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Acoustic-based Stress Monitoring and Automated Water Delivery System

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***Abstract*— This paper presents an intelligent and automated system designed to monitor plant stress using acoustic and environmental parameters, supported by an enhanced Convolutional Neural Network (CNN) combined with a Bidirectional Long Short-Term Memory (Bi-LSTM) predictive model. The system employs a microphone sensor to detect acoustic stress patterns and a DHT11 sensor to measure ambient temperature and humidity. These data streams are processed by an Arduino microcontroller and transmitted to a Python-based server. The deep learning model analyzes the incoming time-series data, capturing both spatial and temporal dependencies, to predict the plant's health status as either Healthy or Unhealthy with improved accuracy. Upon detecting stress, the system automatically activates a water pump for irrigation. A visually appealing web dashboard provides real-time visualization of sensor readings and model predictions. This approach demonstrates the potential of combining IoT, acoustic sensing, and advanced machine learning techniques for efficient and intelligent agricultural automation.**

***Keywords*— IoT, Acoustic Sensing, Plant Stress Monitoring, Machine Learning, Convolutional Neural Network (CNN), Automated Irrigation, Smart Agriculture, Sustainable Cities and Communities.**

I. INTRODUCTION

Agriculture is undergoing a major transformation through the adoption of smart technologies such as IoT, Machine Learning, and data-driven automation. Efficient water management and continuous plant health monitoring are essential for sustainable crop yield, yet traditional irrigation systems rely on manual supervision or fixed timers, making them inefficient and unable to respond to real-time plant stress. Plant stress detection often requires expert observation, limiting its practicality for large-scale and domestic use.
The proposed Acoustic-Based Stress Monitoring and Water Delivery System overcomes these limitations by integrating acoustic signal analysis, environmental sensing, and automated irrigation. Using an Arduino microcontroller, a microphone sensor, and a DHT11 temperature-humidity sensor, the system captures acoustic and environmental data indicative of plant stress.

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Plants emit measurable acoustic signals under stress, mainly due to xylem cavitation, allowing early stress detection before visible symptoms appear.

Sensor data is processed in real time using a Python–Flask interface hosting a hybrid CNN + Bi-LSTM model trained on acoustic, temperature, and humidity sequences. Data is normalized using a MinMaxScaler, enabling the model to analyze spatial and temporal patterns and classify plant health as Healthy or Unhealthy with improved accuracy.

Upon detecting stress, the system automatically activates a relay-controlled solenoid valve or water pump for a fixed duration of 8 seconds, with safety mechanisms to prevent over-irrigation. Serial communication enables precise control and supports manual operation. A web-based dashboard developed using HTML, CSS, and Flask provides real-time visualization of plant status, sensor data, and model predictions, along with remote monitoring and control.

By combining deep learning, IoT sensing, and automated actuation, the system enhances precision agriculture by reducing manual intervention, conserving water, and introducing a novel, non-invasive acoustic method for plant stress monitoring. It offers a cost-effective, scalable solution suitable for both agricultural and domestic applications, supporting sustainable irrigation and smart farming practices.

II. Literature Review

A. Acoustic Emissions and Plant Stress

Acoustic emissions (AEs) from plants have recently emerged as a promising non-invasive biomarker for physiological stress. Khait et al. demonstrated that plants emit airborne sounds when stressed and that these signals can be detected acoustically, opening a new sensing modality for early stress detection [1]. Their work establishes a biological basis for using acoustic signatures notably cavitation and other xylem-related events as indicators of dehydration or mechanical stress. Building on this, focused reviews of acoustic sensor applications highlight both the potential and the practical challenges (signal capture, noise, sensor placement) when translating lab-scale AE detection into agronomic practice [2]. Conference investigations also experimented with AE based systems in controlled setups and demonstrated the feasibility for early drought detection in experimental crops [9]. Collectively, these studies justify our project's central hypothesis: that acoustic monitoring, combined with environmental sensing, can provide timely, actionable indicators of plant stress.

