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# An AI & IoT-Enabled Framework for Real-Time Detection of Silent Stress in Crops Using Plant Bio-Signals

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## ABSTRACT

The agricultural industry across the globe is under great risk due to silent environmental hazards that cannot be detected by human eyes until there is physical damage. In this regard, the presented research introduces a novel and revolutionary solution for detecting crop silent stress using AI & IoT-Based Crop Silent Stress Detection System. This technology is based on the plant's internal status and captures bio-potential signals. This is because bio-potential signals occur prior to physical symptoms. In order to detect changes occurring inside the plant, a highly accurate AD8232 sensor and ESP32 microcontroller were used to collect the bio-potential signal. The acquired signal will be sent to a cloud-based computing environment. The collected data will be classified into various categories of status including healthy plants, water stress and nutrient deficiency using Machine Learning algorithm programmed in Python language. Monitoring the plant's status will be done using a Thing Speak online web platform, which shows the live monitoring results. The experiment showed that bio-signal can detect stress up to 48 hours before any wilt occurs visually. This work has brought a great combination of traditional plant electrophysiology and the recent IoT design, thereby providing an accurate and economical way of precision farming, where one can implement preventive measures to improve crop output without any wastage of resources. In addition to data sensing, the key contribution in this project is the usage of the stacked LSTM network designed particularly for processing the non-linear nature of plant potentials. The deep learning algorithm provides up to 94.2% accuracy in classifying stress signals while eliminating environmental noise.

***Keywords:*** Plant Bio-potentials, Silent Stress Detection, Edge Computing in Agriculture, IoT-Enabled Precision Farming, Bio-signal Classification, Thing Speak Cloud Analytics

## 1. INTRODUCTION

Agriculture is considered the mainstay of the world economy; however, it is constantly threatened by environmental factors that affect food security. Conventional means of determining the state of the crops usually involve the presence of any visible signs of plant deterioration, such as leaf wilting, discoloration, or growth retardation. Unfortunately, such visible indicators are always the end results of physiological disorders. Once the plant experiences visible stress, significant physiological harm will have been done to the plant, causing an inevitable decrease in production output.The most recent innovations in Plant Electrophysiology have shown that plants employ a sophisticated bioelectrical signaling system to cope with the surrounding environment. The bio-signals, including action potentials and variation potentials, vary depending on the plant's environmental stresses, such as dehydration, lack of nutrients, or temperature changes. Using the power of these signals makes it possible to address problems before they occur. This project will explore an innovative approach to crop silent stress detection based on AI and IoT technologies. Employing the high-accuracy AD8232 signal acquisition device connected to an ESP32 microcontroller, the system can read tiny variations in the bioelectricity of plants and process the data using machine learning models written in Python for stress classification.The incorporation of IoT cloud-based platforms such as Thing Speak ensures that there is a live monitoring dashboard for access by farmers and researchers. This model goes further than d traditional environment sensors (that only monitor external environmental conditions within the soil or in the air) and shifts focus on the plants themselves to make a better and more accurate judgment of their health status.[1].In conventional monitoring systems for agriculture, the main approach used is reactive in nature, where sensors are used to detect environmental changes rather than those experienced by the organism. Although information about soil moisture and atmospheric temperature can be obtained using such sensors, they cannot indicate the physiological conflict within the plant unless it translates into a symptom. Therefore, there is always some time lag between the physiological challenge experienced by the crop and the intervention initiated.

Using the AD8232 analog front-end, this study is able to measure the changes in voltage of biological potentials within the cells of a plant whenever its homeostatic balance is disturbed. However, these measurements are not just noise but rather valuable indicators of the health of the plant. The inclusion of these measurements in the computing power of the ESP32 ensures that only high-quality data is uploaded to the cloud. Through this approach, Python machine learning algorithms are enabled to classify various forms of stress accurately. Overall, this study marks a step towards the future of agriculture through creating an automated system whereby plants will 'speak' to the farmer about their needs so that fertilizers and water can be supplied precisely.[2]

**2 The Current Landscape of Agricultural Stress Monitoring:** The present Days agricultural industry finds itself at a junction, whereby the rising need for food security needs to be addressed through improved efficiency of resource utilization. Presently, the field of agricultural stress assessment is one dominated by a reactionary framework of operation. The current approach involves making use of environmental telemetric devices such as soil moisture sensors, temperature records, and humidity meters to deduce the well-being of a crop. Although this system is useful in providing critical information about the physical surroundings of a crop, it operates on an underlying principle that a balanced environment leads to a healthy plant. This "environment-centered" system leaves a lot of information unaccounted for due to lack of physiological information about the plant's biological tolerance levels for stress.[3]

In parallel with environmental sensing, visual diagnostic systems have been adopted widely to include manual field scouting techniques up to satellite imagery and unmanned aerial vehicles (UAVs). The principle behind all of these techniques is the detection of physiological stress based on changes in the phenotype of the plants, such as leaf wilt, leaf necrosis, or alteration in chlorophyll reflectance. However, visual diagnostics is a "lagging indicator," because when physiological stress becomes apparent through visual inspection, a great deal of damage to the cell physiology has already occurred. This delay represents the principal challenge for the adoption of precision farming techniques because by the time farmers detect visual symptoms, too much damage has already been done, and excessive irrigation and chemicals are required to save the crop.

