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Smart Multi-Crop Care System Design using Bipartite Matching

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***Abstract*: This paper presents a solution to optimize water consumption for a multi-crop care system with the help of artificial intelligence and optimization graph algorithms. The proposed system takes advantage of object detection models such as YOLOv5 to identify crop types and their requirements while using moisture sensors to provide real-time data about soil moisture conditions. A key contribution is the implementation of a weighted bipartite graph to optimize watering patterns in order to ensure required soil conditions and reduce water resource usage according to the crop type. The system represents a path forward in precision agriculture by offering a scalable and adaptable approach to smart irrigation, considering different factors of a crop's environment (like moisture level in soil, distance from the sprinkler, etc.) and their associated weights to control water levels in the crop care system for different types of crops.**

***Keywords*: Image recognition, Machine learning, Bipartite Matching, Weighted Bipartite Graph, Optimization, Crop care, Multi-crop, Smart system.**

1. Introduction

Despite rapid developments in the agricultural world, there is a lack of implementation of automation in terms of varying amounts of irrigation needed by different types of crops. Before moving on to crop fields, taking care of houseplants needs to be tackled first, making the watering system automated for ease in their caretaking. In [1], we proposed a small-scale system for automatic watering of plants on the basis of the water level present in the soil. This research involved basic code to set a condition of moisture level, having a specific level of water needed for watering.

Further, in [2], we proposed a new system involving image recognition of different plant types using the YOLOv5 training model. This feature allowed us to set particular thresholds for specific types of plants, which would be recognized by system due to the images provided to the model for training. Based on the threshold value and the moisture present in the plant, the system could decide whether or not the plant needs watering. This Machine Learning solution is now extended to a larger scale by the proposed system in this work, involving weighted bipartite matching incorporated into the algorithm. The aim of this research paper is to depict that the introduction of this kind of matching and the use of bipartite graphs will facilitate convenient and optimal use of sprinkler systems or watering systems present in farms or crop fields.

2. Literature Review

Multiple experiments/research works have been conducted to find optimal crop/plant mapping or recognition methods and implement a smart farming system. In [3], authors use a machine learning environment to detect temporal changes to the map of vegetation, using different time weightages for different parameters. They also track statistics about the change that occurred in the specific area of vegetation. This research does not make use of weighted bipartite matching, but still provides weights to different parameters of change. On the other hand, the system proposed in [4] involves detection of the weather, using factors like humidity, pressure, light intensity and temperature to deduce the amount of rainfall the crops could be exposed to. Similar to our proposed system, this system in [4] facilitates smart irrigation for various types of crops instead of just one crop. Moreover, it considers the case of overflowing of the crop field and aims to solve such problems. [5] contains a system in which there are two web cameras used to take images of plants and thus accurately infer the type of plant. In contrast, our system uses the YOLOv5 image recognition model to detect crop types. A significant feature in the system proposed in [5] is the use of (x, y, z) coordinates within the images, which helps detect plant growth and specific shape changes to the leaves of the plants. The system proposed by authors in [6] strives to improve the traditional method of farming by using Fuzzy logic, Artificial Intelligence, Python and Firebase to store and extrapolate data for soil moisture, atmospheric humidity, soil temperature, atmospheric temperature and sunlight. Similar to our proposed system, this system in [6] takes into account multiple factors to optimize farming results. The difference is that our system matches using bipartite matching instead of Fuzzy logic values which is a simpler method.

Similar to previously discussed papers, [7] consists of a system that uses the Internet of Things (IoT) as well as external factors like humidity and temperature that form conditions for irrigation factors. However, authors in [7] also use a solar panel to power the system as well as a Raspberry Pi4 computer to manage the system. This research contains a sustainable farming system and has been shown to produce fruitful results,

