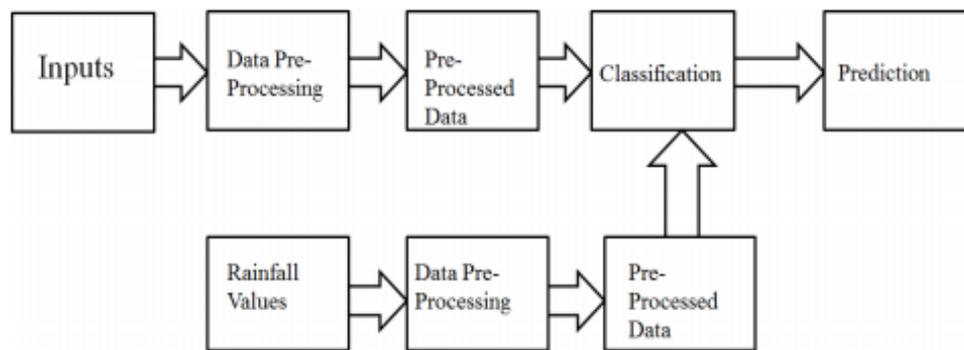
the rice harvest during ripening. The CNN network understands many local traits associated with crop yield within the high definition image of RGB [42]. In-depth reading enabled the crop map strategy to spot crop yields within the appropriate region. Making a map of winter wheat using statistical data indicators below using synthetic neural networks so deep CNN is mimicked by Zhong et al. this enables for automatic identification of the college period without the utilization of samples [43]. Ramesh et al., Proposed a sophisticated neural network algorithm developed and categorized the crop yield supported leave images obtained by image processing method [44]. Babak et al. calculated the study model with the very best plant growth rates by importing the DSSAT model rainfall and irrigation vegetables to predict maize yield [45]. the automated cropping method for automatic crop yields by in-depth study of the CNN network using RGB statistics for plant images [46] suggested by Desai et al. Koirala et al., Proposed a two-phase in-depth study using CNN's mango fruit measurement [47]. From the literature, the ANN-based process is usually appropriately identified as a key predictor, and in-depth study methods can detect the emergence of a dynamic farming feature within the sequential representation of DNN formation. the development of DNN, however, requires a wonderful experience of information and prior comprehension that limits its overall performance. it's therefore important to plan for the deepening of the consolidation study (DRL) so as to require into consideration the prediction of crop yield. within the framework of the DRL, in-depth learning empowers the agent to feel the environment and enhanced learning enables the invention of a way simpler method for real-time problems [48]. DRL makes the creation of an agent that may adapt to a test environment like meta-learning [49]. As a typical thanks to solve problems of excellent through error, DRL finds its application in many fields like agriculture [50], health care [51], power management [52], robotic system [53] and sports vision [54]. the following section provides a fast introduction to the Deep Q-Network DRL algorithm and thus the proposed method.

RL differs from other machine learning algorithms in this it doesn't explicitly advise on performance, but solves it on its own [55]. within the RL learning process, the Markov choice Procedure (MDP) process is enabled to permit for a system during which reinforced learning issues are adopted. The RL algorithm, which is an agent learns about interaction and interaction with the environment. The agent will receive rewards permanently deeds done and penalties for wrongdoing. The agent learns on his own without the intervention of someone by increasing his earnings and limiting his fines. the reinforcement learning method is presented in Figure 1.

The agent present during the empire polishing off the steps 'a'. In performing the action the agent receives the gift  $R(s, a)$  so passes the transition  $s'$ . Policy will be a task that puts maps within the provinces and thus actions. In each region,  $\pi$  policy is employed to specify the action to be

performed by the agent. within the life of an agent, his main goal is to determine the correct policy  $\pi^*$  that maximizes every discounted salary. the proper policy  $\pi^*$  is defined by rating (1).

$$\pi^*(s) = \operatorname{argmax}_\gamma \sum_{a \in A} \sum_{s' \in S} \dots$$



- A value function  $V_\pi(s,a)$  [56] is explained for each state-action pair is an estimate of the expected reward following a policy  $\pi$ . the foremost optimal value function is attained from the best optimal policy, which is identified by the perfect reward obtained by an agent from all the alternative states. This suitable value function is represented in equation (2).

$$V^*(s, a) = R(s, a) + \max \gamma \sum P_{sa} sr, a V^*(sr, a) \quad (2).$$

- The performance of the framework must be adequately viable to embrace consistently dynamic actions.

