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Kenya, Sustainable Agriculture

EchoShield: Harnessing Plant Ultrasonic Emissions for Sustainable Agriculture in Kenya

1. Introduction

Kenya, located in East Africa, spans from the Indian Ocean coast to fertile highlands and the wide arid plains of the north. It has a population of more than 50 million people and is often described as both an economic engine of East Africa and a country of traditions and heritage. While urban Kenya, especially cities like Nairobi and Mombasa, is being rapidly modernized, most of the people of Kenya still live in rural areas, where farming is a way of life.

Agriculture permeates every aspect of life and livelihoods in Kenya. Farming is key to making a living in rural areas and accounts for approximately a third of GDP. Beyond economics, agriculture provides food security for millions of Kenyans and is a cornerstone of community well-being and cultural heritage *(Hornsby, 2012)*.

Till date, a large part of agriculture in Kenya relies on traditional farming practices, rain-fed cultivation, manual observation, and experience passed down through generations. This approach is resilient but leaves crops vulnerable to the challenges of the modern era . Thus there is still a pressing need to modernise agriculture and increase access to modern irrigation, monitoring and pest control systems*(Memon & Lee-Smith, 1993)*

The consequences of these challenges are evident in significant crop losses year after year. Pests and diseases like maize stalk borers, fungal blights, and viral infestations can destroy a substantial portion of harvests if not caught early, and have a prominent presence in Kenyan agricultural fields. Similarly, drought like conditions and erratic rainfall often cause plants to wither before farmers realize the severity of water stress. In severe cases, a pest outbreak or a delayed response to drought can cost farmers 20-30% or more of their expected yield *(Grisley, 1997)*. For rural communities who depend on each season's crop for food and income, such losses are devastating.

A central limitation in crop protection is the absence of reliable early-warning systems for plant stress. Plant stress can be due to lack of water in the plant, pathogen attack or pest invasion. The traditional method to detect them depends on visual diagnosis. But by the time these symptoms manifest, the damage is already advanced and often irreversible..While advanced precision agriculture tools such as multispectral imaging, drone surveys, and soil-moisture probes can identify stress before it is obvious to the naked eye, their adoption among Kenyan smallholder farmers remains minimal. High equipment costs, limited access to stable internet or cloud services, and the technical expertise required for data interpretation create barriers. Consequently, millions of farmers are left without actionable information during the critical early stages of stress, underscoring the need for an alternative detection approach that is both affordable and deployable in resource-constrained environments.

This situation highlights the need for a novel early-warning system that does not depend on visual symptoms or expensive infrastructure. An ideal solution would alert farmers to hidden signs of plant stress in time to act, even in remote, resource-constrained settings. EchoShield is proposed as exactly this solution: an innovative approach to monitor plant health through the sounds of the plants themselves.