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but implements a different circuit than the one we propose. [8] does not use IoT, but focuses on implementing Artificial Intelligence aspects like Supervised Machine Learning to optimize agriculture in a sustainable way. Importantly, this research gives weightages to specific conditions seen in a crop area. [8] also makes use of historical data, environmental parameters and a correlation matrix to find the optimal agricultural solution, with a high accuracy of about 0.996. Authors in [9] use multiple methods of Machine Learning like Unsupervised Learning, Predictive Modelling, Logistic Regression and K-Means Clustering to predict the type of crop that is most suitable to grow in a particular area on the basis of conditions like soil type, humidity, etc. However, this research focuses on finding a few solutions in terms of crops, instead of maximally matching different areas to different crops. [10] portrays the use of Machine Learning in the form of Ensemble Modelling, combining multiple different models to predict the most apt use of the soil. This system uses data mining, evaluating the best output on the basis of multiple models' predictions.

The research seen in [11] is different from multiple papers discussed previously. It makes use of an Artificial Intelligence model, aerial drone images and coordinate calculations to identify and monitor weeds and crops with accuracy. However, this research does not involve smart irrigation for crops and uses a training model different from the one proposed by us. The system proposed by the authors in [12] uses a specific process to detect plant diseases and decide the irrigation time and quantity according to the data collected by the sensors and the use of a trained convolutional neural network. The image detection and plant disease classification are done using a thermal camera, different from the camera in our proposed model. Also, despite the use of a training model, the focus of this work is disease detection algorithm. The research in [13] aims to connect irrigation and a microgrid system using calculations and an energy transfer algorithm. This research focuses more on renewable energy, something our proposed system strives to improve but in a different method of optimal/weighted bipartite matching. In [14], the system proposed is that of a monitoring system that can be implemented in greenhouses and agricultural lands. This system uses sensors to monitor temperature, humidity, light intensity and carbon dioxide concentrations in the air, sending signals to a specific chip, which then connects to the user's device using a Wi-Fi module.

In general, systems proposed in the above-mentioned research papers involve the use of multiple parameters detected using various sensors, and the use of Artificial Intelligence models or other specific algorithms and calculations to deduce the optimal solution for an agriculture related problem. The key difference in our proposed system is the use of a weighted bipartite matching algorithm that uses multiple factors to map specific sprinkler systems to specific areas or regions of crops. Moreover, the image detection models used or the methods of identification of plants/crops used are different and complicated than our proposed method and training model.

3. Smart Crop Care System and Positioning of its Modules

In our proposed system proposed, the camera first captures an image of a specific crop. It also inputs the coordinates of the area the crop is present in, using cartesian coordinates of $(x_{i1}, x_{i2}, y_{i1}, y_{i2})$, where i is the crop number. Next, the crop image is run through the database containing the trained machine learning model that consists of multiple images of various crops and a reinforcement learning algorithm, identifying the type of the crop. Simultaneously, the moisture sensors (for instance $m_1, m_2, m_3, \ldots, m_n$ as shown in Figure 1) present in the soil in the crop areas intake the moisture levels of the soil for each region. The identification of the crop provides the system with an input of the specific amount of watering required by the crop, along with the input of the current moisture level of the crop. These factors are inputted into the bipartite mapping algorithm for water control, as depicted in Figure 1. The output of the algorithm's execution is provided in the form of a trigger for each sprinkler to turn to a specific angle and begin spraying water over a specific region of crops, having separate triggers for sprinklers s_1, s_2, s_3, etc. all the way up to s_m.

