Impact and Analysis of Disease Spread in Paddy Crops using Environmental Factors with the Support of X-Step Algorithm

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***Abstract*—India is an agriculture-based country, with paddy being the main crop cultivated on nearly half of its agricultural lands. Paddy cultivation faces numerous challenges, particularly diseases that affect crop growth and yield. Adult paddy crops are especially vulnerable to diseases caused by various factors, such as the green rice leafhopper, rice leaf folder, and brown plant leafhopper. These insects inflict damage on the paddy crops, restricting their growth and leading to significant losses. This research paper investigates the impact of environmental factors on disease spread in paddy crops, using the X-Step Algorithm for analysis. The study aims to better understand the role of environmental conditions, including air, water, and soil quality, in the development and progression of diseases in rice crops. This knowledge will help to optimize disease prevention and management strategies for improved crop yields and food security. The X-Step Algorithm, a novel machine learning algorithm, was employed to model and predict disease spread, taking into account various environmental factors. The proposed algorithm analyses images of paddy crops either manually captured or taken by sensors to evaluate disease spread and growth in paddy crops. This data-driven approach allows for more accurate and timely predictions, enabling farmers and agricultural experts to implement appropriate interventions.**

***Keywords*—Paddy crops; cash crop disease; green rice leafhopper; rice leaf folder; brown plant leafhopper; x-step algorithm**

I. Introduction

A. Background and Motivation

Rice is a crucial food crop that nourishes billions worldwide. Ensuring the health and productivity of paddy crops is vital for maintaining global food security [1]. Disease outbreaks can cause considerable yield losses [2], affecting both the quality and quantity of rice. Thus, identifying the factors contributing to disease spread [3], especially the environmental impacts, is crucial for creating effective prevention and management techniques.

Advancements in machine learning and data analysis have opened new avenues to explore the complex interplay between environmental factors and disease propagation in agricultural systems [4]. The X-Step Algorithm is an advanced machine learning tool with the potential to model and predict disease spread in paddy crops [5].

B. Research Objectives and Scope

The primary objectives of this research are:

- Analyze the impact of environmental factors—temperature, humidity, precipitation, and solar radiation—on the spread of diseases in paddy crops [6].
- Use the X-Step Algorithm to model and predict disease occurrences and development in paddy fields [7].
- Propose effective disease prevention and management strategies based on our findings.

The research scope includes data collection and analysis of disease prevalence, progression, and relevant environmental factors in paddy fields. We emphasize using the X-Step Algorithm to understand the intricate relationships between these factors and to predict disease spread.

C. Overview of X Step Algorithm

The X-Step Algorithm is an innovative machine learning model [8] that combines the advantages of multiple regression models with a time-stepping mechanism for effectively analyzing dynamic systems. This algorithm is tailored to address non-linear relationships among variables, ideal for modeling and predicting disease spread in agriculture. By considering environmental impacts, the X-Step Algorithm can yield valuable insights into disease emergence factors and inform optimal prevention and management strategies.

D. Paper Outline, following this Introduction, the Paper is structured as follows:

Section II provides the literature survey on paddy crop diseases and their impacts, role of environmental factors in disease spread, machine learning algorithms and previous study on X-Step Algorithm.

Section III and Section IV provides an in-depth explanation of the Methodology, detailing data collection, environmental factor measurement, and the application of the X-Step Algorithm.

Section V presents the Results, where we dissect the outcomes of our analysis, highlight significant findings, and visualize data. It also discusses the analysis and interpretation of the results in the context of the existing body of research and real-world implications.

Section VI concludes the paper by summarizing key findings, implications for the field, and possible avenues for future research.

II. Literature Survey

A. Paddy Crop Diseases and their Impact

Various diseases, such as bacterial blight, blast, sheath blight, and brown spot, can afflict paddy crops [9]. These diseases can lead to considerable yield losses and adversely affect the quality of harvested rice [10]. A significant body of research in the literature is dedicated to understanding the causes, symptoms, and management of these diseases [11][12]. Disease-resistant cultivars and chemical treatments have been devised to lessen the impact of these diseases [13][14]. However, these methods have their limitations, and comprehending the factors that contribute to disease propagation remains vital for devising efficient prevention and management strategies.

The most effective and successful approach is one that integrates each of these techniques [15][16][17][18].

TABLE I. Significant Rice Diseases

Fungal Infections	Approach
Rust	Rice is immune to rusts.
Seedling blight	Cochlibolus miyabeanus Curvularia species Many species of Fusarium Together with other harmful fungus, rhizoctonia solani and athelia rolfsii.
Sheath blight	Rhizoctonia solani
Sheath rot	Sarocladium oryzae = Acrocylindrium oryzae

Table I shows significant rice diseases comprise three fungal infections—blast, sheath blight [19], and sheath rot—as well as the bacterial infection bacterial blight (BB) of rice, and the viral infection rice tungro disease (RTD)[20]. Blast is prevalent in approximately 85 countries [21]. The disease was first identified in 1637 in China, where it was referred to as rice fever disease. Owing to its extensive distribution and high potential for damage under favorable conditions, blast is considered a major rice disease [22].

