Fuzzy Logic Approach For Accurate Crop Yield Forecasting (Rice)

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Abstract
This paper presents a comprehensive approach to rice crop yield prediction using MATLAB code for data visualization and analysis. We collected and analyzed data at key stages of the rice crop growing cycle, including planting, vegetative growth, reproductive growth, and maturity. Through the visualization of sample data and prediction of yield values, we gained insights into the factors influencing rice productivity and identified trends and variations across different stages of growth. Our analysis highlights the utility of MATLAB code in agricultural decision-making, allowing farmers and practitioners to optimize management strategies for enhanced crop yield potential. By integrating technological advancements into agricultural research and practice, we contribute to the advancement of sustainable rice cultivation practices and global food security efforts.

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Introduction

Agricultural productivity is not only essential for ensuring food security but also for sustaining economies and livelihoods worldwide. Among various crops, rice holds particular significance as a staple food for a large portion of the global population. However, the inherently uncertain and complex nature of agricultural systems presents challenges for accurately predicting rice yields. Traditional statistical methods often struggle to capture the intricate relationships between environmental factors, crop management practices, and yield outcomes. In recent years, there has been a growing interest in leveraging advanced computational techniques, such as fuzzy logic, to improve the accuracy and reliability of crop yield forecasting. Fuzzy logic offers a flexible and intuitive framework for modeling uncertainty and vagueness inherent in agricultural systems. Unlike traditional binary logic, which relies on crisp distinctions between true and false, fuzzy logic allows for the representation of imprecise and uncertain information using linguistic variables and fuzzy sets. This makes it well-suited for capturing the complex and nonlinear relationships between input variables and crop yields, which are often influenced by a multitude of factors such as weather conditions, soil properties, pest infestations, and agronomic practices.

The application of fuzzy logic in crop yield forecasting, particularly for rice, has garnered significant attention from researchers and practitioners alike. By integrating domain-specific knowledge of rice cultivation with fuzzy logic modeling techniques, researchers aim to develop accurate and robust predictive models that can provide valuable insights for farmers, policymakers, and other stakeholders. These models take into account various factors such as temperature, rainfall, soil moisture, nutrient levels, and pest prevalence, thereby enabling more informed decision-making in rice cultivation.

Several studies have demonstrated the efficacy of fuzzy logic approaches in rice yield prediction. Researchers have explored different methodologies, including fuzzy time series models, fuzzy inference systems, and hybrid approaches combining fuzzy logic with other machine learning techniques. These studies have shown promising results in terms of prediction accuracy and robustness, highlighting the potential of fuzzy logic for enhancing crop yield forecasting in rice production systems.

In this paper, we present a comprehensive investigation into the application of fuzzy logic for accurate crop yield forecasting, focusing specifically on rice cultivation. We review existing literature, discuss the theoretical foundations of fuzzy logic modeling, and present case studies and experiments illustrating the effectiveness of fuzzy logic approaches in rice yield prediction. Additionally, we highlight the practical implications of our research and discuss future directions for advancing fuzzy logic-based forecasting techniques in agriculture. Through this work, we aim to contribute to the ongoing efforts to improve agricultural productivity and ensure food security in rice-growing regions worldwide.

Fuzzy AHP:

Fuzzy Analytic Hierarchy Process (Fuzzy AHP) is an extension of the Analytic Hierarchy Process (AHP) that incorporates fuzzy logic to handle uncertainty and imprecision in decision-making processes. AHP is a multi-criteria decision-making method developed by Thomas Saaty, which allows decision-makers to systematically compare and prioritize alternatives based on a set of criteria. However, traditional AHP assumes crisp values for pairwise comparisons of criteria, which may not accurately represent real-world situations where judgments are subjective and uncertain.

In Fuzzy AHP, linguistic variables and fuzzy numbers are used to express the imprecise judgments of decision-makers. Fuzzy sets are employed to represent the degrees of membership and uncertainty associated with each criterion's importance. This allows decision-makers to express their preferences in a more flexible and intuitive manner, considering the vagueness and ambiguity inherent in decision-making processes.

