Artificial Intelligence in Agriculture: Reinforcement Learning for Irrigation

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Abstract

With the world populations increasing with such a rapid rate, food crisis is one of the major concerns to the current world. And the major source to food is agriculture. Making agriculture precise, efficient and sustainable would be one of the most significant steps in the prevention of this upcoming crisis. To promote profitable precise and sustainable agriculture with the help of artificial intelligence, we propose a project to create a decision support system for farmers. The system predicts profitable crops in the near future, and integrates with irrigation system to provide optimum water and fertilizer use. Using current literature, we identified viable parameters, artificial intelligence models, and limitations for such a system. Based on these insights, we built a prototype for our system that uses most valuable parameters and successful models to provide optimal information. Research design and evaluation system was also proposed to test and improve such a system.

Keywords— Agriculture, Reinforcement Learning, AI, Drip Irrigation

1 Introduction

1.1 Domain

The project revolves around the idea of Sustainable, Precise and Profitable agriculture.

1.2 Context

In agriculture, a farmer takes multiple key decisions every year, and during every crop cycle. Some of these decisions are as follows: choosing the right crops; choosing the right amount of fertilizers; deciding the amount of water needed

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for irrigation; and choosing relevant farming techniques.

However, these decisions are not always optimal. In many developing nations, like India, there is: distorted cropping pattern that ignores protein and vitamin rich crops; excess use of costly fertilizers; low agricultural yield; and wastage of freshwater on water hungry crops such as sugarcane in arid regions. This leads to increased cost of farming, indebtedness, poor nutrition in food, groundwater depletion, damage to soil health, and in extreme cases, farmer suicide. At a global level, every year, agriculture consumes 70 percent of freshwater resources and contributes about 10 percent of greenhouse gas emissions.

In this context, Artificial Intelligence can help cut down the costs of farming and guide the farmer towards profitable, precise and sustainable agriculture.

1.3 Task

The goal of this project is to create a data-based decision support system for the farmer, that aims to combine profit and sustainability. This system will derive insights from factors such as: soil parameters, groundwater levels, farmer's budget, agricultural land area, weather, commodity prices, government subsidy and so on.

Using these insights, the system will predict and suggest the following: most sustainable and profitable crop for the next season; the amount and type of fertilizer needed to maintain desired soil health for future; and desired amount of water to maintain optimal soil moisture in the field. In terms of information, the system can inform the farmer about likely pests, diseases and weeds to be expected in that region, for the suggested crop. Although the system won't suggest the optimal farming technique, it will certainly make it easier to decide the most suitable one.

This way the farmer will grow the crops in demand, while using her resources sustainably. She can further increase her profits by connecting the system to efficient farming techniques such as drip irrigation system. Thereby saving more money, time and groundwater resources.

In the long run, this approach will significantly reduce freshwater consumption and Green House Gas emissions due to agriculture, and thereby guiding humanity to a more sustainable future

2 Literature

2.1 Prediction and forecasting in Agriculture

Short-Term Price Forecasting for Agro-products Using Artificial Neural Networks: A feed-forward ANN model has been developed for short-term price forecasting of tomato and in comparison with time series model ARIMA in this study. The data used include daily wholesale price, weekly wholesale price and monthly wholesale price collected between 1996 and 2010. The results showed that ANN model evidently outperformed the time series model in forecasting the price before one day or one week.

A good correlation between the modelled and the real prices was observed from the feed-forward ANN model, with a relative error less than 5.0 percent. So we learn that feed-forward Artificial neural networks are an effective way to forecast crop prices in the short run, with 95 percent accuracy and the input features to use for our forecasting model.[1]

Agricultural commodity futures prices prediction via long- and short- term time series network: In the paper, attempt by scholars to predict global agricultural commodity futures prices through analysis of multivariate time series was represented. Data-sets of agricultural commodity futures prices involves a mixture of long- and short-term information, linear and non-linear structure, for which traditional approaches such as Auto-Regressive Integrated Moving Average (ARIMA) and Vector Auto-Regression (VAR) may fail. To tackle this issue, Long- and Short-Term Time-series Network (LSTNet) is applied for prediction.

Empirical results show that LSTNet achieves better performance over that of several state-of-the-art baseline methods on average and in most periods based on three performance evaluation measures and two tests of performance difference. So this means that Long- and Short-Term Time-series Network (LSTNet) is a Recurrent Neural Network (RNN). However, we couldn't grasp the details of how it works [2].

