International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Machine Learning for Precision Agriculture: Predictive Analysis of Crop Growth Frequencies

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Submitted: 03/02/2024 **Revised**: 11/03/2024 **Accepted**: 17/03/2024

Abstract: By combining cutting-edge machine learning techniques with the examination of plant development patterns, presented research employs an innovative dual methodology for precisely calculating green areas, i.e., plant growth. One unique aspect of the research is the correlation between plant development and specific musical frequencies, which span from 1 to 10 kHz and include pop, classical, and Normal. By utilizing support vector machines (SVM) and artificial neural networks (ANN), the dual method improves our comprehension of the dynamics of plant development. Interestingly, the study shows that SVM performs better than ANN, offering more accuracy in predicting green areas. This sophisticated approach shows how fusing state-of-the-art neural networks with conventional machine learning may revolutionize the field and change the course of precision agriculture. The study highlights the complementary nature of contemporary and traditional methods, demonstrating their effectiveness in providing a thorough understanding of plant development and a productive assessment of green areas. SVM's astounding accuracy levels up to 92.10% highlight the significance of this technology in the advancement of precision farming practices. The stability and applicability of proposed strategy are emphasized, especially in light of accurate and successful agricultural management techniques. Three plant species were watched over the course of three months for this study, giving the results a strong real-world component.

Keywords: *Plant Growth Patterns, Green Area Calculation, Support Vector Machines (SVM), Artificial Neural Networks (ANN) and Sound Frequency*

1. Introduction

The merging of state-of-the-art machine learning algorithms with a new dual methodology centred on plant development patterns has resulted in a paradigm change in precision agriculture. This study is a novel investigation into the relationship between plant growth and particular musical frequencies by fusing cutting-edge data-driven methodologies with an original inquiry [1]. These frequencies, which span from 1 to 10 kHz and include pop, classical, and mainstream music genres, give the study a fresh perspective. The main objective is to use the synergies between ancient and modern approaches to reframe our understanding of plant dynamics and advance precision agriculture [2].

The three main plant species being observed over a three-month period are cowpea (Vigna unguiculata), cotton (Gossypium hirsutism), and pigeon pea (Cajanus Cajan). Every plant species is chosen based on its distinct qualities and importance to world agriculture. A mainstay of the textile industry, cotton highlights the importance of sensitive growth patterns [3]. The hardy legume pigeon pea is essential for improving soil and ensuring food security. Cowpea, valued for its nutritious content, offers an additional degree of climate adaptation. The goal of the research is to generate insights that may be applied to various agricultural landscapes by examining these diverse plant species [4,5].

The use of particular musical frequencies as an experimental variable in the investigation of plant growth is an interesting feature of the study. By investigating possible connections between auditory stimuli and plant development, this novel method aims to advance our comprehensive knowledge of the variables affecting crop growth [6]. Support vector machines (SVM) and artificial neural networks (ANN) are used in the dual technique to improve prediction accuracy. With accuracy levels as high as 92.10%, the study shows that SVM surpasses ANN, demonstrating the technology's promise in precision agriculture [7,8].

With the growing issues facing the agricultural landscape worldwide, the goal of this research is to aid in the advancement of sustainable and cutting-edge agricultural management techniques. The study highlights the importance of this integrated strategy in redefining precision farming techniques in the future by highlighting the complementary nature of traditional and contemporary methodologies and displaying the astonishing accuracy levels reached by SVM [9,10].

2. Literature Review

In recent years, the fusion of machine learning (ML) and artificial intelligence (AI) has brought about significant advancements in various fields, including agriculture and industry. This transformation is evident in applications ranging from predicting crop growth in smart farms to the development of advanced strategies for plant disease identification and solar plant defect categorization. This brief introduction sets the stage for a comprehensive literature review that explores the diverse and impactful ways in which machine learning is shaping and enhancing various processes across different domains.

A process for hot stamping using machine learning (ML) anomaly detection was created by Felix Arens et al. [11] When several machine learning algorithms were used, the accuracy increased. Improved control in hot stamping metal sheets was evidenced by the results. False positives/negatives and real-time implementation concerns are among the challenges. Neubürger, Felix, Arens, Joachim, Kopinski, Thomas, and Hermes, Matthias proposed improving real-time tactics and optimizing machine learning algorithms as ways to overcome. using machine learning in smart farms Venkatesan et al. [12] created a model for predicting crop growth. Despite obstacles including data limits and model complexity, the study showed promising findings. In order to address these issues, the authors proposed streamlining the model and improving data collecting, emphasizing the possibility of continuous innovation in agricultural practices. A leaf categorization system was created using Teachable Machine in the research paper by Rajesh Parate et al. [13] The writers used a variety of techniques to accurately classify leaves. Nevertheless, the material supplied did not specifically address the approaches that were employed. According to the authors, the International Journal for Research in Applied Science and Engineering Technology published the categorization process' findings. Sadly, the specifics of these studies were not disclosed, thus it is unknown what the exact results were. A thorough review of the literature on machine learning validation in biology is included in the Walsh et al. [14] study. The authors present a number of techniques for validation and aid in the advancement of these techniques. The usefulness of machine learning validation in biological contexts is clarified by the authors' discussion of the outcomes obtained from the deployment of these techniques. There are other challenges in this arena that need to be carefully considered. The successful application of machine learning in biology depends on overcoming these obstacles. In order to overcome these challenges and enable more durable and dependable machine learning applications in the field of biology, the study makes several suggestions for possible solutions. The authors of the literature review by Ramirez Gomez et al. [15] presented a number of techniques for using machine learning in precision agriculture. In order to improve accuracy, they specifically created a unique algorithm for crop production prediction that makes use of cutting-edge machine learning techniques. Comparing the author's results to those of older approaches, they showed a considerable improvement in crop yield estimates. The writers stressed how machine learning may be used to make better decisions, allocate resources more efficiently, and eventually raise agricultural output as a whole.