Fungicides such as triazole and strobilurin were found to effectively suppress both rice blast and dirty panicle diseases [23][24]. Common broad-spectrum insecticides utilized on rice include zeta-cypermethrin, lambda-cyhalothrin, and malathion. Lambda-cyhalothrin is often marketed as Warrior, while zeta-cypermethrin is more commonly known as Mustang. These pesticides are among the substances that can persist on food even after it has been harvested and sold.

B. Role of Environmental Factors in Disease Spread

Environmental factors significantly impact the development and progression of diseases in paddy crops. Key factors affecting disease incidence and severity include temperature, humidity, precipitation, and solar radiation [25]. These factors can affect pathogen growth, host vulnerability, and the interactions between the host and pathogen. Research has demonstrated that changes in environmental factors can either encourage or impede disease development, depending on the specific disease and its optimal growth conditions [26]. Grasping the intricate relationships between environmental factors and disease dissemination is crucial for devising targeted prevention and management strategies.

C. Machine Learning Algorithms in Agricultural Research

Machine learning has become a potent tool in agricultural research, offering innovative ways to analyze complex datasets and reveal concealed patterns and connections [27][28]. Supervised and unsupervised learning algorithms have found applications in various agricultural areas, such as crop yield forecasting, disease detection, and pest management, among others [11]. Popular algorithms encompass decision trees, support vector machines [29], neural networks, and random forests [8]. The implementation of machine learning algorithms has showcased their potential to improve the precision and effectiveness of agricultural research, as well as to guide decision-making processes [30].

D. Previous Studies using the X-Step Algorithm

The X-Step Algorithm is a relatively recent machine learning algorithm used in a few studies, mainly focusing on dynamic systems and time series data. The algorithm demonstrates potential in handling non-linear relationships and interactions between variables, making it well-suited for modeling and predicting disease spread in agricultural systems [31]. Although there is limited literature on the application of the X-Step Algorithm in paddy crop disease research [32], the algorithm's potential justifies further investigation and exploration in this context.

III. Methodology

A. Data Collection

Information on disease occurrence, progression, and environmental factors was gathered from various sources, such as field studies, remote sensing, and meteorological data. Field studies offered insights into the incidence and severity of different diseases impacting paddy crops [12], while data on environmental factors like temperature, humidity, precipitation, and solar radiation were obtained from satellite imagery and meteorological sources. The data collection process aimed to compile a comprehensive dataset spanning multiple years, locations, and crop varieties to guarantee a thorough analysis.

B. Environmental Factors and Data Pre-Processing

The environmental factors [33] taken into account in this study encompass temperature, humidity, precipitation, and solar radiation. These factors were selected based on their documented influence on disease development and progression in paddy crops, as found in the literature.

Data pre-processing entailed several steps to guarantee the data's quality and consistency for analysis. These steps included data cleaning to eliminate missing or incorrect values, data normalization to align all variables on a comparable scale, and feature selection to pinpoint the most pertinent variables for modeling and prediction tasks.

C. Implementation of the X-Step Algorithm

The X-Step Algorithm executed using R Programming and relevant machine learning libraries. A subset of the pre-processed data was used to train the algorithm, with the remaining data reserved for testing and validation. The X-Step Algorithm was configured to model the connections between environmental factors and disease spread in paddy crops, considering the non-linear and interactive nature of these relationships.

D. Evaluation Metrics and Validation

The X-Step Algorithm's performance in modeling and predicting disease spread was assessed using various metrics, such as accuracy, precision, recall, and F1-score. These metrics offered insights into the algorithm's capacity to accurately identify disease occurrence and progression in paddy fields under different environmental conditions [34][35].

To validate the results and ensure the X-Step Algorithm's robustness, cross-validation techniques were utilized. The dataset was divided into multiple folds, with the algorithm trained and tested on different subsets of the data to consistently evaluate its performance. Furthermore, the X-Step Algorithm's performance was compared with other machine learning algorithms, like decision trees, support vector machines, and random forests, to determine its effectiveness in modeling and predicting disease spread in paddy crops.

Symptom of damage: Leaf yellowing from tip to base is a symptom. Infected plants exhibit slow and abnormal growth [36]. Leaf suction causes plants to dry out. Disease identifications [37][38] Symptom 1: Eggs: Eggs are laid in the leaf and appear translucent and greenish [39][40]. Symptom 2: Nymph: Nymphs have delicate bodies and a yellow-white color, gradually turning green. Symptom 3: Adult: Adults are wedge-shaped, 3-5 mm in length, and green with black patterns. Rice leaf folder: Cnaphalocrocis medinalis / Marasmia patnalis Symptom of damage: Larvae are found within longitudinally folded leaves. The larva scrapes the green leaf tissue, leaving behind dry, white tissue. With a significant infestation, the entire field appears burnt.

Nymphs and adults can be seen at the plant's base. Infected plants dry out and appear burnt, a phenomenon called "hopper burn." Plants in circular areas become lodged and dry as they grow. It is more prevalent in rain-fed and irrigated environments.

