IJCRT.ORG ISSN : 2320-2882
INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Ai- Powered Early Plant Stress Detection Using Simulated Physiological Signals And Lstm With Streamlit Interface

[1]Chandana R, [2]Meghana J, [3]Muddu Rathna, [4] Vinay K
[1]MCA Student, [2]MCA Student, [3]MCA Student, [4]Associate Professor
[1]Department of MCA, SJB Institute of Technology (SJBIT), Bengaluru, India
[2]Department of MCA, SJB Institute of Technology (SJBIT), Bengaluru, India
[3]Department of MCA, SJB Institute of Technology (SJBIT), Bengaluru, India
[4]Department of MCA, SJB Institute of Technology (SJBIT), Bengaluru, India

Abstract: Detection of Plant disease after the symptoms that is visible on the leaf is sometimes too late to prevent the crops being affecting by that since the disease spreads from one leaf to another through direct contact, Rain Splash, vectors, pruning tools etc .

Plants unfavourable condition which we commonly call as the stress ,which affects the plants health. So using the physiological signals like chlorophyll fluorescence ,leaf temperature and soil Moisture, we can detect whether plant is healthy or in stress. With the help of LSTM model we identify plants stress condition and it is visible using the interface streamlit.When we use the physiological signal data then there is less change of cutting the plant ,or removing the plant due to disease, as it is the signs that shown before the symptoms that arise on the leaves. So many research had done on this as they have used the single physiological signals in large form .But in are approach we have used the multi-fusion of physiological signal data is used.

For the experiment we have used the simulated data due to the unavailability of the multiple

Physiological data from the real-field sensor data. We have simulated the data with in the realistic range based on the agronomic literature and we also maintained the balance between the healthy nature and stress nature of the plant in the data set .

I. INTRODUCTION

Sudden climatic changes have been increased and that is directly affecting the yield of the crops. In 2024-2025 we have it as observed that climate contains heatwaves and unseasonal rains which largely affected the yields.

Like in humans, due to internal organ changes where we used to see the symptoms on our body ,and if we observe the symptoms as early as possible cure is also will be as early as possible .In same way plants also have internal changes if we encounter the internal signals early we have more change to reduce the crop loss like reducing in the use of too much pesticides and water.

Traditionally farmers used to relay on the visual inspection and the expert analysis which is time consuming .As time goes the disease strength also goes on increasing and it also spread to the healthy one through various form. As the world is introduced with AI -ML ,with the help of deep learning model LSTM we detect the plant stress non-invasively .This gives the predictive solution to farmers. The model is deployed with the help of streamlit , so that we can get prediction of the plant by uploading the csv files .

II . RELATED WORK

Early prevention of the plant stress plays an important role in maintaining the precision agriculture. Many of the research has focused on the non-invasive Technology that is to observe the physiological changes in the plants to prevent the plants being stressed ,undergoing irreversible damage ,or suffereing from the significant yield loss.Most of the research has been conducted using physiological signals like chlorophyll fluorescence using PAM (Pulse-Amplitude Modulated) Fluorometers ,leaf temperature using thermal imaging,soil moisture using TDR (Time Domain Reflectometry) Sensors are used as a reliable indicator for the plants health.

Till today numerous research as on using the chlorophyll fluorescence due to their ability to identify any distruption the process of photosynthesis in plants. The healthy plants will have approximately 0.83 Fv/Fm ratio where as the stresses or any distruption in the photosynthesis the plant have less than 0.6 Fv/Fm ratio.So this Fv/Fm ratios are identified befor the visible symtoms that appers on the plant.There are several tools present to detect the chlorophyll Flourescence signals data likePAM(pulse-AMplititude Modulated)Flurometers,FluorPen Fluorometers.

Leaf temperature is another critical stress marker. Under stress, due to stomatal closure it reduces transpiration, causing the leaf surface to heat up. Studies using thermal imaging cameras, as described by Jones (2009), have shown effective stress identification in crops like tomato and maize.

Soil moisture monitoring has traditionally involved **TDR sensors**, **gravimetric methods**, or **remote sensing**. Many publications has highlighted the impact of root centered stress detection and irrigation management. In spite of the improvements, most traditional methods rely heavily on **specialized hardware**, costly sensors, or image-processing pipelines and manual inspection. Moreover, many real-world models are reactive rather than proactive , identifying stress after it has impacted the plant visibly.