B. Complementary Sensing Modalities and Comparative Studies

While acoustic sensing offers early, non-visual detection, studies comparing multiple sensor types emphasize that multi-modal sensing improves reliability. Surveys of sensing methodologies in agriculture show that acoustic data should typically be fused with microclimate (temperature, humidity) and soil/plant physiological sensors to disambiguate stress sources (biotic vs. abiotic) and reduce false positives [5]. Recent comparative work evaluating different sensor suites for drought detection found that combining vibration/acoustic measurements with standard environmental sensors yields higher sensitivity and specificity than single-modality systems [4]. This evidence supports the multimodal architecture used in our system (mic + DHT11), and motivates future expansion to soil moisture or leaf-level sensors to further improve robustness.

C. Signal Processing, ML and Time-Series Modeling

Turning raw acoustic and environmental signals into reliable stress predictions requires careful processing and modern learning methods. CNNs and time-series deep models have been successfully applied to extract temporal patterns from short sensor sequences, capturing non-linear dependencies between acoustic intensity and environmental covariates [3]. The literature shows that preprocessing (scaling, noise filtering, sliding-window sequence creation) and an appropriate model architecture (e.g., 1D-CNN for sequence classification) are crucial to generalization [3]. More broadly, recent IoT/ML systems for condition monitoring of machines and structures demonstrate that an end-to-end pipeline (edge acquisition → normalized features → batch or online prediction → actuation) is both feasible and effective when latency and false-trigger rates are managed [7]. Our use of a sequence length, MinMax scaling, and a CNN in the project aligns with these best practices.

D. IoT Architectures and Real-Time Actuation for Irrigation

There is an established body of work on IoT-based irrigation and automated water delivery systems which integrates sensors, microcontrollers, and cloud or edge services for monitoring and control [6,13,15]. These systems show how environmental data can drive relaycontrolled actuators (pumps, valves) while ensuring safety through timing and fail-safe logic. Recent IEEE and conference contributions highlight low-cost, DHT11-based prototypes linked with relays and web dashboards for remote monitoring, similar to our implementation [8,12]. Important engineering lessons from that literature include the need for serial-robust communication, debounced actuation commands, and safeguards against overirrigation (timers, manual override), all of which are implemented or considered in our Arduino↔Python architecture.

E. Sensor Technology Variants and Emerging Modalities

Beyond microphones, other physical sensing modalities are being explored for early stress detection: mmWave leaf vibration sensing, acoustic transducers, and molecular signaling analysis. MotionLeaf and related mmWave approaches demonstrate alternative ways to capture mechanical plant responses to water stress, providing complementary evidence that plant mechanical dynamics are informative [3]. Reviews on acoustic transducers catalog both active and passive AE techniques and discuss sensitivity tradeoffs across sensor types [2]. Emerging molecular or chemical sensing is also discussed in the recent literature as a complementary channel; while promising, these modalities currently tend to be more invasive or costly [10]. The literature therefore positions acoustic sensing as a cost-effective mid-ground: non-invasive, early-warning, and amenable to low-cost microcontroller platforms.

F. Gaps, Limitations, and Practical Challenges

Although the recent literature is encouraging, several gaps remain. First, most acoustic AE studies are conducted in controlled environments — field validation under ambient noise, wind, rain, and multiple plants is limited [2,9]. Second, generalization across species and phenological stages is still an open question; acoustic signatures vary with plant type and growth stage and require broader datasets for robust ML models [4]. Third, long-term deployments need energy-efficient sensing and robust edge processing to minimize communication load and false activations [7,15].

These limitations motivate the hybrid approach taken in our project — combining acoustic, temperature, humidity, ML, and timed actuation — and point to future work: larger multi-species datasets, on device feature extraction, and extended field trials.