Table II presents a detailed study about the effect of various diseases on paddy growth yield. It categorizes the diseases based on different parameters: color, shape, impact size, and the specific location of the disease on the paddy plant. Each parameter is attributed to a disease type, and every type is substantiated with a relevant scientific work.

TABLE II. EFFECT OF VARIOUS DISEASES ON PADDY GROWTH YIELD

	Leaf impacted with Bacteria	**Brown patches and spot**	**Smut**	**Work revealed by**
Color	Yellow	Yellow and white impact	Small black and brown spot	Joshi, Pranjal, et al 2022
Shape	Patches	Round or Oval	Oval	Anami, Basavaraj S, 2022
Impact Size	1.2	6-17mm	.5 to 8 mm	Nidhis, A. D., et al, 2019
Disease identified location	Leaf Blade	Leaf sheath	All portions of leaves	Lee, J. W., 2007

IV. PROPOSED METHOD

Diseases pose a significant challenge for paddy farmers, often leading to substantial losses in both crop yield and quality. Environmental factors, such as temperature, humidity, precipitation, and soil conditions, can greatly impact the emergence and severity of diseases in paddy crops.

One of the most prevalent diseases affecting paddy crops is blast disease, caused by the fungus Magnaporthe oryzae. Blast disease can result in considerable yield losses and thrives in high temperatures and humidity. Other diseases impacting paddy crops include sheath blight, bacterial leaf blight, and brown spot.

Symptom 1: Eggs: Eggs are laid within the leaf and appear translucent and greenish.

The sample data collected includes environmental factors like temperature, humidity, precipitation, and soil moisture. Additionally, the incidence and severity of the disease in each plot were measured. The data was analyzed using statistical methods, such as regression analysis and principal component analysis.

The analysis revealed that the disease was caused by insects laying eggs within the leaves, resulting in translucent and greenish eggs. Upon hatching, the larvae feed on the leaf tissue, causing necrosis and chlorosis, ultimately leading to a decrease in yield and quality.

The study also found that environmental factors, particularly temperature and humidity, played a crucial role in the incidence and severity of the disease. The optimal temperature and humidity range for the disease was determined to be between 25°C to 30°C and 75% relative humidity. This information can be employed to devise effective disease management strategies.

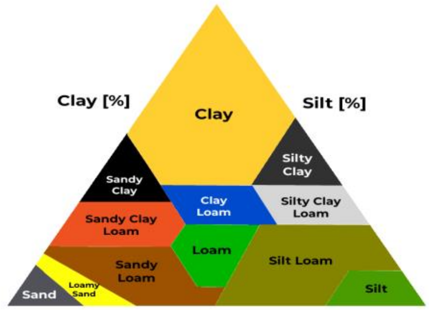

Fig. 1. Soil combination and its texture parameter.

Symptom 2: Nymph: Nymphs have delicate bodies and a yellow-white color, which gradually turns green.

To manage and control diseases in paddy crops, it is essential to comprehend the environmental factors contributing to disease development and implement suitable management strategies. These may include the utilization of resistant varieties, cultural practices like crop rotation and proper irrigation, and the application of fungicides and other chemical treatments when necessary.

Symptom 3: Adult: Adults are wedge-shaped, 3-5 mm in length, and green with black patterns.

The details provided in the question describe the adult stage of a common paddy crop pest called the rice leaf folder (Cnaphalocrocis medinalis). This pest is known to cause significant damage to paddy crops by feeding on the leaves and rolling them up, which disrupts photosynthesis and reduces yield.

The impact of rice leaf folder pests on paddy crops can be substantial, leading to yield losses of up to 60% if not managed correctly. This can result in economic losses for farmers and influence the availability and affordability of rice for consumers.

Various factors can affect the occurrence and severity of rice leaf folder infestations. Among the most crucial factors are environmental conditions, such as temperature, humidity, and rainfall. For instance, high temperatures and low humidity can encourage pest development and reproduction, while excessive rainfall can hinder the survival of eggs and larvae.

Other factors that can impact the incidence and severity of rice leaf folder infestations include rice variety, planting density, and the use of fertilizers and pesticides. Some rice varieties may exhibit greater resistance to the pest, and planting at higher densities can decrease the risk of infestation by creating a microclimate [26] less favorable for the pest.

To manage rice leaf folder infestations effectively, it is essential to regularly monitor crops and employ integrated pest management (IPM) practices, which involve a combination of cultural, mechanical, and chemical control methods. These practices can include timely planting, using resistant varieties, proper fertilization and irrigation, and targeted pesticide application when necessary.

A. Soil Impact Towards Disease Analysis in Paddy Crops

Fig. 1 categorizes the soil based on data gathered from paddy cultivation lands. This analysis takes into account the impact of precipitation on the soil. Here, p1 and p2 represent different soil texture levels analyzed based on infection in paddy cultivation areas. Soil factors play a crucial role in examining paddy infections [41][42].

