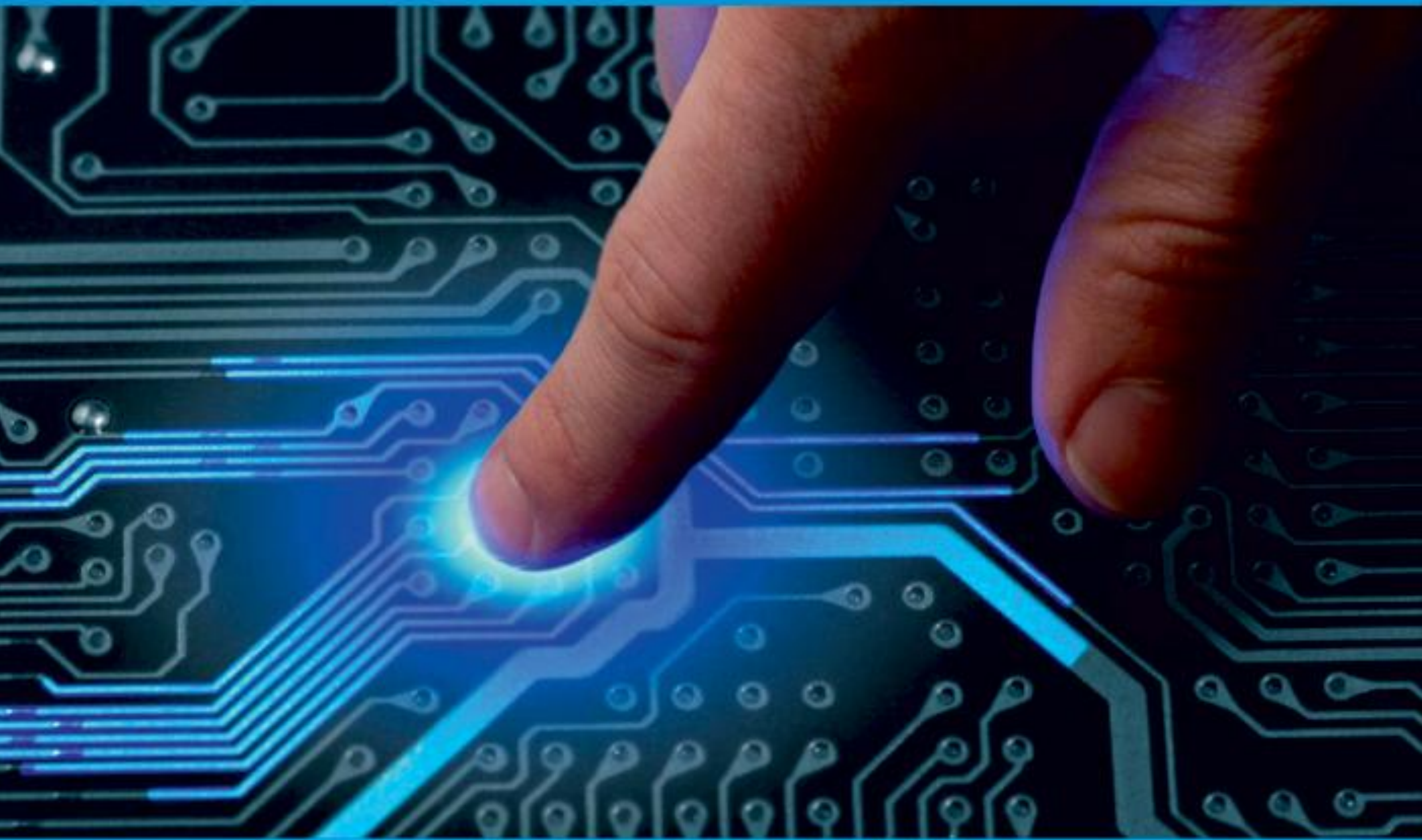
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 11, Special Issue 2, March 2023

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

| International Conference on Recent Innovations in Engineering and Technology (ICRIET'23)|

| Sharadchandra Pawar College of Engineering, Pune, India |

|| Volume 11, Special Issue 2, March 2023 ||

A-Review on Thermal Imaging Based Plant Growth Estimation and Yield Prediction Using Machine Learning

Neeta B Bankhelen, Dr.Rekha Labade

Research Scholar, Dept. of E&TC Engineering, Sanjivani college of engineering & Research Center, Kopargaon, India

Associate Professor, Dept. of of E&TC Engineering, Amrutvahini college of Engineering, Sangamner, India