This section explains very well the reinforcement learning, Q-learning and therefore the deep Q-Network algorithm.

### A. Reinforcement Learning

Learning Strengthening (RL) is a man-made intelligence framework with a robust planning concept that develops and trains algorithms that use the reward strategy additionally. The consolidation learning agency therefore understands from the location through communication. They increase their benefits by determining the best bellman policy and performance value using powerful planning functions.

## **B. Q-Learning**

Q-Learning are often some way of assessing what action an agent will need, looking on the function of the action value. It decides whether it's appropriate to be in an exceedingly certain period of your time and so make a choice action therein situation. is one in every of the foremost important advances in strengthening learning within the event of an algorithm for controlling temporary non-policy differences. Q-Learning assesses the function of the state-of-the-art directed policy action that results from selecting the very best value action. Activity Q takes input because this state 's' and therefore the verb 'a' and returns the expected reward for that action in this state. within the primary steps before environmental analysis, Q functions provide random fixed values. anon with better analysis, Q activity provides the most effective estimates of the suitable action of the action 'a' within the country. Q activity continues to update by giving the right value. The agent will perform a series of actions that may produce all the grand prizes.

## **C. Deep Q-Network**

In-depth Q-networks are a posh learning agency that uses Deep Neural Networks (DNN) to map inter-provincial communication and thus actions like Q-Table in Q-Learning. DNNs like Convolution Neural Networks (CNN), Recurrent Neural Networks (SVM) and a little auto-encoder can directly read data presentations from sensors. The DQN agent communicates with nature through a series of visuals, actions and rewards almost like the work of a Q-Learning agent. Demonstrating the standard frame of a deep Q-Network.

The network takes the country as an input and with each action within the action space, Q-Values is generated. the aim of the neural network is to detect and train parameters. During the forecasting process, this trained network is employed to predict the following best action that may happen within the surrounding. Essentially, Q-Learning determines the function of the worth of the chosen policy action that ultimately selects the most effective value action. Works well with restricted environment and action area. However, with an outsized set of action it's going to require multiple records to be stored in system memory. This results in a decrease within the volume of the amount which ends up in a curse on the scale or unsteady representation of the Q-Function. Q-Learning instability arises thanks to the links within the visual chain. a small refinement associated with the Q value may lead to a big change in agent policy and therefore the relationship between the target and Q-Value. This incompatibility is overcome in Deep Q-Network using two strategies, namely,

replay experience and repetition updates. Repeated renewal reduces the correlation between target and Q values by equally updating Q values on to the required values. While duplication of experience often solves the matter of adjustment by smoothing the change of data distribution through random data. within the proposed task while upgrading the DQN agent, the experience also randomly selects the experience from the memory and so Deep Q-network acquired SVM, which acts as a weight-bearing function  $\theta$ . Q-Network is therefore often corrected by updating the input parameters within the 'it'<sup>th</sup> iteration by reducing the equilibrium error between the Bellman calculator. Lost work, which may be a square discrepancy between Target Q and so Predicted Q is defined in equation (3) as follows:

$$\text{Loss} = (r + \gamma Q(s, a; \theta) - Q(s, a; \theta)) \quad (3)$$

Gradient decrease for particular parameters are often performed so on reduce this loss.