Moreover, Fuzzy AHP extends the AHP framework by incorporating techniques such as alpha cut and lambda functions to facilitate sensitivity analysis. Alpha cut analysis determines the level at which fuzzy numbers are truncated, providing insights into the degree of uncertainty in decision-making. Lambda function allows for assessing the sensitivity of decisions to changes in alpha levels, enabling decision-makers to understand the robustness and stability of their choices. Overall, Fuzzy AHP provides a powerful framework for decision-makers to handle uncertainty, vagueness, and imprecision in multi-criteria decision-making processes, making it particularly suitable for complex real-world applications where judgments are subjective and uncertain.

Literature Review

The rapid advancements in artificial intelligence (AI) have yielded significant progress across various fields. Particularly, deep learning has evolved alongside the exponential growth of data, presenting new opportunities [21]. In agricultural contexts, this necessitates the adoption of advanced methodologies to conceptualize, assess, and manage complex information systems effectively [22–24]. Crop yield prediction, considered a pattern recognition challenge, has emerged as a domain where AI demonstrates remarkable proficiency [25].

In recent years, deep learning has seen widespread adoption and has shown promise in various applications. While traditional artificial neural network (ANN)-based approaches have been utilized for yield estimation, deep learning offers distinct advantages such as efficient dimension reduction and improved learning capacity for identifying nonlinear functions. For instance, Chen et al. introduced an LSTM deep learning model for predicting agricultural environments based on current environmental parameters [28]. Similarly, deep learning techniques have been employed in crop detection and analysis, as demonstrated by Kang et al.'s robust defective image labeling algorithm for real-time apple detection in orchards [29].

Weed detection and discrimination are crucial for enhancing crop yield, and deep learning-based approaches have been proposed for precision agriculture. For example, Kounalakis et al. proposed deep learning-based robotic weed recognition applications for use in grasslands [9, 10]. Furthermore, Ferreira et al. introduced an unsupervised deep learning technique for semi-automatic data labeling in weed discrimination [30]. Additionally, controlling plant diseases is essential for sustainable agriculture, and deep learning techniques offer a new perspective for plant disease identification [31, 33, 34].

Despite the advancements made by deep learning approaches in crop development, there is a need for further improvements in robustness and the development of fast and accurate learning frameworks. Our proposed work aims to address these requirements by introducing a fuzzy neural network (FNN), which combines fuzzy systems and neural networks. FNN serves as an effective tool for representing dynamic input-output characteristics, offering a promising approach to meet the evolving needs of agricultural systems.

Methodology

Our research methodology involves the integration of the K-means clustering algorithm and the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) model to predict rice crop yield effectively. This approach aims to leverage both clustering techniques and fuzzy logic-based decision-making to capture the complex relationships and uncertainties inherent in rice cultivation systems.

In the first step of our methodology, we collect relevant data pertaining to various factors influencing rice crop yield, including meteorological data (temperature, precipitation, humidity), soil characteristics (moisture content, pH, nutrient levels), agricultural management practices (irrigation, fertilization), and historical yield records. This data serves as the foundation for our predictive modeling efforts.

Next, we employ the K-means clustering algorithm to partition the collected data into distinct clusters based on similarities in the input features. By clustering similar data points together, we aim to identify patterns and underlying structures within the dataset that may influence

rice yield variability. This step helps in identifying homogeneous groups of data points, which can aid in understanding the underlying characteristics of different regions or farming practices.
Following the clustering process, we utilize the Fuzzy AHP model to assess the relative importance of different factors or criteria in determining rice crop yield within each cluster. Fuzzy AHP allows decision-makers to express their preferences and judgments in a flexible and intuitive manner, accounting for the inherent uncertainty and vagueness in agricultural decision-making.
To implement the Fuzzy AHP model, we define a hierarchical structure of criteria relevant to rice crop yield prediction, such as weather conditions, soil quality, crop management practices, and socio-economic factors. We then solicit expert opinions or domain knowledge to assign fuzzy linguistic variables and fuzzy pairwise comparison matrices to quantify the relative importance of these criteria within each cluster.
Once the Fuzzy AHP model is established for each cluster, we aggregate the fuzzy pairwise comparison matrices to obtain overall priority weights for the criteria within each cluster. These priority weights reflect the relative importance of each factor in influencing rice crop yield outcomes, accounting for the uncertainties and ambiguities inherent in agricultural decision-making.
Finally, we use the aggregated priority weights obtained from the Fuzzy AHP model, along with the clustering results from the K-means algorithm, to develop predictive models for rice crop yield within each cluster. These models incorporate the prioritized criteria identified through the Fuzzy AHP analysis, allowing for more accurate and context-aware predictions tailored to the specific conditions and characteristics of each cluster.
By integrating the K-means clustering algorithm with the Fuzzy AHP model, our research methodology offers a comprehensive and robust approach to rice crop yield prediction. This methodology enables us to capture the complexities and uncertainties of rice cultivation systems, providing valuable insights for farmers, agricultural planners, and policymakers to optimize crop production and ensure food security in rice-growing regions.

