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CONVOLUTIONAL NEURAL NETWORK BASED RASPBERRY CONTROLLER FOR THE GREENHOUSE MONITORING SYSTEM

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ABSTRACT

The greenhouse monitoring system is a smart approach to monitoring and controlling the greenhouse environment with the regular monitoring of indoor carbon dioxide, humidity, soil moisture, temperature, soil ph level, and light, smoke,and air pressure. Internet of Things (IoT) based sensors are the fundamental components of green monitoring systems and can be utilized in horticulture, agriculture, and many other fields. The IoT-based sensors sense small deviations in the values and forward the signals to the controller to manage the respective switch and make corrections at right time and is a complicated task and to tackle this complication we propose a novel Raspberry pi controller based green monitoring system which includes IoT sensors for the monitoring of light, temperature, smoke, soil moisture, LCD module, 12V DC fan, LDR sensor, pump, and bulb. The smoke sensor will sense if any smoke coming from the electric connection and send an alert message by turning on the alarm, the temperature can be sensed with the temperature sensor and if it measures high then the DC fans are automatically switched on and off if it goes low. The water level in the soil can be sensed by the soil moisture sensor and automatically the pumps get on.The light gets turned on when the LDR sensor senses the absence of light and the status of the monitoring system can be forwarded each 30 sec using the GSM module sensing data from different sensors are detected and analyzed with the proposed Dilated Convolutional Neural Network (DCNN) based Fire Hawk Optimization (FHO) algorithm. Based on the classification outcomes the system takes the necessary actions that are aforementioned. The proposed system uses python programmed Raspberry pi controller and the implementation shows that the proposed system reduces the cost and complications and regularly maintains the monitoring of the greenhouse system without any hardware faults. Further, the detection of data is also superior to the methods that are compared in terms of soil moisture with time 4.11 sec, delay with 3.22, and detection accuracy of 95%.

Keywords: *Greenhouse, sensors, IoT, Dilated Convolutional Neural network, Fire hawk optimization, Raspberry pi, and indoor.*

1. INTRODUCTION

The greenhouse [1] is an entire system planned with greenhouse inner moisture to control and monitor the whole part of the system. The communication that links the moist sensor and microcontroller to associate the mobile phone with software is used for the greenhouse. The monitoring system calculates the soil moisture, humidity, inner carbon dioxide, and light of the greenhouse. The rainfall, wind direction, and speed are the basic framework to calculate the outer part of the greenhouse. Internet of Things [2] controls the greenhouse that assumes external respiration, glacification, and concentration of soil. The smart greenhouse sensors [3] are classified into light, air, carbon dioxide, humidity, temperature, soil moisture, and the PH of the soil. The information is handed over to the nearby smart greenhouse with communication and sensor technology. The basic shape is the classification of a greenhouse [4] in terms of the tunnel, sawtooth, gable, raised dome, and skillion. A glass roof and walls are the greenhouse building used for flowers and plants to stay warm in winter and air is needed to warm the plants and flowers. To plant the right environment is chosen, needs water for growth, monitor the water flow, climate, fertigation, and pro water system is maintained. The temperature is controlled by fog, heat, walls, shade, and vents in the greenhouse environment to promote moisture and warmth of plant growth, stabilize the temperature, and protect the plants from severe cold. The temperature is increased to identify the heat to increase the number of gases from the different greenhouse effects.

To expose the congestion and rarity of the Internet of Things gathering, together an analytical algorithm has been created on the basis of the greenhouse technology [5] for communication. The condition of plants is determined by the greenhouse technology to defend the climatic condition known as temperature, radiation, cold, wind, and rainfall. The climate is controlled by the greenhouse in different terms by mist and fog system, grow room is shaded; the greenhouse is oxygenated and aerified. The low and high values are rejected to control the moisture condition to save energy in higher humidity by circulating and heating and it controls the carbon dioxide by opening the topmost part of the greenhouse. A single-board computer is termed a Raspberry Pi [6] by the different embedded controllers, gadgets, and devices that are the illustration of Raspberry Pi. The wireless controller to play games needs 2.4GHz by plugging the USB receiver to control the system. The two ports describe the size of the expected Pi to increase the playback refresh rate of Raspberry Pi to convert the system setupof hardware devices narrates input and output. Standard deviation [7] narrates a number throughout the values that are close to the average number and spread the deviation of numbers in the larger range.

The layers in the number are larger and require a higher range of data for a high complication, slow to train the data with less time and intensive resources. In each layer, the data increased by stacking the topmost layer from the neural network [8] to perform large data that cannot change the data such as games on the computer. The same indications are different in increasing the variance to decrease the bias to train the dataset for predicting error and describe the variance and bias to reflect the errors. The distribution of data represents the standard deviation to formulate an adequate sample of data from different parameters. The status of the environment is to automate and monitor the greenhouse to grow plants automatically without the care of individuals monitoring the situation without any care. The climatic conditions are maintained, collects data points for extraordinary activity, increasing fertilization and irrigation, and enhancing security. To increase the speed of the data to be transmitted to the user side several controllers are used like Aurdino, PID controller, and more. However, they produce complexity and hence we have taken the Raspberry Pi controller as the processor. Meanwhile, the controller controls all the data from the sensors and forwards it to the database hence it is essential to detect the data to verify whether the data are in the required range and if not the system itself takes necessary action as mentioned above. For the detection, we propose a novel DCNN-FHO algorithm that effectively detects the data and analyzes it to do further action. Major contributions of our work are listed below,

- ❖ For controlling sensors such as temperature sensors, soil moisture sensors, smoke sensors, light sensors, and LDR sensors we have utilized a Raspberry Pi-based microcontroller as the processor. The controller forwards the data to the cloud-based database.
- ❖ The data collected from the database are detected with the proposed DCNN-based FHO algorithm and this proposed approach analyzes the data whether the temperature is in the right quantity if it exceeds the detected data is forwarded to the system itself and it will take action.
- ❖ If there is low moisture then the system or user switches on the pump and pours water accordingly. Likewise, the system will perform an action based on the output of the DCNN-FHO approach.
- ❖ This approach improves the accuracy of the detection and maintains the greenhouse environment without fail.

