

PREDICTIVE MAINTENANCE USING RNN AND LSTM MODELS

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ABSTRACT

The art of farming is the oldest and challenging factor in human life. In this fast phased environment and with the increase in the destruction of atmosphere and other natural resources, it is very questionable to acquire quality crops. This paper focuses to predict options which control and track the natural factors which are involved in the agriculture system. This work focuses on analyzing different features of crop and initiate predictive maintenance activities for all the sensors associated with that farm land. This activity facilitates the farmer with sensor failure reduction and helps in effective monitoring of the crop. Different factors like humidity, soil temperature and the luminosity of the crops are considered for effective maintenance activity. This work is implemented using the forward and backward propagation algorithms using certain attributes of dataset. This paper facilitates an effective prediction ecosystem after investigating the numeric data collected from different sensors attached to plants which are meant for earlier failure prediction of those devices depending on the trained data. Using the forecast model and analyzing time-series data, LSTM model has obtained good accuracy with almost 97% accuracy.

Keywords: *Agriculture, PM, Natural conditions, luminosity, Machine Learning*

1. INTRODUCTION

Predictive Maintenance (PM) is designed to determine the conditions and the problems which are about to occur and when the maintenance should be performed to overcome the problems [1]. This method is broadly applied to distinct machines and systems in regard to many fields like household, agriculture, information technology, automobile, and other various applications. The PM is used to assess the systems performance, integrity, behavior, accuracy and many more factors at any instance. Generally, PM is frequently used in heavy industries to estimate the alternatives to most of the internal tasks. The idea to implement on agriculture to improve the efficiency and provide the machines to overcome the challenges on the smaller obstacles faced by farmers. The demand for agriculture needs to be increased due to growing public demand for raw material and groceries are increased reliably. Due to the demand and supply chain, modern farming with excess volumes of pesticides and chemicals

have gradually been increased, as the modern farming methods increase the yield and the minerals present in the soil are gradually depleting.

Initially, agriculture is not a single and elementary origin. A wide range of plants and animals have been exclusively trained at various times and locations[2]. With the availability of different sensors for understanding and fetching the climatic data at different time intervals has become very affordable. This helps the farmers to understand the crop health and yield without visiting the farm land. The customer can analyze the crop health depending on the data fetched by different sensors. Many times, the sensors get damaged due to different natural factors like excessive sunlight, rain, damage due to insecticides and many other reasons. This will ensure the sensors are damaged at crucial times where the data from the crops is of utmost important. To overcome this, regular predictive maintenance activities should be performed on the sensors which overcome their problems by

analyzing the numerical data generated from them. These activities should be performed before the device completely gets failed and need a careful preventive measure. These predictive maintenance activities are performed on the sensors log data in a timely manner and understand their efficiency in data collection.

Corrective maintenance states that computing the problems which specify the critical setbacks of each category of plant. This strategy will increase the variable costs and hence improve the scope of the green revolution. This type of maintenance is used when there is no negative impact on the cultivation. As a result, effective preventive maintenance entails scheduling activities at distinct times to shorten unexpected losses which occur due to natural disasters and over usage of chemicals. PM is performed using rigorous formulas based on information generated by various sensors at various intervals. The data generated is numeric, and it can be inspected using various measured parameters to ensure cost cutting [4] and maintenance using new age computing techniques [5].

The various scenarios fail the calculations of accuracy and efficient predictions at various phases of information gain and processing. Different models depict the incapability of handling the massive amounts of data generated by a specific sensor of a specific plant or agricultural land. Thus, this system offers to pact with massive amounts of data generated from different sensors [6] which are facilitated with a methodology to acquire, compute, and investigate the information. To support supply chain management, it is essential to forecast the machine's lifetime. Over time, maintenance has become prominent due to the numerous substitutions or upgrades available and are required frequently. This type of issue is solved by constructing effective PM which is a machine learning and deep learning system that provides interest for all kinds of systems [7]. Some crops and plantations just adapt to the surroundings and weather conditions and can resist the behavior of nature.

The log information is collected daily from sensors that are present in the soil. The system collects and analyses a large volume of log data sets in order to arrange time series data for training and testing the proposed model. The subsequent intermediate stages involve avoiding anomalies and retrieving clean data and the model is passed for testing using the predicted model, with the restoration time of any machine

as the focus. This project is part of research aimed at identifying and forecasting heavy machine failures, thereby promoting the PM outlines for adequate machine operation and performance [8].