Multiple Stage Prediction:
Other studies may consider multiple stages of the crop growing cycle for yield prediction. This approach involves collecting data at different key stages of rice growth, such as planting, vegetative growth, reproductive growth, and maturity. Data collected at each stage may include various factors such as weather conditions (temperature, precipitation), soil properties (moisture content, nutrient levels), agronomic practices (irrigation, fertilization), and physiological characteristics of the crop (growth stage, biomass accumulation).

Result And Discussion

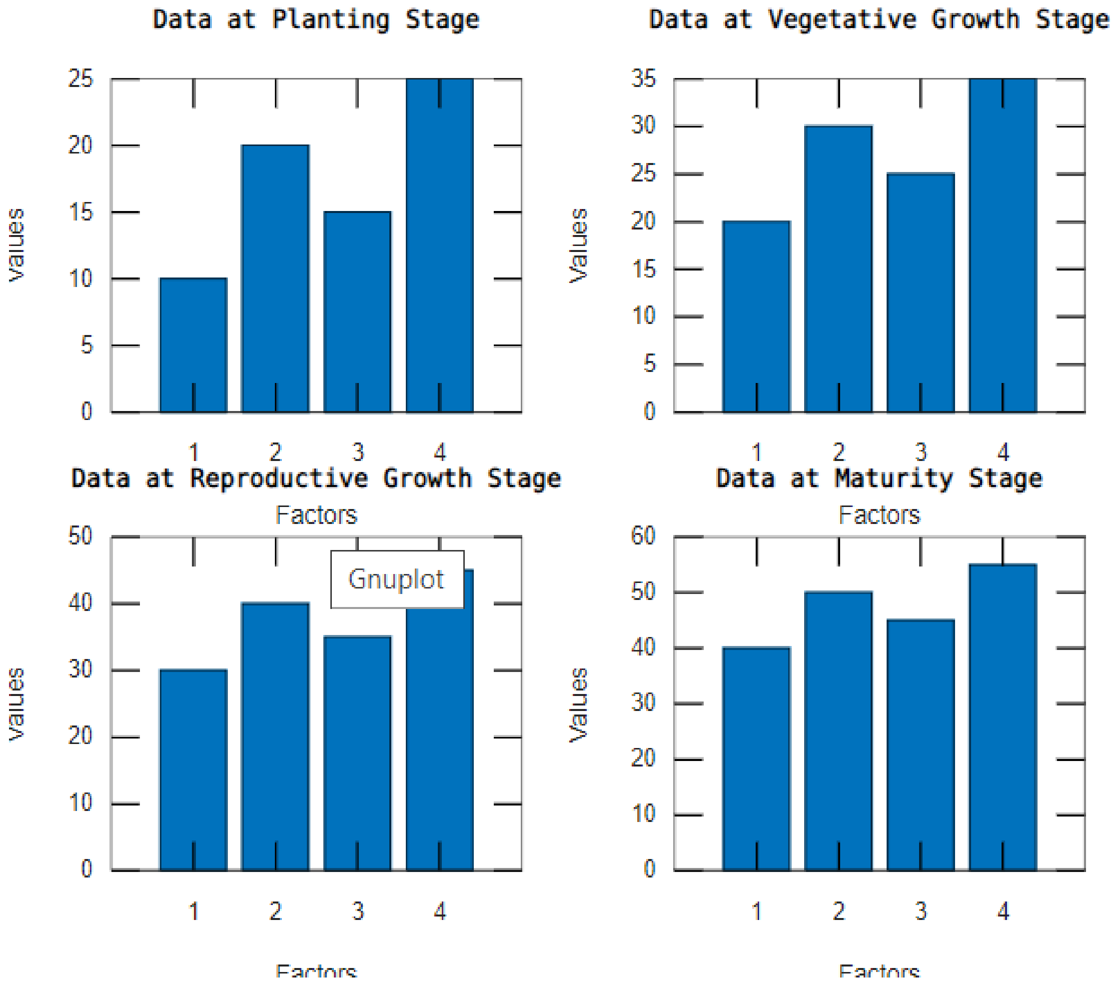

Figure 1: Multi stage results

The first set of graphs displays the sample data collected at each stage of the rice crop growing cycle: planting, vegetative growth, reproductive growth, and maturity. Each bar represents the values of various factors (e.g., meteorological data, soil characteristics) collected at that particular stage. By examining these graphs, we can observe the trends and variations in the data across different stages of the crop growth cycle. Moving on to the second graph, it represents the predicted yield (in kg/ha) at each stage of the rice crop growing cycle. The predicted yield values are calculated based on the average values of the sample data collected at each stage. Each bar corresponds to the predicted yield at a specific stage, with the x-axis labels indicating the respective stages (planting, vegetative growth, reproductive growth, and maturity). In