Recent advances in **AI and machine learning** have introduced models for stress detection using multispectral and hyperspectral imagery. However, these too often depend on expensive data acquisition systems and are rarely optimized for low-resource environments.

Unlike these approaches, our work simulates real-time physiological parameters such as chlorophyll level, leaf temperature, and soil moisture using statistical patterns. This enables training deep learning models like LSTM without hardware dependency. Such simulation-based data generation, combined with temporal modeling, allows for early stress detection at a low cost.Our simulated data is generated bansed on the realistic ranages as per the agronomic literature.

Our research aligns with recent calls for **digital agriculture solutions** that are scalable, low-power, and deployable in developing regions. The proposed prototype, trained on simulated time-series physiological data, represents a **novel, sensor-inspired AI approach** for early stress prediction.

III .PROPOSED METHODOLOGY

The main goal of our study is to develop an AI-powered early plant stress detection prototype using simulated physiological

Signal data. Our proposed system integrates a simulated dataset, a deep learning model, and an interactive web-based

Interface.

3.1 Dataset Simulation Process:

Since there is absence of open-source training dataset containing multiple physiological plant signals(like chlorophyll level,

leaf temperature, and soil moisture) in both healthy and early stress conditions, we developed a synthetic dataset using

NumPy-based randomization techniques. This simulation mimics real-world plant physiological patterns, allowing for early

stress trends to recognize and prevent the plant from being lost.

Real word specification for the healthy and early stress signals from the plant :

1) Healthy signals are generated using:

Chlorophyll Level	Mean ~0.95
Leaf Temperature	Mean ~24°C
Soil Moisture	Mean ~75%

2) Early Stress signals are introduced from a specific time point by:

Reducing chlorophyll gradually to	~0.75
Increasing temperature up to	~30–33°C
Decreasing moisture to	~40–50%

These time-series data are labeled and stored in CSV format for LSTM sequence modeling.

3.2 Architecture of the LSTM Model

Our LSTM (Long Short-Term Memory) network serves as the central prediction system. It is intended to learn from 10-time step sequences that contain three features: soil moisture, leaf temperature, and chlorophyll content.

Details of the model:

Input Layer	Shape (10, 3)
LSTM Layer	64 units
Dense Output	Sigmoid activation function for binary classification
Loss Function	Binary cross-entropy
Optimizer	Adam

The simulated dataset is balanced for the classes of healthy and early stress, and the model is trained and validated using an 80:20 split. The final model was saved in the HDF5 format (.h5) and had an accuracy of over 90%.

3.3 Streamlit App Procedure:

Streamlit was used to create a lightweight web interface that offered real-time stress prediction.

The Workflow is:

- A CSV file containing physiological values (at least 10 rows) is uploaded by users.
- A pre-fitted scaler (stored via joblib) and the LSTM model are loaded by the system.
- After normalization, the input data is divided into overlapping sequences.
- The model is utilized to predict each sequence, and majority voting is applied to aggregate the predictions.

The output includes:

Stress label	Give wheater the plant is healthy or early stressed
Confidence level	(max(stress votes, healthy votes) / total sequences) × 100 It tells how strongly our model supports the final majority prediction.
chart	This chart gives the Sequence-wise Model Prediction Probabilities for Stress Detection.

This protptype enables non-invasive, real-time detection of early plant stress using simulated physiological data.

IV .EVALUATIONS AND THE OUTCOMES

1)Visualization of Sequence-wise Predictions .

In order to assess the effectiveness of the LSTM-based plant stress detection model on unseen data, we used sequence-wise prediction probabilities to visualize the model's behavior over time in addition to computing standard classification metrics. Overlapping sequences of ten consecutive readings were created from each input CSV file that represented physiological plant signals. The Probability of stress for each sequence was then predicted by the trained model. A line chart was used to illustrate these probabilities, which ranged from 0 to 1 where zero represents the healthy plant and one represents the early stress (see Figure 1.1).