#### **D. Proposed Deep Reinforcement Learning Model for Crop Yield Prediction**

Learning reinforcement is widely mapped in areas like research, theory of games, multi-agency systems, and control theory. within the proposed activity, crop yield prediction is studied as a retrospective problem solved by supervised reading. This learning-based learning prediction process should take under consideration yield yield data and related parameters for the input function within the affected region. within RL-based methods, the performance of the training of yield predictive agents is decided by standard remuneration. It ends up in the erratic response of agents to align their performance alongside supervised learning methods. In other words, agents won't be able to see from the input that the samples are often read correctly during the training process. Such a component compels the agent to control efficiently by not obtaining a deep feature brightness within the middle of the crop yield. so as to grasp the DRL-supported yield prediction method, the crop prediction environment is meant to support input strictures that transform a administered learning method into a reinforced learning process. matters is commonly remarked as a 'crop prediction game'. All games incorporate a selected combination of parametric features and parameters that help produce the crop and each combination includes an inventory of samples and their corresponding labels. When the representative starts playing, it determines the number of yield yield parameter by performing prize-winning actions. for every proximity of the target, the agent receives a positive reward, otherwise a negative reward. After completing the whole process, the agent will receive a combined score for his or her actions. This flow of harvest forecast is presented. The proposed DQN agent is meant to insert SVM layers in sequence, starting with parameters using tools stored within the pre-SVM training method and totaling a balanced layer that allows SVM extraction to Q-Values. Figure 4 shows the SVM

format utilized in DQN.  $X_t$  refers to the inclusion of information training during  $t$ ,  $H_t$  describes the hidden state during  $t$ .

The worth of the hidden state during 't' is given equally (4) as follows with certain consolidation methods like Q-learning, it's a challenge to favor and analyze yield predictions thanks to the limited ability of those provincial descriptions. Encouraged by DQN's concept of huge processing, Support Vector Machine Based DNN is utilized within the proposed method of predicting yield yields using numerous environmental, soil and groundwater parameters. is known as due to the in-depth standard Q-Learning model which is SVM over DQN. SVM can help extract temporary and semantic data and is advanced in mathematical analysis, language modeling and speech recognition. SVM will be another to ANN, where this state input is linked to the previous state output. a transparent explanation is that the network will remember the previous information and use it during this network calculation.

In our proposed method the DQN agent is stabilized by inserting the SVM layers in sequence, starting the parameters using the instruments stored within the SVM Pre-training process and adding a particular layer to extract the SVM effect to Q-Values. Figure 4 shows the SVM format employed in DQN.  $X_t$  refers to the inclusion of information training during  $t$ ,  $H_t$  describes the hidden state during  $t$ . Input current  $x_t$  and thus past concealed layer state  $H_{t-1}$  determines  $H_t$ . Here,  $O_t$  signifies the discharge of the present layer during  $t$ . Training details actual output  $Y_t$  therefore the current result  $O_t$  determines the error  $L$  during  $t$ . Distributed weights across all SVMs are represented as  $u$ ,  $v$ , and  $w$ .  $F$  portrays the activation role of the hidden layers. The verges shared across the SVM's are defined as  $b_1$  and  $b_2$ .

$$H_t = f(u \times x_t + w \times H_{t-1} + b_1) \quad (4)$$

The predicted output  $O_t$  of the SVM at time 't' is specified as tracks in equation (5):

$$O_t = f(v \times H_t + b_2) \quad (5)$$

The error  $L$  of the SVM at time 't' is given as surveys in equation (6):

$$L = O_t - y_t \quad (6)$$

Critical features of the SVM, which may effectively block the yield, the depiction of the particular features of the self-study layer subsequently layer and also the fixed barrier that bounds the parameter space that forestalls overcrowding. The SVM within the planned work consists of three concealed layers between the input layer and therefore the Q-value output layer. for every SVM layer, the ReLU initiation function [57] and also the L1 standard [58], [59] are used. The results of charging the full amounts of parameters of information within the neural network if large. before the DRL training process, a pre-training process was applied to any or all sample data training. Then the

agent's yield forecast concept is made by inserting input layers and a totally connected layer to extract the ultimate Q values.