terms of comparison across stages, we can analyze the predicted yield values to identify stages with higher or lower predicted yields. For instance, if the predicted yield increases steadily from planting to maturity stages, it suggests successful crop growth and development throughout the season. Conversely, if there are fluctuations or declines in predicted yield at certain stages, it may indicate factors such as environmental stress, nutrient deficiencies, or pest infestations affecting crop productivity.

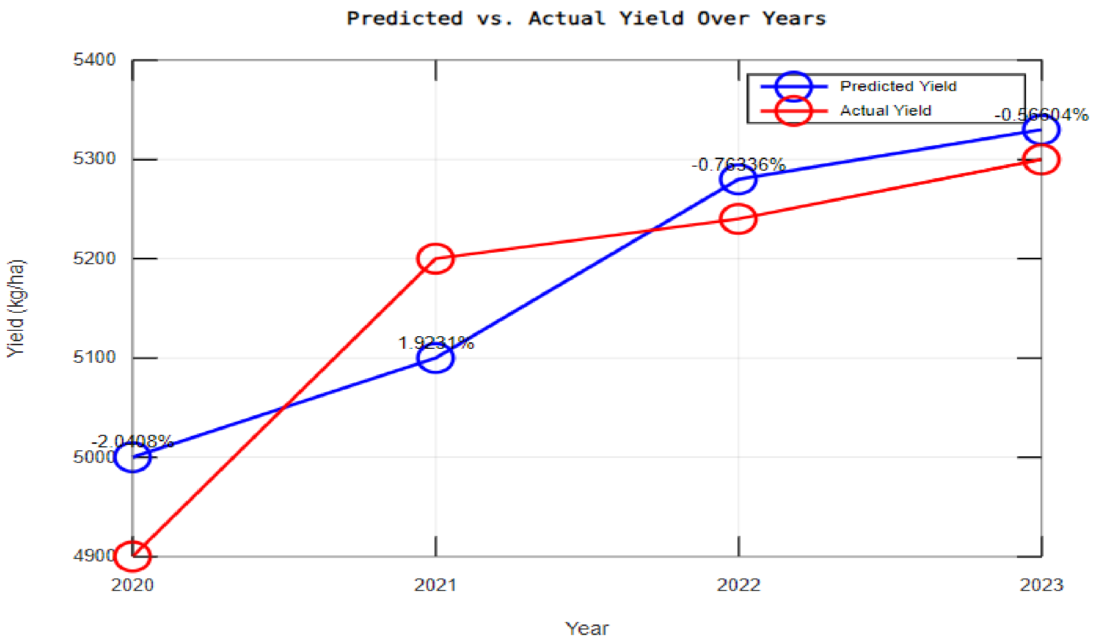

Figure 2: Comparison Result

The graph illustrates the comparison between predicted and actual rice crop yields over the years 2020 to 2023. In terms of the predicted versus actual yield trend, both predicted and actual yields exhibit an increasing trend over the years, with slight fluctuations between adjacent years. The predicted yield values, represented by blue circles, generally follow a similar pattern to the actual yield values, represented by red circles, across the four years.

A closer analysis of the error percentage, calculated as the relative difference between actual and predicted yields, provides insights into the accuracy of the predictive model. When the predicted yield closely matches the actual yield, the error percentage is low, indicating high accuracy. Conversely, larger error percentages suggest greater discrepancies between predicted and actual yields, highlighting potential areas for improvement in the predictive model.