The rest of the work is organized as follows; in section 2 the relevant works are analyzed with their limitations and advantages. Section 3 elucidated the system model of the proposed approach with a vast explanation. In section 4 the proposed DCNN-FHO techniques are explained. The experimental analysis is done in section 5. Finally, the work is concluded in section 6.

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2. LITERATURE SURVEY

Hoyo et al. [9] have described a feedback linearization technique based on a control scheme to arrange greenhouse diurnal temperature. The proposed controller is given for the greenhouse to format the non-linear model and provides a proportional-integral controller to originate a virtual control signal. The first order plus time dead time system is used for both the virtual control system and system output to implement the proposed method and is tested in the plant. The ventilation aperture disturbance is minimized by the proposed system. Hence, the disturbance in the wind speed is high in the virtual control signal.To monitor the greenhouse Bai et al. [10] have presented a wireless sensor network (WSN) to examine the data fusion problems. The data fusion scheme introduces a two-stage hierarchical network to monitor the greenhouse system. The cluster is formed by the data fusion algorithm to evaluate the local state weightage. The various clusters direct the data fusion for consistency analysis in the sink node. The efficiency, accuracy, and performance are increased minimizing energy consumption. However, achieving greenhouse monitoring is a complicated task from the main algorithm.

González-Amarillo et al. [11] have introduced an internal traceability system based on the Internet of Things for agricultural products to monitor and control the greenhouse environment system.The quality and trade value is increased in agricultural products and it is highly competitive and dynamic. The harvested products produced in the greenhouse can approach the seedling information of the user. The consumption of water and energy is minimized and the communication process is increased. Hence, the seedling’s demand impacts the temperature control of the system.Geng et al. [12] highlighted a mobile greenhouse environment monitoring system based on the Internet of Things. In agriculture greenhouse monitoring a Raspberry pi and Arduino chip are united to perform as a data server for the mobile system. The data transmission quality and accuracy are increased. In this application, the Raspberry pi signifies a higher value and in transmission, layer data loss is decreased. Hence, in a greenhouse environment, basic data is not present in monitoring greenhouse alarms and crops.

Karunamoorthi et al. [13] suggested the Internet of Things to track the ability of home and Raspberry-based building equipment. A mobile computer is constructed to track the home-based computer for household requirements. The Internet of Things acts as a process control machine for new functional requirements.The proposed method is quick, secure, and comfortable to use gadgets throughout the world. Nonetheless, smart home products are linked to better security.Nadafa et al. [14] describe a proper illustrative method to detect clear photos based on an intrusion detection system. The security and information are provided by the proposed system and act as a smart mirror. The face view of the image is clearly visible and identifies commands, detects the intruder to send the image to a particular mobile, and expands touch, messages to a system. It can detect the image fast, and securely, and its accuracy is good. Moreover, clear face recognition from large-scale data is a complicated task.Subahi et al. [15] demonstrated a highly scalable intelligent system controlling to monitor the temperature of the greenhouse based on Internet of Things technology. The reference temperature is generated to detect the greenhouse by the Petri nets model to formulate the temperature block. A dynamic model is applied from sensors to manage large-scale data by energy efficiency. It increases productivity, decreases energy consumption, and also the internal temperature is controlled. However, in this approach, the management information system should achieve higher scalability.

Ouammi et al. [16] presented a high-level centralized control scheme for a smart network of greenhouses integrated microgrids (NGIM) to frame a smart grid. The proposed model is regulated by a finite horizon optimization model. The network layer collects the information from sensors to integrate the gathered data. The productivity is enhanced to control the indoor climate in energy management and supervisory system. It is more effective to control greenhouse microgrids from a single controller. Hence, the centralized approach is stretched toa largescale from different data.Ahmed et al. [17] investigated cross-layer-based channel access to sense and actuate the routing solution. The rural areas are the target of achieving the Internet of Things for the enhancement of farming and agriculture. The fog and routing solution from a big network shorten the congestion capable of physical data rate. The performance of the proposed system improves the connectivity, bandwidth, scalable, and throughput. Moreover, the manipulation and circumstance of data are higher possible to attack.

Kitpo et al. [29] stated a novel deep learning based bot system for greenhouse monitoring. The authors selected tomato dataset to analyze the growth of it. The accuracy of the monitoring of tomato fruit is higher, however, the approach only applicable for the specific fruit and not for other fruits. Contreras et al. [30] demonstrated a novel CNN based green house monitoring system which also monitors the diseases of crops, and need for the resources such as fertilizers, water, etc., and controls the usages of resources. The authors stated that the energy consumption has been reduces with the disease detection ratio of 90%. Security is the major concern during this process.

