An IoT PLATFORM FOR IMPROVING DATA-DRIVEN TECHNIQUE IN GRAPES FARMING

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Abstract - *The agriculture yields specifically depend on the fertility level of the soil and the use of appropriate amount of fertilizers and pesticides. The grapes constitute one of the most widely used crops all over the world in making wines, table fresh fruit and also in making raisin. The drastic climate change aggravates the serious problem in grape production and quality. So, it become necessary to develop a smarter agriculture practice through internet of things (IoT) to boost the productivity of crop by increasing yields, minimizing the input cost by reducing losses. This paper presents an end-to-end IoT platform for grape farm that enables the seamless data collection from sensors and drones. The paper also discussed a novel approach for designing an efficient data-driven framework that explicitly monitor soil nutrient level and grapes disease prediction using machine learning algorithms. The paper leveraged an AIoT gateway as a platform for grape farm database management system that monitor, control, analyze, and manage data remotely. The primary aim of this work is to design an automatic system for retrieving unpredictable data for grapes crop. Also the system will enables cloud connectivity for sensors data to be stored and analyzed by the cloud management system that will host the functions like predictive data analysis regarding soil and crop disease as a service to the farmer in order to take preventive actions. These paper state a novel framework of precision agriculture for automation and decision support system in grapes farming.*

Key Words: *Internet of Things (IoT), AIoT Gateway, Precision Agriculture, Cloud system, Machine Learning Algorithm.*

1. INTRODUCTION

Indian grapes exports are becoming an increasing trend in recent years due to its soil quality, climatic conditions that is suitable for grapes cultivation. India is among first 10 countries in grape production. The area under grape is 1.2% of the total fruits crops area in the country and production is 2.8 % of the total fruits crop [1]. India also has remarkable in affiliated industries such as wine making, raisins, etc. Also grape is an important agriculture commodity that provide livelihood to about 65 million of people with remunerative income to millions of farmers all over world [2]. About 60% of grapes cultivated in India are under rain feed condition. Water stress plant or seed cause poor growth leading to fungal disease and low yield as well as exposes to harmful diseases.

The most valuable tools for the farmer are soil analysis. Whenever soils are continuously used for growing crops, nutrients are removed at the time of crop harvest. Low nutrients leads to multiple plant disorders and low yield. Therefore, nutrients must be restored to the soil for the better yield and good productivity. Therefore achieving the increase in grapes productivity is even more challenging because of unpredictable climatic conditions, soil deficiencies, residing water level, and sever other factors. The traditional methods in terms of keeping the soil under control and predictive analysis regarding disease may be inadequate. Satellite images are not always possible and even if the images are removed, the farmer doesn't able to give enough detail for solution to the problem. One of the most important factors for sustainable agriculture is the proper amount of pesticides used.

According to the international food policy research institute (IFPRI), the data driven techniques can helps us to achieve these goals by increasing farm productivity by cutting down agriculture losses [4]. Data driven farming means the ability to map a farm using smart intelligent techniques and overlaid with lots of data. For example: the soil nutrient level throughout the farm, soil moisture level below the land, soil deficiencies, disease detection and prediction. The technological revolution had made this things possible and access information via artificial intelligent technique enabling the precision agriculture. Hence, the automation in agriculture sector has made the seamless data collection that helps farmers in decision making cutting down the input costs and efforts.

Precision agriculture is the ability to do site specific application. For example: Farmers will apply water, pesticides, and fertilizers uniformly throughout the farm. But with precision agriculture, it is possible to apply only where it is needed. To overcome the critical challenges, agriculture requires automation, robotics and sensor, image processing, information services that combine information communication technologies (ICT). Many field trail have shown that techniques that uses sensors measurement for accessing farm parameters, image processing for disease detection and prediction using different machine learning algorithms which is proven beneficial [4,5]. This paper presents an automated data driven technique for grapes farming. Farmers need to do the naked eye observation throughout the farm which results in inadequate information regarding diseases, soil deficiency, etc. Sometimes farmers need to call experts for accessing adequate information and monitor the farm which is time consuming and cost effective.