ABSTRACT: Precision farming has newly grown a top precedence zone due to the enlarging earth population, the need to guarantee the availability of the fresh product in remote areas, and increase the food quality in general. Monitoring of plant growth can be done with appropriate taxonomies using an automated system. This information can be useful for farmers, botanists, industrialists, physicians, and food engineers. It relies heavily on artificial growth systems. It enables the resolution of several issues related with the rising need for environmentally friendly food production in the setting of a growing global population. Accurate evaluation of plant growth dynamics factors is critical for the long-term success of optimizing the whole growing system characteristics. Thermal images of plants have been used as a way of monitoring different plant dynamics since it does provide a non-destructive method that allows its remote evaluation. Even with the facilities provided, it does require a high level of expertise for a human to evaluate these images and this is a time-consuming task. In this context, deep learning techniques are crucial tools that can automatically evaluate the images and estimate the growth dynamics of plants with more accuracy and as fast as possible to deal with the dynamic in time and space of agriculture fields. Crop growth monitoring is a difficult undertaking, and crops are watched throughout their development to ensure that the product meets quality and delivery deadlines. In this research plant growth estimation and yield prediction algorithm is proposed that will accelerate experimental plant cycles by predicting phenotypic qualities prior to measurement, enabling experiments to be completed sooner and more effectively

KEYWORDS: Thermal imaging, growth dynamics, precision agriculture, Machine learning, yield prediction.

I. INTRODUCTION

Li et al. [1] describe plant phenotyping as the evaluation of complex plant features such as growth, resistance, architecture, physiology, ecology, and the important measurement of specific quantitative data. Plant attributes have traditionally been assessed manually in phenotyping studies. This reduces throughput and inhibits detailed analysis, which is known as the phenotyping bottleneck [2]. Image-based phenotyping has been recommended as a solution to this barrier since it has shown considerable promise in terms of boosting the size, throughput, efficiency, and speed of phonemic research. Deep learning algorithms for image segmentation, feature extraction, and data analysis are now widely regarded as the key to development in image-based high-throughput plant phenotyping [3]. Agriculture is a vital industry in the growth of our country's economy. The crop selection is critical in cultivation planning. Using AI approaches, several professionals researched crop production speed prediction, climate forecast, soil characterization, and crop grouping for agricultural planning. Many agricultural breakthroughs are essential to affect changes in our Indian economy. As of late, the people who are producing these products and such items are more hesitant to supply them because of sudden weather natural causes and a lack of ground hydro assets. Occasionally, ranchers are unaware of the crop that best matches their soil quality, soil nutrients, and soil organization. This work entails forecasting winter wheat yields based on spot and climate data. This information science problem is driving it. Climate change, duty, family concerns, and the constant shift in Indian government norms are all reasons for this. As a result, the framework focuses on assessing soil quality to predict crop growth suitable for their soil type and enhancing crop output by recommending appropriate manure. With the fast growth of computer vision and deep learning in recent years, improved research approaches for extracting and processing visual information from image data have emerged. CNN has incredible performance in object classification, localization, detection, and segmentation. It has been widely used in the domains of automated driving, facial recognition, and remote sensing image processing, considerably increasing productivity and yielding enormous economic advantages. Exploring the enormous potential of CNN-based deep learning approaches in image processing and comprehension in the area of plant and agricultural science is quite beneficial. Researchers in the domains of computer vision and plant agriculture started to infiltrate both sides as the tide of artificial intelligence and deep learning rose. Deep-learning-based convolutional neural network (CNN) and Long Short Term Memory (LSTM) architecture for plant categorization is suggested, and its advantages over hand-crafted image analysis are shown [4].

II.OBJECTIVES

1. To Carry Out The Literature Survey Of Various Plant Growth PredictionTechniques.
2. Create A Novel Segmentation Approach To Analyses The Major Fusion.
3. Use Prediction Algorithm To Create A System That Capture Plants Attributes From
4. Thermal Photos And To Predicts Future Plant Traits Based On Current GrowthPatterns.
5. To Create And Execute A Unique Utilization Methodology Based On An Analysis Of Current Techniques.
6. To Provide A Series Of Small-Scale Tests Comparing The System's Performance To Well-Known State-Of-The-Art Approaches.