Research on soil moisture prediction model based on deep learning: The deep learning regression network (DNNR) with big data fitting capability was proposed to construct a soil moisture prediction model. By integrating the data-set, analysing the time series of the predictive variables, and clarifying the relationship between features and predictive variables through the Taylor diagram, selected meteorological parameters can provide effective weights for moisture prediction. Test results prove that the deep learning model is feasible and effective for soil moisture prediction. Its' good data fitting and generalization capability can enrich the input characteristics while ensuring high accuracy in predicting the trends and values of soil moisture data and provides an effective theoretical basis for water saving irrigation and drought control.

The data used in this experiment is provided by the Beijing Meteorological Bureau and is divided into two parts: meteorological data and soil moisture data. The meteorological data types include daily average temperature, daily average air pressure, daily average relative humidity, daily average wind speed, daily average surface temperature, and daily precipitation; soil moisture data includes soil average mass water content at 10 cm and 20 cm depth in farmland. initial soil moisture feature has the greatest weight. Humidity and temperature are second.

So it is clear that we can apply deep learning model to predict soil moisture. We learned about the important features that affect soil moisture and also the data to extract from Meteorological websites [3].

Crop yield prediction using machine learning and decision support system: They performed a Systematic Literature Review (SLR) to extract and synthesize the algorithms and features that have been used in crop yield prediction studies. They selected 50 studies for analysis. The most used features are temperature, rainfall, and soil type, and the most applied algorithm is Artificial Neural Networks in these models.

According to this additional analysis, Convolutional Neural Networks (CNN) is the most widely used deep learning algorithm in these studies, and the other widely used deep learning algorithms are Long-Short Term Memory (LSTM) and Deep Neural Networks (DNN) [4].

Monitoring Citrus Soil Moisture and Nutrients Using an IoT Based System: Combines ZigBee technology, artificial intelligence and decision support technology, in the application of technology in agriculture. Internet of Things for real-time monitoring of citrus soil moisture and nutrients as well as the research on the integration of fertilization and irrigation decision support system. Integrated soil temperature and humidity detection, wireless sensor nodes, and citrus precision fertilization and irrigation management decision support system are used.

The results showed that the system could help the grower to scientifically fertilize or irrigate, improve the precision operation level of citrus production, reduce the labour cost and reduce the pollution caused by chemical fertilizer. The IoT platform design idea is applied to the real-time monitoring system of citrus soil moisture and nutrient. The system is divided into four layers: perception layer, network transmission layer, information service layer and application layer. Air temperature and humidity are measured using SHT17 digital temperature and humidity sensors. So, sensors for humidity, temperature, soil moisture are available; but no suitable on-line soil nutrient detection sensor.

Nutrient change is slow and the measurement takes a long period of time. Therefore, the portable soil nutrient detector is selected to detect soil nutrients. ZigBee wireless communication technology for networking. So, we learned how and which IoT market sensors are used to gather data from the farm and integrated with the decision support module [5].

Forecasting Agricultural Commodity Prices Using Model Selection Framework With Time Series Features and Forecast Horizons: The model selection framework suggested in this article for forecasting agricultural commodity prices uses both time series features and forecast horizons.

Three dominant steps are proposed: feature extraction, feature reduction and classification. First, 29 time series feature of agricultural commodity prices are chosen. Then, by using minimum redundancy and maximum relevance approach (MRMR) way, feature redundancy is reduced and performance of the model selection framework is improved. Afterward, 5 dividers are built to confirm performance of different model selection strategies. Plus, the relation between various commodities and better model is estimated by main parts analysis. Also, the research checks how the model selection framework in selecting best predicting models is effective. According to the observations, with agricultural commodity price series as research samples, many interesting results can be made. First, paying attention to the forecast horizon as one of the features could enhance the performance of classification and prediction, which shows forecast horizon must be counted as one of the principal elements in model selection task.

Secondly, MRMR could enhance model selection framework performance. Third, various distribution of time series features can make various optimal prediction models. The experimental outcomes show priority of the offered model selection framework with regards to prediction correctness. Particularly, the offered method does better than all candidate models and confirms its effectiveness in model selection. Moreover, this method is better than the simple model averaging method and presents that the method is effective in decreasing the risk of model selection for a new time series. The analysis tells us that optimal model for a specific category differs for various forecast horizons and the optimal model is different for different categorizations as well. The main reason is that various distributions of time series features result in various model selection outcomes.