3. SYSTEM MODEL

The system model of our proposed greenhouse monitoring is illustrated in figure 1. It consists of sensors like LDR sensors, smoke sensors, Humidity sensors, water level sensors, temperature sensors, soil moisture sensors, and components like LED light, LCD, 12V DC fan, pump, and Raspberry Pi processor. The data from each sensor are forwarded to the database via the Raspberry Pi-based processor which is coded with Python code. The processor is also responsible for the turning ON and OFF relay and the data collected from the sensors are stored in the cloud database and the data are detected (that is whether the sensed data are in the required condition or not) with the proposed DCNN-based FH optimization approach. Based on the detection output the farmers took the necessary steps remotely with the operation of the valve and pump. The sensors, components, and processors are explained briefly below.

3.1 Raspberry PI

The single-board computer with the Raspberry Pi is the major role of this study. The budget desktop was served by Raspberry Pi which the Arm processor presents in the core. The Raspberry Pi Foundation manufactures the Raspberry Pi [18]. The most important type of Raspberry Pi Foundation is Raspberry Pi 3 which has Bluetooth/Wi-Fi with64 a bit support system. It is widely used to solve real-time issues and optimization problems. The Ethernet port is included in the Raspberry Pi. For other external devices, various interfaces, power source connectors, UART, GPIO pins, Xbee socket, GPU, Ethernet port, the graphics chip, processor, CPU, and RAM are encompassed by the raspberry pi [19]. The SD flash memory cards are used that contain mass storage. The monitors, video cable, power supply Linux OS and US keyboard are the hardware specifications of the raspberry pi board. The Broadcom (BCM2835) based system on chip (SOC) board is the board of Raspberry Pi. The external data connectivity selection is used to equip with the raspberry pi USB 2.0, 256 MB of SDRAM and ARM1176JZF-S core CPU. The model of the Raspberry Pi board is delineated in Figure 1.

3.2 Temperature and Humidity Sensor

The major affordable digital sensors are DHT11 which measures both humidity and temperature. It contains a max-current of 2.5mA and 3 to 5 volts of operating voltage. The humidity percentage ranges from 20% to 80% in the temperature range lies between 0°C to 50°C [20]. The Negative Temperature Coefficient (NTC) was employed by a thermistor in which the moisture in the air is detected via a humidity-sensing component.

3.3 Soil Moisture Sensor

The quantity of moisture content present in the soil is detected with the help of an inexpensive soil moisture sensor called YL69 [21]. A current of 35mA with 3.3v of operating voltage is obtained. When in contact with the soil, this sensor has two electrodes, which cause a voltage fluctuation, meaning that when there is moisture in the soil, the output voltage lowers, and when the soil is dry, the output voltage rises. The soil moisture sensor model is shown in figure 3.

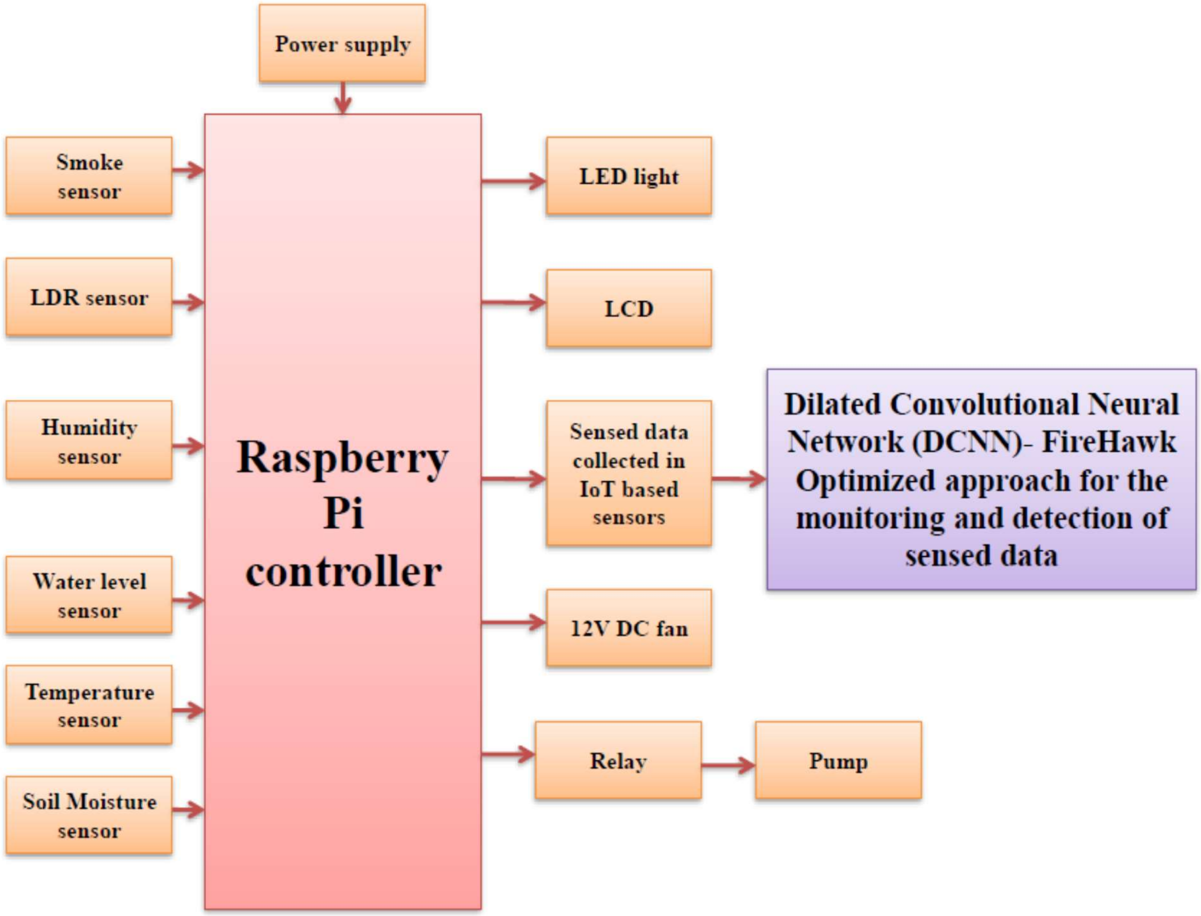

Figure 1. System model of proposed Raspberry Pi-based greenhouse monitoring system