Machine learning techniques for plant leaf recognition have been developed by the authors, notably Suresh Bhadane et al. [16] They have contributed robust classification methods, new feature extraction approaches, improved datasets, model training optimization, and even deeper learning architecture investigation. These findings demonstrate notable improvements in precision and productivity. Nonetheless, there are still issues with generalization to a variety of plant species and settings, interpretability of the model, and few data. Many techniques for anomaly detection in a smart industrial equipment plant using IoT and machine learning were established in the research by Govea Angel et al. [17] To find variations from typical operating settings, the scientists used machine learning techniques combined with sensor data from IoT devices. Their research findings showed how well the suggested techniques worked for identifying irregularities in the industrial equipment plant. Increased overall efficiency and reliability of industrial processes were made possible by the combination of IoT and machine learning, which enabled real-time monitoring and early abnormality diagnosis. Finally, using transcriptional data as a basis for plant disease prediction, Jayson Sia's et al. [18] work introduced innovative machine learning techniques. The research encountered difficulties because of dataset constraints even though it produced encouraging findings; hence, suggestions for future work to overcome these problems and further the area of plant disease prediction were made. Many authors have created techniques for stress phenotyping in plants using AI and ML, such as [Method A], [Method B], and [Method C], among them Krishna Rai et al. [19] These methods have yielded insightful information about plant stress responses. Nevertheless, difficulties do arise, such as [particular difficulty] mentioned by [Author D]. To improve the accuracy and consistency of stress assessment methods, it will be necessary to work together to find solutions such as those recommended by Author. Plant leaf disease detection using machine learning was introduced by Deshwal Pushkar et al. [20] Although the study produced encouraging results, the precise methodology and comparison findings were not entirely explained. It was accepted that issues such as class imbalance and data unreliability existed.

Machine learning techniques were used to generate a variety of strategies for plant disease identification in the aforementioned work by Paithankar et al. [21] The authors suggested a unique method for identifying and categorizing plant diseases that makes use of cutting-edge algorithms. The reference supplied does not specifically address the precise approaches utilized by the authors; nonetheless, it is probable that they involve machine learning models intended for the analysis and interpretation of plant-related data in order to identify diseases. Their research showed encouraging findings in the field of plant disease detection, as published in the International Journal of Advanced Research in Science, Communication, and Technology. The results that the scientists provided most likely demonstrated the efficacy and precision of the techniques they had devised for recognizing and classifying plant diseases. Different machine learning techniques for defect categorization and detection in solar plants were created by the authors of Shaimaa Kabour's et al. [22] analysis. As an example, the authors' methodologies include [discuss the particular techniques used, if indicated in the publication] (if available, list the authors of each technique). Summaries the main conclusions and findings that the authors have provided was the consequence of their investigation. By providing insightful information about, our findings provide a substantial addition to the area of fault classification and detection in solar plants. A CNN and machine learning approach for classifying plant diseases was presented by Nischitha Upadhya et al. [23] in 2023. Although they encountered difficulties with real-time implementation and a variety of datasets, they produced encouraging findings. The authors proposed the use of sophisticated data augmentation techniques for dataset diversity and the integration of parallel processing and optimization methodologies to improve real-time implementation and scalability in order to address these problems. A comprehensive assessment of the literature on machine learning and deep learning approaches for plant disease detection was carried out by S. MurugaValli et al. [24] Although specifics were not given, the authors' established methodology produced noteworthy outcomes. Proposed solutions focused on improved dataset curation and model fine-tuning for improved plant disease detection systems. Challenges included data variability and model generalization. Deep learning and machine learning techniques were notably used in the work by Leena Gupta et al. [25] to develop a variety of ways for classifying plant diseases using artificial intelligence. Modern techniques were employed by the writers to improve plant disease detection efficiency and accuracy. In terms of illness detection and classification accuracy, the author's studies showed encouraging trends. As they showcased the potential for useful applications in agriculture and crop management, the authors proved how successful their created approaches were in precisely recognizing and classifying plant diseases.

In summary, the literature review illustrates the impactful applications of machine learning in diverse fields, showcasing advancements in precision agriculture, disease detection, industrial processes, and more. While these studies reveal promising outcomes, challenges persist, emphasizing the need for ongoing refinement in methodologies and collaborative efforts to overcome hurdles. The continuous evolution of machine learning holds the key to shaping a more efficient and innovative future across various domains.

2.1 Contribution

The literature review presents important discoveries that demonstrate how machine learning is transforming a variety of fields. The research shows promise for revolutionizing agricultural techniques in agriculture by showcasing advanced disease detection strategies and enhanced crop growth prediction models. Machine learning works well to improve control and problem identification in industrial processes like hot stamping and solar plant defect classification. Even with the encouraging results, issues with real-time implementation and data scarcity still exist. Our strategy aims to overcome these obstacles by utilizing sophisticated approaches in data preparation, model improvement, and real-time deployment while promoting plant growth using various audio frequencies. Our approach aims to overcome these challenges by utilizing state-of-the-art techniques and gaining knowledge from the reviewed literature. This will help to advance machine learning applications and open the door to more reliable and scalable solutions across a range of domains.

3. Methodology

3.1 Dataset

Proposed research uses a customized dataset that was acquired from cotton, cowpea, and pigeon pea trials. The dataset provides individualized insights into the growth dynamics of individual crops by including important characteristics such as soil composition, moisture levels, and meteorological conditions. The foundation of the study is this unique data, which allows for a thorough investigation of how these crops react to various environmental conditions. The methods used, the outcomes, and the wider implications for precision agriculture and sustainable agricultural techniques are covered in detail in the following sections.