The offered model selection framework can be enhanced: First, the offered method can be used as a useful model selection tool for other prediction objects. Second, some strong classifiers such as AdaBoost and Bayesian networks can be used to enhance classification ability. Third, this research uses three popular forecast models in agricultural commodity prices prediction, yet, other methods may help improve the framework.

This impacts our project because from this paper we have the insight that multiple models are required for multiple commodities price prediction. Therefore, our system will pick the best model for a commodity to predict the prices.[13]

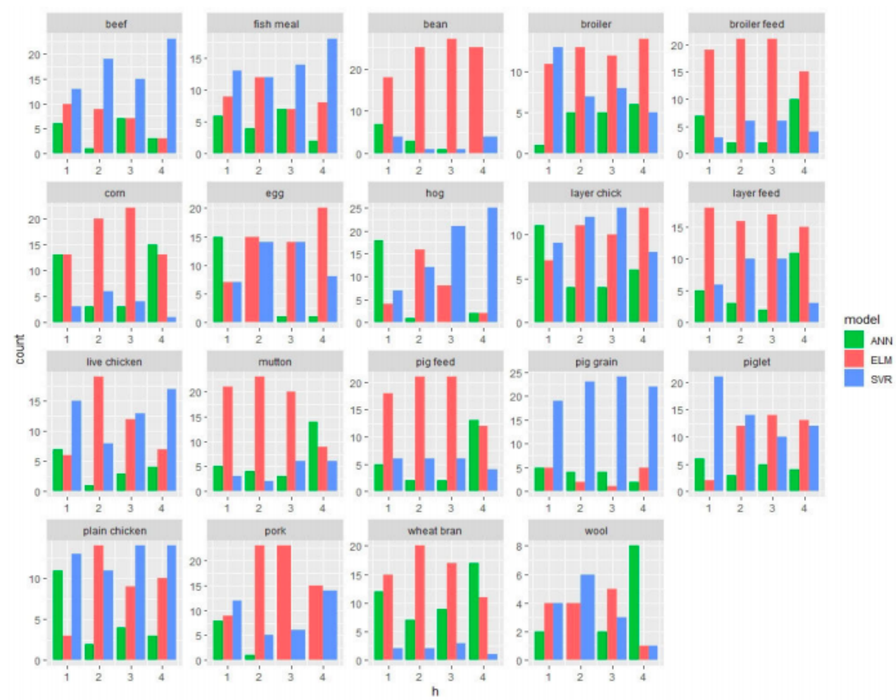

FIGURE 5. Facet plots of the optimal model selected at different horizons for different commodities.

Figure 1: Effectiveness of various models in predicting price for various crops

2.2 Sensors used in agriculture:

WSN: A WSN (wireless sensor network) traditionally consists of a few to dozens and in some cases thousands of sensor nodes which are connected to one or more sensors. Generally, it includes a BS (base station), which acts as a gateway between the WSN and the end users. Each sensor node is consisting of five main components, which are a micro-controller unit, a transceiver unit, a memory unit, a power unit, and a sensor unit. A WSN can be used in combination with sensors to provide data for AI and ML in agriculture, this can work especially well with drip-irrigation and other automation techniques.

pH Sensor: Plant productivity is closely related to nutrient uptake and pH regulation of the nutrient solution. The pH concentration of the nutrient solution affects the availability of the nutrients to plants. Its measurement is essential because the solubility of minerals in acidic, alkaline, and ion concentration of all the species in solutions is different and the solution concentration changes with solubility. pH sensors will be able to provide better quality crops and bigger harvest yields, when used in conjunction with AI.

Humidity Sensor: At present, humidity sensors are widely used in medicine, agriculture, and environmental monitoring. The humidity sensor could be placed in the growth medium to maintain the moisture level. If the moisture level becomes less than the plant requirement, the sensors will forward the signals to a drip- irrigation system which would automatically water the plants. This can be used for the same tasks as humidity sensors. [6]

2.3 AI in Irrigation

Previous studies, researches and findings: A number of good steps have been taken towards automating the irrigation system in an approach to use water sustainably through different studies and projects. The evapotranspiration (ET) process is what counts for maintaining stability in the hydrological cycle, sustainable irrigation methods and water management. It can be determined using different methods using factors like Max. daily temperature, Min. daily temperature, Wind Speed, Relative Humidity, Sunshine Hours, Daylight hours etc. using the information collected by sensors [7].