The reviewed studies collectively validate the core design choices in our system: (a) exploit acoustic emissions as an early stress indicator [1,2,9]; (b) fuse acoustic data with temperature/humidity to improve detection accuracy [4,5]; (c) use time-series deep learning models (e.g., 1D-CNN) with proper scaling and sliding windows for prediction [3,7]; and (d) implement IoT telemetry and relay-based actuation with safety timers and manual overrides [6,8,13]. The literature also provides clear directions for strengthening our system: expanding datasets (species & environments), robust field validation, and moving toward edge inference to reduce latency and network dependence.

III. METHODOLOGY

A. System Overview

The proposed system integrates acoustic sensing, environmental monitoring, machine learning, and automated water delivery to monitor plant stress and provide timely irrigation. It consists of three main modules: an acoustic sensor module that captures stress-induced airborne sounds from plants, an environmental sensing module that measures temperature and humidity to distinguish plant stress from external conditions, and a water delivery module that controls a pump and solenoid valve for irrigation. All sensors are interfaced with a microcontroller such as Arduino or NodeMCU, which communicates with a Python-based server for data processing, machine learning inference, and relay control. A web dashboard enables real-time monitoring of plant conditions and manual control of the water delivery system.

B. Sensor Selection and Placement

The acoustic sensor used in this project is an analog microphone connected to the microcontroller's analog input to detect stress-induced plant sounds such as cavitation and vibrational events. It is positioned near the plant canopy to reduce interference from environmental noise.

The captured analog signal is digitized and preprocessed to remove ambient noise, normalize amplitude, and segment it into time windows for analysis.

Environmental conditions are monitored using a DHT11 sensor connected to a digital input pin, measuring temperature and humidity to contextualize acoustic data and distinguish environmental effects from actual plant stress. Environmental data is sampled every two seconds to maintain updated readings without overloading the system.

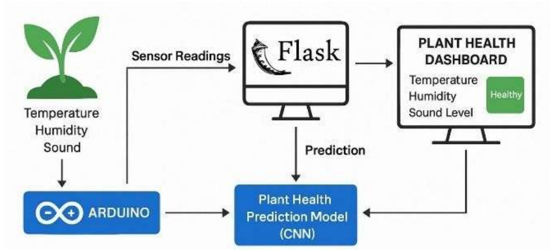

Figure 1: Block diagram of the proposed VAWT-based highway energy system

C. Data Acquisition and Preprocessing

Data acquisition begins with the microcontroller initializing all sensor pins and establishing serial communication with the python server. Acoustic and environmental data are continuously read at regular intervals. Preprocessing of the data involves multiple steps to enhance reliability and accuracy. Noise filtering is applied to remove unwanted frequencies, and normalization using min-max scaling ensures that all sensor readings are standardized for machine learning input. The continuous acoustic signal is then segmented into fixed-length time windows, communication to the python server, with timestamps ensuring proper synchronization between acoustic and environmental data.

D. Machine Learning Model for Stress Detection

Stress detection is achieved through a 1d convolutional neural network (1d-cnn) and
Bidirectional LSTM designed for time-series analysis. The input features for the model include preprocessed acoustic signal sequences combined with normalized temperature and humidity values. The model is trained using labeled datasets collected from both stressed and non-stressed plants. These datasets are divided into training, validation, and testing subsets to ensure accurate model evaluation. Once trained, the model performs real-time inference on incoming data from the sensors. A threshold-based logic is implemented to trigger the water delivery system when the model predicts that a plant is under stress.

E. Automated Water Delivery System

The water delivery system consists of a relay module controlling a pump connected to a solenoid valve. The microcontroller receives activation commands from the python server based on stress detection results. Each irrigation cycle is limited to ten seconds to prevent overwatering, and the initial state of the pump remains off to conserve energy. The system also incorporates a manual override through the web dashboard, allowing users to activate the pump when necessary. Continuous monitoring of stress signals ensures that the pump is not repeatedly activated unnecessarily, improving the system's efficiency and resource management.