Figure 2. Model Of Raspberry Pi Board

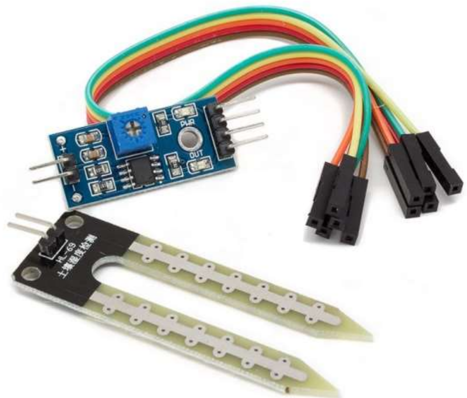

Figure 3. Soil Moisture Sensor

3.4 Light Sensor

The light intensity is increased with the usage of two cadmium sulfide photoconductive cell resistance. It involved alarm and batch counting systems with automatic lighting control.Resistors that are sensitive to light can recall the lighting conditions under which they were collected. The LDRs can be stored in light before use to reduce this memory effect. Light storing reduces the time required for equilibrium to obtain constant equivalent resistance. Model of light sensor is depicted in figure 4.

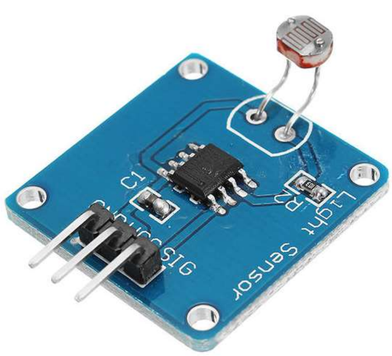

Figure 4. Light Sensor

3.5 LCD Module

A 16x2 dot matrix LCD panel, which is commonly used in projects to display some user information, will be known to the majority of us. The two classes such as composite and HDM1 are the raspberry pi board connection options. The connection options with the HDMI male cable attach the HD TV and LCD monitor. Recommend the 1.4 version cable and support the 1.3 and 1.4 versions of HDMI. The composite video links the older TVs. From composite video, the audio is obtainable when utilizing the composite video connection.

3.6 LDR Sensor

The LDR sensor monitors the light intensity values. It has a resistivity that changes depending on the amount of light falling on it at any one time. Because of this, they are used in light-sensing circuitry. Model of the LDR sensor is shown in figure 5.

Figure 5. LDR Sensor

3.7 Smoke Sensor

The smoke detector is a sensor designed to notice the presence of a fire or smoke and act accordingly, enabling smoke monitoring [22]. Depending on the installation, the smoke control system could be activated, an alarm may ring, and the fuel line may be decoded in response to the smoke being detected. Smoke sensor model is illustrated in figure 6.

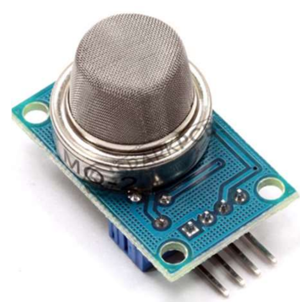

Figure 6. Smoke Sensor

3.8 Pump

The water level is detected by a soil moisture sensor, and as it drops, the pumps turn on. The pump will immediately turn on if the soil moisture value falls below the desired level. If the pump will be turned off while the soil moisture level goes to the desired value

3.9 Bulb

When it falls below the desired level, the temperature is increased via a 20-watt heater. The light intensity is controlled by using another green bulb.When the necessary amount of light intensity is not reached, this bulb will switch on.

3.10 12V DC fan

The temperature is controlled by using a 12V DC fan [23]. Turn on the bulb when the temperature is lower than a predetermined value. If the temperature exceeds the desired level, the fan will activate to bring it down. This approach can be utilized for crops having varying temperature requirements because these temperature threshold values can be modified for different crops using the Blynk app.

4. Proposed optimized DCNN for the sensed data detection

This section presents the detection of data collected from the sensors and analyzed with the proposed DCNN-based FHO algorithm for the evaluation of data range so that if the collected data is above or below the required data then the system will notify the user (farmer) regarding this. After that, the user will take the necessary steps or the system itself automatically do the necessary steps.

4.1 DCNN

To tackle the invariance and overfitting issues of traditional CNN [26] pooling layers are used, however, it will result in the mitigation of the spatial resolution of the sensed data and might lead to the loss of extracted features. Moreover, deconvolutional layers [25] are also used to tackle these, however, it leads to computational complexities. Hence dilated CNN [24] is used which dilates the filters prior to the convolution process to restore the spatial resolution and the structure is illustrated in figure 7. It consists of the input layer, hidden layers with varying dilation values, and output layers. In accordance with this, the size of the convolutional filters is enlarged and replaces the empty locations with *0,* and therein attains the height and weight of the original convolution kernel.It consists of the pooling layer which replaces the pooling and convolutional operator with the sparse kernels. The formulation of the 2D dilated convolutional layer is conducted as,

$$x(a,b)=\sum_{i=1}^{A}\sum_{j=1}^{B}s(a+r\times i,b+r\times j)v(i,j) \tag{1}$$

Here, the output of the dilated convolution of the taken sensor input *s(a, b)* is denoted as $x(a,b)$ and the filter of $v(i,j)$ with size $A\times B$ at the dilation rate of r with the constraint that r=1 denotes the normal convolution.