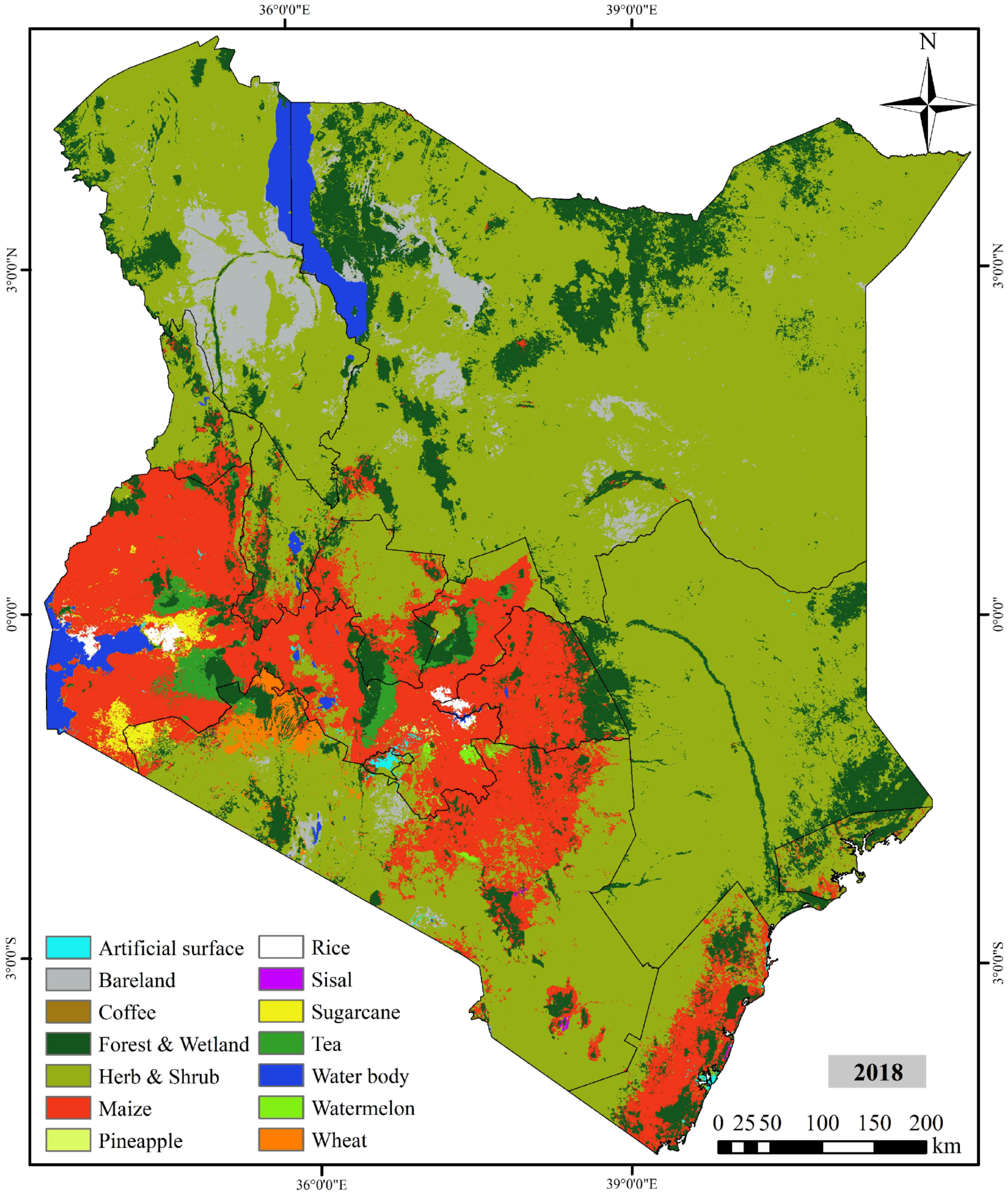

Figure 1 : Distribution of crop types across Kenya (adapted from Ni et al., 2022).

2. Working Principle.

Plants undergoing stress emit ultrasonic acoustic emissions (UAEs) above 20kHz (Khait et al., 2023). These emissions, which are produced when cavitation occurs in the xylem as water is pulled into at a negative tension greater than a critical threshold, emit ultrasonic clicks as embolisms in the xylem form and then collapse.

Biotic stresses such as herbivory, mechanical damage, or pathogen-induced necrosis, also emit acoustic signals (Bonisoli et al., 2024). The spectral and temporal features of these emissions depend on the type of stress and the plant species. As expected, healthy, unstressed plants emit few detectable ultrasonic emissions and represent a progressive increase in emission frequency and emission amount with increasing stress.

Because the ultrasonic emissions are airborne, ultrasonic microphones are typically used to capture the emissions. The amplitude, frequency, and occurrence of the acoustic signals can be analyzed to represent plant health in a non-destructive manner if stress was identified before visible symptoms. This principle confirms the scientific basis for EchoShield as an early warning system for plant health.