III.CHALLENGES AND LIMITATIONS

CHALLENGES:

1] Plant segmentation in photographs is a critical challenge. The proposed research is centred on the most common tomato plant. Although Plants have similar look and form features, the existence of occlusions, diversity in shape and posture, as well as imaging settings make this a difficult challenge to solve.2] Height, Stem diameter varies from plant to plant, making past statistics impossible to estimate.

LIMITATIONS:

1] Require Thermal cameras to monitor of plant growth.2] Accuracy of prediction depends on dataset

IV.RELATED WORK

A comprehensive analysis of the literature reveals that many feature inputs and classification algorithms have been utilised to predict plant growth and yield automatically. As previously said, the most natural technique is based on automated detection through visual feature analysis. Without a shared data-set, it is difficult to compare various approaches at the validation stage, since classification performance metrics are heavily reliant on the quantity and quality of the dataset. Machine learning (ML) approaches have been judged simpler to apply because to the reduced number of variables that must be established. However, this technique has a number of disadvantages, including a lack of robustness to complicated backgrounds, vulnerability to partial or complete shading, and instability under changing lighting conditions. Many aspects that blend textures have improved significantly. The huge number of algorithms used to create the code-words, as well as the work required to find the optimal configuration to achieve acceptable performance in the algorithms, contribute to the model's great complexity, which is a disadvantage of this technique. The fast growing number of papers in the field that use the name Deep Learning reflects the current success of deep learning methodologies. Deep learning algorithms are becoming more accurate when compared to previous approaches. DL architectures are used in this area due of their use in other domains like as image and video analysis. Based on the fundamental facts supplied above, the following is a summary of the research gaps that may be detected in this study. New surveys based on trained and unsupervised deep network architectures are expected to highlight the optimal configuration in the estimated plant development scenario. Other features, such as plant height, area, and volume, are anticipated to be examined in this field in addition to the findings generated by deep learning algorithms. Deep learning algorithms have also improved image analysis performance. Deep learning architectures, as opposed to typical machine learning, use both spatial and spectral information from image analysis..

V. PROPOSED ALGORITHM

Most techniques in high-throughput field phenotyping need robust and automated segmentation of leaves and other backgrounds. So far, the potential of current techniques for this purpose have not been thoroughly explored, owing in part to a lack of publicly accessible, acceptable datasets.

For segmenting the first ROI, the suggested technique incorporates aspects of fuzzy clustering as well as the level-set method. The suggested approach employs fuzzy clustering to initialize the level-set function. It can be seen that the

FCM creates misleading blobs as well as outliers in the image. Gaussian Filtering is used to separate these side-effects. Following the completion of these procedures, the fuzzy clustering results are used to initialize the level-set function.

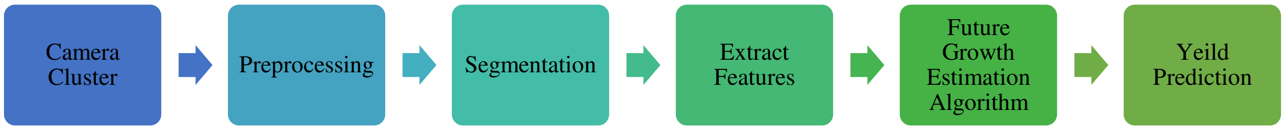


Fig: 1 Block Diagram of Proposed Framework

Markov Random Field (MRF) is a sophisticated stochastic model technique that is computationally convenient for illustrating local interactions between neighbouring pixels characteristics. Furthermore, it can represent the spatial relationship of neighbouring pixels using probability distributions in a Bayesian framework. The labelling space with the highest maximizing posterior probability (MAP) supplied in the visual data is segmented. The MRF MAP explains the steps involved in maximizing energy. The energy function is no convex and shows multiple local minima in the image's solution space, making maximization combinatorial.

The implementation of the Kalman Filter into the plant growth dynamics model for assessing the status of growth on actual experimental data is innovative in this study. It is based on a non-linear growth model that has been validated using both simulated and experimental data.

We constructed an experimental setup as part of this study for the following reasons:

i. continuous growing of plants,
ii. monitoring of their growth dynamics and
iii. iii data gathering under greenhouse settings. The comparison of the Kalman Filter performance to traditional approaches such as nonlinear least squares reveal significant savings in computing time and resource.