A research showing the importance of ANN in determining ET was carried out in the valley of Dehradun; India. Using climate data collected from the Forest Research Institute, it used Supervised learning to train the neural network and it successfully determined the ET with an accuracy of 75

Another study developed two ANN models to predict the soil moisture in paddy fields and so needed to determine the ET for that. They wanted to use less meteorological data. So, one of the models used maximum, average and minimum air temperature while the other model used, solar radiation, precipitation, and air temperature data to estimate the ET. The experiment was a success as both the models resulted in accurate and reliable estimation of the ET [9].

A research paper also discussed the use of neural drip irrigation systems. The water distribution in the lower level of the soil is very important for the proper functioning of drip irrigation methods. So ANN models were developed which predicted the spatial water distributions (which are useful for the user) and in turn results in fast decision-making process and water is supplied. The wetting patterns are provided to the user after the soil is infiltrated with water from the user [10].

But what still remains a challenge is to irrigate crops using AI systems so that they are benefited on the longer run and in the end, results in fresh and healthy crops as well as contributing to the decrease of water scarcity through sustainable irrigation.

So we planned this AI model that will be using reinforced learning to learn the different needs of crops in terms of waters. The AI will be trained on the specific environment of a place, as different amounts of water needs to be supplied to crops even if they are the same species. So this will optimize the water usage and also maintain the water level resulting in good health of crops. The AI system will contain sensors and drippers all over the field and will take as inputs like the relative humidity, air temperature, sunshine hours (accounting solar radiation as well), precipitation and wind speed which will be sent as input into the system. Now the AI will (using the knowledge it has gained from RL) will supply the amount needed at different areas in the field using the drip irrigation system. The AI will also learn from its experience every day and keep improving its performance.

3 Questions for the experts

We had mailed a few authors of these papers, however we did not receive a reply. Still, the questions wanted to ask are as follows:
1. What are the major limitations in applying artificial intelligence to farming?
2. What areas of research are trending recently in agricultural Ai?
3. What have been the unexpected outcomes and failures of trying to apply Ai in farming?
4. Which areas do you wish, had more focus while applying Ai to agriculture?
5. Are there any ethical issues in applying Ai to agriculture?

4 Computational Solution

4.1 Computation of most profitable crops and required fertilizer

Input: Soil sensors and soil samples to provide periodic information on: Moisture, Pressure ,Temperature ,Nutrients (Potassium, Nitrogen, Phosphorus, Zinc etc.) ,Farmer will input ,Budget ,Agricultural area ,Previous crop ,Location via GPS

Publicly available data from Government, Agricultural universities and Meteorological department: Regional cropping patterns ,Taxes and subsidies on crops ,Soil and climate requirements of various crops

Processing: Preparing and cleaning data to process. Removing irrelevant and incomplete features from data. Predicting soil moisture and fertility after current crop cycle ends using appropriate models. Adding these new soil parameters to our data. Filtering suitable crops for the region, budget, soil and cropping area, so the models have more accuracy and less work.

Neural network: We start by choosing the right model for predicting crop prices of suitable crops in near future.

Models may include: Artificial neural network, Convoluted Neural network or LTSM. Using the predicted prices, the system calculates the profit for each crop, considering taxes, subsidy, cost of fertilizers and so on. Within profitable crops, also include crops that keep soil healthy.

Output: Output top 3 most profitable and sustainable crops for the next cycle. Also suggest the fertilizers and inputs needed to prepare the soil for planting that particular crop.

AI methods:

In short term price prediction - in comparison with time series model ARIMA, ANN model evidently outperformed the time series model in forecasting the price before one day or one week. A good correlation between the modelled and the real prices was observed from the feed-forward ANN model, with a relative error less than 5.0

For Long term - Long- and Short-Term Time-series Network (LSTNet) is used, it is a Recurrent Neural Network used for commodity price prediction as it out performs traditional approaches such as Auto-Regressive Integrated Moving Average (ARIMA) and Vector Auto-Regression (VAR) .