During the DRL framework training, an oversized set of state and workplace configurations are founded which will create instability thanks to data clutter. Therefore within the DQN training process, two Q-Learning modifications were made to make sure consistency within the DRL exercise process. the primary is that the conditions of the experience, where the agent's involvement is stored in replay memory (D) by country, action and reward for the present stamp and also the status of the following stamp. Mention at the start of every step  $t$ , the repetition of the experience protects the agent feeling resulting in the gathering of certain sets of experiences. a private experience  $e_t$  at a time  $t$  is described as  $e_t (s_t, a_t, r_t, s_{t+1})$  and therefore the memory at time  $t$  is defined as  $D_t$ , where  $D_t \in e_t$ . Repetition of experience is a good thanks to eliminate variance in parameters that allows practitioners to work out its experience within the learning process. The second change for Q-Learning to use an independent network for goal setting during the Q-Learning refresher process. These changes can significantly improve the steadiness of the DRL. Also, it appears that almost all RL algorithms iteratively stimulate the function of the action value using the Bellman equation. As this method is tedious operational the function of the action value is measured using the SVM function by weight  $\theta$ . Q-Network can therefore be remedied by updating the liver parameters in  $i^{\text{th}}$  iteration 'by reducing the equally double error within the Bellman equation. The training process has two steps. the primary step involves previous SVM training and therefore the second step involves DQN agent training.

## Data Set and Study Are Description

In-depth study types require large amounts of information so on figure effectively. Data with variable features guide the matter of finding common ones by removing features that do not seem to be relevant to the aim of the training. Creating a strong and robust educating model for the agricultural sector - it is very tedious because they're enormously unstable and have unusually strong behaviors. This section briefly describes the information employed within the study to predict yield yields.

- The projected study explores the prediction of a paddy crop yield within the southern Vellore region of India. Here, the regional blocks considered during this study include Ponayi, Arcot, Sholinghur, Ammur, Timiri, and Kalavai. Paddy is one amongst the foremost cosmopolitan cash crops within the region which is why the realm is taken into account to be under investigation. In contrast to climate and soil quality parameters, the database includes specific climatic, terrestrial and groundwater structures in regard to the quantity of fertilizer consumed by the plants within the study area. Various

parameters analyzed within the present study including evapotranspiration, \ frequent snow on the bottom, groundwater nutrients, wet day often, aquifer features that may be seen together within existing literature. Table 1 represents a short overview of the parameters of most of the plants employed in the study. data taken for 35 years. Yields of paddy yield are measured in terms of planting area (hectares), paddy production (in tons) and yield (kg / hectare). Information about normal climate like temperatures, rainfall, reference evapotranspiration, possible evapotranspiration explosions, humidity and climatic parameters like soil snowfall, temperature range, and wind speed were used. Weather information is given by the Indian weather department from its entrance metadata tool. Soil boundaries contain soil compaction, soil PH and thus the abundance of soil macro nutrium (Nitrogen, Phosphorus and Potassium) present. the various characteristics of groundwater aquifers like transport, aquifer type, intrusion, electrical activity, pre-monsoon and post-monsoon micro-nutrient (calcium, potassium, sodium, magnesium, and chloride) found in groundwater study.

The following section presents the experimental results obtained for predicting crop yields using the DRQN model and comparing the results with existing models.

### **3. Results and Discussion**

The efficiency of a learning model is decided by evaluating the model various execution measures or by monitoring the performance by various evaluation metrics. For the proposed work the model is validated in terms of:

- Performance estimation
- Comparison of assorted other algorithms in terms of:
  - Evaluation metrics
  - Data distribution properties
  - Model accuracy measures

#### **A. Performance Analysis**

During the event of machine learning models, the database is categorized by practice within the training and setting of the test, where the simplest information is obtained because the training set is ready. whether or not the test data is little, there are opportunities to go away some important details that may improve the model. Also, there's the importance of high variability within the database. to deal with this issue, K-fold cross-validation is valid. could be a method wont to test

in-depth learning replicas by re-sampling training details to enhance performance. Modeling and predicting statistical data is complex and challenging. Random segmentation of cross-data verification data isn't a decent catch. It'll create a short lived dependency problem as there's an entire dependence on the previous consideration and at the identical time, the leakage from the response variable of the remaining variable will inevitably occur. This results in instability, i.e. common changes in meaning and variation within the knowledge space. In such cases, crossing confirmation is completed during the forward binding. Within the proposed method, a five-fold curtain confirmation is performed, which accurately reflects the prediction of data when the model is performed on previous data and forecasts forward-looking data Results set.