With the utilization of dilated stride *r,* the small kernel $m\times m$ of DCNN can be enlarged into $m+(m-1)(r-1)$. Thus it retains the same resolution even after the appending of multi-scale contextual information and results in flexible accumulation. In general, it can be explained as, considering the convolutional layer of 3×3 then the size of the receptive field is 3×3, whereas, in the DCNN when the dilated convolution layer of size 3×3 is taken then the receptive field is denoted as 7×7 with the $r=2$ and 15×15 for the value of $r=3$. Hence it can be determined as the receptive field is $(2^{i+1}-1)\times(2^{i+1}-1)$ where r=i. thus the expansion of the sensed data is exponentially expanded without any loss of resolution or coverage. Further, to detect the sensed data accurately we utilized FHO incorporated with the DCNN so that it optimizes the detection of sensed data which can be used by the farmer for further actions. The combination of both techniques increases the speed of the detection and therein mitigates the complexities due to the overfitting issues of DCNN.

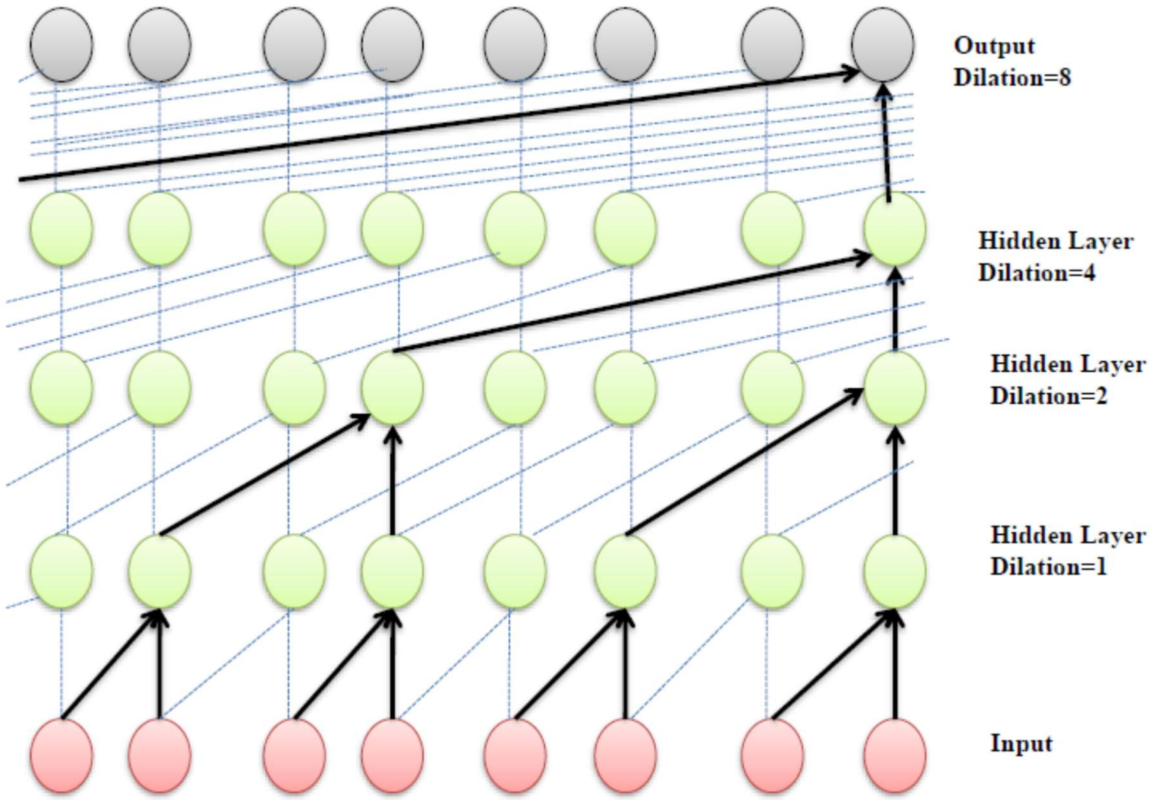

Figure 7. Structure Of Proposed DCNN

4.2 Fire Hawk Optimizer (FHO)

The standard FHO [27] optimizer is elaborated in the following section and followed by the fuzzy-based FHO algorithm. The FHO relies on the foraging characteristics of fire hawks which usethe setting and spreading fires to catch the prey this concept is sued for analyzing the enlarged receptive field to maintain the same resolution of sensed data and therein significantly shows whether the data is in the required condition or not. The total population of hawks is initialized with the consideration of the initial position and can be determined as,

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_i \\ \vdots \\ Y_N \end{bmatrix} = \begin{bmatrix} y_1^1 & y_1^2 & \cdots & y_1^j & \cdots & y_1^d \\ y_2^1 & y_2^2 & \cdots & y_2^j & \cdots & y_2^d \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ y_i^1 & y_i^2 & \cdots & y_i^j & \cdots & y_i^d \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ y_N^1 & y_N^2 & \cdots & y_N^j & \cdots & y_N^d \end{bmatrix}, \begin{cases} i = 1,2,\ldots, N \\ j = 1,2,\ldots., d \end{cases} \quad (2)$$

$$y_i^j(0) = y_{i,\min}^j + random.\left(y_{i,\max}^j - y_{i,\min}^j\right), \begin{cases} i = 1,2,\ldots.N \\ j = 1,2,\ldots, d \end{cases} \quad (3)$$