The revolution of Industrial revolution 4.0 is focused more in this work focuses on successfully appending with crop maintenance which became an important factor. The subsequent part focused on the disparate contributions of various expert analysis with their contributions. The next part focus on the work done on log data which is stored for a period that relates to the required factors and the results obtained from those predictions. Finally, the conclusion of this work along with its benefits and societal advantages are documented.

2. LITERATURE SURVEY

The roots of agriculture are traced long back to 9000 BCE as the main source of food. Later agriculture evolved into different formats like modern agriculture, horticulture, cattle breeding, and aquaculture. The food chain and the supply chains have developed a lot in the past several millenniums. PM is a type of organized activity that focuses on simplification and failure prevention methods. This can be done in regard to systematic periodic machine survey that is typically performed outside of production hours. It is furnished by integrating various maintenance activities such as periodic checks, preventive measures, and so on. The regular scheduling of the crop maintenance checks is essential to avoid pesticides, fertilizers and other insects attacking the crops [9]. These calculations establish a part of PM which monitor the status and situation of the agriculture land using predictive models which prevent the sensor failure after under-going various maintenance activities. PM tool was proposed by researchers [10] based on R-package and web application. It helps developers & engineers to analyze easily datasets generated by machines [11] based on various support decision support systems in machine learning [12] for optimization of maintenance.

Different prediction models are identified as:

- 1) Lifetime Value Model for Customer (LVMC)
- 2) Customer Segmentation Model for Customer (SMC)
- 3) PM Model for Customer (PMMC)
- 4) Quality Assurance Model for Customer (QAMC)

PM is an efficient method for improving the reliability of complex systems through their maintenance strategies. The goal of PM begins with prediction of equipment maintenance through predictive models. Ideally, a maintenance schedule happens frequently which leads to zero sensor failure through this approach. This work proposes a PM modeling mechanism which is implemented as PM based web-application that helps domain experts to analyze multiple time series sensor data which is used for testing PM models based on remaining useful life (RUL) estimation. PM plays a major role in cost and time enhancement [13] models which are required for monitoring systems. The maintenance strategy in this work has three steps: data acquisition, data processing [14], and decision-making. The log data collection is the initial phase in this work, which is divided into two: event and situation monitoring data. The prediction is related with maintenance based on numerical data [15]. The second step is data preprocessing, which is required when the information consists of missing, inconsistent, and noisy data.

Data anomalies [16] are evolved due to variety of factors such as sensor failures, memory leaks and overflows in storage devices, and so on. This is known as data cleaning, and it provides the maintenance function with definite inputs. Many advanced techniques, such as regression and clustering techniques, are also used to estimate missing values [17] to remove noisy values from input by outlier detection. In real-time perspective the least importance given to a large amount of landmass where the production and maintenance are calculated on a huge volume [18] and the maintenance of the small area lead to large principal amount. The predictions are compared mainly based on two major practices in machine learning approaches. The prediction or PM approach [19] is applied using comparisons between the LSTM models which are known for dealing with the time series data frames and ARIMA models which are popularly known for statistical analysis of the time-series data.

The advantages of Crop analysis/ management are

- The crop monitoring helps us to reduce the maintenance costs, provides a higher crop yield.

- Helps the farmers to decide the correct pesticides, insecticides and fertilizers to prevent diseases to the plants.

- The sensors measure various factors like rainfall, temperature, humidity, wind speed, wind direction and air pressure.

- The method of crop monitoring system includes the collection of a certain number of samples per each day, comparing the current values with the historical records, indexing the resources based on the different factors and developing the algorithm to use the historical data sets for prediction analysis.

Cons of Crop management

- Though the PM of crop monitoring is a newly introduced technique it is still under the development phase, and it is important to have specialization in the tasks performed.

- The initial cost of the introduction of crop maintenance may be high and it should be compared to the long-term investment.

- It takes a lot of time to fetch the data which will be sufficient to hold the most accurate prediction.

- Data collection and analysis is the most challenging task which requires expertise.

Agriculture is the most important step in producing food, feed, fiber, and variety of products by growing plants and raising domestic livestock. It is the art of controlling the growth of animals and plants for human consumption. As the population density and demand for livestock has increased a lot the demand for agriculture also increased as the rate of production is being depleted due to various factors like air, water and soil pollution.