This paper present an end-to-end IoT technique and provide a intelligent platform for grapes farm in deriving data that enable data collection from various sensors. The proposed system enables the various application like soil fertility analysis, provides a decision support system via cloud data management system. The software system has the intelligence to recommend the fertilizers after soil analysis at proper amount. Automating sensors data collection requires establishing network connection to these sensors. However, the existing connection solutions [7, 8] like a cellular data logger attached to each sensor is costly. Although, is limited in amount of data exchange. These also rely on sending all their data to the cloud for processing. This paper present wireless sensor network (WSN) for monitoring soil nutrient analysis in real time.

Further, as stated before, a grapes plant disease causes significant damage and economic loses. Subsequently, reduction in plant disease by early diagnosis of disease and its severity leads to inappropriate use of pesticides. This paper presents an intelligent technique to diagnosis the disease using machine learning algorithm. Grapes crops may be affected by different types of disease with early symptom occurs on leaf steam and fruits caused due to fungi, bacteria, and viruses [8]. The subsequently occurring diseases are downy mildew, powdery mildew, bacterial leaf spot, mealy bug, black rot, rust, and bacterial cancer etc. The present research design an expert system application based on an AIoT platform to detect early grape diseases. Various studies shows different techniques of optimizing plant diseases depend on image processing and machine learning [9, 10]. The proposed paper present novel inference techniques for classification of grapes crops major disease like Anthracnose, Bacterial leaf Spot, Bacterial leaf Cancer, downy mildew, powdery mildew, black rot, and Rust discuss in Section 6.4.

The proposed framework will enable three challenges for the farmers as: monitoring- temperature, relative humidity, leaf wetness/Moisture, a real-time soil nutrient analysis system, and early detection of grapes diseases. Although, early detection of disease of grapes crop via sensors, taken from the farm are analyze and sent to the cloud for storage. The mobile application is developed that provide information related to the soil parameters, crop diseases prediction and fertilizer and pesticide suggestions in real-time. Thus, the system divide whole solution into four functional layers, that is, sensing layer, transmission layer, control layer and application layer. In designing the proposed system, the following key challenges could be solved.

First, to enable the connectivity within the grape farm, the paper leverage recent work in the combination of wireless and distributed specific sensor device to track the farm data. The IoT devices deployed into farm exchange the data that is gather by connecting to an AIoT gateway for data to be analyzed remotely i.e. cloud or for the data to be analyzed locally by an edge device i.e. base station.

Secondly, proposed idea enables precision agriculture application in the grapes farms that adapts the inputs over the different parts of the farm depending on the requirement. Third, a development of mobile application for farmers that provide the information related to the farm.

2. The IoT Base Station

The objective introduces several challenges in accessing an environmental variability as farm does not have access to power and high bandwidth internet connectivity [16]. Weak network connectivity to the farm is susceptible to failure due to weather variability. Fig. 1 shows system overview of end-to-end interaction of IoT nodes from sensor to end user application. It is divided into four layer structure as IoT Base station, AIoT gateway (windows PC), Cloud system and Mobile application.

3. Design and development decision

An overview of system is shown in fig.1. Here the main design decision is discussed. At the first layer the WSN link is used to connect the farmers home internet connection to the base station on the farm. The base station will accommodate sensors. At the second layer, the IoT base station will provides the Wi-Fi interface for connection from sensors and other devices. Many research used the newly developed technique called narrowband (NB-IoT) an LPWA (Low power wide Area) technology [12] which is licensed protocol from 3GPP offered. This wireless technology builds a bridge between remote equipment in the field and the farmer's smart devices. However, in emerging agriculture application, LoRaWAN is likely used as an open protocol which uses unlicensed spectrum allowing to set-up their own network at a very low cost with bandwidth of 125 KHz. Its self deployment capabilities and the chipset maturity, cloud services, makes it perfect fit for implementing real time agriculture application. This interface ensures that the farmers can not only connect most off-the-shelf farming sensors, cameras and drones, but they can also access their farming productivity apps by using phone.

Power failures due to environmental factors are the major cause of unavailability. The past work has deal with this problem in context of single sensor by duty cycling the sensor [16, 18]. The same approach does not work for base station. The base station has multiple components with different power requirements and duty cycling costs. The different component of the base station is duty cycled at different rates. For these constraints, a novel duty cycle policy approach is applied.