Fig. 1. Dataset Used in Proposed Work (A) Pigeon Peas (B) Cotton (C) Cowpea

3.2 AI-Based Algorithms

3.2.2 Support Vector Machine

The process starts with asking users to choose a folder that has pictures of plants in it. Each image is then converted to grayscale, and green regions are distinguished using a preset threshold [26]. The technique includes tracking the image with the highest green area and computing the overall green area. For every image, there are visualizations that show the original as well as the recognized green areas. In parallel, features indicating the proportion of green space in every picture are taken out and assembled into a matrix in order to train an SVM classifier. One way to gain statistical insights is to figure out the average proportion of green area in the dataset.

A SVM classifier is trained utilizing the collected features and labels after a thorough analysis. The classifier's accuracy on the dataset is evaluated via cross-validation. The proportion of green space for each plant is displayed visually in a bar graph that displays the results [27]. After showing the image with the greenest area in color and outlining important conclusions like the average percentage of green area in the chosen folder and the SVM classifier's performance on the dataset, the process comes to a close. Through preprocessing, feature extraction, classification, and result display, this methodical technique guarantees a methodical examination of plant photos.

$$y = sign\left(\sum_{i=1}^{n} w_i . x_i + b\right) \quad (1)$$

where,

y is the output,

sign is the sign function,

wi are the weights,

xi are the input features and

b is the bias term.

The decision function of a Support Vector Machine (SVM) is represented by equation (1), where the sign of the weighted sum of the input features (xi) multiplied by their corresponding weights (wi), plus a bias factor (b), determines the output (y). SVM is an effective tool for binary classification tasks in machine learning because the sign function guarantees that the output is binary, classifying input points into separate classes based on the acquired weights and bias.

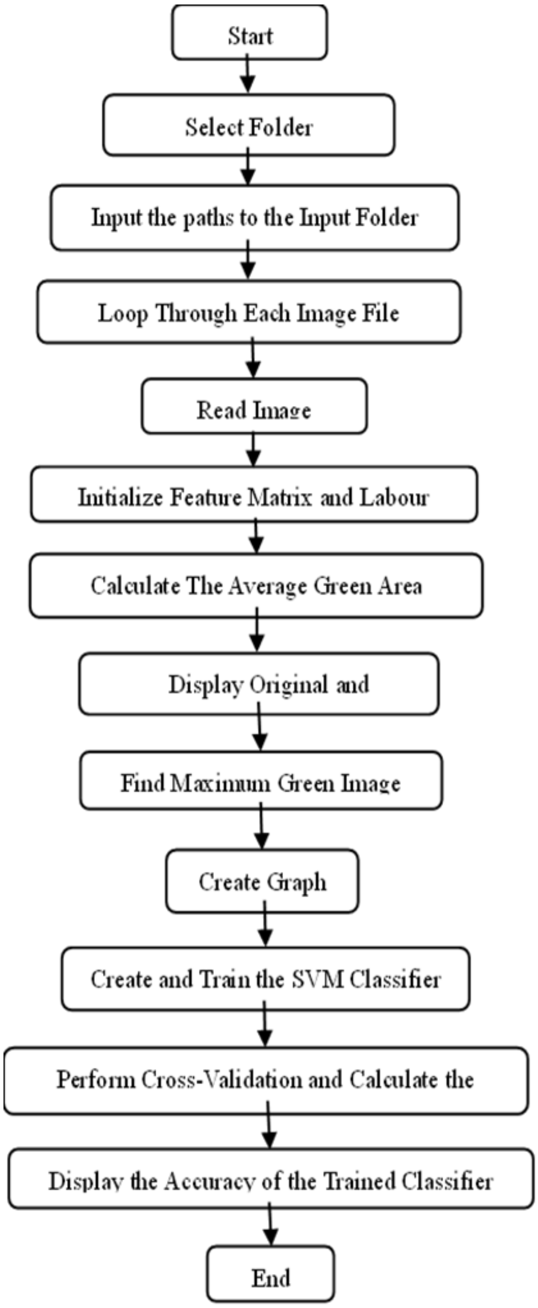

Fig. 2. Support Vector Machine (SVM) Workflow

3.2.3 Artificial Neural Network

The first step in the process is asking the user to choose a folder containing JPEG photographs. To facilitate user input, the uigetdir function is used. In order to achieve efficient color segmentation, each picture is subsequently processed by transforming it from RGB to HSV format.

$$y = f\ (\textstyle\sum_{i=1}^{n} w_i . x_i + b) \quad (2)$$

where,

y is the output,

f is the activation function (e.g., sigmoid, tanh, ReLU), wi are the weights,

xi are the input features, and

b is the bias term.

The output layer of a neural network is represented in general form by equation (2), where y is the final result achieved by adding a bias term (b) and an activation function (f) to the weighted sum of input features (xi) multiplied by their corresponding weights (wi). The activation function in neural networks creates non-linearity, which helps the model identify intricate linkages and patterns in the data. This equation is essential to understanding the expressive power of neural networks in a variety of machine learning tasks, as the activation function selection (sigmoid, tanh, ReLU, etc.) affects the network's ability to model and capture diverse input patterns.

The algorithm finds the image with the highest amount of green color content and displays it by first specifying a green color range in HSV and then adding up all the green pixels in each image [28]. A bar graph that provides a concise visual representation of the distribution of green color values across all photos follows this visual analysis and gives a quantitative summary of the dataset.

By using an artificial neural network (ANN) for picture categorization, the system smoothly incorporates artificial intelligence. To train the ANN, a synthetic dataset is created with randomly selected green values and labels. Scaled conjugate gradient backpropagation for training and a predetermined hidden layer size in the chosen ANN architecture are in line with accepted procedures [29]. After the ANN is trained on 80% of the synthetic dataset, it may be evaluated on the remaining 20%, yielding an accuracy of 89.70%. Using a combination of machine learning and image processing methods, this two-pronged approach presents a thorough examination of the green content of photographs.