## **B. Comparison with Other Models**

The proposed deep reinforcement model DRQN is tested and verified with other key algorithms, namely Deep LSTM network, Artificial Neural (ANN) networks, gradient boosting (GB), random forest (RF) and other learning-based algorithms in-depth like Bernoulli Deep Belief Network (BDN), Bayesian Artificial Neural Networks (BAN), Rough Auto Encoders (RAE) and Interval Deep Generative Artificial Neural Networks (IDANN). An element limiting the testing metrics is their ability to differentiate between the outcomes of various learning replicas.

### **1) Evaluation Metrics**

These types were forced and executed in python within the simplest feature and were tested under the identical conditions of software and computer platforms to make sure reasonable comparisons. Error metaphor was used to describe performance level while modeling. Residues found during the test, which is that the difference between the specials and thus the anticipated values don't usually measure the error rate. In other words, by seeing the size of the remaining spread, it's determined, and since the performance of the model, is resulted. In terms of sophistication and productivity, the proposed deep strengthening model is proven to surpass anti-machine learning models with 93.7% precision and progressive error measures. However, the performance of other deep learning models BDN, BAN, IDANN, RAE and Deep LSTN is in danger of the DRL method. Fig. 6 and Fig. 7 describe the tested performance actions of the pilot models of the crop yield forecast.

## 2) Data Distribution Models

In order to regulate whether the anticipated DRQN model retains the first data distribution structures, the function of the quantitative availability of certain crop yield data is therefore experimental models are identified. The Strength of Quantity (PDF) is an analytical term that represents the distribution of opportunities for endless diversity in numerous variations. By clearly explaining the PDF, the region below the curve will signify the world where the expected variance falls. totally the realm within the graph interval measures the likelihood of incessant occurrence. It permits us to investigate the probability range of outcomes.

## 3) Model Accuracy Measures

Modeling accuracy testing is a very important a part of the model progress process. It enables you to spot the most effective information representation model and also the performance of the long-term stamp model.

Accuracy means an estimate of a prediction model that accurately predicts. Accuracy indicates the proximity of an mean value to a given value or value. Figure 10 represents diagrams for the accuracy of the expected data using the projected deep reinforcement process and thus other machine learning algorithms are tried.

In recognizing the new values and outcomes obtained from the paddy plant database, a more robust learning model is obtainable to forecast data with better correctness and 93.7% accuracy over different test algorithms.

Although the precision methods of other advanced learning algorithms like BDN, BAN, IDANN, RAE and Deep LSTN are at the tip of the proposed method the worth and complexity of your time is that the proposed model. BDN and IDANN are emphasized that they're better suited to predict continuous data that permits the enrichment of a wider layer by rapid cross-border testing. What's worse is that the speculation process is restricted to a personal passport that the existing avaricious process is slow and ineffective.

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provides a monthly regional description and an annual description of every metrological indicator value. they might also prefer to acknowledge the Joint Director of Agriculture, Vellore, Tamil Nadu, India, for giving information ashore and groundwater in various blocks.

## 5. Conclusion

The proposed system solves the problem of crop selection and makes the farmer aware of the new crops which can be cultivated on their land and increase profit of the farmers. The system in advance also suggests the best suited fertilizers which can help and monitor the growth of crops. Thus, the system will help reduce the difficulties faced by farmers on the agricultural land and reduce the number of suicides attempts of the farmers due to losses. The system provides the benefits for pre-planning the agricultural activities for effective implementation to maximize yield rates and reduce losses. As the system gives the list of crops suitable to be grown, it also gives new crops to the farmers for cultivation which saves the land of the farmers from getting infertile. The system will be of great help to the farmers to increase the accuracy of farming and increasing profit.

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