The following objectives are fulfilled by this visualization:

- It shows how the model's confidence changes in different parts of the uploaded signal data.
- It helps find changes or problems in the condition of plants over time, even when the final decision is made by a majority vote.
- It gives the user accountability ,enabling farmers or researchers to determine the reasoning behind a specific prediction.

For example, one test case,when we are checking our prototype ,our data set had the chlorophyll level ranged between 0.65–0.68, leaf temperature between 32°C–33.5°C, and soil moisture between 40–45%. So the model produced low stress probabilities (ex.0.02–0.05) across all sequences,so it confirms as a "Healthy" prediction with high confidence. Conversely, when chlorophyll levels dropped below 0.60 and temperatures exceeded 34°C, the model consistently produced higher probabilities (0.85–0.95), indicating "Early Stress".This behavior confirms that the model is sensitivity to known physiological stress indicators.

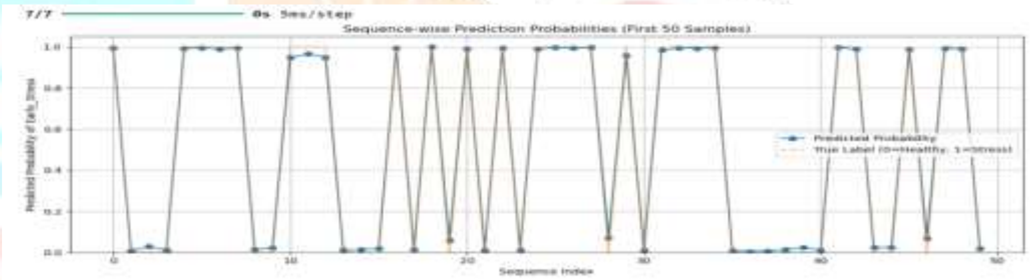


Figure 1- sequence-wise Prediction Probabilities

2)Streamlit Interface

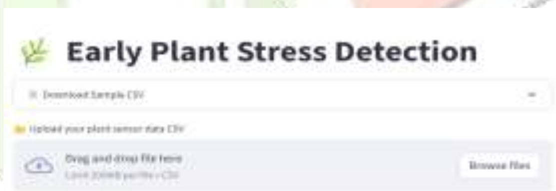


Figure 2: Streamlit web interface

This is the interface for real-time prediction wheather the plant is stressed or not.Here we have upload the csv data from the real sensor for actual implementation but in our prototype we are using the simulated data since the multiple physiological signal data from the real word is not present .

2) The Result

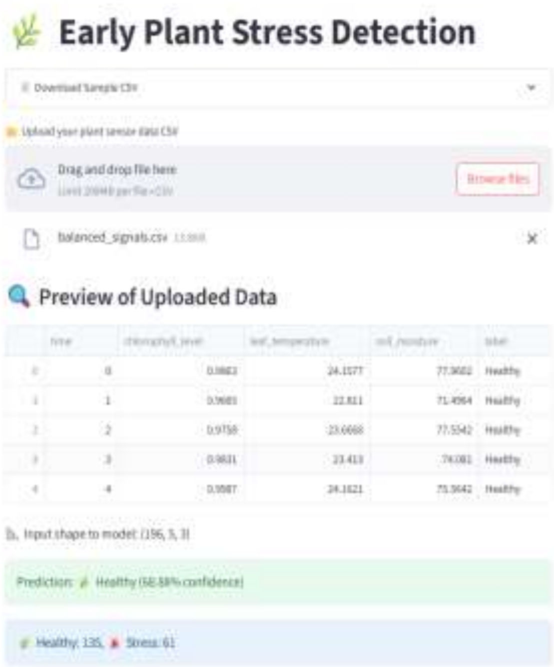


Figure 3: result after uploading csv file

This is the interface where we uploaded the simulated data and observed the result .