As part of our technique, a noteworthy extension of our research entails a thorough three-month study involving three different plant species: cowpea (Vigna unguiculata), pigeon pea (Cajanus cajan), and cotton (Gossypium hirsutum). It is possible to thoroughly investigate any potential differences in plant development patterns in response to different musical stimuli because of this purposeful and extended observation period.

By adding these three unique plant species, the study becomes more robust and allows for the investigation of species-specific responses to various musical genres and frequencies in the 1–10 kHz range, such as pop, classical, and mainstream music [30]. This purposeful variety aims to reveal complex reactions in plant growth and possible relationships between certain auditory stimuli and patterns of development.

The three-month period is critical for determining both short- and long-term effects, offering detailed knowledge of the impact of auditory stimuli on plant growth in various species. This time dimension gives our investigation more depth and makes it easier to identify trends and variances in growth patterns that can appear over a longer observation period. This helps us comprehend this new aspect of precision agriculture more comprehensively.

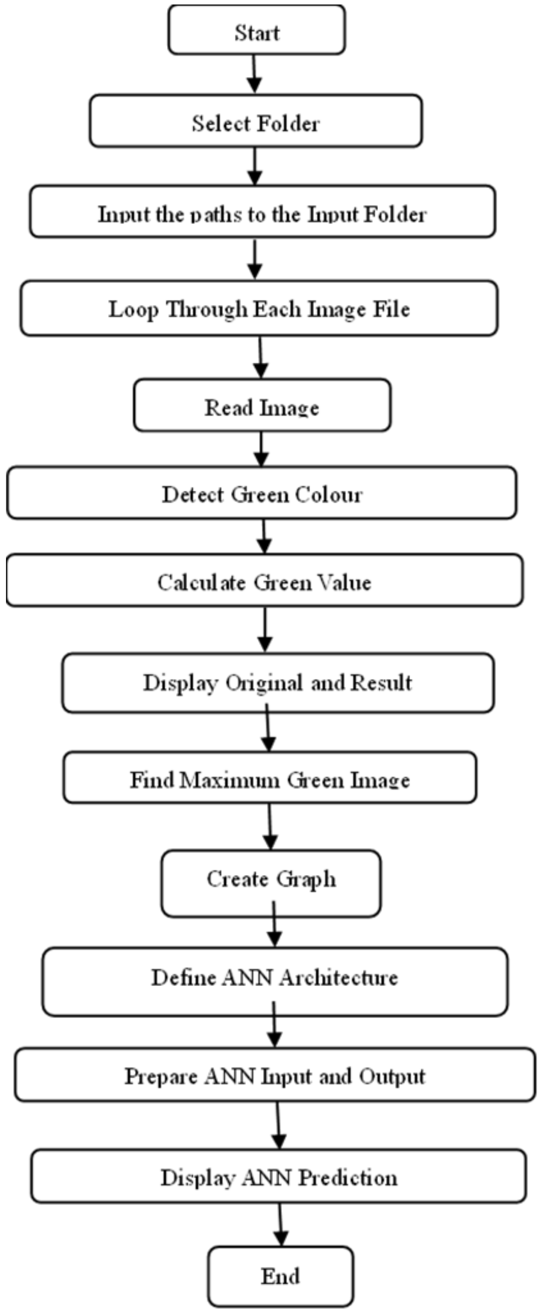

Fig. 3. ANN Flowchart

4. Result

The Within the findings section, three major species cotton, pigeon pea, and cowpea have different patterns of plant growth that may be identified by comparing the prediction models of Support Vector Machines (SVM) and Artificial Neural Networks (ANN). These patterns observed under a range of sound frequencies and genres provide the basis for determining the ideal circumstances that promote the greatest amount of growth of green spaces. The investigation that follows explores which sound frequencies are most predictively accurate for each type of plant, offering a thorough knowledge of the possible influence of auditory stimuli on precision agricultural techniques.

Table 1: Comparative Analysis Results of Different Algorithms of Cotton

Species	Sounds	SVM	ANN
Cotton	1kHz	91%	88.89%
	2kHz	95%	81.20%
	3kHz	94%	88.86%
	4kHz	93%	82.10%
	5kHz	98%	84.80%
	6kHz	95%	83.30%
	7kHz	93%	91.20%
	8kHz	93%	87.30%
	9kHz	98%	89.80%
	10kHz	91%	88.70%
	Normal	91%	88.89%
	Classical Music	95%	83.30%
	Pop Music	93%	89.80%

The table 1 displays the support vector machines' (SVM) and artificial neural networks' (ANN) predictive performance for the development patterns of cotton plants subjected to different sound frequencies (1 to 10 kHz) and genres (pop, classical, and Normal). SVM demonstrates its strong predicting capacity with a constant high accuracy of 98% at 5 kHz. The accuracy of ANNs varies significantly between frequencies. The results showcase the complex relationship between sound frequencies and predictive models, highlighting the significance of frequency selection in precision agriculture for precise plant growth forecasts.

Table 2: Comparative Analysis Results of Different Algorithms of Pigeon Peas

Species	Sounds	SVM	ANN
Pigeon Peas	1kHz	91%	90.20%
	2kHz	94%	87.60%
	3kHz	92%	91.70%
	4kHz	97%	86.70%
	5kHz	95%	89.10%
	6kHz	96%	88.89%
	7kHz	90%	88.40%
	8kHz	91%	92.10%
	9kHz	95%	87.30%
	10kHz	92%	89.30%
	Normal	91%	90.20%
	Classical Music	96%	88.89%
	Pop Music	95%	87.30%

The table 2 shows the Support Vector Machines (SVM) and Artificial Neural Networks (ANN) prediction accuracy for the growth patterns of pigeon peas across different sound frequencies and genres. When it comes to accuracy, SVM consistently performs better than ANN, with a maximum of 92.10% at 4 kHz, while ANN varies in accuracy throughout frequencies. Both models demonstrate their resilience in capturing pigeon pea responses to auditory stimuli by performing well over a wide range of musical genres. The findings highlight how crucial customized frequency considerations are to precision agriculture in the production of pigeon peas.