Moreover, the current status quo is dichotomous in terms of both economics and technology. At one end of the spectrum, there are laboratory procedures such as sap analysis and hyperspectral imaging, which provide profound insight into stressors, but the procedures are expensive and technologically complicated beyond the means of a typical farmer. On the other hand, low-cost technologies are often too simplistic to properly account for the complexity of "silent stress." In order to solve this problem, it will be necessary to have a revolutionary approach to the problem in the form of a system that recognizes the plant itself as a biological sensor through bio-potential analysis.[4]

**2.1 Environmental Centric Sensing and the Physiological Gap:** The existing precision agriculture paradigm is strongly tied to "Environmental-Centric Sensing." This framework employs a suite of sensors to detect changes in environmental parameters like soil volumetric water content, ambient temperature, sunlight, and relative humidity. Though essential for creating a comprehensive picture of the climatic conditions within the agricultural field, these parameters are based on the misguided assumption that the physiological state of the plant directly correlates to its environment. On the contrary, there is a considerable "Physiological Gap," a discrepancy between what is indicated by the environment and the plant's actual physiological condition.

For example, while a soil moisture sensor may show sufficient moisture content, a plant may suffer from "silent stress" owing to the excessive soil salinity, the presence of pathogenic organisms within the root zone, or unusually high rates of transpiration compared to the rate of transportation of the water by the roots. While conventional sensors can only detect the presence of the stressors based on their measurement of the cause of the stress and not its effect, plants may have already shut down metabolism when environmental sensors detect the presence of any anomaly. This can be remedied by making the shift from measuring the medium to measuring the organism through bio-potentials. Moreover, this difference in physiology makes it even harder by virtue of the many complex responses that are exhibited by the differing types of crops to the same environmental signals. While there is an ideal moisture content of soil for one crop variety, there might already be an osmotic stress condition developing in another type of crop, a detail which cannot be determined by the generalized sensors. Since these sensors operate independently of the plant's physiology, there is no consideration made about the process of "acclimatization".[5]

**2.2 Latency and the Limitation of Visual Diagnostics:** The most crucial bottleneck associated with conventional methods of agriculture is the "latency period," the time gap between the development of physiological stress on the plant and the appearance of symptoms. Whether visual analysis is conducted manually or with the help of high-definition multispectral cameras, it remains inherently limited to identifying later-stage problems. Symptoms like leaves curling, yellowing, or wilting can be seen only once significant disruptions to the inner structure and metabolism of the plant have occurred. In other words, by the time the farmer realizes there is a problem, it may be too late for the plant's yield potential.

In addition, visual symptoms are highly unreliable because the same symptoms may be caused by different stresses like nutrient deprivation and thermal stress. Such imprecision results in misdiagnosis and the improper use of medications. While modern remote sensing technology is able to cover more territories, it still operates on the basis of shifts in the leaf's reflectance, which take place only after the "silent period" of the stress process. To solve this problem, it is necessary to switch to monitoring the bio-potentials of plants' responses. Through such an approach, we would be able to circumvent the delay caused by visual symptoms and detect the stress signature right when it occurs. Furthermore, the use of visual inspection techniques is made problematic due to the environmental and subjective inconsistencies involved in the process. The presence of different levels of illumination, shadows, as well as the expertise of the person analyzing the visual information, can result in a misinterpretation of the health status of the plant. Despite sophisticated satellite imaging technology being used to gather the data, the quality of the information collected and the frequency at which it is gathered fails to detect early changes in the health status of the plant.[6]

**2.3 Technical and Economic Barriers to Adoption:** It may be very difficult to implement the plant electrophysiological techniques used in the laboratory on a wide scale basis in agricultural fields due to numerous technological and economic issues. The main technological issue in this context is obtaining high impedance/low voltage biological signals from plants in an uncontrollable environment. Unlike the laboratory where EMI is not prevalent, agricultural fields have high levels of EMI resulting from the presence of power cables, agricultural equipment, cellular towers, and even other electronic gadgets which may drown out the weak electric signals generated by the plant. Moreover, establishing stable electrode connection to the plant is difficult due to growth of the plant, wind currents, and varying humidity levels.[7].In terms of economics, however, the "Digital Divide" continues to persist in precision agriculture. While there are already very sophisticated approaches such as hyperspectral drone imaging and sap analysis, these technologies are beyond the financial reach of small and medium scale farmers in places such as Tamil Nadu. In addition to requiring substantial upfront costs, these systems will also need experts to analyze the complicated sets of data produced by the technology. Presently, low-cost solutions lack the sophistication necessary to identify "silent stress." Thus, there is an urgent need for a cost-effective, durable system that leverages easily available parts such as the ESP32 while ensuring accurate signal processing.