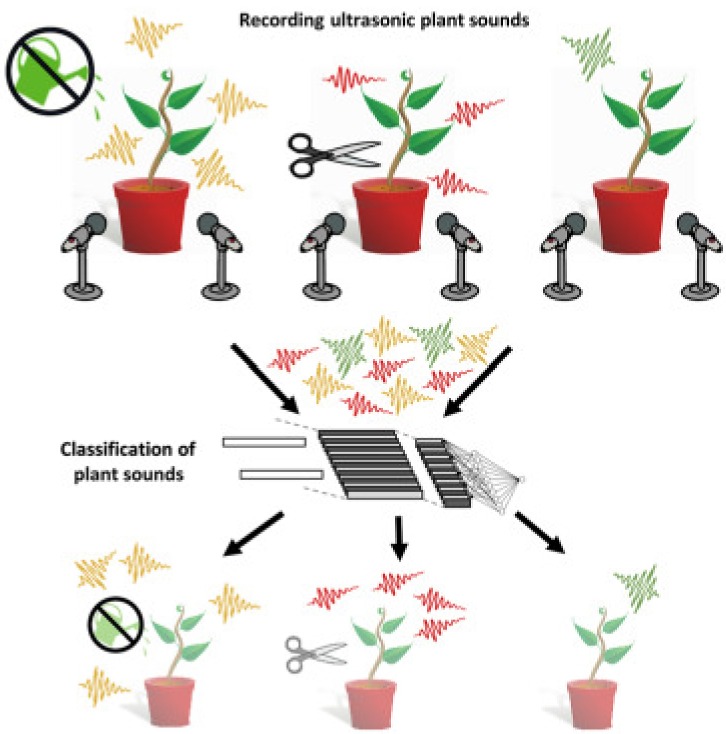

Figure 2 : Distribution of crop types across Kenya (adapted from Ni et al., 2022).

3. EchoShield

3.1 Concept

EchoShield is an early‑warning crop monitoring system that detects plant stress via ultrasonic acoustic emissions (UEs). Water deficit or pest attack, xylem cavitation events produce very short (≪1 ms) ultrasonic clicks (≈20-100 kHz) as gas bubbles form in the sap. EchoShield continuously records these high-frequency signals using a contactless ultrasonic microphone. The audio is converted into spectrograms and fed to an onboard AI classifier trained to recognize stress-induced emission patterns. This non-invasive approach requires minimal equipment, essentially an ultrasound mic and a computing unit, and can run on low-cost hardware. EchoShield's processing is done on Raspberry Pi, allowing offline operation without cloud connectivity. The device is designed to be energy-efficient and rugged for smallholder farms. In practice, units can be deployed as fixed field sensors or mounted on a mobile rover that patrols crop rows. The rover prototype carries the sensor array and autonomously scans plants, enabling wide-area surveys. This low-cost, self-contained design philosophy fits rural Kenyan contexts with intermittent connectivity and limited infrastructure.

Application in Kenya

Maize: Kenya's maize is the dominant staple crop, accounting for ~30% of national agricultural production. Production rebounded to about 47.6 million 90-kg bags (~4.28 million tonnes) in 2023 but dipped ~6.1% in 2024 to 44.7 million bags as erratic rains hit. Most maize is grown in the Rift Valley and other rainfed zones, so drought and heat are the primary abiotic stresses. For example, unreliable rains drove a ~12.8% drop in output from 2020 to 2021. Biotic pressures are also severe: the Fall Armyworm and stem borers periodically infest maize and can destroy large yield fractions (as observed after the 2017 outbreak). Combined, these stresses often impose double-digit yield losses in bad years. EchoShield could mitigate such losses by detecting stress onset early. Water-deficit signals in the xylem would generate UEs before leaves wilt, prompting earlier irrigation or mulching. A rover-mounted EchoShield could traverse maize fields in the Rift Valley, acoustically "listening" along crop rows and flagging localized stress hotspots. Farmers could then target those areas for scouting or treatment via. spot-irrigation, fertilization, or pest control. The system's AI model would be fine-tuned on local maize varieties and calibrated for ambient noise wind, wildlife, farm machinery to distinguish true plant emissions. Early acoustic warning thus enables proactive management, like irrigating before visible wilting and applying inputs only where needed, improving water use efficiency and smallholder resilience.