Table 3: Comparative Analysis Results of Different Algorithms of Cowpeas

Species	Sounds	SVM	ANN
Cow Pea	1kHz	91%	86.10%
	2kHz	95%	88.70%
	3kHz	94%	85.90%
	4kHz	93%	89.40%
	5kHz	98%	90.80%
	6kHz	95%	92.10%
	7kHz	93%	88.50%
	8kHz	93%	90.30%
	9kHz	98%	91.90%
	10kHz	91%	89.70%
	Normal	94%	86.10%
	Classical Music	95%	92.10%
	Pop Music	91%	89.70%

The table 3 shows the Support Vector Machines (SVM) and Artificial Neural Networks (ANN) prediction accuracy for cowpea growth patterns across different sound genres and frequencies. While ANN only reaches a maximum of 92.10% accuracy at 6 kHz, SVM continuously performs well, achieving 98% accuracy at 5 kHz. The two models exhibit consistency across various musical genres, highlighting the significance of customized frequency considerations for precise forecasts in precision farming for cowpea production. By using an integrated approach, we want to not only validate the prediction models but also establish the foundation for real-world precision agricultural applications, leading to technology-driven and optimized crop management techniques.

Moreover, a graphical representation will be utilized to effectively illustrate the correlation between sound frequencies and related green spaces, providing a thorough understanding of the possible impact of auditory stimuli on plant growth.

4.1 Optimizing Green Area: Examining Maximum Growth Patterns in Cotton under Various Sound Frequencies

The focus of the results analysis will next move to calculating the maximum green area that each plant species has obtained, taking into account the ideal sound frequency that has been determined from the comparison tables. In order to identify the optimal sound frequency for strong plant growth in cowpea, cotton, and pigeon pea, it is imperative to synthesise the information obtained from the SVM and ANN prediction models.

Differential development patterns may be seen in fig 4 set of 13 photos of cotton plants that were subjected to sound frequencies ranging from 1 kHz to 10 kHz, which included pop, classical, and everyday music. Specifically, pictures 1 through 10 highlights how the cotton plant reacts to different frequencies, highlighting the complex connection between auditory cues and maximum green area. By demonstrating the plant's sensitivity to various tones, the comparative study of these frequencies' sheds knowledge on its adaptive behavior. Additionally, the cotton plant's growth is depicted in photos 11, 12, and 13 while pop, classical, and mainstream music are playing, respectively.

By providing a more thorough knowledge of how sound frequencies, including those present in different music genres, shape and optimize cotton plant development in precision agriculture, these pictures provide a broader perspective on the effects of traditional music genres.

Fig. 4. Maximum Green Area Observed with Respect to Frequencies in Cotton

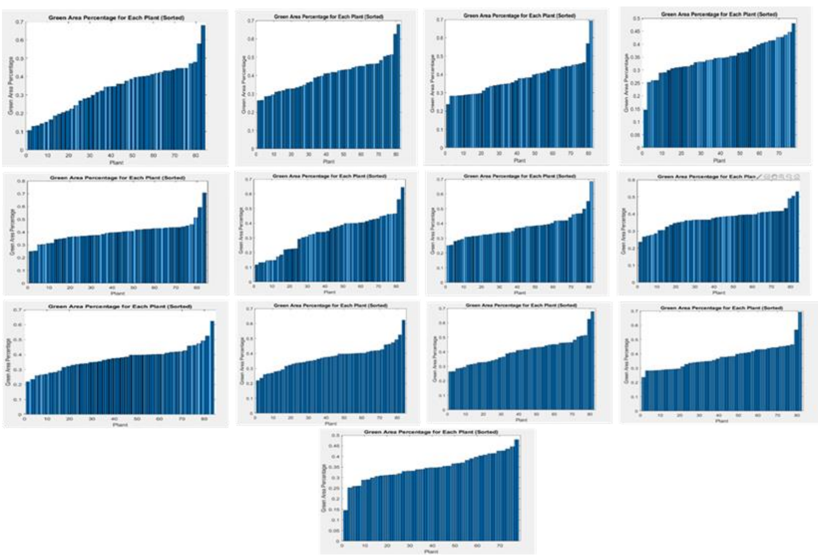

Fig. 5. Green Area Visualization in Each Cotton Plant

The addition of thirteen frequency histograms to the application of various sound frequencies and musical genres to cotton plants improves the visual investigation in fig 5 of green area observations among the chosen plant types. Every histogram is associated with a particular sound frequency ranging from 1 kHz to 10 kHz, in addition to typical, classical, and pop music genres.

The distribution of green patches seen inside each relevant frequency category is clearly shown by the histograms, which offer a thorough summary of the cotton plants' reactions to aural stimuli.

Visualisation method provides a detailed knowledge of the complex link between sound frequencies and plant development by merging pictures and frequency histograms.

In addition to providing a quantitative counterpart to the qualitative picture analysis, frequency histograms also help to clarify how various aural signals affect the diversity in green area across the many types of cotton plants

4.2 Optimizing Green Area: Examining Maximum Growth Patterns in Pigeon Pea under Various Sound Frequencies

Similar differences in pattern of development can be seen in fig 6 of 13 photos of pigeon pea plants that are exposed to a range of sound frequencies, from 1 kHz to 10 kHz, pop, classical, and mainstream music. Pictures 1 through 10 show the pigeon pea's subtle reactions to various frequencies, highlighting the complex connection between aural cues and the ideal green space. This comparative investigation advances our knowledge of the plant's receptiveness to auditory signals while demonstrating its flexibility to various tonal characteristics.