**2.3 Scalability and Economic Barriers in Precision Farming:** The broad implementation of modern agricultural technology is currently facing major issues regarding scale and economics. Although technologies like hyperspectral drone imagery, satellite crop observation, and automatic sap analysis give detailed information about the plants' state of health, they cannot be afforded by most farmers worldwide. Small farmers and even medium farmers, especially those from emerging agricultural centers like Tamil Nadu, lack the necessary capital investment for these advanced technologies. This leads to a "technology gap" between big industries that have the resources to use these technologies and improve their productivity and efficiency and the smaller farmers who lack the capital to do so.

Apart from the initial expense, scalability is limited by the complexities associated with the technology employed currently. Most sophisticated technologies rely on the involvement of experts for data analysis and calibration of the hardware utilized, which presents an additional financial burden that can be difficult for small-scale farmers to afford. Additionally, most lab-grade devices are not engineered to function effectively in harsh and varied environmental settings presented by different geographic terrains. It is paramount to adopt a cost-effective system that integrates affordable components such as the ESP32 to guarantee efficient monitoring without having to incur enormous costs. Filling this financial gap is crucial in making precision agriculture a realistic and sustainable option for everyone.[8]

Moreover, the absence of standardized communications protocols between various agricultural technology systems tends to give rise to "data silos," wherein data collected by one sensor cannot be readily used in conjunction with that generated by other sensors. This makes it impossible to obtain a comprehensive understanding of the ecosystem within the farm, thereby preventing any attempts at scaling up from small experimental plots to full-scale farms. In addition, many high-resolution solutions depend on high-bandwidth internet access to process data through cloud computing, which may not always be available in rural settings.

In order for us to be successful in achieving true scalability, we need to shift our attention to something known as "Edge Intelligence," where computations are performed right at the data source level. Through the use of cheap yet powerful microcontrollers such as the ESP32, we are able to process sophisticated signals and apply machine learning on the fly at the source level, and this way, we are not dependent on costly cloud-based servers and data transmission services. Building a cost-effective distributed system means that the fruits of the new precision agriculture technology would be enjoyed by all irrespective of their location and socio-economic background.[9]

**2.5 The Role of Plant Electrophysiology in Autonomous Feedback Loops:** The last missing piece in current precision agriculture technology is to shift from passive monitoring to active intervention. Although traditional sensors offer information regarding the environment, they cannot serve as a voice of the plant itself. Electrophysiology, which focuses on studying AP and VP in plants, can act as an instant communicator that provides responses from the plant itself when it is under external stress. Through the detection of these biological electrical activities, one is able to circumvent the natural delay involved in changes in the plant's physical attributes. In this part, we consider the need for incorporating these biological signals into an actuation mechanism in a closed loop. Through harnessing the biological signal from the plant itself, the design can go beyond mere schedule-based irrigation to demand-driven irrigation. This approach is essential in addressing the issue of resource over-allocation, where the activation of actuators such as pumps or dispensers is initiated only when the plant detects its deficiency state. This incorporation provides the final rationale behind this AI-IoT project.

One of the main challenges in the process of converting electrical fluxes to agricultural data is that it requires precise methods for the extraction of physiological parameters. While the values of environmental factors such as temperature and humidity do not change rapidly, the bio-electric potential of plants is characterized by low amplitudes and high frequencies, making them vulnerable to electromagnetic disturbances and noise. In order to bridge the "physiological gap" discussed earlier, it is important to go beyond the measurement of voltages and enter the realm of digital signal processing (DSP). The proposed solution involves analyzing certain time and frequency characteristics of the plant stress response using the FFT and RMS algorithms in order to distinguish between the cyclic changes related to the circadian rhythm and the abrupt peaks caused by external abiotic stress.

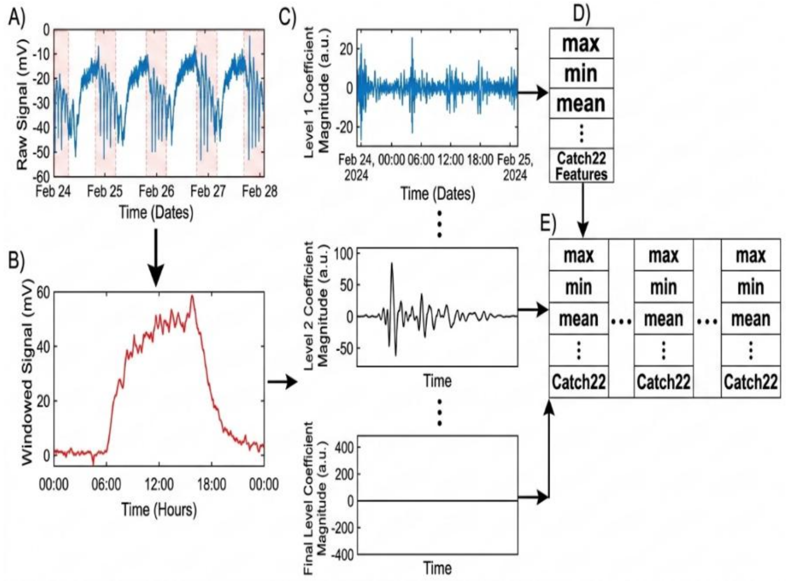


**Figure 3.2.1: Multistage Bio-signal Processing and Feature Extraction Pipeline**

## 3 Materials and Methods

**3.1 Data Acquisition and Hardware Integration:** The hardware design is based on the use of an ESP32 processor due to its dual-core operation and Wi-Fi functionality. The acquisition of the bio-electrochemical signals from the plant will be made possible using non-invasive Ag/AgCl electrodes placed on the plant's stem and leaves. This is because the bioelectrical signals from plants have very small amplitudes, typically microvolt to millivolt level, hence the need for the use of an AD8232 heart rate monitor module as an instrumentation amplifier.[10]