Markov Random Field (MRF) is a sophisticated stochastic model technique that is computationally convenient for illustrating local interactions between neighbouring pixels characteristics. Furthermore, it can represent the spatial relationship of neighbouring pixels using probability distributions in a Bayesian framework. The labelling space with the highest maximizing posterior probability (MAP) supplied in the visual data is segmented. The MRF MAP explains the steps involved in maximizing energy. The energy function is no convex and shows multiple local minima in the image's solution space, making maximization combinatorial. The implementation of the Kalman Filter into the plant growth dynamics model for assessing the status of growth on actual experimental data is innovative in this study. It is based on a non-linear growth model that has been validated using both simulated and experimental data. We constructed an experimental setup as part of this study for the following reasons: I continuous growing of plants, (ii) monitoring of their growth dynamics and (iii) data gathering under greenhouse settings. The comparison of the Kalman Filter performance to traditional approaches such as nonlinear least squares reveal significant savings in computing time and

VI.EXPECTED OUTCOMES

1. Proposed method estimates a reliable and automatic assessment of individual plant heights, Stem diameter and density for tomato plants. It will also predict height, Stem diameter based on previous week estimatedheight.
2. Accurate yield forecasts can improve industry sustainability by delivering better environmental and economic outcomes

VII. PERFORMANCE MEASURE

We'll see how many of the total P images are properly categorized as Normal (Class-0). This statistic represents the total number of properly categorized images, also known as True Positive (TP). This image count is termed False Negative if any samples from the P class are incorrectly categorized (FN). The total number of properly identified images from the N class (i.e., they are classified as lesions) is referred to as True Negative (TN). False Positives are images from the N class that have been incorrectly categorized as normal (FP). To determine their correctness, the same process will be followed for each lesion individually. Then we'll figure out the following numbers:

TRUE POSITIVE (TP): Total correctly recognized class of P Class
TRUE NEGATIVE (TN): Total correctly recognized class of N class
FALSE POSITIVE (FP): Total incorrectly recognized class of N Class
FALSE NEGATIVE (TN): Total incorrectly recognized class of P class
Accuracy = [TP + TN] / [P + N]
False Positive Rate= [FP] / [N]
Specificity= [TN] / [N]
Sensitivity= [TP] / [P]
False Negative Rate= [FP] / [P]

VIII.CONCLUSION AND FUTURE WORK

Precision agriculture relies heavily on artificial growth systems. It enables the resolution of several issues related with the rising need for environmentally friendly food production in the setting of a growing global population. Accurate and accurate evaluation of plant growth dynamics factors is critical for the long-term success of optimising the whole growing system characteristics. In this study, we also offer the Extended Kalman filter technique for assessing plant development dynamics.

REFERENCES

[1] Li, X.; Zeng, R.; Liao, H. Improving crop nutrient efficiency through root architecture modifications. J. Integr. Plant Biol. 2015, 58,193–202.
[2] Furbank, R.; Tester, M. Phenomics–technologies to relieve the phenotyping bottleneck. Trends Plant Sci. 2011, 16, 635–44.
[3] Tsaftaris, S.; Minervini, M.; Scharr, H. Machine Learning for Plant Phenotyping Needs Image Processing. Trends Plant Sci. 2016,21, 989–991.
[4] Namin ST, Esmaeilzadeh M, Najafi M, Brown TB, Borevitz JO. Deep phenotyping: deep learning for temporal phenotype/genotype classification. Plant Methods. 2018;14(1):66.
[5] Bashar Alhnaity, Stefanos Kollias, Georgios Leontidis, Shouyong Jiang, Bert Schamp, Simon Pearson, " An autoencoder wavelet based deep neural network with attention mechanism for multi-step prediction of plant growth, Information Sciences,Volume 560,2021,Pages 35-50,ISSN 0020-0255, https://doi.org/10.1016/j.ins.2021.01.037.
[6] Zhou, S., Chai, X., Yang, Z. et al. Maize-IAS: a maize image analysis software using deep learning for high-throughput plant phenotyping. Plant Methods 17, 48 (2021). https://doi.org/10.1186/s13007-021-00747-0
[7] Carla do Carmo Milagres, Paulo Cezar Rezende Fontes, July Anne Amaral de Abreu, José Maria da Silva & Mairon Neves de Figueiredo (2021) Plant growth stage and leaf part to diagnose sweet corn nitrogen status using chlorophyll sensor and scanner image analysis, Journal of Plant Nutrition, 44:18, 2783-2792, DOI: 10.1080/01904167.2021.1921197
[8] Wang, C., Liu, B., Liu, L. et al. A review of deep learning used in the hyperspectral image analysis for agriculture. Artif Intell Rev 54, 5205–5253 (2021). https://doi.org/10.1007/s10462-021-10018-y
[9]Jong, KO., Han, KM., Kwak, SI. et al. Simple estimation of green area rate using image analysis and quantitative traits related to plant architecture and biomass in rice seedling. Theor. Exp. Plant Physiol. 33, 225–234 (2021). https://doi.org/10.1007/s40626-021-00207-z
[10] Fowler, J., Amirian, S. (2021). Integrated Plant Growth and Disease Monitoring with IoT and Deep Learning Technology. In: Stahlbock, R., Weiss, G.M., Abou-Nasr, M., Yang, CY., Arabnia, H.R., Deligiannidis, L. (eds) Advances in Data Science and Information Engineering. Transactions on Computational Science and Computational Intelligence. Springer, Cham. https://doi.org/10.1007/978-3-030-71704-9_26

