IoT Based Smart Agriculture To Avoid Post Harvest Losses Using Machine Learning Algorithms

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Abstract

This research paper explores the potential of using Internet of Things (IoT) technology to reduce post-harvest losses in the agriculture sector. Post-harvest losses have been a major challenge in the agricultural industry, leading to significant economic losses and food waste. Post-harvest losses (PHL) refer to the significant reduction in the quantity and quality of food produced from the time it is harvested until it is consumed. The paper provides a detailed analysis of the current state of post-harvest losses in the agricultural sector, the potential benefits of IoT technology in reducing these losses, and the existing IoT-based solutions that are already in use. The research also highlights the various challenges and limitations of implementing IoT technology in agriculture and provides recommendations on how to overcome them. The findings of this research have significant implications for the agricultural industry and can help stakeholders in the sector to make informed decisions about adopting IoT-based solutions to reduce post-harvest losses. Machine learning(ML) based model generated to identify and avoid losses association with IoT devices. The proposed Random Forest ML based methodology evaluate the results and report the alert messages to farmers for decision making purposes.

Keywords: IoT Sensors, Random Forest, Machine Learning, Smart Farming, Accuracy, ML Classification, Precision Agriculture

INTRODUCTION

Agriculture is one of the most crucial sectors for human survival, providing food, fiber, and fuel to sustain the growing population. However, post-harvest losses have remained a persistent challenge in the agricultural industry, leading to significant economic losses and food waste. According to the Food and Agriculture Organization (FAO), global food waste accounts for about one-third of the total food produced for human consumption, which translates to approximately 1.3 billion tons per year. Post-harvest losses contribute significantly to this waste, with losses estimated at around 14% of the total food production in developing countries.

Reducing post-harvest losses is essential for achieving food security, reducing food waste, and improving the livelihoods of smallholder farmers who often bear the brunt of these losses. Internet of Things (IoT) technology has emerged as a promising solution to address this challenge. IoT technology provides real-time monitoring and control of various post-harvest processes, such as storage, transportation, and packaging. This technology has the potential to significantly reduce post-harvest losses by ensuring optimal storage conditions, minimizing damage during transportation, and facilitating timely interventions.

RELATED WORK

Bhakta et al [1] present a research that focuses on the most current trends in precision agriculture. The current situation, benefits, and downsides of various technologies are examined. Its goal is to examine various precision agricultural applications. Jha et al. conducted a review of agricultural automation based on artificial intelligence. They examined several market innovations and found that the combination of sensors, Internet, and ML may be utilised to automate agricultural activities [2]. Patricio and Rieder investigated the use of machine learning and computer vision in precision agriculture. They analysed 25 publications from 2013 to 2017 using six databases (ScienceDirect, Scopus, Springer, Web of Science, ACM, and IEEE) but only with five crops (maise, rice, wheat, soybean and barley)[3]. Tian et al. investigated agricultural machine learning technologies. They looked at 41 papers published between 2017 and 2019 and came to the conclusion that "computer vision technology combined with artificial intelligence algorithms will improve the economic performance, general performance, coordination performance, and robust performance of agricultural automation systems." [4]. Paul et al. focused on computer vision and machine learning in agriculture, reviewing over fifty works from 2007 to 2018. And they have just seen a considerable advancement [5]. Rehman et al. did an excellent job of analysing over 200 articles on machine learning techniques for agricultural machine vision systems[6]. Chlingaryan et al. investigated machine learning in agriculture for agricultural production prediction, with an emphasis on nitrogen control. They also stated that ML and sensing use had improved quickly during the previous 10 years [7-8]. Sharma et al. narrowed their emphasis even further, analysing the effectiveness of sustainable agriculture supply chains using machine learning. They analysed 93 publications using the databases Business Source Premier, Scopus, Emerald Insights, and Web of Science. The article demonstrates significant benefits of machine learning deployed in agricultural supply chain systems [9-12]. Behmann et al. investigated sophisticated machine learning approaches for detecting biotic stress in crop protection. Curiously, the authors cited over a hundred studies, yet they did not include CNNs, which are currently state-of-the-art neural networks[13-19].

IOT AND MACHINE LEARNING IN AGRICULTURE

IoT and machine learning are two rapidly evolving technologies that have significant potential to revolutionize the agriculture industry. IoT technology provides real-time monitoring and control of various agricultural processes, such as irrigation, soil monitoring, and crop monitoring, while machine learning algorithms can analyze large amounts of data generated by IoT devices to provide insights and make predictions. Together, these technologies can help farmers make informed decisions and optimize agricultural processes, leading to increased productivity and reduced costs.One of the most promising applications of IoT and machine learning in agriculture is precision agriculture. Precision agriculture involves using data-driven insights to optimize various agricultural processes, such as irrigation, fertilization, and pest control. IoT sensors can provide real-time data on soil moisture levels, temperature, and other environmental factors, while machine learning algorithms can analyze this data to provide insights on optimal crop management practices. For example, machine learning algorithms can analyze crop images captured by drones or satellites to identify early signs of crop disease or nutrient deficiencies.

Another application of IoT and machine learning in agriculture is supply chain optimization. IoT sensors can provide real-time data on the location and condition of agricultural products during transportation and storage, while machine learning algorithms can analyze this data to optimize logistics and reduce waste. For example, machine learning algorithms can predict the optimal time for harvesting and transporting crops based on weather forecasts and transportation availability.Despite the significant potential of IoT and machine learning in agriculture, there are also challenges and limitations to their implementation. These include the high cost of IoT devices, the need for reliable internet connectivity in rural areas, and concerns about data privacy and security. Nevertheless, as these technologies continue to evolve and become more accessible, they have the potential to transform the agriculture industry and provide significant benefits to farmers, consumers, and the environment.

Biodegradation

On the positive side, biodegradation can enhance the nutritional value and sensory quality of grains. For example, the fermentation of grains by microorganisms can increase the bioavailability of nutrients such as proteins, carbohydrates, and vitamins. Additionally, the biodegradation of grains can enhance their flavor, aroma, and texture, making them more appealing to consumers. However, biodegradation can also have negative impacts on the quality and safety of grains. For example, the growth of fungi on grains can produce mycotoxins, which are toxic compounds that can cause illness or death in humans and animals. Additionally, the biodegradation of grains can lead to spoilage, reducing their shelf life and market value.To manage the biodegradation of grains, various strategies can be employed. These include using appropriate storage conditions, such as temperature and humidity control, as well as implementing effective pest control measures to prevent infestations by insects and rodents. Additionally, using preservatives and antimicrobial agents can help prevent the growth of microorganisms on grains.

Soil

Soil is a complex and dynamic natural resource that plays a critical role in supporting life on Earth. It is a mixture of minerals, organic matter, water, air, and living organisms, and serves as a home and source of nutrients for plants and other organisms. Soil is also important for water filtration, carbon sequestration, and climate regulation.Soil is formed over long periods of time through the physical, chemical, and biological weathering of rocks and other geological materials. Factors such as climate, topography, and vegetation also influence soil formation. There are various types of soil, each with unique physical and chemical properties, such as texture, pH, and nutrient content.The combination of Internet of Things (IoT) technology and machine learning models can provide valuable insights for soil data analysis in agriculture. IoT sensors can be used to collect data on various soil parameters, such as moisture content, temperature, and nutrient levels.

Machine learning models can then be trained on this data to identify patterns and make predictions about soil health and crop performance.

PROPOSED MODEL FOR REDUCE THE POST HARVEST LOSSES USING IOT AND MACHINE LEARNING ALGORITHMS

Here is a proposed methodology for using IoT and machine learning models for soil data analysis in agriculture:

Identify relevant soil parameters: The first step is to identify the soil parameters that are most relevant to crop growth and health. These may include moisture content, temperature, nutrient levels, pH, and more.

Install IoT sensors: Next, IoT sensors should be installed in the soil to collect data on these parameters. The sensors should be strategically placed throughout the field to ensure adequate coverage and accuracy.

Collect and store data: The IoT sensors should collect data on a regular basis, such as hourly or daily. The data should be stored in a centralized database or cloud platform for easy access and analysis.

Pre-process and clean data: Before the data can be used for machine learning models, it must be pre-processed and cleaned to remove any outliers or errors. This may involve filtering, normalization, or other data cleaning techniques.