Tea: Tea is Kenya's top foreign-exchange crop, grown mainly in the highlands (e.g. Kericho in the West Rift) under smallholder and estate systems. Annual production is on the order of 0.6 million tonnes (594.5 million kg were exported in 2024). Tea plants in Kenya face chronic pest and disease stress. Mites and blister blight fungi regularly afflict tea, and losses of ~50% have been reported in infested small-scale farms. Soil-borne root rots and nutrient stress also degrade yields. In favorable weather tea yields are high, but drought or pest outbreaks can sharply cut the crop. EchoShield could provide early alerts of water stress even in tea gardens: ultrasonic clicks from developing xylem tension could be detected before shoot quality declines. In Kericho and Nandi Highlands, the mobile sensor could be driven between rows of tea bushes or mounted on plucking machines to scan plants. An alert would prompt farmers to adjust irrigation or apply biocontrols in that sector. Although detecting pests acoustically is more exploratory, monitoring moisture status alone helps farmers optimize irrigation timing and leaf plucking schedules. The classifier would be trained on the acoustic signature of Kenyan tea clones and adapt to the background noise of humid, windy plantations. In practice, EchoShield could help target agrochemicals and inputs more precisely, for example, identifying rows with mite stress for spot treatment - thus enhancing tea productivity and sustainability.

Coffee: Kenyan Arabica coffee (Central Highlands regions like Nyeri and Kirinyaga) is a high-value smallholder crop (~51,600t produced in 2022). Coffee farms here are drought-sensitive and disease-prone. Major threats include Coffee Wilt (a Fusarium fungus) and leaf pathogens, which can kill plants and cause total loss in affected trees. Even mild drought or heat waves worsen pest damage (e.g. stem borers) and shrink berry yields. In fact, the coffee sector is beset by climate challenges and high input costs, and yields have fluctuated in recent seasons. EchoShield's acoustic monitoring could alert growers to early moisture stress in coffee trees. A rover could be sent along farm lanes to acoustically test trees one by one. An early warning might trigger mulching, strategic irrigation, or pruning before coffee fruit is lost. Likewise, if stressed sounds cluster in a spot, farmers could inspect those trees for wilt infection and apply localized fungicide. The system would be calibrated for local coffee varieties and ambient conditions (e.g. filtering out wind in the highlands). By enabling early, targeted responses, EchoShield can help maintain coffee yields: for example, watering only the nearest thirsty plants and avoiding whole-field treatments. This targeted scouting and intervention approach boosts efficiency and resilience in small coffee plots.

4. Proof of Concept

To validate EchoShield's scientific and engineering feasibility, we performed controlled laboratory experiments and developed a mobile prototype.The existing literature focuses more on stress caused due to drought, hence the aim of the proof of concept was to study ultrasonic emissions from plants while they are infected by a pathogen.

4.1 Hypothesis : The acoustic emissions from blast disease-infected rice are significantly different compared to those from healthy rice plants, even before visible symptoms of infection appear, and can be classified using machine learning.