[11] Ronneberger, O., Fischer, P., and Brox, T. (2015). U-net: convolutional networks for biomedical image segmentation, in International Conference on Medical Image Computing and Computer-Assisted Intervention (Springer), 234–241.
[12] Yu, F., and Koltun, V. (2015). Multi-scale context aggregation by dilated convolutions. arXiv [Preprint]. arXiv:1511.07122v3.
[13] Chen, L.-C., Zhu, Y., Papandreou, G., Schroff, F., and Adam, H. (2018). Encoder-decoder with atrous separable convolution for semantic image segmentation, in Proceedings of the European Conference on Computer Vision (ECCV), 801–818.
[14]Wang, J., Sun, K., Cheng, T., Jiang, B., Deng, C., Zhao, Y., et al. (2020). Deep high-resolution representation learning for visual recognition. IEEE Trans. Pattern Anal. Mach. Intell. doi: 10.1109/TPAMI.2020.2983686
[15]He, K., Zhang, X., Ren, S., and Sun, J. (2016). Deep residual learning for image recognition, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (Las Vegas, NV: IEEE), 770–778.
[16]Huang, G., Liu, Z., Van Der Maaten, L., and Weinberger, K. Q. (2017). Densely connected convolutional networks, in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (Honolulu, HI: IEEE), 4700–4708.
[17]Zhuang, Shuo, et al. "Early detection of water stress in maize based on digital images." Computers and Electronics in Agriculture 140 (2017): 461-468.
[18]Giménez-Gallego, Jaime, et al. "Intelligent thermal image-based sensor for affordable measurement of crop canopy temperature." Computers and Electronics in Agriculture 188 (2021): 106319.
[19]Zainuddin Z, Manjang S, Wijaya AS, et al. (2019) Rice farming age detection use drone based on svm histogram image classification. In: Journal of Physics: conference series, vol 1198. IOP Publishing, p 092001
[20]Yu Z, Cao Z, Wu X, Bai X, Qin Y, Zhuo W, Xiao Y, Zhang X, Xue H (2013) Automatic image-based detection technology for two critical growth stages of maize: emergence and three-leaf stage. Agric For Meteorol 174:65–84
[21]Zhao S, Zheng H, Chi M, Chai X, Liu Y (2019) Rapid yield prediction in paddy fields based on 2d image modelling of rice panicles. Comput Electron Agric 162:759–766
[22]Yalcin H, Razavi S (2016) Plant classification using convolutional neural networks. In: 2016 Fifth international conference on agro-geoinformatics (agro-geoinformatics). IEEE, pp 1–5
[23]Malik, Zeeshan, et al. "Detection and counting of on-tree citrus fruit for crop yield estimation." International Journal of Advanced Computer Science and Applications 7.5 (2016).
[24]Dias, Philipe A., Amy Tabb, and Henry Medeiros. "Apple flower detection using deep convolutional networks." Computers in Industry 99 (2018): 17-28.
[25]Liu, Guoxu, Shuyi Mao, and Jae Ho Kim. "A mature-tomato detection algorithm using machine learning and color analysis." Sensors 19.9 (2019): 2023.
[26] P. Tiwari, and P. Shukla, "Crop yield prediction by modified convolutional neural network and geographical indexes," International Journal of Computer Sciences and
Engineering, vol. 6, no. 8, pp. 503-513, 2018.
[27] J. Sun, L, Di, Z. Sun, Y. Shen, and Z. Lai, "County-level soybean yield prediction using deep CNN-LSTM model," Sensors, vol. 19, no.20, pp. 4363, 2019.

INNO SPACE
SJIF Scientific Journal Impact Factor
Impact Factor: 8.379

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

निस्केयर
NISCAIR

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING