SMART FARM PEST MONITORING AND DETECTION SYSTEM USING MACHING LEARNING TECHNIQUE

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ABSTRACT

This paper introduces a smart farm pest monitoring and detection system utilizing machine learning techniques. The objective of this study is to develop an intelligent system for monitoring and detecting pests in rice farms using machine learning. The methodology involves data collection, data processing, feature extraction, and training of K-nearest neighbor (K-NN) algorithm with the feature vectors to generate the smart pest monitoring and detection model. The model was implemented and tested through simulation approach. Comparative analysis was used for the validation model. The results demonstrate a notable 2% improvement when compared to existing classification models.

Keywords: Pest Control Hyper Spectra Sensor, Smart Farm, K Nearest Neighbor, Matlab

1. INTRODUCTION

Agriculture, as defined by elementary science, encompasses the cultivation of crops and the rearing of animals to meet human needs. It comprises two main categories: crop production and animal husbandry. Notably, animal husbandry has demonstrated remarkable success over time, evident in the wide variety of meat available in the market for human consumption.

In Nigeria, agriculture has emerged as a vital source of food production and income generation in numerous localities. Particularly renowned are the farmers in this region, who cultivate substantial quantities of rice, which they sell to other parts of the country after harvest, thereby generating income. The demand for locally produced rice has surged due to a government ban on rice imports, prompting farmers in this region, along with a few other states, to work tirelessly to meet the country's needs. Despite their achievements, these farmers face a significant obstacle to their crop yield efficiency: plant pests.

Plant pests manifest as biochemical symptoms that damage crops, resulting in poor yield. It is imperative to address this issue promptly. Over the years, various techniques have been proposed to detect and monitor farm pests. The traditional approach involves manual observation of plant behavior and decision-making based on visual cues, such as plant greenness. Alternatively, smart farm monitoring systems utilize wireless sensors, image processing, artificial intelligence, satellite imagery, and other technologies to collect and analyze data, enabling informed decisions. Each approach possesses distinct advantages and disadvantages, which are explored in (Katrin, 2016). Among them, wireless sensor usage stands out as the most extensively researched method.

Artificial intelligence (AI) comprises algorithms capable of learning and making accurate decisions based on training data or predefined rules. Four classes of AI exist: expert systems, fuzzy logic, genetic algorithms, and machine learning (ML), as discussed in (Sharma, 2018). Notably, machine learning outperforms other AI techniques in solving classification problems. ML algorithms can learn patterns from data and make highly accurate classification decisions. This research will leverage ML to enhance the performance of the wireless sensor network, ensuring that farmers receive accurate and reliable data.

At Ebonyi state, plant pests have been a major hindrance to achieving optimal rice harvest. These pests have significantly impacted the performance of rice farms, resulting in poor yields despite farmers' substantial efforts. The traditional pest detection system lacks sensitivity to chlorophyll response due to plant reflectance, thus failing to accurately identify pests and communicate this information to farmers. This persistent challenge carries social and economic implications, including poor harvests, farmer frustration, reduced interest in agricultural investments, and low yields. Therefore, there is a pressing need for a reliable and affordable system for smart pest monitoring in farms. Solving this problem would not only improve rice yields but also contribute to eradicating hunger in the nation

2. RELATED WORKS REVIEW

Nehenih et al. (2018) proposed a hybrid technique combining support vector machine and fuzzy logic for paddy plant pest detection. Achieved a pest detection accuracy of 93%, but experienced a delay in real-time detection due to the training algorithm used. Mukesh et al. (2016) explored machine learning-based approaches for pest detection and classification. Artificial neural networks were identified as the most effective technique due to their high prediction accuracy. Yun et al. (2015) introduced the concept of using the Internet of Things (IoT) for monitoring plant pests and insect pests. The paper emphasized the potential of IoT to improve real-time agricultural monitoring using various user interfaces. Rajesh et al. (2018) developed a hardware system using IoT for plant pest detection. Detected unhealthy plants but had limitations in identifying specific pest types affecting plant performance. Srdjan et al. (2016) conducted research on deep neural network-based recognition of plant pests through leaf image classification. The paper achieved a detection accuracy of over 91% on a test set of infected plant leaves. Guiling et al. (2018) focused on plant pest recognition based on image processing technology. Utilized multi-linear regression analysis and image segmentation, but the detection accuracy was not provided in the study. Ataga (2017) presented a lecture on plant pests and food security, emphasizing the need to address plant pathogens. Proposed that artificial intelligence techniques can complement manual approaches to optimize smart farming performance and increase food yield.

2.1 Research Gap

While several studies achieved high accuracy in detecting pests, they often focused on a limited range of pest types and did not consider a pest which is a major problem with rice farming in Nigeria.

3.0 METHODOLOGY

Firstly, an expanded data collection approach which incorporated pest infected rice data from the Ebonyi State Ministry of Agriculture and the Enugu State Ministry of Agriculture. The wavelength band of the data collected was within 400 to 495nm and 559 to 700nm which indicated pest infected rice. This broader dataset improved the generalizability of the model, making it more applicable to various agricultural settings.