The i^{th} solution of sensed data search space is denoted as Y_i and the dimensionality of the deemed issue is d with the total number of solution N. the j^{th} decision variable of the i^{th} solution is denoted as y_i^d ; the initial location of the candidate solution is represented as $y_i^j(0)$. The minimum and the maximum constraints of the j^{th} decision variable for the i^{th} candidate solution is $y_{i,\min}^j$ and $y_{i,\max}^j$ respectively, and the uniformly distributed random number (random) falls under the range of 0 to 1. The position of the fire hawks [28] in the search space can be evaluated with the objective function; the better objective function denotes the correct range of the values to be maintained in the greenhouse environment and others represent the critical values. So based on the exact value the other values are detected and make the necessary action. The global best solutions can be used for the fire hawks to make the fire spread in the search space and numerically it can be expressed as,

$$TR = \begin{bmatrix} TR_1 \\ TR_2 \\ \vdots \\ TR_k \\ \vdots \\ TR_a \end{bmatrix}, \; k = 1,2,....,a \qquad (4)$$

$$Fh = \begin{bmatrix} Fh_1 \\ Fh_2 \\ \vdots \\ Fh_l \\ \vdots \\ Fh_b \end{bmatrix}, \; l = 1,2,....,b \qquad (5)$$

The kth prey in the search space is denoted as TR_k with the total prey equal to a and the l^{th} fire hawk in the total number of b fire hawks in the search space is denoted as Fh_l. Moreover, the distance between the best objective function valued fire hawk and the nearest prey can be evaluated as,

$$Dist_k^l = \sqrt{(w_2 - w_1)^2 + (z_2 - z_1)^2}, \; \begin{cases} l = 1,2,....,b \\ k = 1,2,....,a \end{cases} \qquad (6)$$

The distance between the l^{th} fire hawk and k^{th} prey is denoted as $Dist_k^l$ and the coordinates of the fire hawks and the prey are denoted as (w_1, z_1) and (w_2, z_2) respectively. the next stage is to set fire by collecting the burning sticks and taking necessary action to make the greenhouse work in a proper condition. It can be expressed numerically as,

$$Fh_l^{new} = Fh_l + (r_1 \times G_B - r_2 \times Fh_{Near}), \; l = 1,2,...,b \qquad (7)$$

The new position of the position vector of the l^{th} fire hawk is taken as Fh_l^{new}. The global best solution is denoted as G_B and the nearest fire hawk is Fh_{Near} and the random numbers r_1 and r_2 falls under the range 0 to 1. Henceforth if the burning stick is dropped and so the prey tries to hide and therefore the new location of the prey can be updated as,

$$\Pr_q^{new} = \Pr_q + (r_3 \times Fh_l - r_4 \times S_{p1}), \; \begin{cases} l = 1,2,...,b \\ q = 1,2,....,r \end{cases} \qquad (8)$$

The newly updated location of the prey is taken as $\Pr_q^{new}$ when the fire hawk Fh_l is surrounded by them. The safe place under the l^{th} fire hawk's territory is taken as S_{p1} and random numbers r_3 and r_4 are uniformly distributed and fall under the range of 0 to 1. Apparently, while the prey searching for a hidden place to hide there might be chances to be near the fire hawk and it is necessary to update the position to the safest place hence it can be numerically denoted as,

$$\Pr_q^{new} = \Pr_q + (r_5 \times Fh_A - r_6 \times S_p), \; \begin{cases} l = 1,2,...,b \\ q = 1,2,....,r \end{cases} \qquad (9)$$

Where, Fh_A denotes another fire hawk from the search space and the random numbers r_5 and r_6

are uniformly distributed under the range of 0 to 1. Numerically the safe places S_p and S_{p1} expressed as follows,

$$S_{p1} = \frac{\sum_{q=1}^{r} \Pr_q}{r}, \begin{cases} q = 1,2,...,r \\ l = 1,2,....,n \end{cases} \quad (10)$$

$$S_p = \frac{\sum_{k=1}^{a} \Pr_k}{a}, \ k = 1,2,....,a \quad (11)$$

Here, $\Pr_q$ is the qthprey which is encircled by Fh_l and $\Pr_k$ is the k^{th} prey in the search space. The pseudocode of the FHO is illustrated in Algorithm 1.

Algorithm 1: Pseudocode for Proposed FHO
Initialize the locations of N candidates and population (Y_i)
Estimate the fitness values for the initialized solution
Estimate the Global best solution
while I_{ter}< Maximum Iterations
The number of Fire Hawks can be set by generating the random integer b
Initialize the fire hawks and prey in the search space
Estimate the distance between them
Initialize the territory of the fire hawks with the dispersion of prey
for $l = 1 : b$
Using Eqn. (6) estimate the updated location of fire hawks
for $q = 1 : r$
Using Eqn. (10) estimate the safe place for the territory of l^{th} fire hawk
Using Eqn.(8) the new location of prey is estimated
Using Eqn. (11) estimate the safe place outside the l^{th} fire hawk
Using Eqn. (9) estimate the new location of the preys
end
end
Calculate the fitness values for the generated fire hawks and prey
evaluate the global best solution
end while
return the global best value

5. EXPERIMENTAL INVESTIGATION

Figure 8 illustrates the model of hardware implementations. The python-programmed Raspberry pi controller is used as the implementation platform. Raspberry Pi is the major component of a controller. To measure the environmental condition, the IoT sensors for the monitoring of light, temperature, smoke, soil moisture, LCD module, 12V DC fan, LDR sensor, pump, and bulb. Observe the readings at various time intervals. The buzzer beeps to determine the smoke or provides the alarm.