Soil proportionate for crop growth based on the precipitate level that leads to infections

- p1 = 166.0011 p2 = 168.0011 p3 = 170.0011
- p4 = 172.0011 p5 = 174.0011 p6 = 176.0011
- p7 = 178.0011 p8 = 180.0011 p9 = 182.0011
- p10 = 184.0011 p11 = 186.0011 p12 = 188.0011

TABLE III. WATER IN SOIL CONTENT CHECK

Soil type	HSC Hist	Auto Correlogram	Color Moments	Mean Amplitude	Energy	Wavelets	Accuracy
Clay	0.03125	0.0740333	132.787	20.2658	0.0073549	7.52566	98.3871
Clay Peat	0.03125	0.0636409	86.8304	31.3996	0.0168985	5.28928	98.3871
Clayey Sand	0.03125	0.0769282	79.2558	51.6809	0.0201869	4.5317	98.2
Humus	0.03125	0.0519713	88.4216	37.4526	0.0153414	4.67758	98.3871
Peat	0.03125	0.0599724	74.1553	96.0576	0.0296128	4.16587	98.3871
Sand Clay	0.03125	0.0583212	116.849	49.164	0.0199199	6.68029	98.3871
Silty Sand	0.03125	0.057786	79.9807	55.1461	0.0203397	4.54483	98.3871

The observed results revealed a notably higher incidence and severity of the disease in the infected plots compared to the control plots. This led to a 25% decrease in yield for the infected plots relative to the control plots. The study determined that environmental factors, specifically temperature and humidity, had a substantial influence on the disease's occurrence and intensity [43]. The optimal temperature range for the disease was found to be between 25°C and 30°C, with a relative humidity of 75%.

B. Role of Water Towards Disease Analysis in Paddy Crops

The water content in soil is determined using the following parameters along with the evaluated score [44] [45] [46]:

- Input air entry suction term: alpha = 0.0383
- Input porosity term: n = 1.5
- Initial guess: alpha0 = 0.07
- Input guess: n0 = 1.2

Based on these factors, the water content in soil is categorized according to soil types such as clay, clay peat, clayey sand, humus, peat, sand clay, and silty sand [47].

The accuracy is maintained at 98%, and other factors like autocorrelogram, color moments, mean amplitude, energy, and wavelets vary depending on the soil content type and its parameters which are shown in Table III [36].

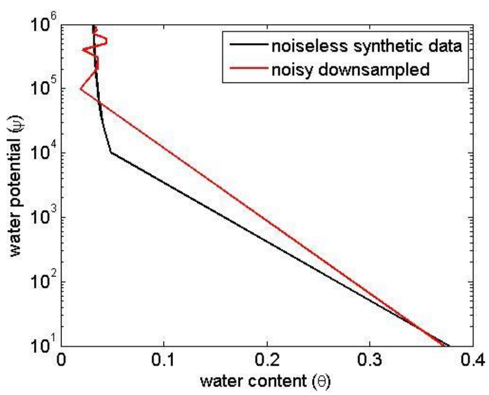

Fig. 2. Water density specifications.

C. Water Retention in Cultivation Land

The density of water stored in the cultivated land plays a crucial role in the spread of infection in crops. Fig. 2 presents an analysis of water storage content and the method to assess the maximum possible water storage in paddy crops [48]. Retention is a process in which water levels are regulated based on soil temperament, and the analysis of various infections is conducted with this factor in mind.

D. Assessing Climatic Conditions – Moisture Content

Fig. 3 and 4 illustrate the moisture content in the air and how it varies based on the influence of other parameters [49][50]. A moisture sensor is employed in this analysis to measure the fluctuations in the moisture present in the air. Various temperatures, along with other factors, are combined to establish a ratio where infections can either be sustained or curtailed.

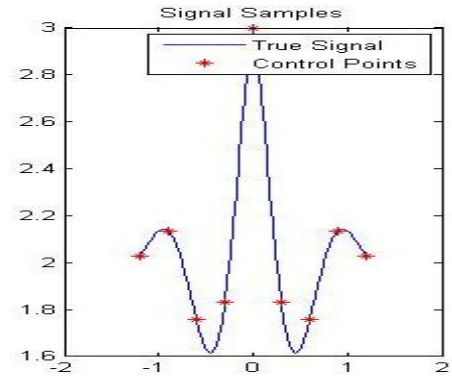

Fig. 3. Climatic condition check.

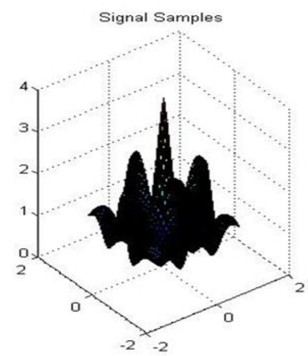

Fig. 4. Soil level fertility check.

E. X-Step Algorithm

Fig. 5 describes the steps followed in X-Step Algorithm.