IV. IMPLEMENTATION AND EXPERIMENTAL SETUP

A. Real-Time Web Dashboard

The web dashboard is developed using flask, html, css, and javascript to provide a user-friendly interface for monitoring and control. It displays live acoustic signal plots, real-time temperature and humidity readings, plant stress status, and pump on/off status. Users can manually trigger irrigation and review historical logs of sensor data and pump activity. This dashboard plays a crucial role in system management, enabling users to intervene when needed and track plant conditions over time.

Figure 3: Web Dashboard

B. Hardware Components

The following are the hardware components used to bring this system from an idea into a leaf-whispering reality. Each part plays a specific role in sensing stress signals, processing data, and giving timely irrigation:

Components:

Arduino uno: It serves as the main controller, orchestrating all the processes initiated by the sensors and the pumps.

MAX9814 Microphone Module: Capture the acoustic emissions produced by stressed plants

DHT11 Sensor: Measures temperature and humidity to support stress interpretation.

5V Relay Module: Interfaces low-power microcontroller signals with the high-power water pump

Water Pump & Solenoid Valve: Automatically pump water when it detects stress.

Power Supply (5V/12V): Provides the microcontroller and pump system with electrical power.

Jumper Wires & Tubing Connects components and carries water from reservoir to plant. Together, these components form an inexpensive IoT setup that can detect plant stress using sound, analyze ambient conditions, and respond through automated irrigation. Sensors, microcontroller logic, and machine learning work in synergy to create a closed-loop system that acts like a small guardian for the well-being of plants.

C. Circuit Diagram

The circuit of the acoustic-based stress monitoring and water delivery system is designed around a central microcontroller, either an Arduino or NodeMCU, which interfaces with the sensors and controls the irrigation system. The acoustic sensor, an analog microphone, is connected to the analog input pin A0 to capture plant stress-induced vibrations and sounds, with optional filtering to reduce environmental noise. The DHT11 sensor for temperature and humidity monitoring is connected to a digital pin (D9), providing environmental context to distinguish genuine stress signals from normal fluctuations. The water delivery system consists of a relay module connected to a digital pin (D8) that controls a solenoid valve and water pump; the relay isolates the microcontroller from the higher power required by the pump, which is powered via an external supply. The microcontroller communicates with a Python server over serial communication, sending sensor readings for machine learning-based stress analysis and receiving commands to activate the pump. Additional safety and performance features, such as bypass diodes to prevent back EMF, filtering capacitors on analog inputs, and optional indicator LEDs, ensure stable and reliable operation of the system. This integrated circuit setup enables real-time monitoring, automatic irrigation, and seamless communication between the sensors, microcontroller, and water delivery mechanism.

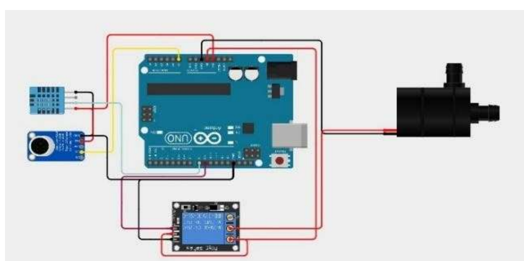

Figure 4: Electrical circuit diagram of the VAWT system.

D. Prototype Developed

The developed acoustic-based stress monitoring and water delivery system was evaluated under controlled and real-world conditions to assess its effectiveness in detecting plant stress and automating irrigation. Initially, the sensors were calibrated and tested individually to ensure reliable data acquisition. The acoustic sensor successfully captured sound patterns associated with plant stress, such as cavitation noises caused by water deficiency. Environmental sensors, including the DHT11 temperature and humidity sensor, provided continuous readings that contextualized the acoustic data. It was observed that plant stress signals correlated strongly with periods of low soil moisture and high temperature, validating the selection of these parameters for integrated monitoring