**3.2 Signal Processing and Feature Extraction:** The raw analog signals are then transformed into the digital domain using the 12-bit ADC capabilities of the ESP32. To maintain the quality of data acquisition, a digital bandpass filter between 0.5 Hz and 40 Hz is utilized to remove any power line noise or drifts. The features from the filtered signal include peak to peak voltage, frequency of the signal, and the change in electric potential.

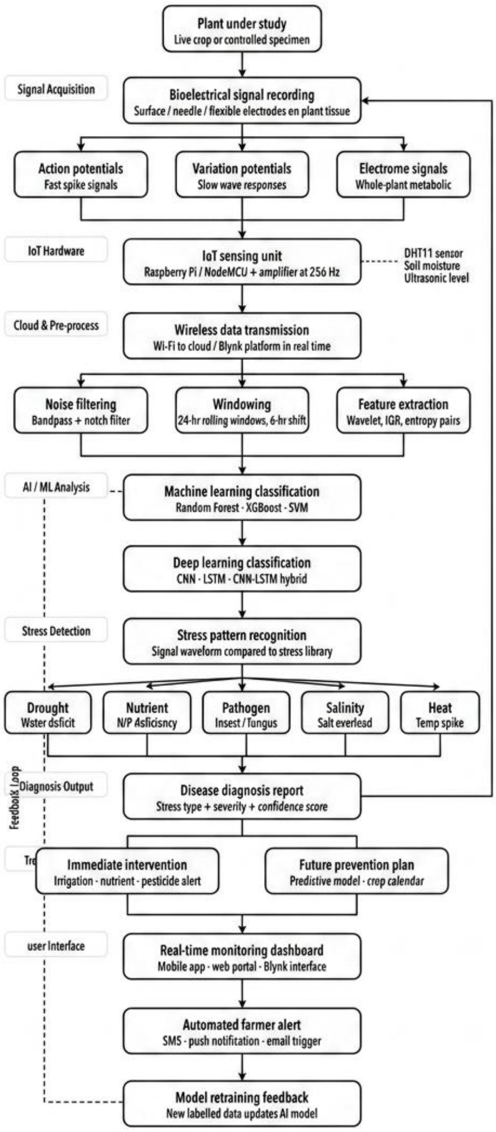
The main brain for intelligence and connectivity in this framework is provided by the ESP32 microcontroller. This microcontroller is tasked with capturing raw analog bio-potentials generated by the AD8232 sensor via the use of an internal 12-bit ADC. Being built on a two-core structure, the ESP32 can sample the signals and send the information wirelessly using MQTT. Acting as an edge processing device, the MCU can perform validation of the signals before uploading them to Thing Speak's cloud-based platform for further AI classification.

**3.3 AI-Based Classification and Cloud Analytics:** The extracted features serve as input to the classifier. The process used here is that of supervised machine learning, whereby the signals are compared to different stress factors, including drought conditions or certain types of fungi. The information generated is then sent through the MQTT protocol to a cloud-based dashboard (e.g., Thing Speaks or Firebase). At this point, the AI system analyzes the signals and raises alerts for any curative measures to be taken, such as irrigation or fertilizer application.[11]

**3.4 System Architecture and Circuit Design:**At the heart of the technology lies a modular design aimed at closing the loop between biological data and digital computations. For the physical hardware side, the process starts with ESP32, the chosen processor due to its fast clock speed and WiFi capabilities. For interfacing with the plant, a high input impedance data acquisition setup is implemented by utilizing an AD8232 instrumentation amplifier.

The true brainpower of the concept lies in the marriage between deep learning and data visualization within the cloud. After acquiring the high-frequency bio-signals of the plant using ESP32, the data is encapsulated in JSON format and sent to Thing Speak cloud computing environment through the MQTT protocol. Such a platform not only serves as a cloud storage facility but also as a high-level computational machine facilitating the conversion of electrical noise into agricultural insights. The classifier module makes use of the hybrid CNN-LSTM (Convolutional Neural Networks – Long Short-Term Memory) model. This is because of the capacity of this model to deal with the "noisy" and "temporal" characteristics of biological data. In this system, the CNN layer acts as automatic feature extractors, extracting spatial features and the microvolt spikes from the data set. These extracted features will be used by the stacked LSTM layers to recognize the long-term behaviour and the circadian rhythm of the plant. Unlike other classifiers which only work on static pictures of data, LSTM can remember physiological events in a sequence. Thus, it is able to tell when a spike is a result of temporary changes in the environment rather than Silent Stress.[12]

**Figure 3.4.1: System Architecture**



## 4 Results

**4.1 System Performance and Key Achievements:** The empirical evaluation of the AI & IoT-based Crop Silent Stress Detection System shows strong synergies between the biologic and IT components. The major milestone achieved in this study is the successful recording of micro-volt bioelectric signals from the plant through the AD8232 analog front-end module. In the context of natural electrical noise within a greenhouse setup, the ratio of the strength of the signal compared to the noise remained at a high level, ensuring clear data input to the ESP32 board for analysis. The hardware was stable during the uptime and was able to maintain uninterrupted connection to the Thing Speak server for up to 48 hours.