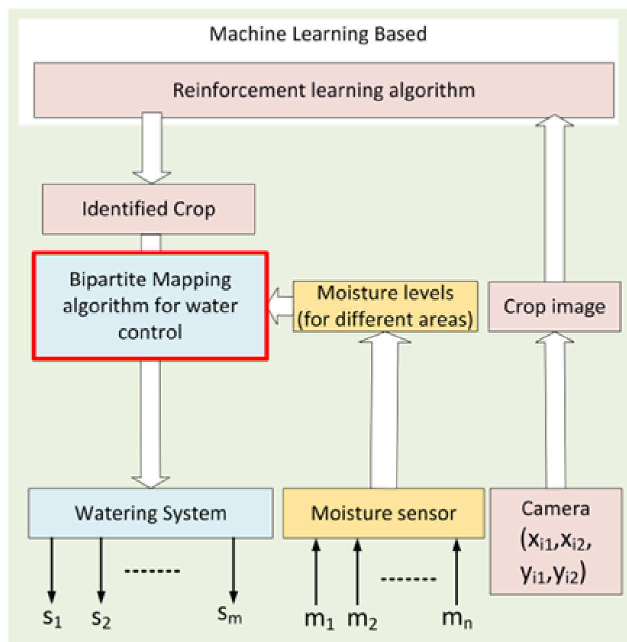

Fig. 1. Block diagram of AI/ML based smart crop care system (with bipartite matching based controlling)

A. *Crop Recognition and Their Associated Parameters*

The system proposed by us makes use of an image detection model called YOLOv5, which requires training or machine learning in the form of multiple images of a specific type of crop as classes, with more accurate detections as the number of input images increases during training and testing.

The system uses cameras to scan the crops and then map it to a specific name depending on the images in the trained model. Varied images or images with different perspectives of a specific crop will enhance the quality of prediction or recognition of the crop by the YOLOv5 model. Thus, the base requirement for the training model to determine the type of crop or plant is by simply increasing the variety in training level, or by adding pre-existent images of the crop in various backgrounds, weathers, soils, etc. Figure 2 shows the modeling of Crop types with its associated parameters.

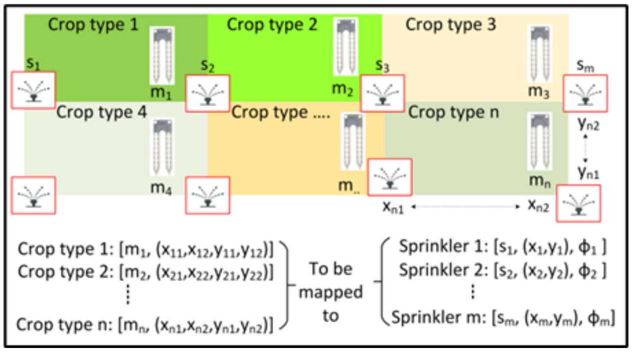

Fig. 2. Crop types with associated parameters

B. *Mapping Using Weighted Bipartite Matching*

Bipartite matching involves mapping a specific vertice in one set of vertices to another vertice in the second set of vertices. Each vertice is matched with a unique vertice in the other set. Each match or edge between vertices can be given specific weightage if there are multiple factors on the basis of which the match is made. This is the basic concept of weighted bipartite matching, which can be implemented in systems like the one we are proposing. In our proposed system, the factors taken into consideration are type of crop and its specific water requirement, and distance of sprinkler to plant. In this system, there are multiple sprinklers, which act as a set of vertices of a bipartite graph, represented by $s_1, s_2, ..., s_m$ as seen in **Figure 3**. The other set of vertices consists of separate regions of crops that could be watered, represented by $C_1, C_2, ..., C_n$. Depending on the inputs gained for each of the parameters, each sprinkler is mapped to a specific area of the field that can be watered, with different weightages given to each parameter, the most important parameters being the specific water requirement of the crop and the current moisture level. In **Figure 3**, each of the weights of the bipartite matches are shown by $w_{11}, w_{12}, w_{21}, ...,$ w_{nm} for multiple different matching cases.

Further, the weighted and matched bipartite graph will contain a specific match for each sprinkler, optimizing efficiency of the watering system. The output of the match will result in each sprinkler adjusting its angle to reach the specific area of crops assigned to it for watering, represented by ϕ_1, ϕ_2, ϕ_3 …, ϕ_m.

Following are the algorithms used for recognizing the crop type and for mapping its requirements for controling sprinklers.