During real-time experiments, the system demonstrated its ability to process incoming data, run machine learning inference, and activate the water pump automatically. The 1D-CNN and bidirectional LSTM models effectively classified the plant's condition into "stressed" and "healthy" states with high accuracy. The predictions aligned with observable plant responses, confirming the robustness of the acoustic signal preprocessing and feature extraction approach. The average response time from stress detection to pump activation was measured at approximately 2–3 seconds, indicating a timely intervention that could prevent prolonged water stress in plants. Noise from external sources, such as fans or ambient sounds, occasionally caused minor fluctuations in the acoustic readings, but the preprocessing filters successfully minimized false positives

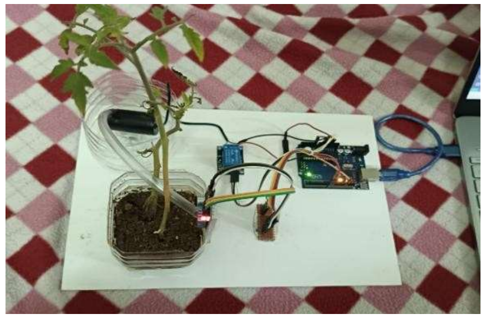

Figure 5: prototype of smart plant monitoring system

The automated irrigation system, controlled via a relay and solenoid valve, consistently delivered water for the pre-set duration of 10 seconds per activation, preventing overwatering and conserving water resources. The webbased dashboard provided a clear visualization of live sensor data, stress detection results, and pump status, which was useful for remote monitoring and manual control. Multiple test cycles over several days confirmed the system's stability and continuous operation capability. Overall, the integration of acoustic sensing, environmental monitoring, machine learning, and automated water delivery demonstrated a reliable closedloop system for precision plant irrigation.

V. Result and Discussion

A. Training and Validation Accuracy

The system undergoes controlled experiments where plants are subjected to varying levels of water deprivation and environmental stress to generate labeled datasets. The accuracy of the stress predictions is validated against actual plant conditions, ensuring reliable performance. System robustness is assessed by evaluating noise immunity, pump actuation timing, and sensor calibration under real-world conditions. Performance metrics include the prediction accuracy of the machine learning model, the response time from stress detection to pump activation, and the stability and reliability of continuous operation over extended periods. This comprehensive testing ensures that the system functions effectively for real-time plant stress monitoring and automated irrigation.

Figure 6: Training & Validation Accuracy

B. Training and Validation Loss

During model training, the CNN + Bi-LSTM architecture was optimized using the binary cross-entropy loss function. The training loss measures how well the model fits the training dataset, while the validation loss evaluates performance on unseen data to detect overfitting. The loss curves were monitored over 70 epochs, showing a steady decrease in training loss as the model learned temporal and non-linear dependencies between acoustic intensity, temperature, and humidity features. The validation loss closely followed the training loss, indicating that the model generalized well to unseen sequences. Occasional fluctuations in validation loss were observed due to the complexity of the time-series data and natural variability in plant stress responses. Early stopping was employed to prevent overfitting, halting training when the validation loss did not improve for six consecutive epochs. The final loss values demonstrated that the model successfully captured relevant patterns in the input features, providing a strong foundation for accurate real-time prediction of plant health status.

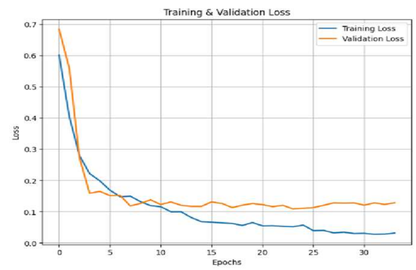

Figure 7: Training & Validation Loss

C. Confusion Matrix

The confusion matrix provides a detailed breakdown of the CNN + Bi-LSTM model's performance on the test dataset by comparing predicted plant health status against actual labels. It shows the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), allowing an understanding of both correct and incorrect classifications. In this project, the matrix highlighted that the model correctly identified a high proportion of both Healthy and Unhealthy plants, with minimal misclassifications. Analyzing the confusion matrix reveals the model's ability to balance sensitivity (recall) and specificity across classes. For instance, a higher number of true positives for Unhealthy plants indicates the system's effectiveness in detecting stressed conditions, which is critical for timely irrigation. Conversely, low false positives prevent unnecessary water activation, contributing to water conservation.