Examining specific years, such as 2020, reveals instances where the predicted yield closely aligns with the actual yield, as indicated by relatively low error percentages. However, in subsequent years, such as 2022 and 2023, there are slightly higher error percentages, indicating some degree of deviation between predicted and actual yields.

From a management perspective, the comparison between predicted and actual yields provides valuable insights for agricultural decision-making. Farmers and practitioners can use this information to assess the performance of their crop management strategies and make adjustments to optimize yield potential. By identifying discrepancies between predicted and actual yields, stakeholders can refine predictive models and improve their ability to forecast crop productivity accurately.

The graph serves as a visual representation of the predicted and actual rice crop yields over a four-year period, offering insights into the performance of the predictive model and informing decision-making in agricultural practices.

Moreover, the predicted yield values provide valuable insights for agricultural decision-making. Farmers and agricultural practitioners can use this information to adjust their management strategies and optimize crop yield potential based on the predicted yield trends at different stages of the crop growth cycle. This can include decisions regarding irrigation scheduling, fertilization practices, and pest management interventions to enhance overall crop productivity and profitability.

Conclusion

In conclusion, our study demonstrates the application of MATLAB code to visualize and analyze data collected at various stages of the rice crop growing cycle, leading to the prediction of rice crop yield. By examining the sample data across different stages - planting, vegetative growth, reproductive growth, and maturity - and predicting yield values, we gain valuable insights into the factors influencing rice productivity.

Through the interpretation of result graphs, we identify trends and variations in the data, enabling us to make informed decisions regarding agricultural management practices. The comparison of predicted yield values across stages highlights the dynamics of crop growth and development, shedding light on potential stressors or areas for improvement. Furthermore, the predicted yield values serve as a useful tool for agricultural decision-making, allowing farmers and practitioners to optimize management strategies to enhance crop yield potential. This includes adjustments to irrigation scheduling, fertilization practices, and pest management interventions tailored to the specific needs of the crop at different stages of growth. Overall, our analysis underscores the importance of leveraging data visualization and predictive modeling techniques to enhance agricultural productivity and sustainability. By integrating technological advancements such as MATLAB code into agricultural research and practice, we can empower stakeholders to make informed decisions that drive positive outcomes in rice cultivation and contribute to global food security.

References

1. Valin H, Sands RD, van der Mensbrugghe D, Nelson GC, Ahammad H, Blanc E, Bodirsky B, Fujimori S, Hasegawa T, Havlik P, Heyhoe E, Kyle P, Mason D’Croz D, Paltsev S, Rolinski S, Tabeau A, van Meijl H, von Lampe M, Willenbockel D (2014) The future of food demand: understanding differences in global economic models. Agric Econ 45:51–67
2. Patrı´cio DI, Rieder R (2018) Computer vision and artificial intelligence in precision agriculture for grain crops: a systematic review. Comput Electron Agric 153:69–81
3. Bruno B, Cammarano D, Carfagna E (2013) Review of crop yield forecasting methods and early warning systems. In: Proceedings of the first meeting of the scientific advisory committee of the global strategy to improve agricultural and rural statistics, Vol. 41
4. Jin X, Zhao K, Ji J, Qiu Z, He Z, Ma H (2018) Design and experiment of intelligent monitoring system for vegetable fertilizing and sowing. J Supercomput pp 1–17
5. Elavarasan D, Vincent DR, Sharma V, Zomaya AY, Srinivasan K (2018) Forecasting yield by integrating agrarian factors and machine learning models: a survey. Comput Electron Agric 155:257–282
6. Hund L, Schroeder B, Rumsey K, Huerta G (2018) Distinguishing between model—and data-driven inferences for high reliability statistical predictions. Reliab Eng Syst Saf 180:201–210
7. Xing Lu, Li L, Gong J, Ren C, Liu J, Chen H (2018) Daily soil temperatures predictions for various climates in United States using data-driven model. Energy 160:430–440