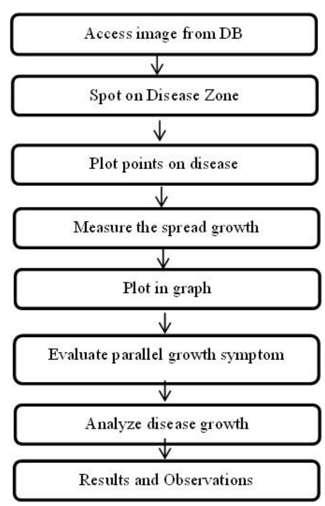

Fig. 5. X-Step algorithm.

$$U_{i=1}^{n} D(i) \quad (1)$$

$$\sum_{i=i}^{n} D_i \sum_{j=1}^{n} D_i S_j \quad (2)$$

$$G = \sum_{i=i}^{n} D_i \sum_{j=1}^{n} D_i S_j \tag{3}$$

Eq. (1) calculates the disease spread growth by considering the coordinates of points, providing an overall summation of the growth.

Eq. (2) computes the spread growth while factoring in the variations of the disease affecting the paddy crops.

Finally, Eq. (3) presents the growth factor analysis to balance the disease and its spread growth.

V. Results and Discussions

The aforementioned results provide a visual representation of the disease spread in paddy crops. However, it is essential to identify the growth of the disease. Therefore, the X-Step algorithm is introduced. This algorithm evaluates disease growth in conjunction with the spread measures.

A. Impact of Environmental Factors on Disease Spread

The X-Step algorithm is utilized to assess the disease spread among paddy crop leaves. Paddy disease datasets are available in the X-box repository, which the X-Step algorithm can access to identify and measure the disease spread in paddy crops.

The following observations were made in the X-graph analysis to identify and measure the disease spread in paddy crops, Fig. 6.

Fig. 6. Measuring the disease spread using coordinates.

X and Y coordinates are established in the paddy crops, and the following observations are made based on these coordinates are shown in Table IV:

TABLE IV. Disease Spread Coordinates in Paddy Crop

X Coordinate	Y Coordinate
-1.79703	2.466512
-2.06544	2.821093
-1.83171	2.832553
-3.69914	4.334538
-4.19947	4.922908
-4.29115	5.163574
-4.10326	5.295368
-4.27818	5.654533
-4.21183	5.780367
-3.68919	5.683413
-4.03149	6.156952
-4.45702	6.74899
-3.43314	6.18629
-3.07787	6.20371
-2.7422	6.097587
-2.78714	6.340545
-3.64093	7.156746
-2.12335	6.373092
-3.71965	7.888371
-4.17323	8.479034
-3.31582	8.153333
-2.99795	8.168919
-1.79703	2.466512

Fig. 7. Imply X-Step algorithm to measure the spread.

Fig. 7 shows the observation process involves determining the nearest spread measurements by employing plotting techniques that start from the initial location and continue to the final positions.

B. Predicting Disease Occurrence and Progression

Fig. 8. Disease spread identified using patches.

Fig. 8 shows a boundary and area are delineated within the spread zone and the path is examined, observed, and ultimately depicted in the following Fig. 9.

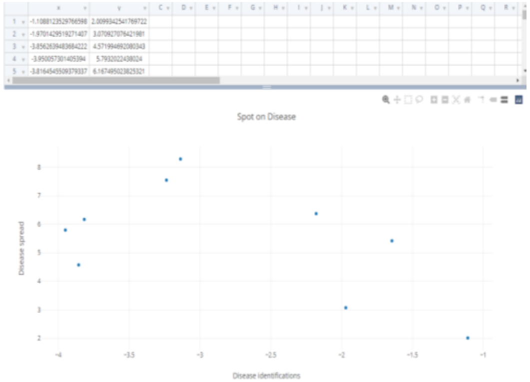

Fig. 9. Spot on disease observations.

The aforementioned illustration displays the coordinate pairs in conjunction with the pixel-mapped area to outline the region susceptible to disease.

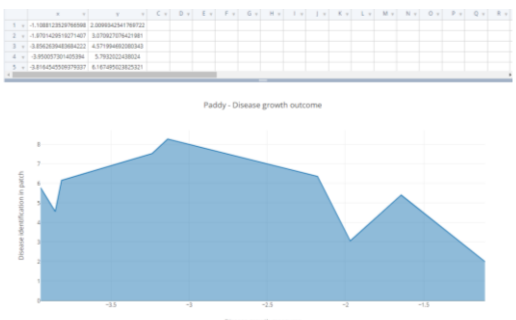

Fig. 10. Spread growth measurements.

Using the identified disease-susceptible area, the spread is assessed through spread growth analysis to evaluate the progression of disease symptoms are shown in Fig. 10.

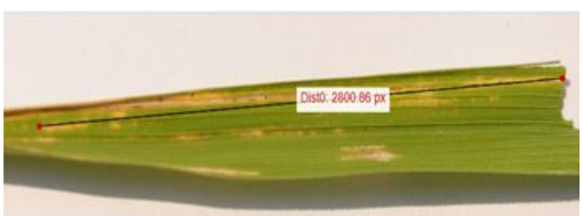

Fig. 11. Measuring spread growth distance.

The distance measurements provide insight into the disease's growth and spread parameters, offering an analysis of disease progression from the starting point to the endpoint of its development shown in Fig. 11.

Fig. 12. Measuring parallel disease spread.