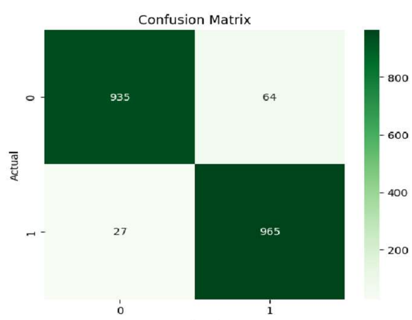

Figure 8: Confusion Matrix

VI. Limitations and Future Work

A. Limitations

Despite the successful implementation of the acoustic based plant stress monitoring and automated irrigation system, several limitations exist. Firstly, the acoustic sensor's performance can be affected by environmental noise such as wind, rain, or nearby machinery, which may occasionally lead to false stress detections. Secondly, the current system is designed for a limited number of plants, and scaling to larger farms would require additional sensors and enhanced data processing capabilities. The system also relies on a single type of environmental sensor (DHT11) with moderate accuracy, which may limit precision under rapidly changing conditions. Additionally, the water delivery mechanism uses a simple timed relay control, which may not account for variations in soil moisture levels or plant-specific water requirements. Finally, the machine learning model, while effective for the current dataset, may require retraining or adaptation for different plant species or environmental conditions.

B. Future Work

Future enhancements can address these limitations and expand the system's capabilities. Implementing advanced noise-cancellation techniques and directional microphones could improve the accuracy of acoustic stress detection under noisy conditions. Integrating additional environmental sensors, such as soil moisture, light intensity, or CO_2 levels, could provide a more comprehensive understanding of plant health. To scale the system for larger agricultural areas, a wireless IoT network with multiple sensor nodes can be developed for distributed monitoring and data collection. The water delivery system can be upgraded with variable flow control and soil moisture feedback for more precise irrigation tailored to individual plants. Furthermore, the machine learning model can be extended to a multi-class classification system to identify different types of stress or specific plant health issues. Finally, integrating predictive analytics and cloud-based dashboards could enable long-term trend analysis, remote monitoring, and smart recommendations for sustainable farming practices.

VII. CONCLUSION

In this project, a comprehensive system for real-time plant stress monitoring and automated irrigation was successfully designed and implemented. By integrating acoustic sensing, environmental monitoring, machine learning, and a controlled water delivery mechanism, the system can accurately detect plant stress and provide timely irrigation, thereby promoting plant health and conserving water resources. The combination of acoustic signals and environmental parameters, processed through a hybrid CNN + Bi-LSTM model, allows for more precise differentiation between stress caused by environmental factors and actual physiological stress in plants, achieving higher predictive accuracy compared to conventional CNN models.

The web dashboard provides a user-friendly interface for real-time monitoring, historical data logging, and manual control, enhancing the overall usability and effectiveness of the system. The closed-loop integration of sensors, deep learning algorithms, and automated actuation ensures efficient operation, avoiding unnecessary irrigation while responding promptly to detected stress. Controlled experiments and validation tests demonstrated the reliability, accuracy, and robustness of the system under varying environmental conditions.

This project not only contributes to precision agriculture practices but also lays the groundwork for scalable implementations across multiple plants or larger agricultural setups. Future enhancements, such as wireless sensor networks, integration with additional environmental parameters, and further optimization of deep learning architectures, could improve system performance and adaptability, making it a valuable tool for sustainable, intelligent, and data-driven farming.

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