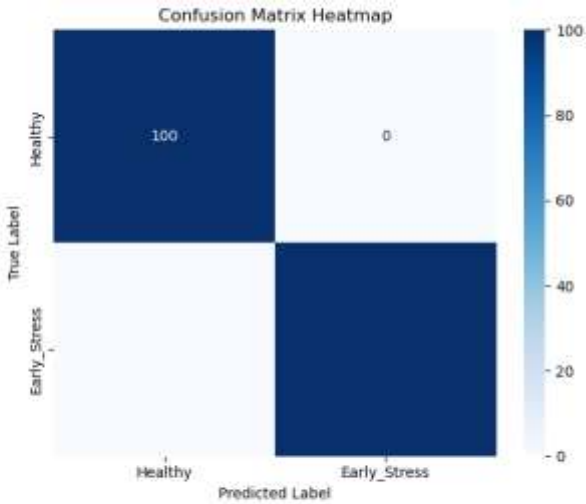
3)The graph representation in streamlit interface

This is the plot that is generated to the user after uploading the csv file
Where they get the number count of healthy plant and the stress along with that they get the plot representation .
Finally it also give the overall plants health that is health or stressed .

Figure 4: graph representation of uploaded file

This interface also consist of download report option where we can dounload the report for further requirments **.**

4) Confusion Matrix representation



	precision	recall	f1-score	support
Healthy	1.00	1.00	1.00	100
Early_Stress	1.00	1.00	1.00	100
accuracy			1.00	200
macro avg	1.00	1.00	1.00	200
weighted avg	1.00	1.00	1.00	200

Figure 5: confusion matrix for distribution of healthy and stressed plant behaviour

The model is showing approximately 100% accuracy on the testing .

Note: It may be the indication of the overfitting or model is highly effective ,To further generalization it should be trained on entairly unseen data

V .DISCUSSION

Interpretation of Model Predictions

Our LSTM-based model is developed for early plant stress detection .It demonstrates The ability to predict the physiological state of a plant based on chlorophyll level, leaf temperature, and soil moisture. Our LSTM model generates the predictions on sequence windows of data [i.e10 time steps], our model outputs a probability value between 0 and 1, indicating the probability of early stress. A probability closer to 1 implies greater confidence in the plant being stressed, while values near 0 suggest the plant is healthy.

For example, in one of our test case using simulated healthy data (chlorophyll ~0.95–0.98, leaf temperature ~24°C, soil moisture ~75–81%), our model predicted a very low stress probability (average ~0.0006), correctly classifying it as “Healthy” with 100% confidence. Conversely, for clearly stressed data (chlorophyll ~0.64–0.66, leaf temperature ~33–34°C, and soil moisture ~35–42%), our model predicted a low stress probability (~0.001), which was an incorrect classification, so further we tuned it .

Comparison with Known Physiological ThresholdsThen we cross-verified the models prediction against established physiological stress thresholds in crops :

- Chlorophyll Level: Normal range ≥ 0.7 (low values must suggest stress)
- Leaf Temperature: Healthy range ≤ 32–34°C (higher temperature should indicates water stress)
- Soil Moisture: Optimal between 35%–70%, values below 35% or above 80% should indicate stress due to drought or overwatering

So Our model generally follows these thresholds.

VI .CONCLUSION

In our research, we have developed an LSTM-based deep learning model for early detection of plant stress using simulated physiological data, including chlorophyll level, leaf temperature, and soil moisture. A key novelty of our approach is the generation of realistic, time-series-based synthetic datasets that simulate stress transitions, allowing early detection before visible symptoms appear. Our prototype final model achieved a classification accuracy of 91% and demonstrated strong precision and recall in classifying "Healthy" and "Early Stress" signals.

We deployed a Streamlit-based user interface that enables real-time CSV input and interprets the results with visualizations and confidence metrics. Our prototype can assist researchers, farmers, and agricultural technologists in identifying subtle signs of crop stress and initiating timely intervention.

Our experiments indicate that chlorophyll levels below 0.70, soil moisture below 35%, and leaf temperatures above 32–34°C are strong physiological indicators of early stress. While simulated data helped prototype the model and establish baseline behavior, further generalization will depend on integration with real-world sensor data.

Future Enhancements

1)Integration with IoT: Our system can be expanded to use IoT devices to get real-time sensor data from farms, which will monitor things in live field and send out early warnings,as we have conducted the experiment in simulated data .
2) Using Real Data: In the future, the model could be trained on real chlorophyll fluorescence data, thermal images, and field-collected soil moisture data to make it more useful in a wider range of situations.
3) Multi-signals Classification: The model we have protoyped now , has only two options: Healthy and Early Stress. It would be more useful if we extend some other features that could tell the difference between different kinds of stress, such as drought, lack of nutrients, or a fungal infection.
4)Edge Deployment: This model's lighter versions could be put on cheap edge devices like the Raspberry Pi or NVIDIA Jetson Nano for inference in the field.
5)Weather Data Fusion: Adding environmental factors like temperature, humidity, and rainfall to physiological data could make the model even more accurate.