The modern type of agriculture is an evolutionary method to agricultural modernization and farming practices that help farmers to increase efficiency and reduce the no. of natural sources like water, and land which is essential to meet the requirements of the current trends and pace of consumption of the food. Due to fear of crop failure and loss of investment and income modern farming is largely practiced over the world. Modern agriculture has increased food affordability, increased food supply, food safety, and increased sustainability [20]. The environmental issues are concerned as it is based on a high inflow/outflow technique that employs hybrid seeds of greater-yielding varieties as well as abundant irrigation water, fertilizers, and pesticides. The causes of modern farming are mentioned as follows:

1. Soil Erosion
2. Contamination of groundwater
3. Waterlogging and salinity
4. Eutrophication

5. Excessive use of pesticides

3. Proposed Work

Prediction helps in discovering new alternative methods for farming and developing an environment to lower the maintenance cost and side effects of particular and man-made pesticides and man-made fertilizers. It helps in the improvement of crop yield and improves total turnover. The dataset is collected from sensors equipped with different plants which facilitates their overall growth. The data is dynamic as they change depending on climatic changes but they are numeric. The data is pre-processed before classification stage as performance analyzed is required to compute the most recent failure date of system.

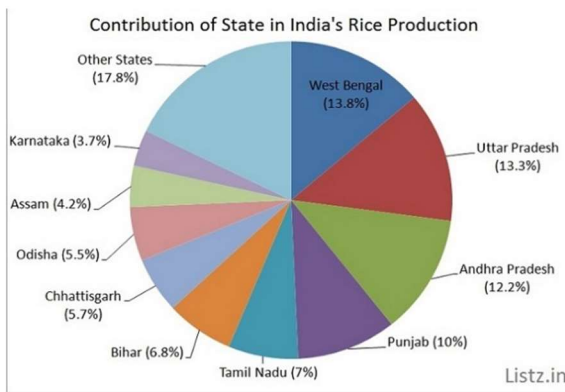


Figure 1. Average Agricultural Contribution Across Country

After the dataset analysis, the model is created and trained to provide accuracy. The model is structured to represent numerical time-series data. The data is combined, and scaled between the ranges of (0 - 1) which is performed using various scaling algorithms such as the standard scaling and min-max scaling method.

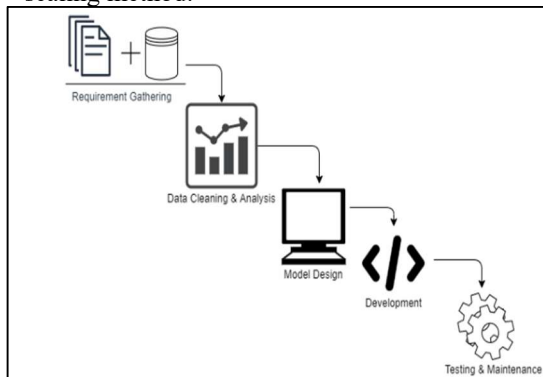


Figure 2. Waterfall Methodology Implementation For Agricultural Maintenance

The available time-series data is fed into the classification model to analyze accurate values are based on the correlation rate (R-value). The data is divided into training and testing using Splitting techniques, such as the shuffle splitting (classical) technique, are used to cross-validate data frames. Finally, the model's conclusion is generated using a single data frame after analyzing the relevant indexes.

3.1. Log data & Database configurations

The database is used for the project is in the form of log data, which is in the form of comma-separated-values (CSV) files. The log data is structured in a format that contains the important details of logs and makes it easier to interact with them in different ways. The default structuring of the data logs as plain text. The drawbacks of the log files are unstructured or raw data. This makes it hard to query and sort the information from the database. Hence the log data is structured in the form of tables and CSV to sort and find the values easily.

3.2. Prediction of Measurement Data

3.2.1 Forward Propagation

The model used for PM uses the principle of multilayer perceptron's which provides us with concepts like forwarding propagation (forward pass) and backpropagation. The forward pass relies on the computing and storing of the intermediate variables of a network from input to output layer.

Let's consider,

- Take the input: $x \in \mathbb{R}^d$
- The intervening variable: $z = W(1)x$,
- Let the activation function be ϕ and hidden activation vector of length h , i.e., $h = \phi(z)$.
- The hidden variable h is intervening variable $o = W(2)h$.
- Assuming that the loss function is l and sample label is y , then the loss term calculation for a single data sample, $L = l(o, y)$.