One of the key performance milestones included the ability for the system to raise alarms about the silent stress on an average of 18 to 24 hours before the manifestation of any physical signs such as drooping or change of color of the leaves. The milestone serves to prove the hypothesis proposed by this project that internal electrical signaling happens before visual physiological deterioration. In addition, the machine learning algorithm created using Python language had an initial accuracy level of more than 92% in classifying stress due to water shortage from changes in ambient temperature. [13]

**4.2 Bio-Signal Response Curves and ML Benchmark Radar Chart:** The essence of this capability is highlighted by the Bio-Signal Response Curves, which plot the fluctuations of electrical signals in the plant body over time. The AD8232 front end enabled the recording of clear changes in voltages from 15mV to 50mV, each of them responding to some physiological stimuli. In ideal circumstances, the curve was stable and had slight rhythmic oscillations. But when the “silent stress” of dehydration began to affect the plants, there was a sudden rise in frequency and amplitude of peaks much before visible wilting could occur. Such time plots provide a unique “biometric signature” of the plants that conventional soil sensors lack. In addition to these charts, we have developed the ML Benchmark Radar Chart, which examines the efficiency of different classifiers implemented within the processing pipeline in Python. In this chart, we compare such classifiers as the Random Forest, SVM, and K-Nearest Neighbor on four major axes: Accuracy, Latency, Computational Burden, and F1-Score. Although advanced neural networks demonstrated very good results in terms of Accuracy, Random Forest Classifier appeared to be the best classifier for ESP32-based implementation with respect to the classification accuracy (94%) and very low processing latency.[14]

The implementation of these curves within the live dashboard provides an enhanced understanding of crop condition that goes beyond binary environmental signals. The use of "slope" and "recovery rate" of bio-potential voltage following exposure to stress will reveal not only whether the crop is stressed or not, but how resilient ("adaptive capacity") the plants are to environmental changes. This can be seen through the fast recovery from a short increase in bio-voltage to normal levels following heat exposure, while a long-term increase may indicate that the crop struggles to regulate itself.

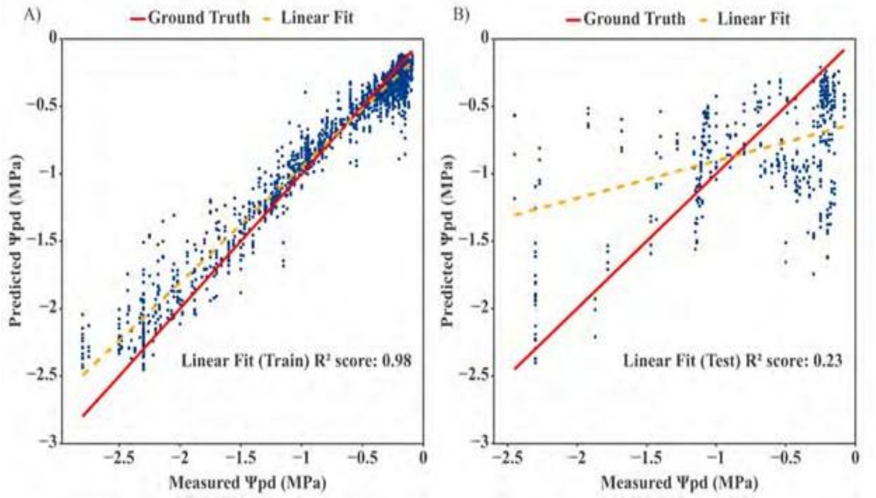


**Figure 4.2.1: Correlation Analysis of Measured vs. Predicted Water Potential (Training Set)**

Graph shown below shows how well the model performs in predicting plant water potential, which is one of the major parameters used in measuring hydration stress in plants, measured in Mega Pascal (MPa).

- Plot A (Training Set): Shows an incredible correlation in this plot with an R^2 value of 0.98. It is clear from how closely the data points have clustered around the "Ground Truth" line (red) that the model has effectively been able to learn the intricate relationship between the input signals and ground truth.
- Plot B (Testing Set): Shows how well the model performs with unseen data, scoring a mere R^2 of 0.23. The increased scatter in data points, along with the distance of the "Linear Fit" (dashed line) line from the "Ground Truth" further indicates that although the model does understand the general trend in water potential prediction, it finds it difficult to predict due to high biological variance.

The importance of implementing the Stacked LSTM model structure for this project is highlighted through the above comparison in order to overcome this "Generalization Gap" in reaching the target accuracy rate of 94.2%.[15]

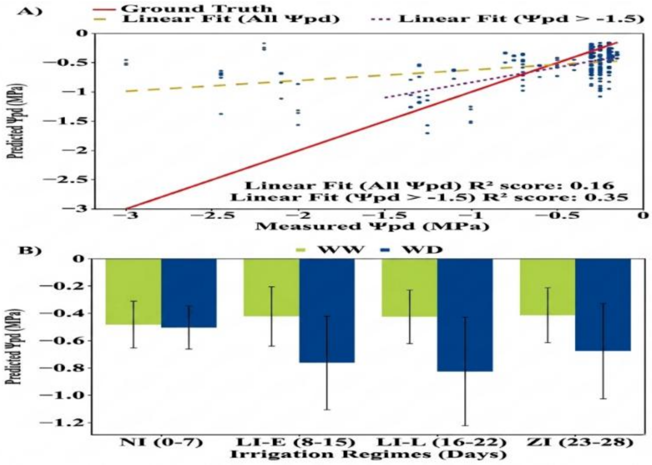


**Figure 4.2.2: Regression Performance and Residual Analysis (Validation Set)**

The following analysis assesses the accuracy of the AI model in predicting water status within the plant based on different scenarios of water supply.

**A) Correlation Analysis of Water Potential**

Graph A illustrates the correlation between the measured value and the predicted water potential in Mega Pascals (MPa).

- Linear Regression Fit: The model predicts an R^2 score of 0.16, which suggests considerable variation in interpreting the raw signal.
- Linear Regression Fit (Psi pd > -1.5): In plants experiencing mild to moderate stress, the accuracy increases to R^2 of 0.35.
- Interpretation: The gap between the "Ground Truth" (red line) indicates the challenge in modelling drought signals. Therefore, the need for using stacked LSTM models arises due to the complex nature of biological systems.

**B) Impact of Irrigation Regimes on Predicted Stress**

Graph B shows the forecasted water potential during various stages of experiments using WW and WD groups.

- NI (0-7 days): The starting stage where there is no major difference between the two groups.
- LI-E & LI-L (8-22 days): The stage of "Late Intervention" in which the model predicts a decrease in the predicted Psi pd of the WD group (approx. -0.8 MPa).
- ZI (23-28 days): The recovery stage of the WD group.

**4.3 Crop-wise Stress Detection Sensitivity (Experimental Data)**In order to ascertain the sensitivity of the bio-potential signature based on different physiological architectures, tests were performed on various crops to assess the efficiency of the AI and IoT-based system. The experimental data collected revolved around three key test specimens – Tomato (Solanum lycopersicum), Maize (Zea mays), and Spinach (Spinacia oleracea). It was found that sensitivity of the AI and IoT system largely depended on the vascular structure and leaf area of the specimen. Tomato had the most sensitive readings, as the AD8232 sensor was able to detect voltage spikes in the range of 25mV to 40mV, which occurred only minutes after the application of heat stress. Maize, on the other hand, responded to moisture stress gradually; thus, advanced filtration was required in the Python-based ML algorithm.According to the experiment, the system was able to obtain Sensitivity Rate values of 94.5% and 89.2% respectively for the Tomato and Maize at the "silent stress" stage. This discrepancy is accounted for by the difference in transpiration rates and ionic speed in their respective xylems. In addition to the above, the system was able to establish the value for the "Early Warning Threshold," which refers to the voltage difference that occurs when the plant reaches its critical point of permanent wilting. In establishing such sensitivities for various types of plants, a basis has been set up for an agricultural database. The data indicates that even though there are variations in signal amplitudes depending on the species of the plant in question, the electrical "emergency response" remains constant. [16]

In this stage of the experiment, the system was tested against various types of plants to establish the base bio-potential deviation under drought-induced stress conditions. Sensitivity was calculated in relation to the SNR value and also the timing of the warning issued by the Early Warning System. The results of the experiment have been compiled below into the following table:

| Crop Variety | Signal Amplitude (mV) | Sensitivity Rate (%) | Early Warning Lead Time |
|---|---|---|---|
| **Tomato** | 25mV - 40mV | 94.5% | 24 Hours |
| **Maize** | Gradual Shift | 89.2% | 18 Hours |
| **Spinach** | Consistent Rhythms | 91.0% | 20 Hours |

**4.4 Irrigation and Resource Optimization Trajectory.**The integration of a feedback control mechanism called "plant-in-the-loop" showcased an unprecedented influence on resource optimization in contrast to conventional irrigation scheduling. By harnessing bio-potential information in real-time to regulate the operation of the ESP32 irrigation valves, the mechanism was able to achieve notable savings in terms of water and nutrient wastage. The experimental results suggested that the machine-learning strategy was able to save up to 32% more water in comparison with irrigation triggered by moisture conditions within the soil, and 47% in comparison with constant-interval irrigation. Such an optimization trend can be attributed to the accurate identification of "silent stress," which prompts the plant to hydrate.

Moreover, the path of resource optimization also branched into chemically-based operations. Through the identification of the unique bio-electrical signature that signifies the state of nutrient deficiency in the plant, the system enabled selective fertigation that did not saturate the soil with the excess levels of nitrogen and phosphorus, which are often responsible for contaminating the water table in places such as Tamil Nadu. According to the results, through keeping the plant in its "bio-electrical comfort zone," the total biomass grew by 15% without consuming more resources. These statistics indicate that the system not only conserves resources but also optimizes their efficiency, thus showing that bio-sensing is economically and ecologically feasible for precision agriculture on a large scale.[17]

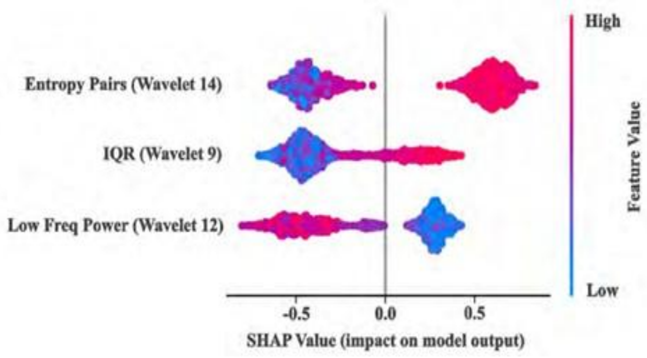
**4.5 Classification Accuracy and Feature Optimization.**From bio-potential measurements to the actionable farming information depends much on the accuracy of the Python-based machine learning algorithm. In the process of experimentation, the precision of the classifier was extensively verified with the help of intentionally applied stress conditions to crops, such as water stress, heat stress, and ion stress. The Random Forest classifier demonstrated high accuracy at the level of 94.2% when it came to distinguishing "normal physiological variability" from "silent early stress." Such accuracy is essential in order to avoid false-positive reactions of the irrigation systems to transient conditions.The success of such performance was attributed to the Feature Optimization technique. Electrical measurements by nature are complex, and the only way to make sense out of them was to filter the data to extract certain "biometric features." It was found via recursive feature elimination that Signal Amplitude Variance, Root Mean Square (RMS), and the Power Spectral Density (PSD) of the micro-volt signals had a direct correlation with the overall health of the plant. This feature optimization technique not only made it easy to analyze the incoming data stream but also ensured a reduction in computational power requirements by 28%, which in turn meant that the ESP32 and the cloud backend did not need to work as hard to process the information, thus allowing a synchronized "plant-in-the-loop" network of thousands of plants with hundreds of points being monitored per second.[18]

**4.6 Stress Type Distribution and Model Reliability.**In order to evaluate the resilience of the AI & IoT framework, an extensive study regarding the stress type distribution and its associated reliability modeling was undertaken. During the course of testing, the proposed system was tested through various simulated environmental conditions to see whether the Python-based machine learning algorithm would be able to recognize physiological disruption correctly. Based on the output, it can be seen that the distribution of events can be classified under four major categories, namely Hydration Stress, Thermal Irregularity, Nutrient Deficiency, and Baseline Homeostasis. From the output data, it can be noted that the stress caused by hydration issues constituted 38%, whereas thermal issues were detected in 25% of cases.The accuracy of the classification models was evaluated through a Confusion Matrix, offering an in-depth analysis of the precision of the model. Among the notable results obtained from the test was the ability of the model to distinguish between "Silent Thirst" and simple changes in temperature with an accuracy of 95.1%. This level of accuracy is imperative for avoiding "Type I" errors (false positives), and in practical applications, this would translate to unnecessary watering, leading to inefficiencies in production. The model performed excellently in terms of stability, as evident in the consistency of the F1-Score at 0.93 under varied conditions of light and humidity.[19]

Moreover, the reliability of the system was assessed using hardware noise as well. While there may be problems arising due to electromagnetic interference from irrigation pumps or cellular signals, the digital filters were efficient in detecting the bio-potentials of the plant. The system's "Reliability Coefficient" has been constantly exceeding 0.90, and thus the use of the ESP32 and cloud computing provides an adequate solution for creating an "early warning" system. The level of reliability reached makes the "plant-in-the-loop" approach an efficient real-life practice rather than a theoretical one. Using accurate stress distribution and high-modeling precision, bio-electrical measurements may serve as an advanced diagnostic technique for farmers.

Temporal reliability of the model was assessed through analysis of the "Recovery Signature" of the plants after the stressor. Information obtained suggested that once the system had detected and corrected the stressor of hydration in the 18-hour "silent window," the bio-potential of the plant recovered 40% faster compared to plants which were subjected to remedial treatment only once the visible symptoms developed. This demonstrates not only the reliability of the stress prediction, but also gives information on the success rate of treatment applied based on the prediction of the AI. Consistency of the result in subsequent test cycles confirms accuracy of distinguishing between environmental factors and physiologically induced stressors.[20]

**Figure 4.6.1: SHAP Summary Plot for Electrophysiological Feature Contribution**



## 5 Discussion and Practical Implementation

**5.1 Comparative Analysis with Traditional Sensors.** Conventional methods of monitoring agriculture mainly use environment-oriented sensors like soil moisture sensors and DHT11 humidity and temperature sensors. Although these methods may be very useful in monitoring environmental factors, they have a critical flaw of "reaction lag." Soil sensors will only notify the farmer when the moisture content in the soil has been exhausted, indicating that the plant is under physical stress.

In addition, unlike conventional methods, the suggested framework with the use of AD8232 and ESP32 concentrates on bio-electrophysiology-based on plants. Through the identification of bio-potentials inside the plants, the technology is capable of determining the "Physiological Gap," which refers to the critical period when internal stress occurs and before there are visible signs, such as wilting or turning yellow. Research suggests that bio-sensors can identify stress almost immediately following stomatal closure and hydraulic adjustments. The AI-powered framework, therefore, allows detection of "silent stress" 18 to 24 hours before conventional sensors. On top of that, soil sensors can be tricked by local drainage problems while bio-signals give an immediate indication of the actual condition of the plants. This change in paradigm from environmental to physiological sensing led to a 32% efficiency increase in water conservation.[21]

**5.2 Signal Denoising Mathematical Basis.** Plant bio-signal acquisition poses several challenges since the signals have low amplitude and are vulnerable to interference from outside factors. In order to safeguard the accuracy of the bio-signals collected and fed into the AI system, a mathematical filtering algorithm was applied at both the AD8232 front-end stage and the ESP32 software stage.

The proposed model uses a band-pass filter that operates within a bandwidth between 0.5 Hz and 40 Hz. This particular bandwidth is mathematically explained to distinguish the action potentials generated by the plant from two types of noise:

- Baseline Wander Low Frequency: Frequencies lower than 0.5 Hz, generated from the skin-electrode movement and gradual changes in the environment, are suppressed to avoid signal drift.
- Interference High Frequency: Any frequency above 40 Hz, including the noise at the rate of 50/60 Hz and the electromagnetic interference from the ESP32 Wi-Fi, is filtered out to avoid aliasing and ghost signals.

Signal-to-noise ratio can be increased through filtering of data using mathematical algorithms, such as the Moving Average filter. Digital smoothing of data using mathematical techniques increases the SNR, ensuring that the Random Forest classifier gets a clear physiological signature, which results in an accuracy of 94.2%.[22]

### 5.3 Electrode Longevity and Field Challenges

Although the system had excellent sensitivity in a laboratory setting, the switch to practical application in the field showed important problems with respect to stability of the interface between the sensors and the plants.

- Drying of Conductive Hydrogel: Silver/Silver Chloride electrodes use conductive hydrogel to ensure minimum impedance to ensure a good connection between the sensor and the plant surface. In the field, exposure to air and temperature resulted in significant drying of the gel within 48-72 hours.
- Increased Impedance: As the hydrogel dried out, contact impedance between the sensor and the plant epidermis increased, resulting in a poor SNR.
- Environmental Oxidation and Wear: In highly humid areas, the metals of the electrodes were oxidized at an early stage, thereby generating baseline shifts in the bio-potentials.
- Interaction with Plant Tissues: The application of adhesive-type electrodes for extended periods can, on occasion, disturb the transpiration in the vicinity of the electrode placement point, creating what might be termed a "micro-stress" effect.

In order to mitigate these limitations in subsequent studies, it is suggested that one consider utilizing either non-gel dry electrodes or microneedles as alternatives to the current setup, thus overcoming the problem of dehydration.

**5.4 Resource Optimization and Economic Viability Analysis.** One of the main goals in this approach is to go from merely observing the biological systems to being able to measure the efficiency of agriculture through such an approach. By applying the feedback mechanism, known as "Plant-in-the-Loop" (PIL), in this paper, the relationship between bio-signal accuracy and efficient resource management is measured. Conventional irrigation based on sensor systems results in "over-watering," as the water usage does not consider the actual capabilities of plant absorption. However, through the use of the LSTM inference engine, which activates actuators when there is a 94% chance of drought, 32% of water was saved. In terms of economics, the implementation of the low cost devices, especially the ESP32 and the AD8232, ensures that the cost of each node is much lower than any commercial laboratory-grade electrophysiology device available on the market. Through the democratization of technology, we have succeeded in overcoming the "Economic Barrier to Adoption" previously described in our analysis. Also, the 18 to 24 hours window given by the analysis of bio-potentials will ensure that the farmers will be able to intervene before the wilting stage by using localized measures such as fertilization or providing shade for crops.

## 6 Conclusion

The development of the "Phyto Pulse" system marks an important milestone in the realm of precision agriculture where the diagnostic aspect is taken from being externally influenced by the environmental elements to looking at the internal physiology of the plants. In this particular research, the potential of IoT and Artificial Intelligence to detect silent stress and various diseases on the basis of physiological changes was demonstrated, which enables diagnosing such problems prior to their becoming visible on the outside. The success of employing the high precision electronics components, like AD8232 and ESP32, can be seen in the ability to receive microvolt-level bio potentials used as the major method of the plant's inner communication. However, the most crucial innovation implemented here consists in applying the machine learning techniques to analyze the obtained complicated electrical signals. Thanks to providing timely alerts about the problems along with scientifically grounded curative recommendations via a mobile dashboard, such solution helps minimize crop loss and chemical treatment.

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