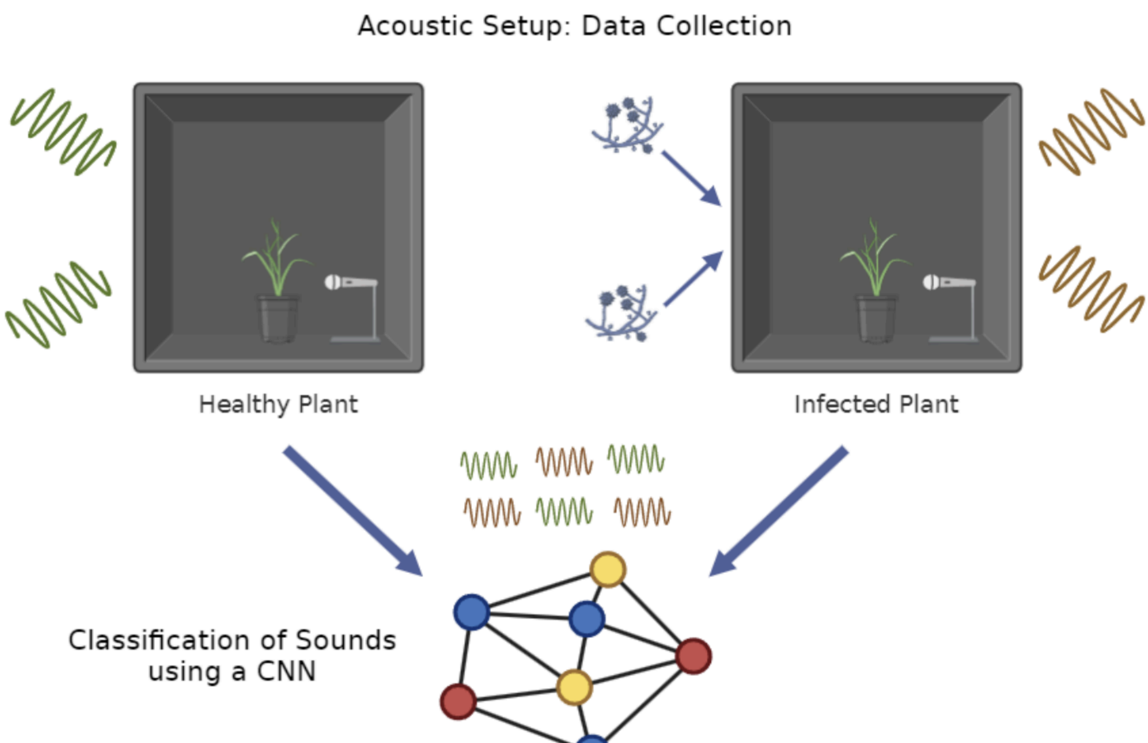

Figure 3 : Experiment Methodology

4.2 Purpose : The study aims to show that plant acoustics can be used as a novel, non-invasive method for the early detection of rice blasts using machine learning. By capturing and analyzing ultrasonic emissions from rice plants, we investigate whether stress-induced frequencies can serve as early indicators of infection.

4.3 Methodology : In a phased study on 30-day-old rice (*Oryza sativa*), healthy and *Magnaporthe oryzae*(Rice Blast Fungus) infected plants were recorded in acoustically isolated environments (quiet lab room and a custom 15×18×30 inch acoustic box lined with foam). High-frequency ultrasonic microphones (Avisoft CM16 condensers and Dodotronic Ultramic 384K BLE) were placed ~10 cm from each plant stem. The Dodotronic Ultramic 384K allows capturing emissions up to ~192 kHz. Each plant was recorded for 30 min (16-bit, 384 kHz) with the system dark and electrically quiet to minimize noise. The audio was then bandpass-filtered (20-100 kHz) and transformed into time-frequency spectrograms for analysis.

Figure 2 : Experimental Set Up Outside and Inside Acoustic Box

4.4 Data analysis: Using Audacity and Python, we automatically identified ultrasonic emission peaks via an RMS-based threshold algorithm. In brief, the mean track RMS was scaled by a constant (0.7797) and offset to set a threshold; any pulse exceeding this level was marked as an event. We then discarded non-plant signals (peaks lasting >1 ms or coincident with audible noise). This pipeline yielded labelled spectrograms for each 30-min recording. All processing steps (filtering, thresholding, peak selection) were identical for healthy and infected plants to ensure an unbiased comparison.