Figure 8. The Model Of Hardware Implementations

5.1 Performance metrics

A total data flow inside the greenhouse begins with the sensor nodes, which transmit the data they have gathered to the central controller, and finishes with the actuators, which acquire the controller's instructions for the appropriate actions.As a result, the metrics that show whether or not the various simulation scenarios are operating as planned or not are developed so that it is possible to assess the performance of the proposed system. Accuracy is defined as the degree to which a measurement is accurate in relation to its true value.

$$Accuracy = \frac{(TN + TP)}{(FN + TN + FP + TP)} \quad (1)$$

5.2 Performance analysis

Figure 9 plots the training and testing accuracy. The training and testing loss performances are plotted in Figure 10. The number of iterations varies from 20 to 100 iterations. Both testing accuracy and training are varied and also testing loss and training loss are varied.

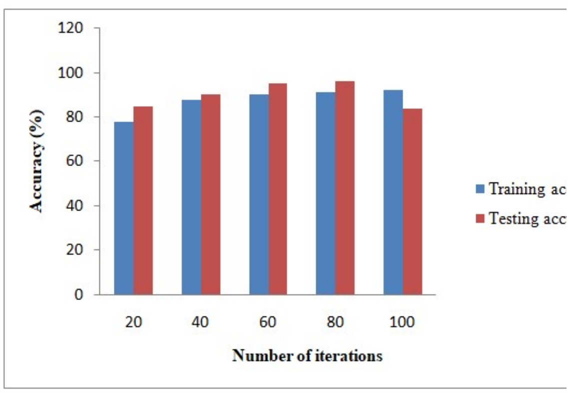

Figure 9. The Training And Testing Accuracy Performances

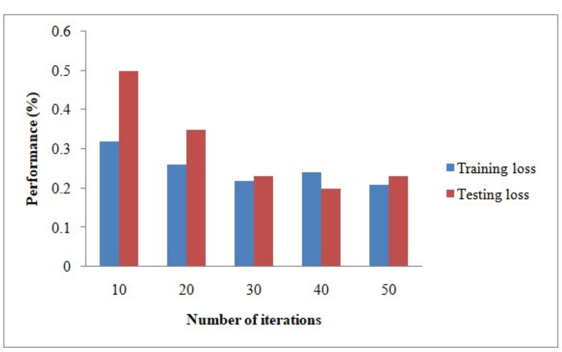

Figure 10. The Training And Testing Loss Performances

Various vegetables have varied water needs during growing as shown in Figure 11. Different kinds of vegetables such as kidney beans, peas, onion, lady’s finger, and tomatoes with water production requirements are shown below. The lady’s finger demands more water production than the other vegetables like kidney beans, peas, onion, and tomatoes respectively.

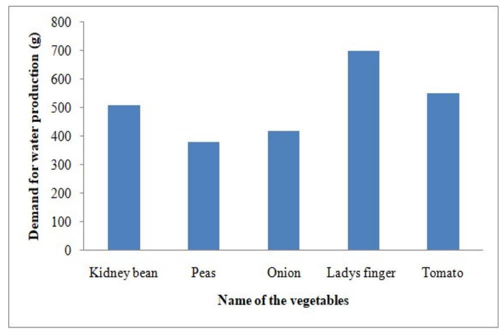

Figure 11. The Water Requirement Plot With Respect To Different Vegetables

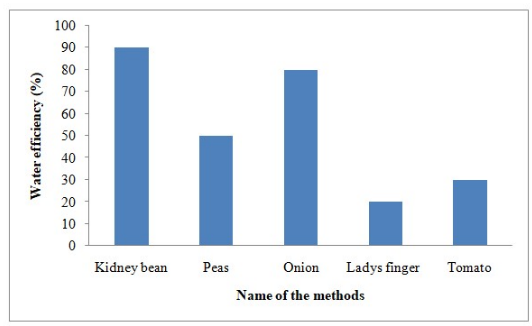

Figure 12. The Water Efficiency Plot With Respect To Different Vegetables

The water efficiency plot with respect to different vegetables is depicted in Figure 12. The graphic illustrates how different types of vegetables have quite varying transpiration rates and water needs. Vegetable water requirements cannot be controlled using the conventional planting method, and transpiration rates cannot be precisely detected and controlled. IoT technology must be used for regulation and detection as a result. The underlying supervision of farmers is examined in the secondary section. Gardeners must monitor the greenhouse's carbon dioxide levels, humidity, temperature, and other variables in realtime and promptly make adjustments to the environment. Figure 13 illustrates the state-of-art result of humidity with respect to time. The methods like support vector machine (SVM), random forest (RF), k-nearest neighbor (KNN), artificial neural network (ANN) and the proposed methods are state-of-art methods. The time values are measured in terms of seconds. Based on humidity, the proposed method takes very less time 5.21 seconds, which is lower when compared to the previous methods like SVM, KNN, ANN, and RF.