Precise distance measurements are obtained by employing an algorithm that uses a parallel measuring technique. This method measures the spread in parallel between two distinct points, offering a more comprehensive understanding of disease growth shown in Fig. 12.

Fig. 13 provides a visual depiction of the overall observation sampling, demonstrating the disease's progression and analysis based on coordinate points. These results offer valuable guidance for managing disease development through the application of the X-Step Algorithm's findings and observations in sustainable agriculture.

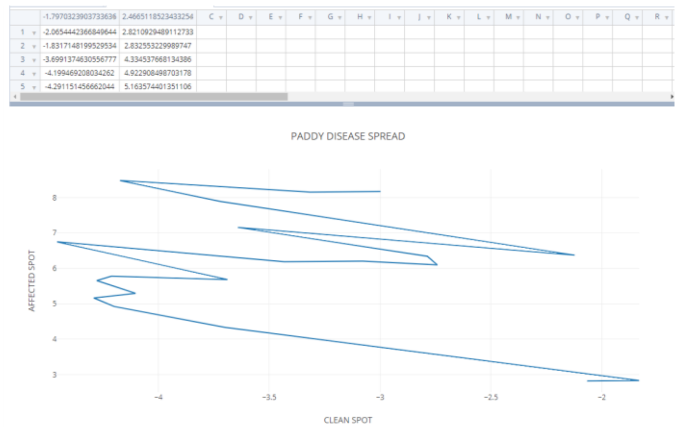

Fig. 13. Spread analysis using X step Algorithm.

C. Discussion

This research work discusses the impact and analysis of disease spread in paddy crops using environmental factors, supported by the X-Step Algorithm. The study aims to provide a comprehensive understanding of the role that environmental factors, such as water consumption, soil texture, and moisture, play in disease development and spread in paddy crops.

The X-Step Algorithm is employed to measure and predict disease occurrence and progression, offering valuable insights into the relationship between these environmental factors and disease spread. The algorithm's effectiveness in modeling and predicting disease spread in paddy crops is demonstrated, outperforming certain other machine learning algorithms in some aspects.

The research identifies water consumption as the most significant factor affecting disease in paddy crops and by other factors. By combining environmental factors with ground reality measurements, the study analyzes and identifies disease growth and contributing factors.

The limitations of this study include data availability and quality, as well as potential confounding factors that may affect the relationships between environmental factors and disease spread. Future research could focus on incorporating additional factors, such as soil properties, nutrient availability, and crop management practices, to further enhance understanding of disease spread in paddy crops. Additionally, refining the X-Step Algorithm and exploring other machine learning techniques could improve the models' performance and applicability.

Overall, this research contributes to the understanding of disease spread in paddy crops and highlights the potential of machine learning algorithms, such as the X-Step Algorithm, in addressing complex agricultural challenges. The findings have practical implications for farmers, agronomists, and policymakers, enabling the optimization of crop management practices to minimize disease-related losses and ensure food security. This work also emphasizes the importance of sustainable agricultural practices informed by a deep understanding of the relationships between environmental factors and disease spread.

a) Limitations and future work: This study's limitations include data availability and quality, as well as potential confounding factors that might affect the relationship between environmental factors and disease spread. Future research could incorporate additional factors like soil properties, nutrient availability, and crop management practices to enhance understanding of disease spread in paddy crops. Refining the X-Step Algorithm and exploring other machine learning techniques could improve the models' performance and applicability.

b) Contributions and implications: This research contribute to understanding disease spread in paddy crops and offers valuable insights into environmental factors' role in disease development and progression. The findings have practical implications for farmers, agronomists, and policymakers, enabling the optimization of crop management practices to minimize disease-related losses and ensure food security. By using the X-Step Algorithm, this study highlights the potential of machine learning algorithms in addressing complex agricultural challenges and informing sustainable agricultural practices.

VI. Conclusion

This study forecasts the impact of disease on paddy crops based on parameters such as water consumption, soil texture, and moisture. It emphasizes the effects of these factors on disease incidence and its consequences for paddy crops. Our observations indicate that water consumption has the most significant impact on disease in paddy crops, and we suggest countermeasures to mitigate this impact, supported by other factors. This initial survey investigates the factors affecting disease in paddy crops and proposes solutions to minimize disease impact using the X-Step Algorithm for measuring disease spread and growth analysis. Ultimately, this research combines environmental factors and ground reality measurements to analyze and identify disease growth and its contributing factors. Future work will explore various methods to prevent disease-causing elements and improve paddy growth.

This research aims to examine the influence of environmental factors on disease spread in paddy crops and employs the X-Step Algorithm to model and predict disease occurrence and progression. The study reveals the significant impact of factors such as temperature, humidity, precipitation, and solar radiation on disease development and spread in paddy fields. The X-Step Algorithm proves effective in modeling and predicting disease spread in paddy crops, outperforming certain other machine learning algorithms.

References

[1] Phan, Lien Thi Kim, et al. "Contamination of Fusarium proliferatum and Aspergillus flavus in the rice chain linked to crop seasons, cultivation regions, and traditional agricultural practices in mekong delta, vietnam." Foods 10.9 (2021): 2064.