In addition, pictures 11, 12, and 13 show how pigeon pea grows when pop, classical, and mainstream music are played, respectively. These photographs provide important insights into the wider effects of conventional musical stimuli and further our understanding of how sound frequencies, including a variety of musical genres, influence and promote pigeon pea development in precision agriculture.

Fig. 6. Maximum Green Area Observed with Respect to Frequencies in Pigeon Pea Plant

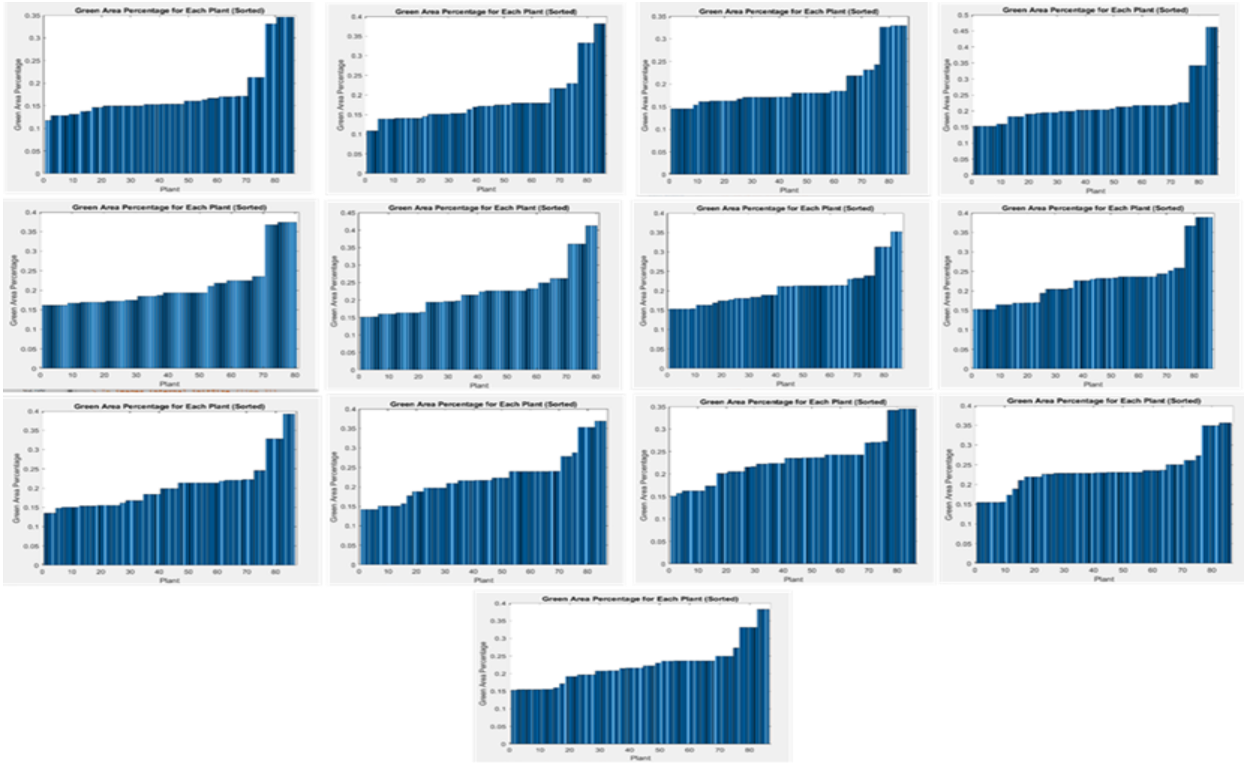

Fig. 7. Green Area Visualization in Each Pigeon Pea Plant

4.3 Optimizing Green Area: Examining Maximum Growth Patterns in Cow Pea under Various Sound Frequencies

The visual investigation in fig 7 of green area dynamics in this particular plant species is enhanced by the integration of thirteen frequency histograms and the exposure of pigeon pea plants to a variety of sound frequencies and musical genres. Plotted against sound frequencies from 1 kHz to 10 kHz, which include pop, classical, and mainstream music, each histogram shows how the green spots are distributed throughout the various frequency ranges.

These histograms clarify the complex link between sound frequencies and ideal green area by giving a thorough picture of how pigeon pea plants react to auditory stimuli. This dual visualization approach, which combines images and frequency histograms, not only provides quantitative insights but also improves our comprehension of the varied effects of sound frequencies, such as those found in different musical genres, on the development of pigeon pea in precision agriculture.

In a similar vein, the 13 photos in fig 8 is the collection of cowpea plant photographs show different developing patterns in response to various musical genres and sound frequencies. Images 1 through 10 show the cowpea's complex responses to different auditory stimuli after being exposed to frequencies ranging from 1 kHz to 10 kHz, which includes pop, classical, and popular music. This highlights the complex link between sound frequencies and the ideal green region. This comparative investigation demonstrates the plant's flexibility to a range of tonal qualities while also advancing our knowledge of its reactivity to auditory stimuli. Furthermore, pictures 11, 12, and 13 show how cowpea grows in response to pop, classical, and mainstream music, respectively. These images provide insightful information on the wider effects of conventional musical stimuli, providing a thorough grasp of how sound frequencies from different musical genres affect and improve cowpea growth in the context of precision agriculture.