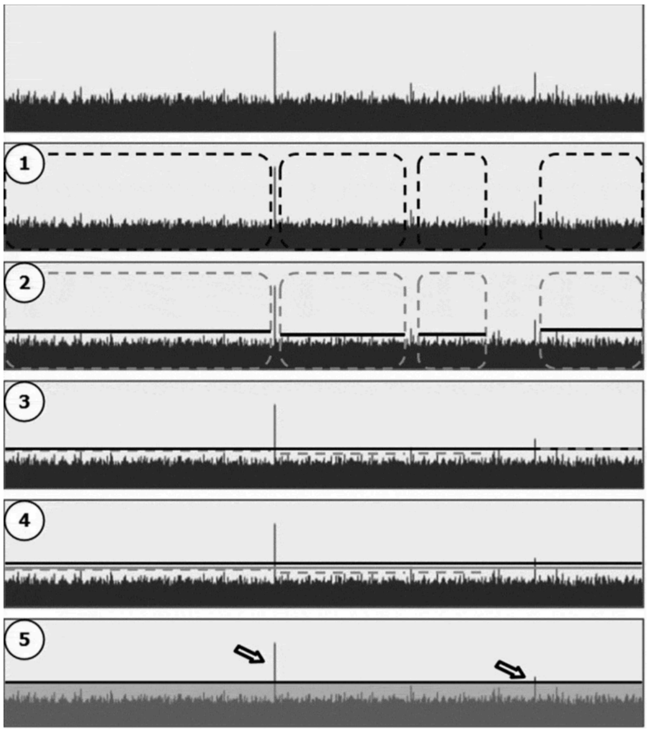

Figure 4: Visual representation of the automated procedure used to identify potential UEs. The horizontal axis represents time and the vertical axis represents the sound level (dB FS). (Bonisoli et al., 2024)

4.5 CNN Model :

To leverage these subtle acoustic differences, we converted each 30-min audio clip into a 2D spectrogram (time vs frequency) and labeled it as “healthy” or “infected.” A supervised CNN was implemented in TensorFlow to classify these spectrograms. The network comprised input preprocessing (image resizing and normalization), two convolutional blocks (each with 2×2D convolution layers + max-pooling), and a final dense layer with softmax outputs. (Figure 6 of our paper summarizes the model.) Training data included our recorded samples plus a reference dataset from (Khait et al., 2023) to augment size and prevent overfitting. In total, ~3,000 spectrograms were used (70% for training, 30% held out for validation/testing). The model was trained over 5 epochs (using sparse categorical cross-entropy loss).

CNN rapidly learned the characteristic time-frequency patterns of stress. On the independent test set (455 clips), it achieved **≈99.1% accuracy**, with only 3 false negatives and 1 false positive out of 455. (Training and validation accuracy were similarly >99%.) This performance far exceeds random chance and indicates robust discrimination. The spectro-temporal signature (distinct ultrasonic bursts in the 20-100 kHz band) allows clear separation: infected-plant spectrograms show persistent high-frequency peaks absent in healthy plants. To guard against overfitting, we used early stopping and data augmentation (mixing our lab data with published samples). The high test accuracy and a confusion matrix demonstrate that the model reliably generalizes. Cross-validation and hold-out testing showed consistent results, and the model’s loss converged smoothly. Together, these results confirm that a CNN can leverage ultrasonic “cavitation” signatures to flag disease with very high confidence.

Input shape: (30, 129, 1)
Model: "sequential"

Layer (type)	Output Shape	Param #
resizing (Resizing)	(None, 32, 32, 1)	0
normalization (Normalization)	(None, 32, 32, 1)	3
conv2d (Conv2D)	(None, 32, 32, 64)	640
conv2d_1 (Conv2D)	(None, 32, 32, 64)	36,928
max_pooling2d (MaxPooling2D)	(None, 8, 8, 64)	0
dropout (Dropout)	(None, 8, 8, 64)	0
conv2d_2 (Conv2D)	(None, 8, 8, 128)	73,856
conv2d_3 (Conv2D)	(None, 8, 8, 128)	147,584
max_pooling2d_1 (MaxPooling2D)	(None, 2, 2, 128)	0
flatten (Flatten)	(None, 512)	0
dense (Dense)	(None, 256)	131,328
dense_1 (Dense)	(None, 2)	514