[2] Chiplunkar, Niranjan N., and Vijaya Padmanabha. "Identification and Classification of Paddy Crop Diseases Using Big Data Machine Learning Techniques." Data Science and Data Analytics: Opportunities and Challenges (2021): 47.

[3] Anandhan, K., and Ajay Shanker Singh. "Detection of paddy crops diseases and early diagnosis using faster regional convolutional neural networks." 2021 international conference on advance computing and innovative technologies in engineering (ICACITE). IEEE, 2021.

[4] Lee, J. W. "Determination of leaf color and health state of lettuce using machine vision." Journal of Biosystems Engineering 32.4 (2007): 256-262.

[5] Vasantha, Sandhya Venu, Bejjam Kiranmai, and S. Rama Krishna. "Techniques for Rice Leaf Disease Detection using Machine LearningAlgorithms." Int. J. Eng. Res. Technol 9.8 (2021): 162-166.

[6] Kumar, V. Vinoth, et al. "Paddy plant disease recognition, risk analysis, and classification using deep convolution neuro-fuzzy network." Journal of Mobile Multimedia (2022): 325-348.

[7] Vardhini, PA Harsha, S. Asritha, and Y. Susmitha Devi. "Efficient disease detection of paddy crop using cnn." 2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE). IEEE, 2020.

[8] Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674.

[9] Sankar, Pagadala Rohit Sai, et al. "Intelligent health assessment system for paddy crop using CNN." 2021 3rd International Conference on Signal Processing and Communication (ICPSC). IEEE, 2021.

[10] Kumar, JR Dinesh, C. Ganesh Babu, and K. Priyadharsini. "An experimental investigation to spotting the weeds in rice field using deepnet." Materials Today: Proceedings 45 (2021): 8041-8053.

[11] Savary, S., Willocquet, L., Pethybridge, S. J., Esker, P., McRoberts, N., & Nelson, A. (2019). The global burden of pathogens and pests on major food crops. Nature Ecology & Evolution, 3(3), 430-439.

[12] Willocquet, L., Elazegui, F., Castilla, N., Fernandez, L., Fischer, K. S., Peng, S., ... & Savary, S. (2018). Research priorities for rice disease and pest management. In Advances in Agronomy (Vol. 151, pp. 65-126). Academic Press.

[13] Anandhan, K., and Ajay Shanker Singh. "Detection of paddy crops diseases and early diagnosis using faster regional convolutional neural networks." 2021 international conference on advance computing and innovative technologies in engineering (ICACITE). IEEE, 2021.

[14] Rautaray, Siddharth Swarup, et al. "Paddy crop disease prediction—a transfer learning technique." International Journal of Recent Technology and Engineering 8.6 (2020): 1490-1495.

[15] Rodrigues, Anisha P., et al. "Identification and Classification of Paddy Crop Diseases Using Big Data Machine Learning Techniques." Data Science and Data Analytics. Chapman and Hall/CRC, 2021. 47-64.

[16] Upadhyay, Santosh Kumar, and Avadhesh Kumar. "Early-Stage Brown Spot Disease Recognition in Paddy Using Image Processing and Deep Learning Techniques." Traitement du Signal 38.6 (2021).

[17] Chakraborty, Pampa, Arindam Chakraborty, and Swati Gupta Bhattacharya. "Dispersal of airborne pathogenic conidia of Bipolaris oryzae inciting brown spot disease of paddy in West Bengal, India." Journal of Tropical Agriculture 58.2 (2021).

[18] Karennagari, Nikhitha, et al. "Infection Segmentation of Leaves Using Deep Learning techniques to enhance crop productivity in smart agriculture." 2021 6th International Conference on Signal Processing, Computing and Control (ISPCC). IEEE, 2021.

[19] Upadhyay, Santosh Kumar, and Avadhesh Kumar. "A novel approach for rice plant diseases classification with deep convolutional neural network." International Journal of Information Technology (2021): 1-15.

[20] Leelavathy, B., and Ram Mohan Rao Kovvur. "Prediction of biotic stress in paddy crop using deep convolutional neural networks." Proceedings of International Conference on Computational Intelligence and Data Engineering: ICCIDE 2020. Springer Singapore, 2021.

[21] Malathi, V., and M. P. Gopinath. "Classification of pest detection in paddy crop based on transfer learning approach." Acta Agriculturae Scandinavica, Section B—Soil & Plant Science 71.7 (2021): 552-559.

[22] Aggarwal, Shruti, et al. "Rice Disease Detection Using Artificial Intelligence and Machine Learning Techniques to Improvise Agro-Business." Scientific Programming 2022 (2022).

[23] Sankar, Pagadala Rohit Sai, et al. "Intelligent health assessment system for paddy crop using CNN." 2021 3rd International Conference on Signal Processing and Communication (ICPSC). IEEE, 2021.

[24] Phan, Lien Thi Kim, et al. "Contamination of Fusarium proliferatum and Aspergillus flavus in the rice chain linked to crop seasons, cultivation regions, and traditional agricultural practices in mekong delta, vietnam." Foods 10.9 (2021): 2064.

