Vol. 4 Issue- 6, February 2024 (e-ISSN: 2582-8223)

JUST AGRICULTURE
multidisciplinary e-Newsletter

Enhancing Crop Resilience: Harnessing Machine Learning Models for Abiotic Stress Management

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ARTICLE ID: 17

Abstract

Machine learning (ML) has emerged as a powerful tool for gaining new insights and solutions for dealing with abiotic stressors. Abiotic stresses are non-living environmental factors that have a detrimental effect on crop productivity and plant growth. These include extreme temperatures, salinity, drought, nutrient deficiencies, and other pollutants. When exposed to these stresses, plants may experience stunted growth, lower productivity, and, in extreme circumstances, even death. By harnessing the power of ML models, we can revolutionise abiotic stress management in crops, allowing us to make more informed decisions and mitigate the impact of environmental challenges. This article explores the ML model's potential application in managing abiotic stress on crops for a resilient and sustainable agricultural future.

Introduction

Providing food security and sustainable agriculture in today's rapidly changing climate has become a critical challenge. To lessen the adverse effects of abiotic stress on crops, researchers and farmers are turning to cutting-edge technologies as the world struggles with the problems posed by climate change and its impact on agriculture. Machine learning (ML) has emerged as a powerful tool among these technologies, offering new insights and solutions for managing abiotic stressors. Abiotic stresses are non-living environmental factors that have a negative impact on plant growth and crop productivity. Extreme temperatures, drought, salinity, nutrient deficiencies, heavy metals, and other pollutants are among these factors (Pathak *et al.*, 2022). When plants are exposed to these stresses, they may experience stunted growth, lower productivity, and in extreme circumstances, even death. We can revolutionise abiotic stress management in crops by harnessing the power of ML models, allowing us to make more informed decisions and mitigate the impact of environmental challenges. In this article, we explore the potential application of the ML model in the abiotic stress management of crops for a sustainable and resilient agricultural future.

Keywords: Abiotic Stresses; Machine Learning; Spatial Mapping

Application of ML Models in Managing Abiotic Stresses on Crops

Predicting and managing the effects of abiotic stresses on crop productivity can be difficult. However, machine learning models (McQueen *et al.*, 1995) can assist in addressing these issues. These models are capable of analysing large datasets to identify patterns and relationships between environmental variables and crop productivity. Neural networks, decision trees (Breiman *et al.*, 1984), gaussian processes (Rasmussen and Williams, 2006), random forests (Breiman, 2001), and gradient boosting (Friedman, 2001) are a few examples of ML models that can analyse complex relationships between various environmental variables and crop productivity. These ML models can be trained on huge volume datasets to identify the most important factors influencing crop growth and predict how these factors will affect crop yields in the future. Furthermore, these models can be used to develop customised management strategies for a particular crop and growing region. A machine learning model, for example, could be trained on weather data for a specific region to predict when drought conditions are likely to occur. The development of irrigation strategies to reduce the effects of drought on crop productivity could be done using this information. Here are some ways in which machine-learning models can help:

Data Analysis and Recognising Patterns:

Machine learning models can analyse huge volumes of data about environmental factors, plant physiological parameters, and soil conditions. These models can reveal insightful information about the effects of various abiotic stresses on plants by identifying patterns and relationships in the data. This knowledge assists researchers and farmers in understanding the underlying mechanisms of stress and developing effective management strategies.

Predictive Model Building and Crop Yield Prediction:

Huge volumes of data can be analysed by machine learning models, which can also reveal hidden patterns that can help to develop efficient stress management strategies. We can develop predictive models that can predict the likelihood and severity of abiotic stress events by training ML models on historical data on crop yields, weather data, soil characteristics, and other relevant variables and researchers or farmers can assess the potential impact of stress on

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crop productivity by incorporating abiotic stress factors into these models. This information can assist farmers in making informed decisions about resource allocation, such as adjusting irrigation schedules or implementing protective measures to maximise crop productivity.

Figure 1 depicts simulated data on crop yields under different abiotic stress conditions (low, medium, and high) based on temperature and precipitation values. The distribution of point sizes within each stress level (colour) provides insights into the impact of stress on yield variability. The colour of each point represents the level of abiotic stress, with green indicating low stress, orange indicating medium stress, and red indicating high stress. The size of each point corresponds to the crop yield. Larger points represent higher yields, while smaller points represent lower yields. Overall, the plot provides a visual representation of the relationship between abiotic stress levels, environmental variables, and crop yields. It emphasises the general trend of decreasing yields with increasing stress levels and provides insights into the distribution and variability of yields under various stress conditions.