The methodology also focused on the selection of relevant data features and implemented preprocessing technique such as principal component analysis. The prioritization of these features contributed to more accurate classification after the training with K-Nearest Neighbor (K-NN) algorithm, which was adopted as the primary classification method.

The implementation of the model was carried out using the classification learner app in Matlab. Evaluation of the model's performance involved considering parameters such as reflection factor, accuracy and area under the curve.

To improve model selection and evaluation, k-fold cross-validation was employed. This technique helped assess the model's performance by dividing the data into subsets for training and testing. Additionally, comparative analysis was conducted to compare the proposed model against existing systems, ensuring its effectiveness and superiority.

4. MODELLING OF THE SMART FARM PEST MONITORING SYSTEM (SFPMS)

The ML adopted is the K-Nearest Neighbor (K-NN) which is a supervised learning algorithm that can solve both classification and regression problem (Devansh et al., 2020). To train the K-NN, the data collected was loaded into the K-NN using classification application software which then automatically divided the data into training and test data in the ratio of 80:20 and then trained with the equation 3.1; The algorithm was used in this research to classify data (D) of the rice plant without pest and with pest using euclidean model as shown in equation 1

$$D_{(p,q)} = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \qquad (1)$$

Where p and q are two points in the euclidean n-space, q_i is the vectors from the training set, p_i is the vectors from the testing set, n is the total clusters in the n space. The model of the K-NN is presented in the graphical model.

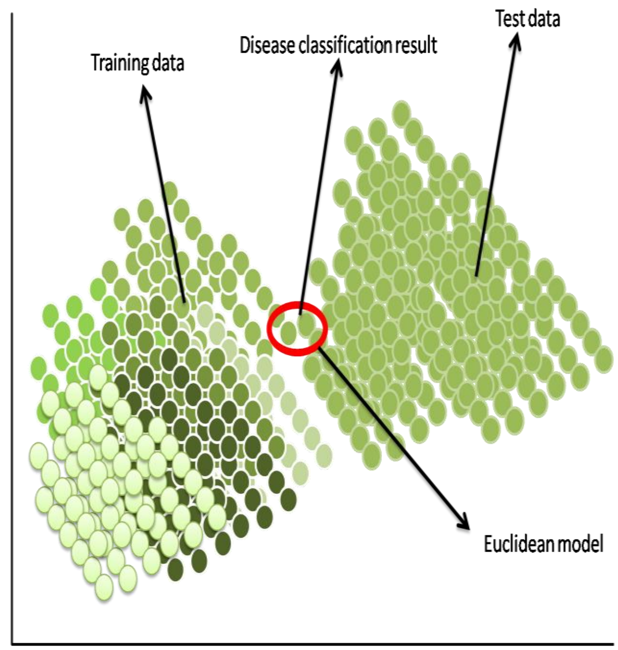

Figure 1: graphical model of K-NN algorithm

The figure 1 presented the algorithm of the KNN showing how plan clusters extracted from the training set and then test set were used to detect plant pest based on similarity difference. The training data consist of data of health rice data at all level of growth starting from the nursery bed to the harvesting period. The test data was used to test the learning processes and then classified the similarity features with euclidean model. The flow chart of the SFDMS is presented in figure 2. While the algorithm of the KNN for SFPMS is presented as;

4.1 SFPMS Pseudocode

1. Load training and test hyperspectral data
2. Extract features from the hyperspectral data for both the pest-infected class (p) and healthy class (q)
3. Implement an improved distance metric model (weighted Euclidean distance in equation 1) that takes into account the relevance and importance of different features in determining the similarity between samples
4. Classify the extracted features of class p and q based on the updated distance metric model
5. Determine the optimal value of k (the number of nearest neighbors to consider) using techniques such as cross-validation or grid search to find the best performing k value for the given dataset
6. Return the classification results and the optimal k value
7. Stop

5. RESULTS AND DISCUSSION

This section discussed the performance of the new K-NN algorithm trained for the SFPMS. The performance was measured using the relationship between true classification which is the true positive rate and false classification which is the false positive rate of rice pest to determine the Area under Curve (AUC) performance as shown in figure 3;