Finally, as the sensor deployed in the farm are responsible to generate data at continuous intervals. The data is transmitted to the n-gate via Wi-Fi which is ultimately sent to the cloud where data is stored in the database for processing. These sensors data are further used for analysis, classification, identification, etc [19].

4. Architecture and Deployment goals

The present paper leverages the work from paper [14, 11]. The system has following components:

4.1 Sensors

The Grape farm is equipped with different sensors that measure Temperature, pH, Moisture, Relative humidity, NPK Nutrient, grapes leaf wetness for different parameters like soil, weather, crop, etc. Each sensor is responsible for measuring characteristics of the farm such as soil- pH, temperature, Moisture and nutrient, weather-temperature, humidity and moisture, etc. likewise different sensor is deployed for accessing different characteristics of farm. Sensor measurement is reported to the IoT base station over Wi-Fi connection. In case of the sensor without Wi-Fi support, it is also possible to interface them with Arduinos, to add Wi-Fi capability. Also it is possible to deploy cameras and drones for monitoring and accessing farm data in the form of images and videos. But due to the higher cost and to avoid potential damages from the environment impact the proposed system makes the use of sensors data for soil nutrient analysis and crops disease detection.

4.2 Base Station Controller

The Base station is consists of WSN, Sensor connectivity module and Base station controller. The base station on the farm is power by solar panels, backed by batteries.

1 The WSN enables the connection and ensures that the base station at the farm can send data to the AIoT gateway, which than send it up to the cloud system.
2 The sensors are interface with the base station through router. The sensor connectivity module as shown in fig.1 is the read out circuitry that established the connection between base station and the sensors deployed on the farm. How the module is duty cycled is discussed in section [5].
3 From the technical point of view, a Raspberry Pi with LoRaWAN –compliant connectivity (i.e. 868 MHz Antenna and an iC880A-SPI concentrated board) act as a gateway node in wireless sensor network which perform sensors reading and data forwarding.
4 The base station controller are responsible for the functions like- when the WSN is switched on, it serves as a hidden reserve for the sensor data which is collected by the sensor module and synchronize the data with AIoT gateway.

4.3 AIoT Gateway

This paper state the mechanism that leverage the artificial intelligence of the things (AIoT) i.e. combination of artificial intelligence technique with internet of thing (IoT) infrastructure to enhanced IoT operation and evaluate the farm data management and analytics. The paper presents an AIoT gateway to enable the end-to-end data management and communication system. The goal of the AIoT gateway is to enable local services and create summaries from the existing data received via sensors to be sent to cloud for processing and analysis as stated previously. The gateway is divided into three different layers as sensing interface, data acquisition and data visualization (services) as shown in fig.1.

The gateway provides an interface for application to run and create the farm data summaries to be sent to the cloud and post those data to the local web server. Also it enables the services like soil fertility level, early disease detection or prediction, and fertilizer and pesticides suggestion, etc. Thus, it includes farmer with web services to access detail information when they are on the farm or outside farm network.