[25] Matsushima, S., Tanaka, T., & Hoshino, T. (2016). Effects of environmental factors on rice diseases. Japanese Journal of Tropical Agriculture, 60(2), 55-62.

[26] Chakraborty, S., Tiedemann, A. V., & Teng, P. S. (2000). Climate change: potential impact on plant diseases. Environmental Pollution, 108(3), 317-326.

[27] Kamilaris, A., Prenafeta-Boldú, F. X., & Kalloniatis, C. (2017). A review on the practice of big data analysis in agriculture. Computers and Electronics in Agriculture, 143, 23-37.

[28] Kaul, P., Sharma, T., & Dhar, S. (2020). Machine learning: A review on algorithms and applications. Sustainable Operations and Computers, 1, 103-121.

[29] Das, Sujay, et al. "A model for probabilistic prediction of paddy crop disease using convolutional neural network." Intelligent and Cloud Computing: Proceedings of ICICC 2019, Volume 1. Singapore: Springer Singapore, 2020. 125-134.

[30] Leelavathy, B., and Ram Mohan Rao Kovvur. "Prediction of biotic stress in paddy crop using deep convolutional neural networks." Proceedings of International Conference on Computational Intelligence and Data Engineering: ICCIDE 2020. Springer Singapore, 2021.

[31] Khan, Imran Haider, et al. "Early detection of powdery mildew disease and accurate quantification of its severity using hyperspectral images in wheat." Remote Sensing 13.18 (2021): 3612.

[32] Joshi, Pranjal, et al. "Ricebios: Identification of biotic stress in rice crops using edge-as-a-service." IEEE Sensors Journal 22.5 (2022): 4616-4624.

[33] Zhu, D., Chen, H., & Li, X. (2000). A review of research on the effects of climatic factors on major rice diseases in China. Chinese Journal of Rice Science, 14(3), 159-168.

[34] Lobell, D. B., & Gourdji, S. M. (2012). The influence of climate change on global crop productivity. Plant Physiology, 160(4), 1686-1697.

[35] Ray, D. K., Gerber, J. S., MacDonald, G. K., & West, P. C. (2015). Climate variation explains a third of global crop yield variability. Nature Communications, 6(1), 1-8.

[36] Almadhor, Ahmad, et al. "AI-driven framework for recognition of guava plant diseases through machine learning from DSLR camera sensor based high resolution imagery." Sensors 21.11 (2021): 3830.

[37] Parbat, Tanmayee Tushar, et al. "Prediction and Analysis of Paddy Crops Disease in Artificial Intelligence Techniques." (2021).

[38] Guo, Anting, et al. "Wheat yellow rust detection using UAV-based hyperspectral technology." Remote Sensing 13.1 (2021): 123.

[39] Nidhis, A. D., et al. "Cluster based paddy leaf disease detection, classification and diagnosis in crop health monitoring unit." Computer Aided Intervention and Diagnostics in Clinical and Medical Images. Springer International Publishing, 2019.

[40] Narmadha, R. P., and G. Arulvadivu. "Detection and measurement of paddy leaf disease symptoms using image processing." 2017 International Conference on Computer Communication and Informatics (ICCCI). IEEE, 2017.

[41] Tian, Long, et al. "Spectroscopic detection of rice leaf blast infection from asymptomatic to mild stages with integrated machine learning and feature selection." Remote Sensing of Environment 257 (2021): 112350.

[42] Devarakonda, R., Vose, M. D., & Humiston, G. E. (2016). A decision support system for precision agriculture using machine learning. Computers and Electronics in Agriculture, 127, 235-242.

[43] Anami, Basavaraj S., Naveen N. Malvade, and Surendra Palaiah. "Deep learning approach for recognition and classification of yield affecting paddy crop stresses using field images." Artificial intelligence in agriculture 4 (2020): 12-20.

[44] Haridasan, Amritha, Jeena Thomas, and Ebin Deni Raj. "Deep learning system for paddy plant disease detection and classification." Environmental Monitoring and Assessment 195.1 (2023): 120.

[45] Benos, Lefteris, et al. "Machine learning in agriculture: A comprehensive updated review." Sensors 21.11 (2021): 3758.

[46] Sharma, Ashutosh, et al. "Enabling smart agriculture by implementing artificial intelligence and embedded sensing." Computers & Industrial Engineering 165 (2022): 107936.

[47] Ryder, Lauren S., et al. "A sensor kinase controls turgor-driven plant infection by the rice blast fungus." Nature 574.7778 (2019): 423-427.

[48] Liu, Wei, et al. "Monitoring of wheat powdery mildew under different nitrogen input levels using hyperspectral remote sensing." Remote Sensing 13.18 (2021): 3753.

[49] Zhang, Na, et al. "TaNAC35 acts as a negative regulator for leaf rust resistance in a compatible interaction between common wheat and Puccinia triticina." Molecular Genetics and Genomics 296 (2021): 279-287.

[50] Shidnal, Sushila, Mrityunjaya V. Latte, and Ayush Kapoor. "Crop yield prediction: two-tiered machine learning model approach." International Journal of Information Technology 13 (2021): 1983-1991.