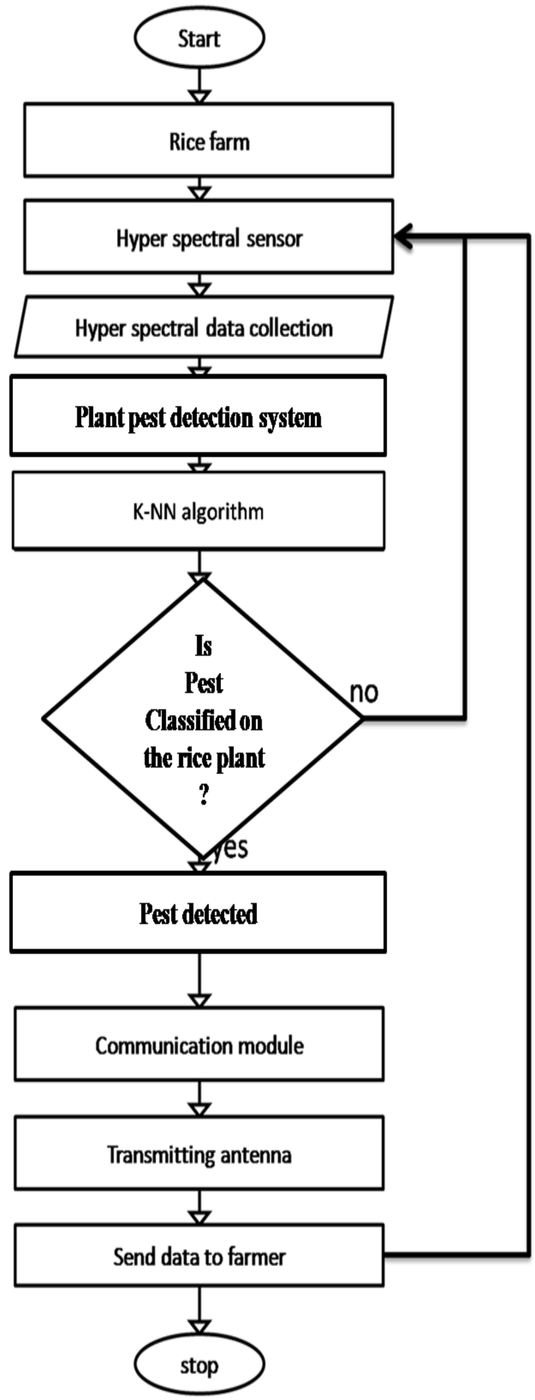

Figure 2: Flow chart of the SFPMS – KNN

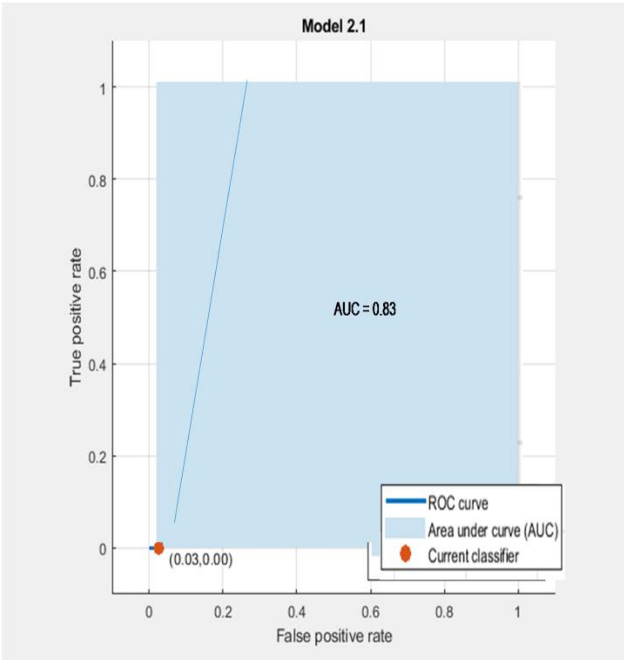

Figure 3: Area under Curve Result

The figure 3 was used to measure the capacity of the K-NN algorithm developed for correct classification of plant pest. The aim was to ensure that AUC equal or approximately 1 is achieved. From the result the AUC is 0.83 which is good as it is approximately 1. The accuracy of the classifier was also analyzed and reported 91% from the classification app. The K-NN based algorithm was validated using tenfold cross validation approach which evaluated the AUC of the SPMS iteratively and the result reported in table 1;

Table 1: Validation Result

S/N	AUC	Accuracy (%)
1	0.87	91.0
2	0.91	91.0
3	0.89	91.0
4	0.90	91.0
5	0.85	89.0
6	0.87	91.0
7	0.85	89.0
8	0.91	92.0
9	0.89	92.0
10	0.87	89.0
Average	0.88	90.9

The table 1 presented the validation performance of the algorithm developed and the result showed that an average of 0.88 AUC score was achieved. The implication of the result showed that the algorithm developed for SFPMS was able to detect pest on the rice farm correctly, with high classification rate.

5.1 Comparative Analysis

The comparative analysis compared the various algorithms which have been developed for the classification of farm diseases as reported in table 2.

Table 2: Comparative analysis

Author	Technique	Accuracy (%)
Pranjali et al. (2016)	K-mean	83
Ryan (2018)	Segmentation and genetic algorithm	69
SFPMS	K-NN	91
Tanyimehera et al. (2016)	K-mean	73
Tejoindhi et al. (2016)	Bhattacharya's distance calculation model	67
Juan (2019)	image processing and machine learning techniques	89

From the comparative table 2, it was observed that the SFPMS reported a classification accuracy of 91% which is very good as it exceeds the performance of other algorithms. However, it is worth mentioning that the model be further validated with practical experiment to enhance the trustworthiness.

6. CONCLUSION

This research presented improving the performance of smart farm pest monitoring and control system using machine learning technique. The study collected data from the Ebonyi and Enugu state ministry of agriculture and trained K-NN algorithm to generate the SFPMS. After evaluation with tenfold validation approach, the classification accuracy for pest in rice arm reported 91% and Area under curve of 0.88. when compared with other algorithm considering accuracy, the percentage improvement reported is 2%.

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