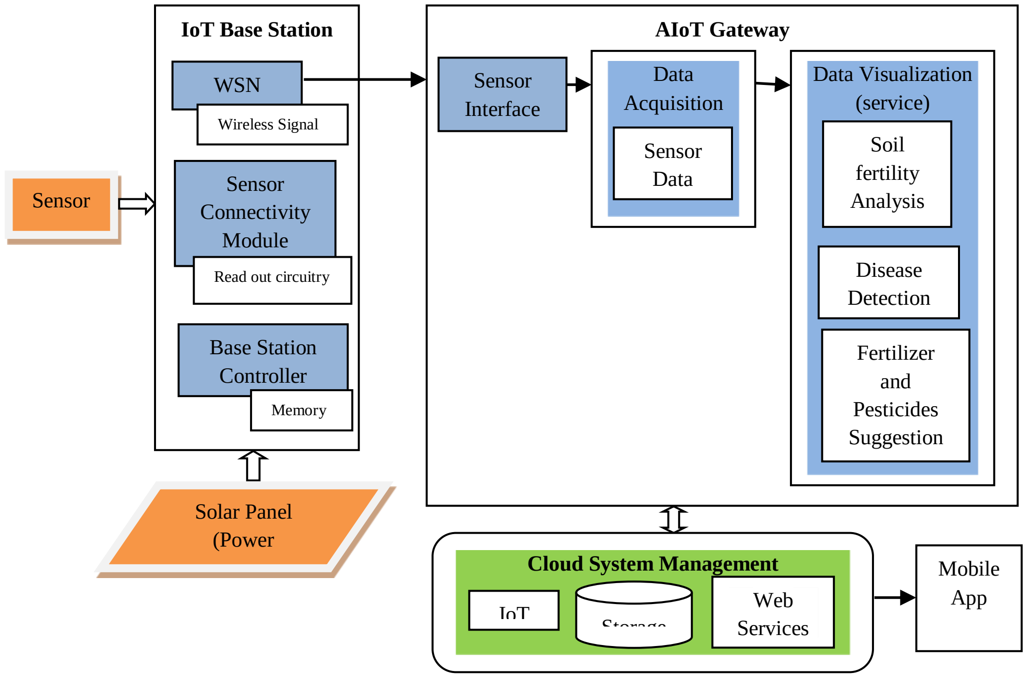

Figure 1.System Overview

Section 6 states the methods and technique for functioning gateway that enable data driven farming. The three aspects of AIoT gateway are- First, the gateway implements a web service, provide unique services, and in context of precision agriculture, it has access to data from multiple sensors, etc. that enables unique feature based summarization technology.

5. Duty Cycling: Base Station

The farm base station is powered by solar energy conclude in Section 3. It is periodically duty cycled to account the weather forecast and current charge state of batteries. In context of duty-cycling sensors, it is backed by energy harvesting sensor system [20]. The proposed system aims to achieve the objective of energy neutrality. The power source for the base station is a set of solar panel. The solar power out is varies with the time of day and the weather condition. Therefore, the system uses the standard methods to estimate the output of solar panel [17].

6. The AIoT Gateway: Methods and Solutions

This section discussed the key components of AIoT gateway. Also it states and discussed the methods and techniques which is used to implement the precision agriculture application in grapes farming.

6.1 Soil Nutrient Analysis

The crop yield primarily depends on soil fertility and the appropriate use of fertilizer. The basic nutrients are Nitrogen (N), Phosphorus (P) and Potassium (K). As discussed before, different sensors are used for different purpose. Each sensor measures the characteristics of the farm and reports the data to the base station over Wi-Fi connection. There are pH and moisture sensors available in market at a very low rate. But in case of NPK sensor the paper [14] states s novel soil fertility sensor that measure soil NPK. The NPK is the major nutrient that enables crop growth, yield, color, size and taste. The quantity of fertilizers to be used is dependent on present content of nutrient in soil.

Many researches show the ways to optimize crop yield while minimizing the consumption of fertilizer [19]. As macronutrients vary on a small scale throughout the field, many researches are engaged in developing sensors to map these nutrient contents [18, 19]. The paper presents efficient techniques from [14] that enable integrated crop management system to check the spatial and temporal behavior of NPK nutrient analysis in real time.

6.1.1 Data Analysis

Soil nutrient analysis using wireless sensor network (WSN) enable the application of monitoring soil fertility level remotely and provide a fertilizer suggestion model in order to build a decision support system.

The sensors deployed into soil, undergoes the chemical reaction, which than leads to change in an analog deflection voltage. The analog deflection voltage is converted into digital voltage. The value which is measured of such a voltage deflection is mapped and NPK values are derived. The values are derived using the formula as:

$$N_m = \frac{(x - N_{in-min}) * (N_{out-max} - N_{out-min})}{(N_{in-max} - N_{in-min})} + (N_{out-min})$$

Where, N_m is the measured nitrogen, x is the analog voltage read from the sensors, N_{in_min} is the *lower bound* of the value's current range, N_{in_max} is the *upper bound* of the value's current range, N_{out_min} is the *lower bound* of the value's target range, and N_{out_max} is the *upper bound* of the value's target range.

Similarly, same formula is used for calculating P and K nutrient value's using the range provided as per the sensor guidelines. In case of sensor without Wi-Fi support, it is possible to interface them with Arduino to add Wi-Fi capability. Microcontroller transmits the data to the n-gate and report the data to base station over Wi-Fi connectivity. The WSN as discussed in section 4.2 ensure that the base station on the farm can send the data to the AIoT gateway, which then send it up to the cloud system. There are many cloud database management system that delivers fast growing application data. The cloud database is created for storing the ideal NPK values and for processing intermediate results.

(a)

Nitrogen	**Recommendation**	
	For low fertile soil, increase nitrogen by	For high fertile soil, decrease nitrogen by
$N_d \leq \pm 50$	No change	
51 to 100 kg	+12.5 kg	-12.5 kg
100 to 175 kg	+25 kg	-25 kg
175 to 250 kg	+37.5 kg	-37.5 kg
251 to 325 kg	+50 kg	-50 kg

(b)

Phosphorus	**Recommendation**	
	For low fertile soil, increase Phosphorus by	For high fertile soil, decrease Phosphorus by
$P_d \leq \pm 25$	No change	
26 to 75 kg	+12.5 kg	-12.5 kg
76 to 125 kg	+25 kg	-25 kg

(c)

Potassium	**Recommendation**	
	For low fertile soil, increase Potassium by	For high fertile soil, decrease Potassium by
$K_d \leq \pm 25$	No change	
26-50 kg	+12.5 kg	-12.5 kg
51-100 kg	+25 kg	-25 kg
101-175 kg	+37.5 kg	-37.5 kg

Table 1.Guideline to calculate the fertilizer recommendation for Nitrogen, Phosphorus and Potassium

Let N_i , P_i , K_i be the *ideal* N, P and K recommended for grapes crop and let N_m , P_m , K_m be the *measured* N, P, and K recommended for the soil from the farm under consideration. And the difference of *measured* NPK and *ideal* NPK denotes as N_d , P_d , K_d . Therefore, the difference of *ideal* and *measured* nutrients is obtained by following steps:

$$N_d = (N_m - N_i)$$
$$P_d = (P_m - P_i)$$
$$K_d = (K_m - K_i)$$

And finally the guideline to calculate the fertilizer to be recommended is given in Table 1 as (a), (b), (c).

Thus, the system generates the NPK values and calculates the proper amount to bring the level of nutrients in the soil to the ideal nutrient values. Although, the mobile application consisting of display and suggestion module are integrated to that uses the data in the cloud. As discussed previously, the cloud also hosts the software application that provides recommendation of fertilizer along with nutrients to be supplemented. The application has interfaced to various other modules for acquiring farm data is discussed further.

6.2 Grapes disease detection

The primary objective of the system is to develop early disease detection system to inform farmers about sudden appearance of the disease. For example, most of the disease is spread easily in highly humid climate. Several research have analyzed climatic factor such as temperature, precipitation and humidity [9, 24]. In most traditional way, crop models usually work at daily and monthly rates, which simply means that the possible results of threats are not received until the model are run and that period could be too much late to apply treatment to the crops. Thus, there is need for such a model that is capable of being run at the same rate and the time as per the observation coming.

Suyash S. Patil *et.al* [11] states a novel technique for developing early disease detection model in real time for the grapes crop. The model is develop in order to warn a disease in grapes farm using infield IoT nodes (i.e. sensors device) and enable the decision support system.

6.2.1 Data Transmission

For the early detection the data is collected from temperature, Relative humidity, and leaf wetness sensors. The sensor generates data at continuous intervals. The digital data is collected for transmission. Further, the data is serially transferred to the server for data analysis. Table 2 state the favorable condition for growth of diseases for grapes crop.

Table 2 Favorable condition for growth of diseases

Disease Name	Temperature (C^0)	Relative Humidity (%)	Leaf Wetness (hrs)
Bacterial leaf spot	25-30	80-90	-
Black Rot	23-29	80-90	6-7 hrs
Downy Mildew	17-32.5	More than 48	2-3 hrs
Powdery Mildew	21-17	More than 48 Less than 70	
Anthracnose	24-26	-	12
Bacterial Cancer	25-30	>80	-
Rust	24	75	-

6.2.2 Data Analysis

The next phase is to analyze the data for classification. The data of conditions responsible for spreading disease is taken from National Research Center for Grapes (NRCG). The tab.2 shows the favorable condition for the growth of disease.

In the statistical method, the input data is restricted by NRCG [24]. And due to the data restriction, results are classified incorrectly. So, paper [11] proposed an alternate solution that develops a novel technique based on the concept of Hidden Markov Model (HMM). This model enables the classification of disease from input data and NRCG data.

6.2.3 Applying HMM Model:

HMM uses a Baum Welch algorithm which is also called as forward backward algorithm. The algorithm is used to find the unknown parameters of HMM model. It makes use of forward-backward algorithm for calculating expected steps to complete the statistics. We have three training data set of Temperature, Relative Humidity and Leaf wetness duration. The model is consisting of three *hidden states* as S_1, S_2, S_3 and eight *observing state* as *BLS, BR, DM, PM, AH, BC, RU, No Disease* which denotes Bacterial Leaf spot, Black Rot, Downy Mildew, Powdery Mildew, Anthracnose, Bacterial Cancer, Rust and No Disease.

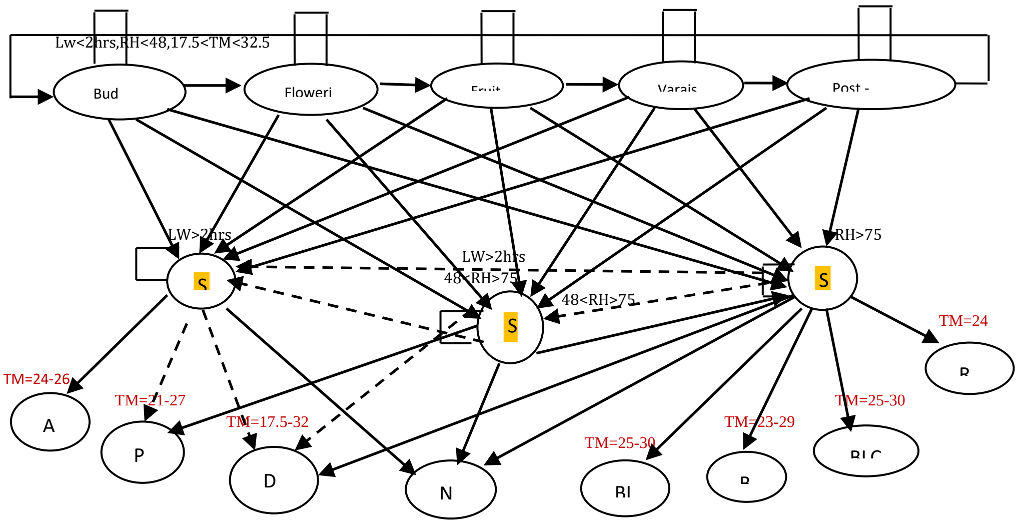

Figure 2.Hidden Markov Model for Grapes Data Set

The fig. 2 shows the HMM model with three *hidden* state and eight *observing* state. Each state has a certain condition like, for *LW*, period is more than two hours, or the state change from initial state to S_1, or when *RH* is between 48 to 75 then state changes to S_2 and when *RH* is more than 75, at that time stage is S_3.

In the following, let *observed* state denote by Z and *hidden* state denote by Y. The constraint is given as:

$$Z_k\ (t_{k,1}),\ Z_k\ (t_{k,2}),\ldots,\ Z_k\ (t_{k,n_k}) \quad (1)$$

The sequence (1) is a *observed* outcomes recorded as 1,2,or 3 and measured at time $t_{k,1}, t_{k,2}, \ldots, t_{k,n_k}$ on subject k and n_k is the number of observations on subject k.