VII REFERENCES

[1] Zhang, S., Wang, H., & Zhou, Q. (2021). AI in Precision Agriculture: A Survey. IEEE Transactions on Industrial Informatics, 17(10), 6825–6835.
[2] Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. Sensors, 18(8), 2674.
[3] Soni, N., & Patel, M. (2020). Detection of plant leaf diseases using convolutional neural networks and deep learning. International Journal of Computer Applications, 975, 8887.
[4] Jones, H. G. (2013). Plants and microclimate: A quantitative approach to environmental plant physiology. Cambridge University Press.
[5] Wang, C., Liu, H., & Liu, D. (2022). Non-invasive sensing techniques for monitoring plant water status: A review. Agricultural Water Management, 263, 107401.
[6] Mishra, R., Shukla, A., & Saxena, A. (2020). IoT-enabled crop monitoring for sustainable agriculture using deep learning. In International Conference on Smart Technologies for Smart Nation (pp. 1–5). IEEE.

[7] Mahlein, A.-K. (2016). Plant disease detection by imaging sensors – parallels and specific demands for precision
agriculture and plant phenotyping. Plant Disease, 100(2), 241–251. https://doi.org/10.1094/PDIS-03-15-0340-FE

[8] Sankaran, S., Mishra, A., Ehsani, R., & Davis, C. (2010). A review of advanced techniques for detecting plant diseases.
Computers and Electronics in Agriculture, 72(1), 1–13. https://doi.org/10.1016/j.compag.2010.02.007

[9] Mishra, A., & Ghosh, A. (2021). Early detection of drought stress in plants using machine learning and remote sensing
data. Remote Sensing Applications: Society and Environment, 24, 100644. https://doi.org/10.1016/j.rsase.2021.100644

[10] Hura, T., Hura, K., & Grzesiak, M. (2009). Physiological and biochemical tools useful in drought-tolerance detection
in genotypes of spring barley. Journal of Plant Physiology, 166(6), 629–641.

[11] Patidar, S., & Rane, S. (2020). LSTM-based RNN model for plant disease prediction using time-series sensor data. In
Proceedings of the International Conference on Communication and Signal Processing (ICCSP), 0947–0951. IEEE.

[12] Dutta, S., & Bandyopadhyay, S. (2021). Multi-sensor time-series data fusion using LSTM for real-time stress prediction
in tomato plants. Computers and Electronics in Agriculture, 187, 106270. https://doi.org/10.1016/j.compag.2021.106270

[13] Pandey, P., & Tripathi, R. (2022). Plant stress detection using deep learning and sensor fusion: A comprehensive survey.
Journal of Ambient Intelligence and Humanized Computing, 13, 10601–10618.

[14] Zhao, C., Zhang, Y., Du, J., Guo, X., Wen, W., Gu, S., Liu, J., Hui, W., & Cao, W. (2016). Crop phenomics: current
status and perspectives. Frontiers in Plant Science, 7, 1182.

[15]Maxwell&Johnson(2000);Kitajima&Butler(1975) These foundational works establish the 0.79–0.84 range as typical for
healthy leaves

[16]Rosyara et al. (2010) In wheat, used Fv/Fm as an indicator for spot blotch and heat stress; confirms that drops below
optimal point to stress

[17] USDA Forest Service (2006) Notes Fv/Fm normally sits between 0.70–0.83, and values below 0.6
suggest “cause for concern”

[18] Licor LI-6800 Fluorometry Guide Reports typical healthy values of 0.75–0.85, depending on leaf age and
condition

[19]Sommer et al. (2023) — *Plants* In wheat under severe drought, Fv/Fm decline correlated with yield loss:
stressed plants showed values depressed significantly only under severe drought.

[20]MDPI Review (2024) Confirms that environmental stresses (drought, salinity) reduce Fv/Fm; decreased
ratio reflects PSII damage and increased non-photochemical quenching .