Train machine learning models: Once the data has been pre-processed and cleaned, machine learning models can be trained to analyze the data and make predictions about soil health and crop performance. This may involve supervised learning, unsupervised learning, or a combination of both.

Validate and test models: The trained machine learning models should be validated and tested on new data to ensure their accuracy and reliability. This may involve using a separate dataset or conducting field trials.

Use models for soil data analysis: Once the machine learning models have been validated, they can be used to analyze soil data in real time. This may involve making recommendations for irrigation management, fertilizer applications, crop rotation, or other land management practices.

Monitor and refine models: The machine learning models should be monitored and refined over time to ensure their continued accuracy and effectiveness. This may involve updating the models with new data, adjusting the parameters, or using different algorithms or techniques.

Here is an example of a mathematical equation for the optimized Random Forest approach in the proposed model:

$$Y = RF(X) \ldots\ldots (1)$$

where Y is the predicted crop yield or other measure of crop performance, X is the vector of soil parameters collected by IoT sensors, and RF is the Random Forest model that maps X to Y.

The Random Forest model combines multiple decision trees and is optimized to minimize the error between the predicted crop yields and the actual crop yields. Each decision tree in the Random Forest is trained on a random subset of the input data, and the final prediction is the average of the predictions from all the decision trees.

The equation for the Random Forest model can be expressed as:

Y = ∑i=1n(Ti(X) / n)….(2)

where n is the number of decision trees in the Random Forest, Ti is the ith decision tree in the Random Forest, and Ti(X) is the prediction of the ith decision tree for the input vector X.

The Random Forest model uses a combination of feature selection and bootstrap aggregating (bagging) to reduce the variance and improve the accuracy of the predictions. The optimized Random Forest approach also involves tuning the hyperparameters of the model, such as the number of decision trees and the maximum depth of each decision tree, to further improve the performance of the model.