Parameters and best models -Generally, in price prediction, most used features are temperature, rainfall, and soil type. The meteorological data types include

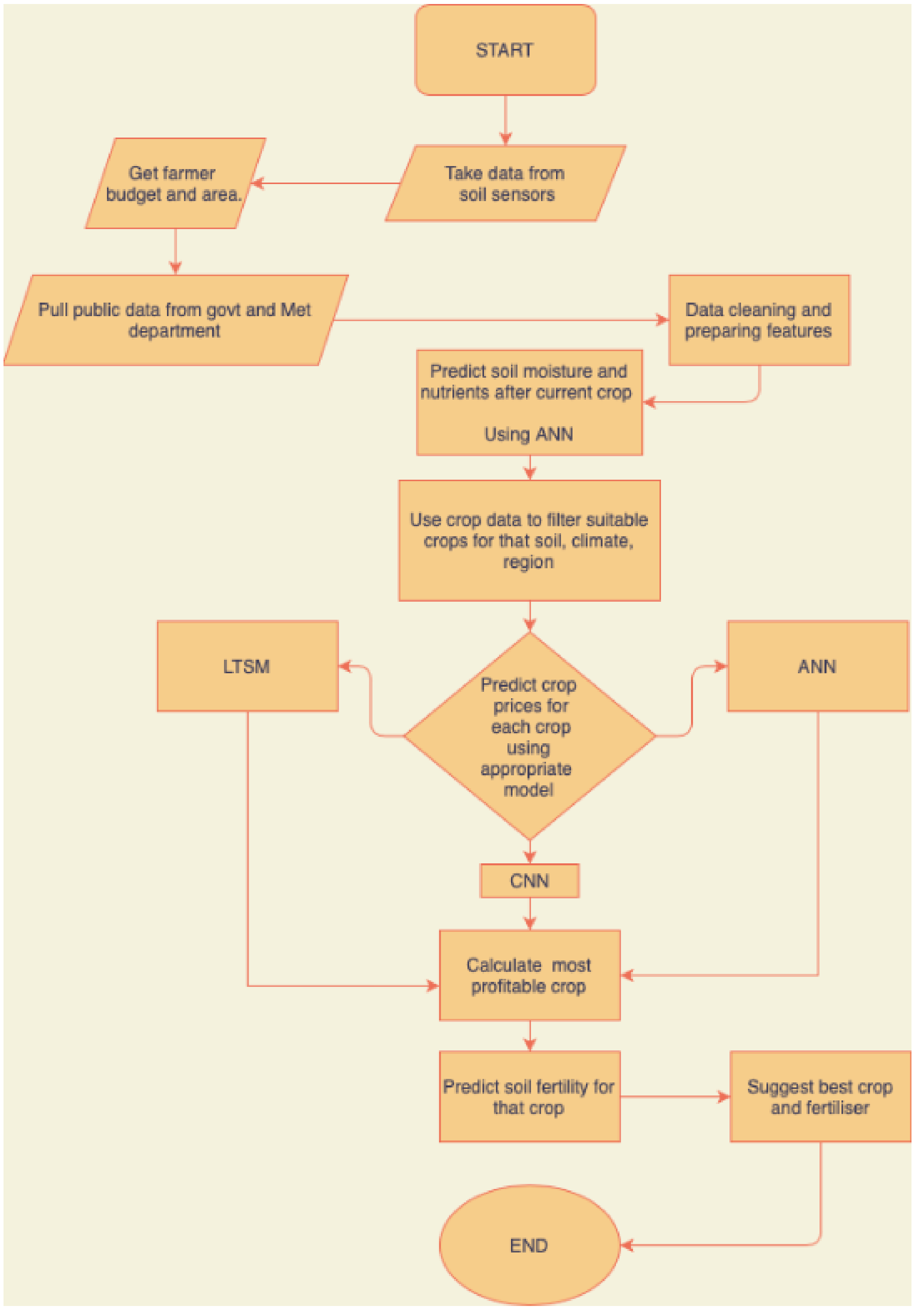

Figure 2: The functional demonstration of our predictive AI model

daily average temperature, daily average air pressure, daily average relative humidity, daily average wind speed, daily average surface temperature, and daily precipitation; soil moisture data includes soil average mass water content at 10 cm and 20 cm depth in farmland. initial soil moisture feature has the greatest weight. Humidity and temperature are second.

The most applied algorithm is Artificial Neural Networks in these models. According to this additional analysis, Convolutional Neural Networks (CNN) is the most widely used deep learning algorithm in these studies [12]. However, different models perform differently for different crops. So, for each crop, most suitable model of price prediction is needed. Using most recent research, we can pick best models for predicting prices.[13]

Soil fertility prediction - The deep learning regression network (DNNR) with big data fitting capability will be used to construct a soil moisture prediction model. By integrating the data-set, analyzing the time series of the predictive variables, and clarifying the relationship between features and predictive variables through the Taylor diagram, selected meteorological parameters can provide effective weights for moisture prediction.