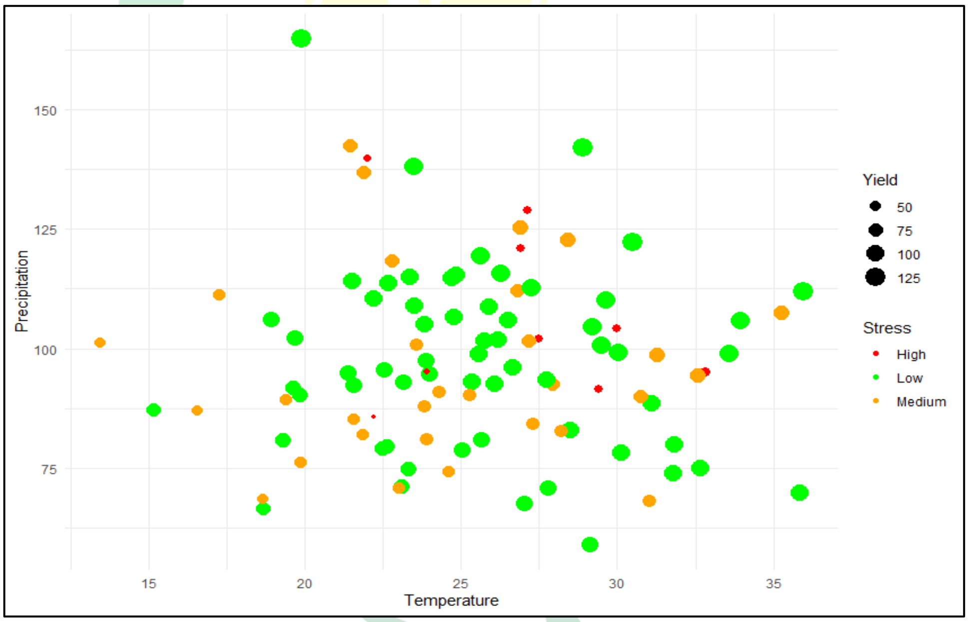

Figure 1. Schematic representation of the relationship between abiotic stress levels, environmental variables, and crop yields.

Remote Sensing and Spatial Mapping:

Machine learning models can be used with remote sensing data, such as satellite imagery or drone-based images, to assess the spatial extent and severity of abiotic stress across large agricultural areas. These models can be trained to identify stress-related changes in vegetation indices or leaf reflectance, enabling early detection and spatial mapping of the stress-affected regions. This information assists farmers and researchers in effectively targeting interventions and allocating resources.

Forecasting Weather Aberrations (Early Warning Systems (EWS)):

A machine-learning model trained on historical weather data, soil moisture levels, and crop performance data can learn the hidden patterns and relationships between these variables and predict the likelihood of future weather conditions. Several of the free but crude forms of EWS are now available as weather apps or agriculture apps utilising near real-time information derived using weather API's. These apps nowcast (upto 2-6 hours in advance), and forecast the short-term (5-day) and short-medium term (15-day) weather events with improved localised accuracies. The nowcast and forecast services offered by these apps allow anticipating weather events such as heatwaves, cold waves, rain, storm, etc. and thus empower farmers to take appropriate executable measures to minimise the losses.

Precision Nutrient Management and Optimising Inputs:

Machine learning models are capable of analysing soil data, plant nutrient requirements, and crop responses to nutrient applications in drought-stressed conditions. The model can recommend precise nutrient management strategies while taking into account factors like nutrient availability, water availability, and crop demand. This improves nutrient use efficiency and ensures that crops receive the nutrients they require even during drought stress.

Challenges in ML Approaches for Abiotic Stress Management Solutions:

ML approaches are data-centric and require in general thousands of data points to improve upon their prediction accuracy. Additionally, the quality and reliability of datasets are most important in the absence of which the models fail in real-world scenarios despite of been trained on larger datasets. The mechanism for generation and making available reliable and good-quality datasets is core to developing successful ML-based solutions. The use of sensors, digitisation of agricultural ecosystems, scalable computational hardware and software frameworks, improved data connectivity, and policy support are pillars that need to be systematically strengthened for Indian agriculture to harness the potential of advances in the ML arena in providing abiotic stress management solutions. Though Indian agriculture is progressing on all fronts, synchronising and converging these advances into a simplified offering for farmers is critical to harnessing ML for abiotic stress management.

Conclusions

Machine learning has emerged as a potent tool for managing abiotic stress in crops. ML-driven early warning with real-time decision support systems can help farmers adopt appropriate measures to avoid heavy economic losses in their production systems thus improving the resilience of food production systems. Overall, machine learning models help farmers make more informed crop management decisions by providing insights into the complex relationships between environmental factors and crop productivity. While the use of the ML model in abiotic stress management is promising, there are still issues to be addressed. Data availability, algorithm robustness, and model interpretability are areas of ongoing research. The adoption of advances in machine learning is the key to improving global food security and paving the way for a more sustainable and productive agricultural future.

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