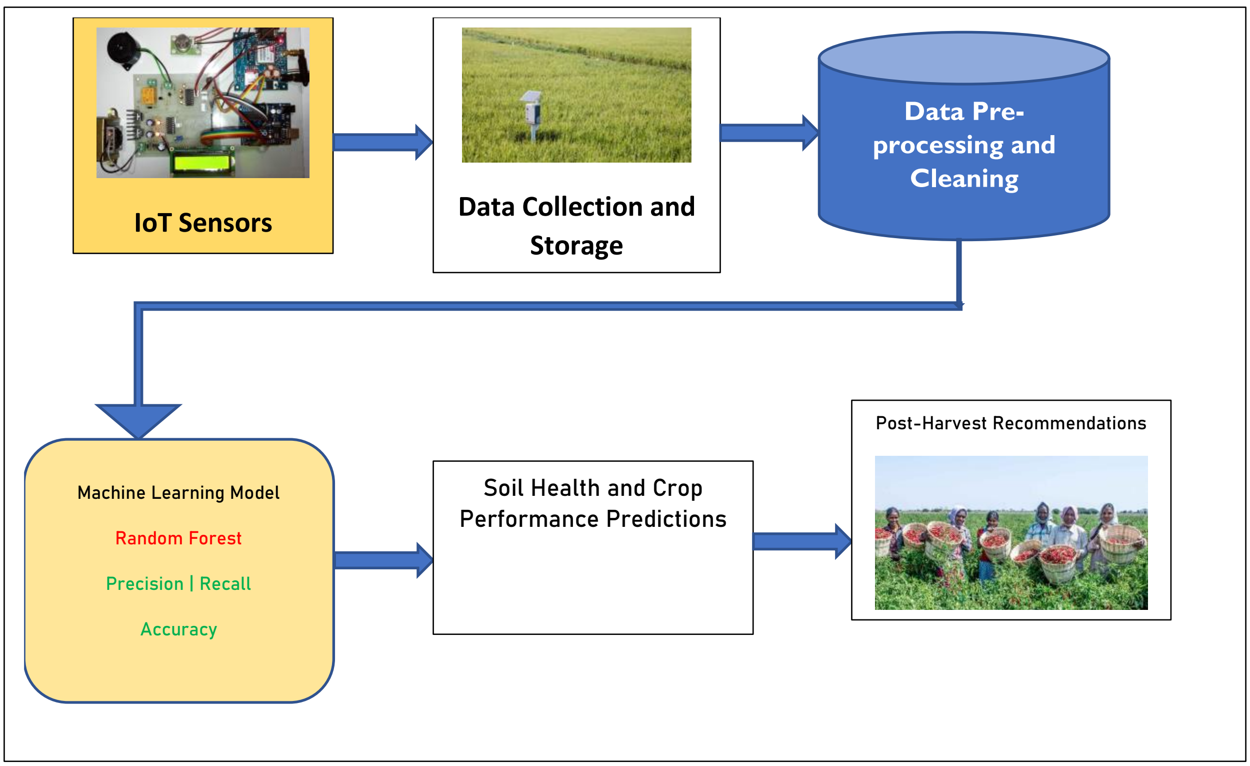

Figure 2 : Proposed Optimized Random Forest Approach

In this model(figure 2), IoT sensors are installed in the soil to collect data on various parameters such as moisture content, temperature, and nutrient levels. The data is then collected and stored in a centralized database or cloud platform. Next, the data is pre-processed and cleaned to remove any outliers or errors.The pre-processed data is then fed into machine learning models, which analyze the data and make predictions about soil health and crop performance. These predictions can then be used to make recommendations for land management practices such as irrigation management, fertilizer applications, or crop rotation.

RESULTS AND DISCUSSION

In this model, Dataset named smart-agricult ural-production-optimizing-engine is collect ed from Kaggle repository which Consists of 22 Unique Crops such as Maize, Wheat, Ma ngo, Watermelon, Mango etc.The dataset als o consists of soil conditions required to gro w the crops

- N: The Ratio of Nitrogen Content in Soil.
- P: The Ratio of Phosphorus Content in Soil.
- K: The Ratio of Potassium Content in Soil.

The following table 1 and Figure shows the average climatic and soil requirements of the proposed model to reduce the post harvest lo sses in smart farming.

Table 1 : Average Climate and soil requirements

N	**P**	**K**	**Temperature**	**Humidity**	**ph**	**Rainfall**
count	2200	2200	2200	2200	2200	2200
mean	50.551818	53.362727	48.149091	25.616244	71.481779	6.46948
std	36.917334	32.985883	50.647931	5.063749	22.263812	0.773938
min	0	5	5	8.825675	14.25804	3.504752
25%	21	28	20	22.769375	60.261953	5.971693
50%	37	51	32	25.598693	80.473146	6.425045
75%	84.25	68	49	28.561654	89.948771	6.923643
max	140	145	205	43.675493	99.981876	9.935091

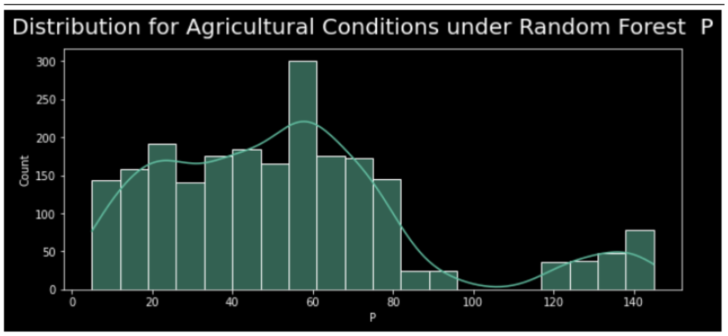

Figure 3: Agriculture conditions based on p using Random Forest

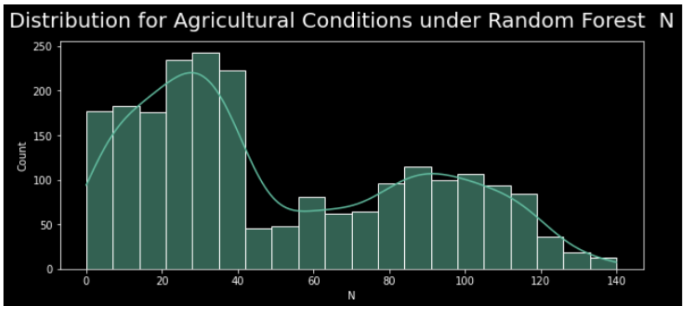

Figure 4: Agriculture conditions based on N using Random Forest

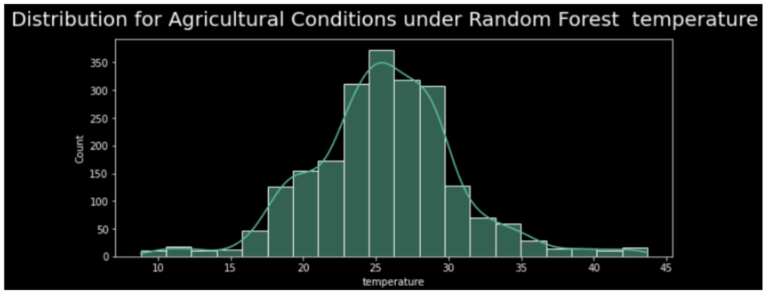

Figure 5: Agriculture conditions based on Temperature using Random Forest

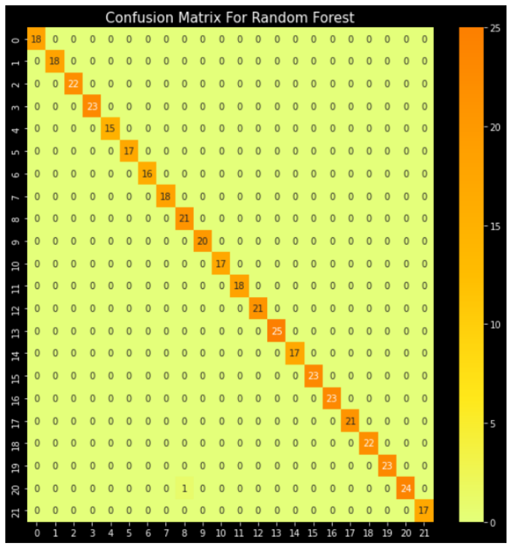

Figure 6: Confusion Matrix for Random Forest

	precision	recall	f1-score	support
apple	1.00	1.00	1.00	18
banana	1.00	1.00	1.00	18
blackgram	0.86	0.82	0.84	22
chickpea	1.00	1.00	1.00	23
coconut	1.00	1.00	1.00	15
coffee	1.00	1.00	1.00	17
cotton	0.89	1.00	0.94	16
grapes	1.00	1.00	1.00	18
jute	0.84	1.00	0.91	21
kidneybeans	1.00	1.00	1.00	20
lentil	0.94	0.94	0.94	17
maize	0.94	0.89	0.91	18
mango	1.00	1.00	1.00	21
mothbeans	0.88	0.92	0.90	25
mungbean	1.00	1.00	1.00	17
muskmelon	1.00	1.00	1.00	23
orange	1.00	1.00	1.00	23
papaya	1.00	0.95	0.98	21
pigeonpeas	1.00	1.00	1.00	22
pomegranate	1.00	1.00	1.00	23
rice	1.00	0.84	0.91	25
watermelon	1.00	1.00	1.00	17
accuracy			0.97	440
macro avg	0.97	0.97	0.97	440
weighted avg	0.97	0.97	0.97	440

Figure 7: Classification of the model

```
randomforest = RandomForestClassifier()
randomforest.fit(x_train, y_train)
y_pred = randomforest.predict(x_test)
acc_randomforest = round(accuracy_score(y_pred,y_test) * 100, 2)
print(acc_randomforest)
99.77
```

Figure 8 : Radom Forest model

The above figure 3 – 8 shows the proposed model execution in Colab using Python, under the IoT based Machine learning algorithm evaluation on the agriculture data, the proposed model provide 99.77% accuracy to predict the post harvest scenario and avoid losses to recommend to the farmers.

CONCLUSION

Water content and absorption are important factors to consider in various applications, and understanding these properties can help optimize processes and products for improved performance and quality. Various methods are available to measure water content and absorption, including gravimetric methods, moisture sensors, and spectroscopic techniques. IoT technology offers a powerful tool for monitoring and managing water content and absorption in various applications. By providing real-time data and insights, IoT sensors can help optimize processes and products for improved performance and quality.The combination of IoT and machine learning models offers a powerful tool for soil data analysis in agriculture. By providing real-time data and insights, this approach can help optimize crop performance, reduce waste, and promote sustainable land management practices.This IoT model provides a powerful tool for soil data analysis in agriculture, helping to optimize crop performance and promote sustainable land management practices.

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