3.2.2. Backpropagation

This method facilitates in determining the peak (gradient) from neural network models which traverse the network from the input to the output layer. While calculating the gradient for some parameters, the gradient stores intermediate variables (partial derivatives).

Let us consider the function:

- $Y = f(X)$ and $Z = g(Y)$, in which the input and the output X, Y, Z are tensors

- of arbitrary shapes. By using the chain rule, we can compute the derivative of Z to X via: $\partial z/\partial x = \text{prod}(\partial z/\partial y, \partial y/\partial x)$
- To calculate the gradients of the objective function $J=L+sJ=L+s$ for the loss term L and the regularization term s. $\partial J/\partial L=1$ and $\partial J/\partial s=1$
 - To calculate the gradients of the regularization term for both parameters:
 $\partial s/(\partial W^{(1)}) = \lambda W^{(1)}$ and $\partial s/(\partial W^{(2)}) = \lambda W^{(2)}$
 - To obtain the gradient concerning W(1) we need to continue back propagation along with the output layer to the hidden layer.
 - The gradient is given by: $\partial J/\partial h = \text{prod}(\partial J/\partial o, \partial o/\partial h) = W^{(2)} \partial J/\partial o$

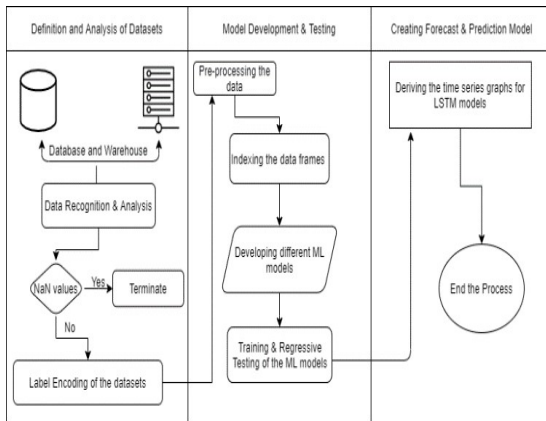


Figure 3: Proposed Methodology

3.3 Initialization of the algorithm

The forward and backward propagation algorithms are implemented at certain levels. The first level i.e., forward propagation is used in training the predictive model with the sample dataset and the second level includes back-propagation used in acquiring the predicted result from the model. Further, the median values of each iteration are neglected as the resultant graph will be the straight line which would not help in PM. For the LSTM model to perform predictions, the model is compiled with different optimizers. The loss functions as binary cross-entropy are used for binary outputs and categorical entropy for multiple classifications. The activation functions such as sigmoid and SoftMax are used to determine whether they should be activated or not based on the models' predictions.

3.4. Model Deployment

This model deployment is divided into regard priority and in hierarchy manner. The forecasting model is developed, including data

analysis, preprocessing, creating, training the model, data classification, and forecasting the system's recent failure [24]. Every timestamp in dataset contains an hidden state (ht) and memory. The model development facilitates in sensing anomalies in dataset, while providing an index for the data frames.

Forecasting Model Algorithm

Step:1. Retrieve the dataset from the directory.

Step:2. Preprocess the data which do not affect the model i.e., constant values.

Step:3. Visualize the time series data report using fbprophet.

Prediction Algorithm

Step: 1. Load the forecasting model after preprocessing.

Step: 2. Analyzing the forecasted data.

Step: 3. Run the model with the predicted data to obtain the timestamp.

This model deployment involves three phases as below:

- Model Training.
- Model Analysis from the trained network.
- Obtaining the predictions from the model.

The system's training method is known as the offline training approach.

4. Experimental Results

The data frames are considered for developing various types of prediction models to monitor the crop or a piece of agricultural land [25].

	A	B	C	D	E	F
1	TimeStamp	Id_no	Humidity	Soil_temp	Amb_temp	Illuminance
2	03-08-2019 11:58	1	65	32.3	30.9	18
3	03-08-2019 11:59	2	65	31.9	30.9	18
4	03-08-2019 12:00	3	63	31.9	31.8	19
5	03-08-2019 12:00	4	65	31.9	31.4	16
6	03-08-2019 12:00	5	69	31.9	31.3	16
7	03-08-2019 12:01	6	70	31.9	31.3	16
8	03-08-2019 12:01	7	55	31.9	31.1	16
9	03-08-2019 12:01	8	61	31.9	31	17
10	03-08-2019 12:02	9	62	31.9	30.9	16
11	03-08-2019 12:02	10	64	31.9	30.9	16
12	03-08-2019 12:02	11	65	31.9	30.9	15
13	03-08-2019 12:03	12	67	31.9	30.9	15
14	03-08-2019 12:17	13	64	32.1	30.4	580
15	03-08-2019 12:18	14	68	32.4	30.6	335
16	03-08-2019 12:18	15	67	32.5	30.6	513
17	03-08-2019 12:18	16	65	32.6	30.7	739
18	03-08-2019 12:19	17	66	32.8	30.8	237
19	03-08-2019 13:58	18	63	31.6	30.3	173
20	03-08-2019 13:58	19	65	31.6	30.3	171
21	03-08-2019 13:59	20	66	31.6	28.9	169
22	03-08-2019 14:00	21	68	31.7	28.9	169
23	03-08-2019 14:00	22	69	31.6	28.9	169

Figure 4: Data Set Overview

Various models are considered and the results are acquired to compare the best fit of the output for the given task. The different types of prediction models considered are:

- LSTM
- Standard Scalar
- Simple RNN

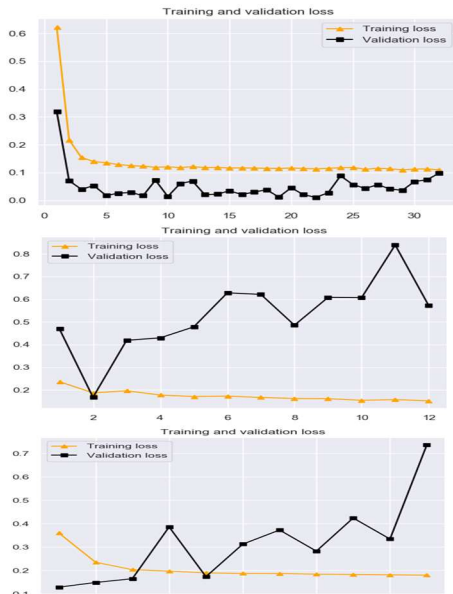


Figure 4. Training And Validation Data Loss In A) LSTM, B) Standard Scalar, C) Simple RNN. X-Axis: Training Data Loss (Epoch Values), Y-Axis: Validation Data Loss (Epoch Values)

The ROC is the type of graphical plot according to the variable threshold the binary classification is estimated. This ROC curve is obtained by plotting the positive rate against the false-positive rate which is used for plotting the timestamp and other feature in the data set. The training and verifiable losses for our model are displayed using ROC curves[26]are analyzed using the epoch number asrequired to train the RNN and LSTM model.

The number of epochs is determined from one to the higherstretch of the accuracy ranges. The loss is identified as a metric for poor prediction.A loss is a numerical valuewhich analyses the predictionswith epochs = range(1, len(acc) + 1)

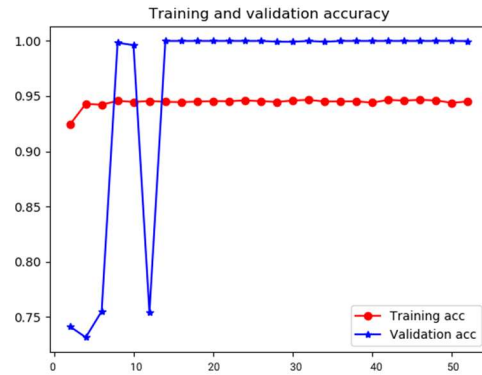


Figure 5. Training Vs Validation Accuracy A) LSTM, B) Standard Scalar, C) Simple RNN. X-Axis: Training Data Loss (Epoch Values), Y-Axis: Validation Data Loss (Epoch Values)

The accuraciesare used to represent the precision data of our model. It is based on the values fed to the model.

$$\text{epochs} = \text{range}(1, \text{len}(\text{acc}) + 1)$$

Similarly,its accuracy is identified using model analysis which facilitates identifying relationships between variables and datasets based on input data. It is observed that 97% accuracy is obtained using LSTM model which best fits for PM.

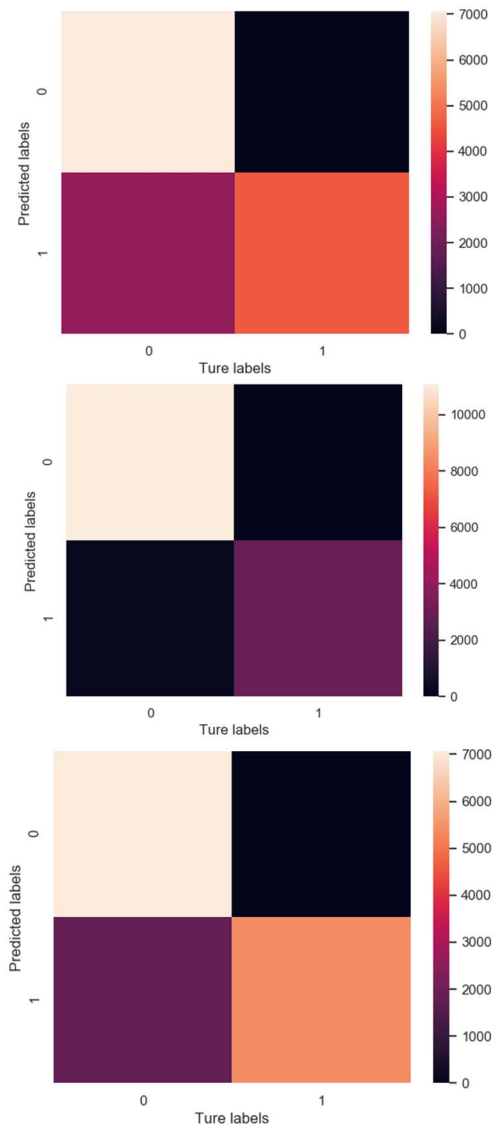


Figure 6. Confusion Matrix For Predicted Class With Actual Class A) LSTM, B) Standard Scalar, C) Simple RNN

This graph depicts the deviation between the total distortions and the total clusters in our model analysis. Clusters are different data samples grouped together having dissimilar properties whereas the theoretical metrics that define finite metric space are known as distortions. The graphs visualize [27] time-series data, used for displaying the forecasted model with selected features from the dataset. The confusion matrix facilitates a visual representation [28] of any model's performance [29].

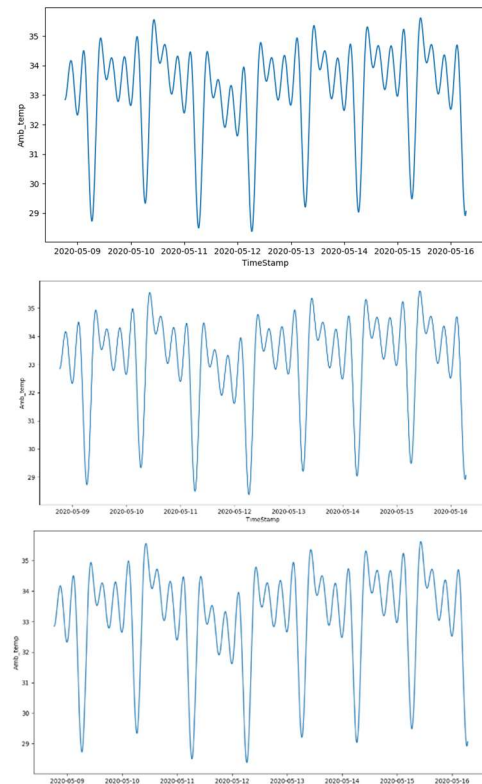


Figure 7. Final Output Of Predicted Maintenance To Improve Crop Yield A) LSTM, B) Standard Scalar, C) Simple RNN, X-Axis – Timestamp, Y-Axis – Selected Feature Ambience Temperature

The relationship between predicted and actual classes showcased in the above graphs includes the heat maps on both the axes based on time-series data. The precision values are used to understand the accuracy of the model.

5. CONCLUSION

Crop maintenance can be performed manually or automatically with the help of machines for reliable results. Many tools exist in the market which assist the users in developing and executing PM models for estimating crop yield, sales maximization, and cost optimization. Sensors fail to perform their activity on crops due to variety of external factors like rain and sunlight. This work helps in early identification of the sensor failure which helps the farmer for incorporating preventive measures and ensure efficiency of crop analysis ecosystem. This paper focused initially on effective PM mechanism for small, medium, and large crop monitoring methods. The scope of the model can be flourished so that it can predict numerical data samples and can be shrunk to a specific point for prediction which can be widely applicable for different crops.

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