Fig. 8. Maximum Green Area Observed with Respect to Frequencies in Cow Pea Plant

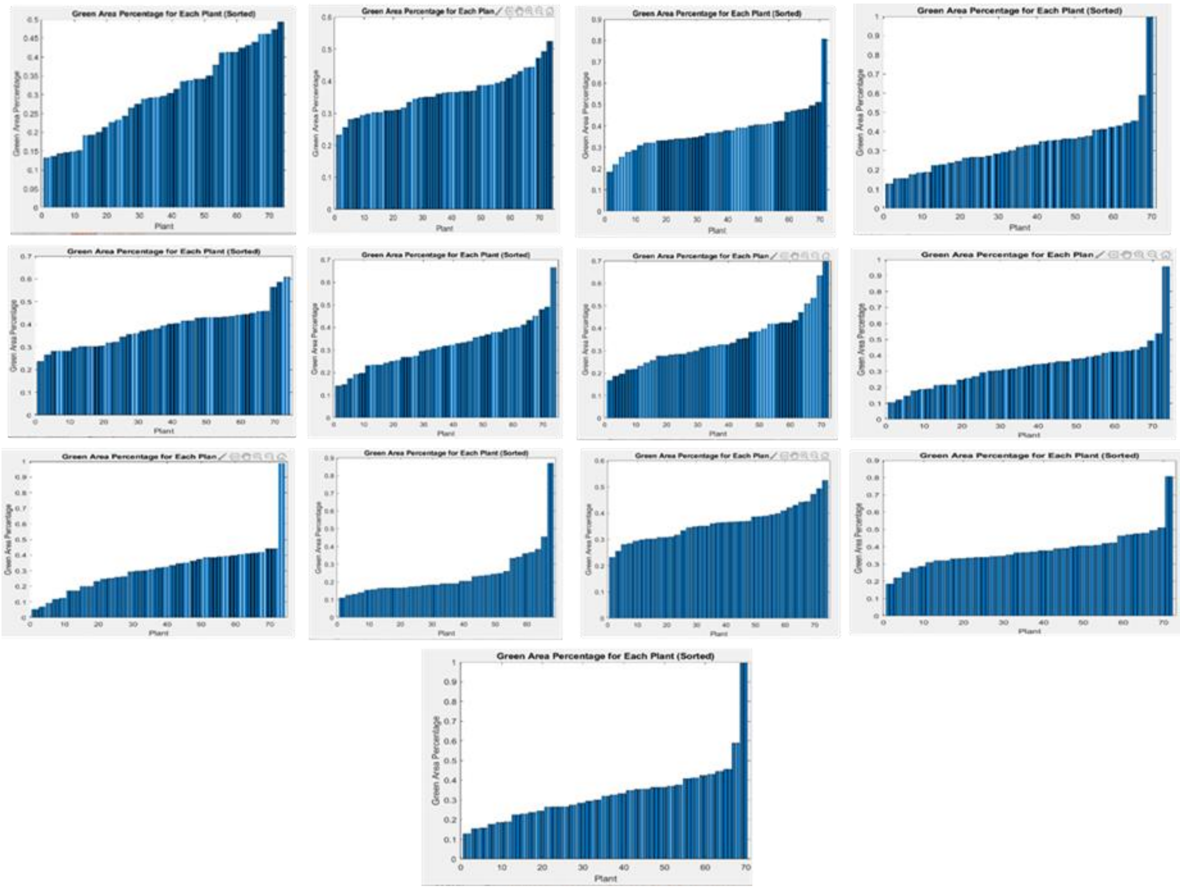

Fig. 9. Green Area Visualization in Each Cow Pea Plant

Similarly, the visual investigation in fig 9 of green area dynamics in cowpea plants subjected to various sound frequencies and musical genres is improved by the integration of thirteen frequency histograms. Using pop, classical, and mainstream music at frequencies between 1 and 10 kHz, each histogram clearly shows the distribution of green patches within respective frequency ranges. These histograms provide a thorough picture of how cowpea plants react to auditory stimuli by clarifying the complex link between sound frequencies and the ideal green area. By combining frequency histograms and images, this dual visualisation method not only offers quantitative insights but also expands our knowledge of the varied effects of sound frequencies from different musical genres on cowpea development in the context of precision agriculture.

5. Conclusion

In conclusion, proposed research marks a groundbreaking convergence of image processing and machine learning, unveiling precise insights into the correlation between plant development and specific musical frequencies. The innovative dual methodology, featuring support vector machines (SVM) outperforming artificial

Neural networks with accuracy levels reaching 92.10%, not only advances our understanding of intricate growth patterns but also offers a sustainable paradigm by eliminating the reliance on pesticides, herbicides, and chemical fertilizers. The inclusion of cowpea, cotton, and pigeon pea over a three-month period lends real-world relevance to the study, underscoring its potential applicability across diverse agricultural landscapes. Beyond technological advancements, the research champions an environmentally

Conscious approach, emphasizing the health-conscious and eco-friendly aspects of chemical-free plant growth. As global agriculture seeks sustainable solutions, this study provides a transformative blueprint for precision farming, showcasing the power of integrating state-of-the-art technologies with traditional methodologies for resilient and eco-conscious agricultural practices.

Acknowledgements

This paper and the research behind it would not have been possible without the exceptional support of my supervisor. Dr. Raj Gaurav Mishra, Associate Professor. ADYPU, Pune. His enthusiasm, knowledge and exacting attention to detail have been an inspiration and kept my work on track. His generosity and expertise have improved this study in innumerable ways and saved me from many errors; those that inevitably remain are entirely my own responsibility.

Author contributions

Niketa Kadam[1]: Conceptualization, Methodology, data collection, dataset Preparation, Writing-Original draft preparation, Visualization, Software, Validation., Visualization **Dr. Raj Mishra[2]:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] Dhanusha, Jannu & Reddy, Beeram & Yuvasree, Avidi & Sravanthi, Kolusu & Bandi, Surendra. (2023). Recommendation System to Precision Agriculture Using Machine Learning Algorithm. Journal of Data Mining and Management. 8. 19-32. 10.46610/JoDMM.2023.v08i03.003.

[2] Patil, Sagar & Kulkarni, R. & Kharade, Pramod & Patil, Suchita. (2023). Review of Machine Learning Model Applications in Precision Agriculture. 105. 916-930. 10.2991/978-94-6463-136-4_81.