And let Y be the *observed* sequence that provides the information for the *hidden* sequence as:

$$Y_k\ (t_{k,1}), Y_k\ (t_{k,2}),\ldots, Y_k\ (t_{k,n_k}) \quad (2)$$

At time $t_{k,1}, t_{k,2}, \ldots, t_{k,n_k}$ for subject k, assumed to be measured with possible misclassification which is modeled as three state S_1, S_2, S_3 with state occupancy valued *1,2,3*. Assumed the dependency of the *observed* state on the state of the *hidden* process openly at the matching time points, not on the previous history of either observed or hidden process which imposes following constraint:

$$P_r(Z_k\ (t_{k,s})\ \big|\ Y_k\ (t_{k,1}),\ldots, Y_k\ (t_{k,s}), Z_k\ (t_{k,1}),\ldots, Z\ (t_{k,s-1}))$$

$$\Rightarrow P_r(Z_k\ (t_{k,s})\ \big|\ Y_k\ (t_{k,s})) \quad (3)$$

$$\Rightarrow \varepsilon Y\ (t_{k,s}), Z_k\ (t_{k,s}), S = 1, \ldots n_k$$

Equation (3) defines the probability that the *observed* state correctly classifies the *hidden* state of the process. The three states S_1, S_2, S_3 fully described by the instantaneous transition rates, a_{ij} is the rate at which the process transition from state 'i' to state 'j', where $i, j = 1,2,3$ and $i \neq j$. Matrix R is formed by these parameters as:

$$= \begin{bmatrix} -(a_{1\,2} + a_{1\,3})\text{^}R & a_{1\,2} & a_{1\,3} \\ a_{2\,1} & -(a_{2\,1} + a_{2\,3}) & a_{2\,3} \\ a_{3\,1} & a_{3\,2} & -(a_{3\,1} + a_{3\,2}) \end{bmatrix}$$

From the property of a continuous-time markov chain, the amount of time a process stays in category 'i' before exiting follows an Exponential Distribution (E.D) and is generally unobservable. At transition time, the probability of transitioning into state 'j' is given as, the process is currently in state 'i'. The following formula is derived for three scenarios and function of $a_{i\,j}$ parameter is estimated. Thus the current state probability depends on the previous state probability and it is estimated as:

$$State\ Trasition\ Probability\ (a_{i\,j}) = \mathrm{P}\ (S_j\ (t)\ \big|\ S_j\ (t\text{-}1))$$

The state is called as transition probability if the state changes from *initial* state to *hidden* state and it are called emission probability when state changes from *hidden* to *observed* state.

For calculating probabilities at hidden state we need to calculate Euclidean distance (E.D) by using equation (4):

$$E.D\ at\ Hidden\ State = \sqrt{(RH - \overline{RH})^2 + (LW - \overline{LW})^2} \quad (4)$$

Where, RH is input relative humidity, LW is input leaf wetness duration, $\overline{RH}$ is Mean relative humidity of *hidden* state and $\overline{LW}$ is the mean leaf wetness duration at *hidden* state. At *observing* state the E.D is calculated as:

$$E.D\ at\ Oserving\ State = \sqrt{(TM - \overline{TM})^2} \quad (5)$$

The next step is to find the state transition probability at each point. Therefore the probability at each state calculated shown in equation (6) state the probability at *hidden* and *observing* state that changes with highest probability.

$$P_{i,j\ \epsilon\ all\ possible\ state} = 1 - \min_{0<i<n}\left(\frac{d_{i,j}}{d_{i\ ,0} + d_{i\ ,1} + \cdots d_{i,j}}\right) \quad (6)$$

Hence it is possible to evaluate the early disease detection system using HMM machine learning technique. The decision is based on classification framework, where HMM is used as a probabilistic model describing the data or training sequences.

7. Conclusion

In this article we have shown an approach to estimate a Data-Driven technique for Grapes farming to boost the grape productivity and quality. The paper presents a novel end-to-end IoT platform that enable precision application that support high bandwidth sensors technology using WSN. The framework uses the solar powered IoT base station and an intelligent AIoT gateway that ensures the data processing and analytics and the services available through the cloud system. The framework facilitates the automation of data collection of soil characteristics, crop disease and enables the supportive decision making system. The cloud system host the mobile application that provide the service regarding fertilizer and pesticides recommendation that has an interface to various modules such as view nutrient level, disease detection module, etc. Moving forward we are working on the duty cycling the sensors devices and cloud system analysis.

The current paper is the comprehensive studies from the previous research related to the current research. Further, for the real-time anylysis the paper can be expanded with different techniques and development in real-time. The Mobile application development is to be expanded in real-time development. Also the different Machine learning algorithm can be carried out for developing an atomization in grapes farming like generating Precision maps of soil and adding more IoT devices will helps to boost the required aspects.

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