Algorithm 1: AI Based Image Recognition Algorithm

Input: *I (Images from camera), V (moisture levels from sensors), C (coordinates of crops from camera)*
Output: *W (Watering signal to specific station)*

Initialisation :
Initialize system and sensors
D ← detection model(I)
R ← map image to moisture(D)
if *R < V* ***then***
W ← False
else
W ← Water_Optimizer(C, S)
w *is proportional to* ***R-V***
end if
return *W*

Algorithm 2: Watering Optimizer algorithm

Inputs: *C (coordinates of crop), R (moisture level)*
Outputs*:* *B (bipartite results), A (angle of sprinkler)*

G ← empty graph
add_crop_nodes (G, C)
add_station_nodes(G)
distance_weight, angle_weights ← assign weights
for each *crop-station pair* ***do***
    calculate distance
    A ← calculate angle needed
    calculate weight
end for
B ← min(weight)
return *B, A*

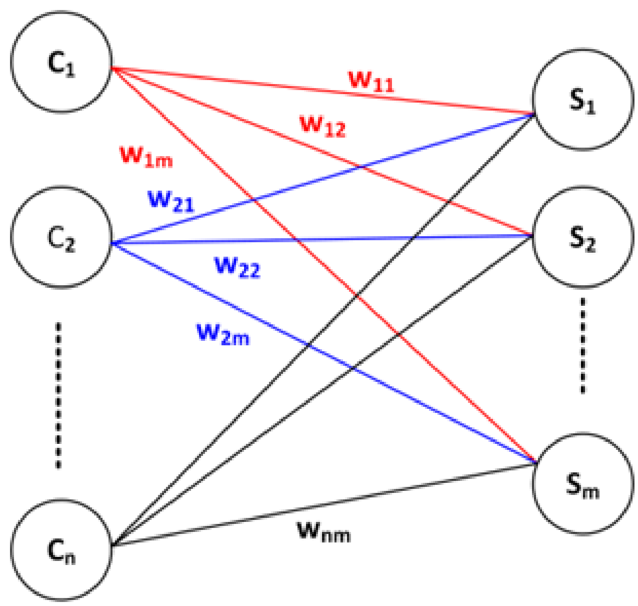

Fig. 3. Weighted bipartite matching graph

4. Prototype Simulation and Result

The prototype simulation demonstrates how the bipartite matching algorithm can be implemented to optimize multi-crop irrigation systems. The experimental setup consisted of six crops arranged in a 3x2 grid with eight different watering systems, sprinklers, positioned at the intersections of the grid. The system receives important information such as the type of crops located at a specific coordinate through a camera and image recognition. Additionally, through a moisture sensor the system receives real time updates on moisture levels in the soil.

By processing these inputs about the crop and mapping them to stored required moisture levels, the system is able to make decisions about how to water plants.

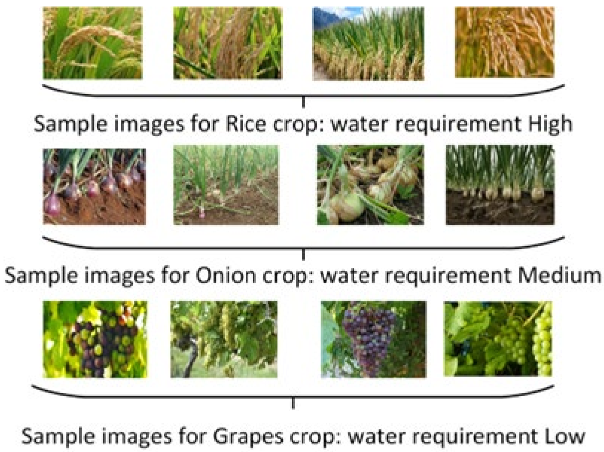

Fig. 4. Sample images for different types of crops and associated required water level

Having multiple watering sprinklers can create an optimization problem. In order to tackle this, we decided to use a bipartite algorithm, Algorithm 2, that helped select the most optimal sprinkler and the angle needed to cover the crop section. For example, take Figure 4 where we have three different crops as our sample. We used the moisture requirements for onions as the base moisture requirements as mentioned in [15]. From this, we were able to calculate the moisture requirements of our other crops such as grapes and paddy rice. These are the moisture values used in our Algorithm 1 and Algorithm 2 to create the simulation for watering.