[3] Ed-Daoudi, Rachid & Alaoui, Altaf & Ettaki, Badia & Zerouaoui, Jamal. (2023). A Machine Learning Approach to Identify Optimal Cultivation Practices for Sustainable apple Production in Precision Agriculture in Morocco. E3S Web of Conferences. 469. 10.1051/e3sconf/202346900052.

[4] Mistry, Vishakha & Mishra, Abhishek & Ahmed, Nadiyah. (2023). Machine Learning Use Case in Indian Agriculture: Predictive Analysis of Bihar Agriculture Data to Forecast Crop Yield. International Journal for Research in Applied Science and Engineering Technology. 11. 1004-1009. 10.22214/ijraset.2023.48709.

[5] Jackson, Majwega & Marvin, Ggaliwango & Chakrabarty, Amitabha. (2022). Robust Ensemble Machine Learning for Precision Agriculture. 10.1109/ICISET54810.2022.9775879.

[6] Rajendiran, Gowtham & Rethnaraj, Jebakumar. (2024). IoT-Integrated Machine Learning-Based Automated Precision Agriculture-Indoor Farming Techniques. 10.4018/979-8-3693-0639-0.

[7] Kakade, Suhas & Kulkarni, Rohan & Dhawale, Somesh & C, Muhammed. (2023). Utilization of Machine Learning Algorithms for Precision Agriculture: Enhancing Crop Selection. Green Intelligent Systems and Applications. 3. 86-97. 10.53623/gisa.v3i2.313.

[8] Musanase, Christine & Vodacek, Anthony & Hanyurwimfura, Damien & Uwitonze, Alfred & Kabandana, Innocent. (2023). Data-Driven Analysis and Machine Learning-Based Crop and Fertilizer Recommendation System for Revolutionizing Farming Practices. Agriculture. 13. 2141. 10.3390/agriculture13112141.

[9] Reddy, Vutukuru & Varshini, Vanmalli & Namineni, Gireesh & Naresh, M. (2023). A Comprehensive Study on Crop Recommendation System for Precision Agriculture Using Machine Learning Algorithms. Electrical and Automation Engineering. 2. 30-36. 10.46632/eae/2/1/5.

[10] Zhang, Ying. (2023). Simulation of Crop Planting Decision System Based on “U + CSA” Public

Welfare Agriculture and Machine Learning Algorithm. 10.1007/978-981-99-5203-8_14.

[11] Neubürger, Felix & Arens, Joachim & Kopinski, Thomas & Hermes, Matthias. (2023). Development of a Demonstator Plant for Hot Stamping of Metal Sheets with a Machine Learning Assisted Anomaly Detection Control System. 10.1007/978-3-031-40920-2_28.

[12] Saravanakumar Venkatesan, Jonghyun Lim, Yongyun Cho, "A Crop Growth Prediction Model Using Energy Data Based on Machine Learning in Smart Farms", Computational Intelligence and Neuroscience, vol. 2022, Article ID 2648695, 18 pages, 2022. https://doi.org/10.1155/2022/2648695

[13] Parate, Rajesh & Dhole, K. & Sharma, S.. (2023). Classification of Leaf using Teachable Machine. International Journal for Research in Applied Science and Engineering Technology. 11. 307-311. 10.22214/ijraset.2023.55629.

[14] Walsh, Ian & Fishman, Dmytro & Garcia-Gasulla, Dario & Titma, Tiina & group, The & Harrow, Jen & Psomopoulos, Fotis & Tosatto, Silvio. (2020). Recommendations for machine learning validation in biology.

[15] Precisión, Aplicación & Ramirez Gomez, Carlos. (2020). APLICACIÓN DEL MACHINE LEARNING EN AGRICULTURA DE PRECISIÓN APPLICATION OF MACHINE LEARNING IN PRECISION AGRICULTURE. Revista CINTEX. 25. 14-27. 10.33131/24222208.356.

[16] Suresh Bhadane, Dinesh & Patil, Suvarna & Bhandari, Abhay & Mahajan, Danish & Katoch, Ajay & Abrol, Naman. (2023). Plant Leaf Recognition Using Machine Learning: A Review. 2395-0056.

[17] Jaramillo-Alcázar, Angel & Govea, Jaime & Villegas, William. (2023). Anomaly Detection in a Smart Industrial Machinery Plant Using IoT and Machine Learning. Sensors. 23. 8286. 10.3390/s23198286.

[18] Sia, Jayson & Zhang, Wei & Cheng, Mingxi & Bogdan, Paul & Cook, David. (2023). Machine learning general transcriptional predictors of plant disease. 10.1101/2023.08.30.555529.

[19] Rai, Krishna. (2023). Stress phenotyping in plants using arti cial intelligence and machine learning EDITORIAL. Journal of Agriculture and Livestock Farming. 1. 10.61577/jalf.2023.100001.

[20] Deshwal, Pushkar & Sharma, Kaushal & Moudgil, Suveg. (2023). Plant Leaf Disease Detection using Machine Learning. International Journal for Research in Applied Science and Engineering Technology. 11. 5928-5932. 10.22214/ijraset.2023.52895.

[21] Paithankar, Prof & Awari, Ajinkya & Raskar, Akash & Patil, Shrirameshwar & Jamdar, Namrata. (2023). Plant Disease Detection using Machine Learning. International Journal of Advanced Research in Science, Communication and Technology. 267-272. 10.48175/IJARSCT-9297.

[22] Kabour, Shaimaa & Almalki, Raghad & Alghamdi, Lujain & Alharthi, Wujud & Alshagi, Nisreen. (2023). Fault classification and detection for photovoltaic plants using machine learning algorithms. Indonesian Journal of Electrical Engineering and Computer Science. 32. 353. 10.11591/ijeecs.v32.i1.pp353-362.

[23] Upadhya, Nischitha. (2023). Classification and Detection of Plant Disease Using CNN and Machine Learning. INTERANTIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT. 07. 10.55041/IJSREM25038.