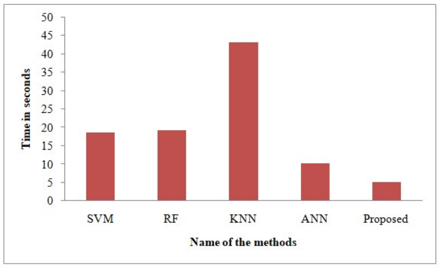

Figure 13. State-Of-Art Result Of Humidity With Respect To Time

The comparative result of soil moisture with regard to time is shown in Figure 14. The state-of-the-art techniques include support vector machine (SVM), random forest (RF), k-nearest neighbor (KNN), artificial neural network (ANN), and the suggested techniques. Seconds are used to measure the time values with respect to soil moisture. In comparison to previous methods like SVM, KNN, ANN, and RF, the proposed method based on soil moisture, requires much less time of 4.11 seconds.

Table 1. Various Kinds Of Vegetables Requiring Temperature

Name of the vegetables	Most comfortable temperature (ºC) during growth	The cultivation is based on the average temperature (ºC)		
		Lower temperature (ºC)	More comfortable temperature (ºC)	Higher temperature (ºC)
Onion	11-17	17	21-30	34
Tomato	12	6	15-20	36
Peas	6-12	5	15-19	26
Lady’s finger	7-18	8	11-21	32
Kidney bean	6-15	15	15-20	29

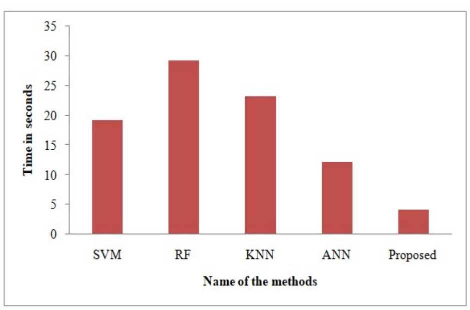

Figure 14. State-Of-Art Result Of Soil Moisture With Respect To Time

Table 2. *Comparative Analysis Based On Delay*

Name of the methods	Delay (*s*)
SVM	19.20
RF	18.28
KNN	24.31
ANN	19.90
Proposed	3.22

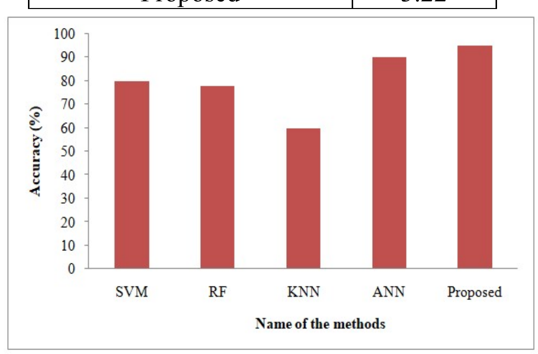

Figure 15. State-Of-Art Result Of The Accuracy

Table 3. Illustration Of Experimental Results Based On The Different Days

Dates	Temp.	Time	Soil moisture	Smoke detector
12/07/2022	33ºC	3.22s	High	No smoke
20/07/2022	66ºC	4.36s	Low	Smoke detected
10/08/2022	35ºC	5.21s	High	No smoke
27/08/2022	40ºC	4.21s	Low	Smoke detected
10/09/2022	38ºC	3.21s	High	No smoke

The need for planting in greenhouses is split into two categories. The initial component in managing the crops grown in greenhouses is the need for crops, and a secondary factor is the backstage management activity of farmers or humans. Table 1 tabulates different variety of vegetables that requires the temperature. A different variation of lower, most comfortable, and higher temperature is illustrated during the cultivation based on the average temperature. The comparative analysis of accuracy is depicted in Figure 15. The state-of-art techniques such as SVM, ANN, KNN, RF and the proposed method are selected to validate the performance of accuracy. We have obtained 80%, 78%, 60%, 90% and 95% accuracy with respect to the SVM, ANN, KNN, RF and proposed method. The proposed method offers superior detection accuracy than the previous methods like SVM, ANN, KNN and RF respectively. Table 2 tabulates the comparative analysis based on delay. The proposed method and previous techniques like SVM, ANN, KNN, and RF are chosen to validate the delay performance. In comparison to the SVM, ANN, KNN, RF, and proposed technique, we were able to achieve a delay of 19.20s, 19.90s, 24.31s, 18.28s, and 3.22s. In comparison to earlier techniques like SVM, ANN, KNN, and RF, the proposed method gives a minimum level of delay. Table 3 illustrates the experimental results based on the different days.

6. CONCLUSION AND FUTURE WORK

This work focused to design a greenhouse environment with the Raspberry Pi-based microcontroller which was used to collect all the data from IoT sensors such as light sensors, temperature sensors, smoke sensors, LDR sensors, and soil moisture sensors that were used to monitor the green house. The Raspberry Pi-based processor is used to reduce the cost and complexities that were noted in the previous works. Then the data were forwarded to the cloud-based database and from that, the data were analyzed to detect the conditions of the greenhouse environment with proposed DCNN-FHO techniques. This effectively analyzed the data and verified the actual requirement and made the system act accordingly. The proposed detection technique was analyzed with different techniques based on the performance metrics such as accuracy and delay. Our proposed approach showed less delay 3.22 seconds, with improved accuracy of 95% for data transmission. Furthermore, we analyzed various terms such as temperature required for various crops, humidity, and water efficiency.

In the future, the work can be improved with the addition of secured transmission of data and also can be used to predict the diseases of crops with the inclusion of advanced technology.

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