4.2 AI controlled drip-irrigation

The AI system for the automated drip-irrigation will be the practical prospect of our project. The system will be connected to different sensors and drippers, of the drip-irrigation system, all over the field (assuming that the farmer will be harvesting on a large area, but applicable on small area as well). The system will learn using machine learning(ML), and use that knowledge to manage the whole irrigation system for the farmer. There is very less, almost zero, commitment needed from the farmer except for checking whether his/her crop is getting the amount of water it needs and are in good condition.

We will be using reinforcement learning(RL) to train the AI. The AI will be trained specifically for specific areas as different areas (locations) have different distinguishing environment and the same species of crop may need different amount of water to be supplied when grown in different places. So, for a specific region using previous data of watering of crops; like how much water needs to be supplied, how many times a day or watering patterns; a simulator is created.

The AI system is then trained using the simulator, how to water crops so that they finally end up as fresh and healthy crops and, have a good yield as well at the end (so that plants don't die from water availability, decreasing the yield) which is basically the feature of reinforcement that we are using it for (may not be instantly advantageous, but finally ends up in reward). The AI could also be trained in real agricultural fields, but that would waste a lot of crops

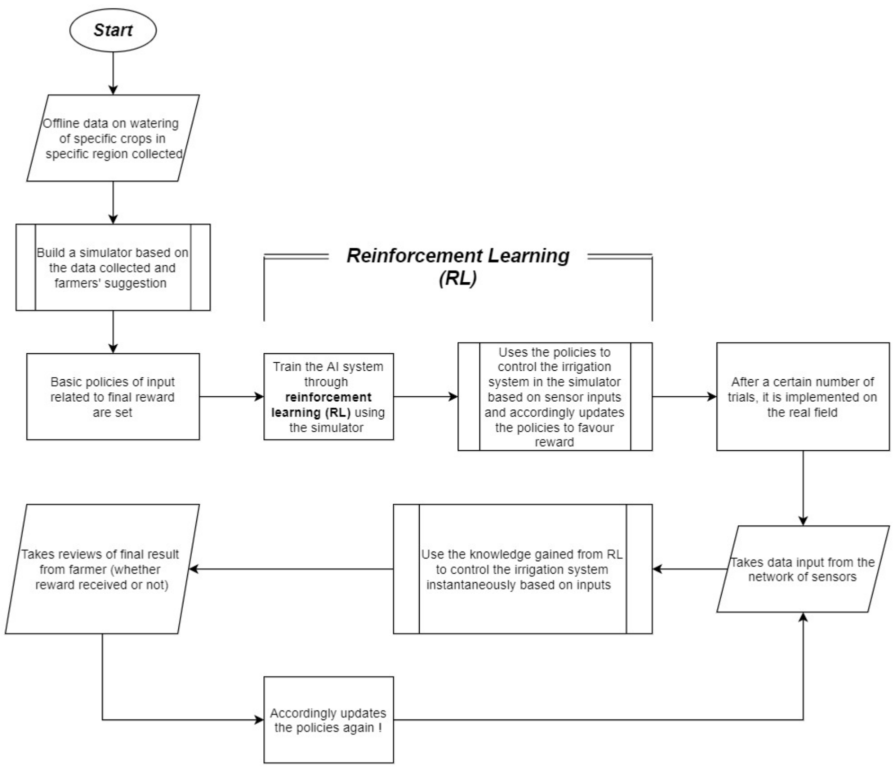

Figure 3: This is how our AI system works

(causing plants to die) by mistakes as its knowledge will technically be zero at the beginning and moreover, would take a long time to be prepared.

When at action, the sensors will collect readings of the relative humidity, air temperature, sunshine hours (accounting solar radiation as well), precipitation and wind speed which will be sent as input into the system. This is where the AI will use the knowledge it has gained through RL and process the information inputted, evaluate (using reasoning and what it has learned through the simulation in RL) and decide which area of the field needs to watered, when or how much and simultaneously control the drip-irrigation systems to supply water accordingly through the drippers.