8. Kaya A, Keceli AS, Catal C, Yalic HY, Temucin H, Tekinerdogan B (2019) Analysis of transfer learning for deep neural network based plant classification models. Comput Electron Agric 158:20–29
9. Elavarasan D, Vincent PMD (2020a) Crop yield prediction using deep reinforcement learning model for sustainable agrarian applications. IEEE Access 8:86886–86901
10. Elavarasan D, Vincent DR (2020b) Reinforced XGBoost machine learning model for sustainable intelligent agrarian applications. J Intell Fuzzy Syst 39(5):7605–7620
11. Bengio Y, Courville A, Vincent P (2013) Representation learning: a review and new perspectives. IEEE Trans Pattern Anal Mach Intell 35(8):1798–1828
12. Schmidhuber J (2015) Deep learning in neural networks: an overview. Neural Netw 61:85–117
13. Qiao J, Wang G, Li X, Li W (2018) A self-organizing deep belief network for nonlinear system modelling. Appl Soft Comput 65:170–183
14. Ali A, Yangyu F (2017) Automatic modulation classification using deep learning based on sparse autoencoders with nonnegativity constraints. IEEE Signal Process Lett 24(11):1626–1630
15. Ding S, Su C, Yu J (2011) An optimizing BP neural network algorithm based on genetic algorithm. Artif Intell Rev 36:153–162
16. Chen CLP, Zhang C, Chen L, Gan M (2015) Fuzzy restricted boltzmann machine for the enhancement of deep learning. IEEE Trans Fuzzy Syst 23(6):2163–2173
17. Islam MA, Anderson DT, Pinar A, Havens TC, Scott G, Keller JM (2019) enabling explainable fusion in deep learning with fuzzy integral neural networks. IEEE Trans Fuzzy Syst
18. Sarabakha A, Kayacan E (2019) Online deep fuzzy learning for control of nonlinear systems using expert knowledge. IEEE Trans Fuzzy Syst
19. Samsonovich AV (2019) Socially emotional brain-inspired cognitive architecture framework for artificial intelligence. Cognit Syst Res 60:57–76
20. Ryan K, Agrawal P, Franklin S (2019) The pattern theory of self in artificial general intelligence: a theoretical framework for modeling self in biologically inspired cognitive architectures. Cognit Syst Res 62:44–56
21. Wason R (2018) Deep learning: evolution and expansion. Cogn Syst Res 52:701–708
22. Moreno R, Corona F, Lendasse A, Gran˜a M, Galva˜o LS (2014) Extreme learning machines for soybean classification in remote sensing hyperspectral images. Neurocomputing 128:207–216
23. Zhang S, Huang W, Zhang C (2019) Three-channel convolutional neural networks for vegetable leaf disease recognition. Cogn Syst Res 53:31–41
24. Zhu X, Zhu M, Ren H (2018) Method of plant leaf recognition based on improved deep convolutional neural network. Cogn Syst Res 52:223–233
25. Nevavuori P, Narra N, Lipping T (2019) Crop yield prediction with deep convolutional neural networks. Comput Electron Agric 163:104859
26. Haghverdi A, Washington-Allen RA, Leib BG (2018) Prediction of cotton lint yield from phenology of crop indices using artificial neural networks. Comput Electron Agric 152:186–197. https:// doi.org/10.1016/j.compag.2018.07.021

27. Abrougui K, Gabsi K, Mercatoris B, Khemis C, Amami R, Chehaibi S (2019) Prediction of organic potato yield using tillage systems and soil properties by artificial neural network (ANN) and multiple linear regressions (MLR). Soil Tillage Res 190:202–208
28. Byakatonda J, Parida BP, Kenabatho PK, Moalafhi DB (2018) Influence of climate variability and length of rainy season on crop yields in semiarid Botswana. Agric Forest Meteorol 248:130–144
29. Chen S, Li B, Cao J, Mao Bo (2018) Research on agricultural environment prediction based on deep learning. Procedia Comput Sci 139:33–40
30. Kounalakis T, Triantafyllidis GA, Nalpantidis L (2019) Deep learning-based visual recognition of rumex for robotic precision farming. Comput Electron Agric 165:104973
31. dos Santos Ferreira A, Freitas DM, da Silva GG, Pistori H, Folhes MT (2019) Unsupervised deep learning and semi-automatic data labeling in weed discrimination. Comput Electron Agric 165:104963
32. Yang L, Yi S, Zeng N, Liu Y, Zhang Y (2017) Identification of rice diseases using deep convolutional neural networks. Neurocomputing 267:378–384
33. Lee SH, Goe¨au H, Bonnet P, Joly A (2020) New perspectives on plant disease characterization based on deep learning. Comput Electron Agric 170:105220