As seen in Figure 5, the six different crops patches all have a path to all 8 watering sprinklers. Here we see that each node on the left connects to multiple nodes on the right and not to a node on the left creating two distinct sets, a quality of the bipartite matching. Using this to our advantage we calculated the weight of each edge connecting the set of on nodes on the left, crops, and on the right, water sprinklers. The weight of the edges was calculated using various factors such as the distance from the crop zone and the difference in moisture need as shows by Equation 1 where α is the coefficient for the physical distance, d is the distance, and Δm is the difference is required moisture and current moisture.

$$w(c,s) = \alpha d(c,s) + \Delta m \quad (1)$$

By employing bipartite matching, the simulation's main aim is to ensure that the crops receive adequate watering while resource consumption is minimized. In Figure 5, we see that the optimized paths are colored in a dark blue indicating the minimal distance between an unused water station and crop. If we look at a grid representation of this instance in Figure 6, we can see that each water sprinkler is assigned to an individual crop. Each of these sprinklers have to provide a certain water level in order to cover the crop region efficiently and ensure minimal water wastage. As seen by Table 7, based on assignment, each sprinkler has its own angle of rotation to spray over. This makes sure that each sprinkler is properly covering the region it is assigned to without watering regions where additional water is not needed. Additionally, we see that all crops are being watered, however, some sprinklers are not in use. This is ensuring that water consumption caused by overwatering is reduced.

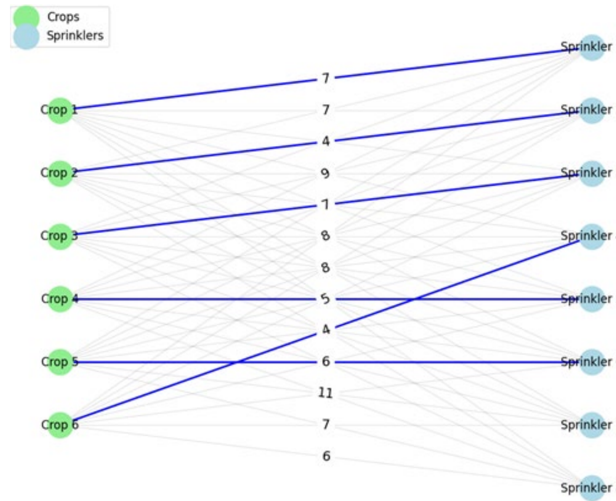

Fig. 5. Output of the weighted bipartite matching algorithm: Crop assigned to the sprinklers

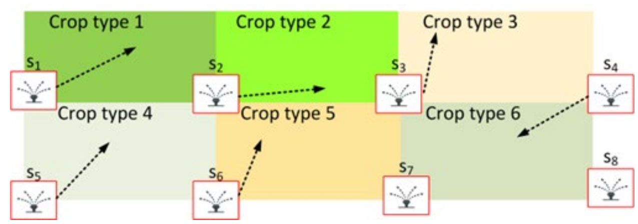

Fig. 6. Simulation output

Sprinkler	Target	Angle	Water Diff
S_1	Crop 1	65^0	5.5
S_2	Crop 2	5^0	5.5
S_3	Crop 3	83^0	3.7
S_4	Crop 6	208^0	6.7
S_5	Crop 4	58^0	3.7
S_6	Crop 5	72^0	6.7

Fig. 7. Sprinkler configuration for the controller

5. Conclusion and Future work

The smart multi-crop care system proposed in this paper will allow for multiple crop types to be optimally watered, depending on various factors like watering requirements and distance from sprinkler. Presently, with this system we aim to provide more efficient and sustainable irrigation of crops, especially in specific farming areas. In the future, this system can be extended to a multi-machine system where there are movable machines with motors that travel short distances to provide the crop areas with irrigation, an instance of automating the system to a greater extent. Furthermore, the machines can include the aspect of adding fertilizer to the soil on which the crops are grown. This idea can be implemented for multiple types of fertilizer as well, adding more parameters to the weighted bipartite matching algorithm, producing outputs that are more efficient.

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