The AI system will also keep learning every day from its own actions. But for that, the farmer will have to input the results; like how did the crops turn out to be, were they getting enough water, or more water delivered; into the system so it understands its mistakes, trying to avoid those and will understand which steps were right during which conditions and, try to replicate those in the future. This will be making our AI more experienced and improve its performance as time proceeds. There might be a connection between the app the system so that the farmer can input the results directly there, otherwise he might have to input in the system itself. The use, proper training and installation of this project is expected to lower the usage of unnecessary water and maintain crops quality as well, thus bringing stability in the farmer's production as well as the sustainable use of water in the irrigation process, optimizing the agricultural output as well.

5 Evaluation

5.1 AI controlled irrigation in simulator and on field

Our AI irrigation system will undergo two evaluations, both internal and external. The main idea is to ensure the good quality of the crops by providing proper irrigation. So the dependent variables here, except the final reward, are the amount of water to be supplied and the times of watering; which are dependent on the input taken from the different sensors (humidity, air temperature, sunshine hours, precipitation and wind speed), the independent variables. Pests or technical problems in other stages of the agricultural production could be the possible confounding variable in the external evaluation which might affect the final results by damaging the crops. Experts or farmers with knowledge about crops and irrigation of a specific place needs to be involved in both the evaluating stages.

The internal evaluation will take place in the simulator. The RL itself is an evaluation as the results are evaluated after each trial and the system is updated. Yet, we do a final evaluation by creating a range of probable environments by changing the independent variables, consulting the expert. Then, we run trials and record the results to check if the final reward was achieved or not.

One trial in a specific area would be enough as it takes a very long to get to the final results. But, we aim to implement RL in the external part as well which will again be evaluation itself as well as improving its performance by updating the policies the AI system, but it is much of a hypothesis till now. The assumption we make is that no external factors affect this real-life RL implementation. But it's really interesting and optimistic to think of having a system that will keep on learning forever. So basically, after the internal evaluation, the external evaluation of our system will continue as long as it is in use. And that will make its performance way better and more consistent that other machines, and may even cross humans if used for that long to gain that much experience!

5.2 The predictive AI system

During design stage: Firstly, we will involve farmers and researchers to evaluate the designing of the system, so we have definite system requirements and clear target group in mind. Then we will be testing each component of the system and evaluate the performance, and fine tune the parameters. After that, a system-wide testing, by checking every component is working in unison.

Then, we will be testing the systems correctness by evaluating: Is the agriculture system providing good suggestions? Are formals using what it is suggesting? Is it providing personalized recommendations?

In test runs, we will be using historical data of crop prices in the last 3 years to verify our predictions. Can the system provide expected output based on a given input? If not, we'll adjust the models.

During working stage: In real time: Actually using the system with validation and user evaluations. From the app and feedback we will extract information such as: Did the farmers get good crop and fertiliser suggestions ? How is the overall User experience ? Did farmers actually implement it ? Did they use the system and recommend others ? Did they benefit from it? what feature would they want was it cost effective or practical which feature did they like the most?

Techniques and methods:

Questionnaires on acceptability based on likert scale 0 to 5.

Statistical tests such as T test repeated measures design anova test ancova test. Output of the intervention should be statistically significant.

Test on historical data - determining which farmers have benefited.

Inference - deducing from the data if farmers benefitted, even if they didn't fill the feedback form.

Research protocol that we will follow for our evaluation:

Research question - Is it possible to to predict commodity prices and soil health in the future, and suggest farmer best crop and fertiliser in his situation.

Hypothesis - Machine learning and Neural network led systems lead to better results in profit and farming sustainability as compared to just providing the farmer information.

Experimental and control condition - Half the farmers are given the Ai system, and other half is given information only.

Independent variable - Availability of a system to the farmer.

Dependent variable - Their profits and sustainability of soil

Subject or participants - Middle income farmers who have limited budget and not growing crops in a sustainable way with average profits.

Removing possible confounding variables - Variables that may affect the experiment but do not have any relevance to the experiment. May be the monsoon or the weather suddenly changed or there was a global crisis in the suggested crops. Sudden epidemic like Locust disrupted the crops.

6 Conclusion

With the help artificial intelligence, we hope to provide farmer with an accurate picture of the future. With right information on crop prices, water and fertiliser usage, we expect the farmer to practice profitable and sustainable agriculture. The system only provides numbers to the farmer, but it is up to the farmer what to do with it. Because in the end, humans must make their own choices.

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