Total params: 390,853 (1.49 MB)
Trainable params: 390,850 (1.49 MB)
Non-trainable params: 3 (16.00 B)

Figure 5 : Model Summary

4.5 Results : Infected rice plants (including one batch inoculated only 2 days prior with minimal lesions) emitted many more ultrasonic clicks than healthy controls. The mean count of emissions per 30 min was ~3.50 for infected plants vs ~1.16 for healthy (Mann-Whitney $p<0.05$). In one dataset, infected plants had 7 and 5 clicks per half-hour (early and late infection), while healthy ones had 1-2 clicks. This confirms that even asymptomatic infection produces a significant acoustic signal. So, we can say, the ultrasonic emissions by an infected rice plant without any clear physical symptoms were significantly higher than that of a completely healthy rice crop.

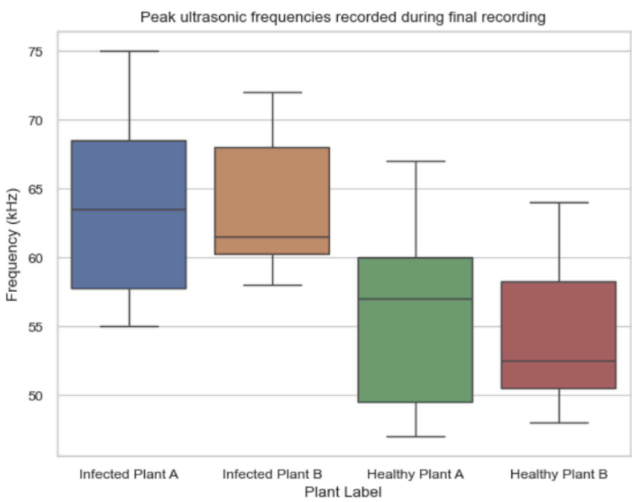

Figure 6 : Peak ultrasonic emissions observed during recording sessions

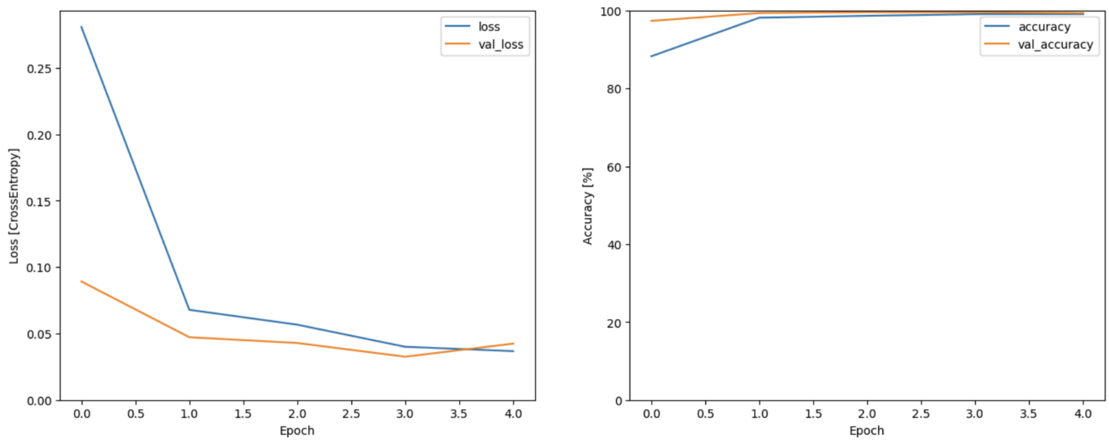

Figure 7 : Loss and Accuracy of the machine learning model during training

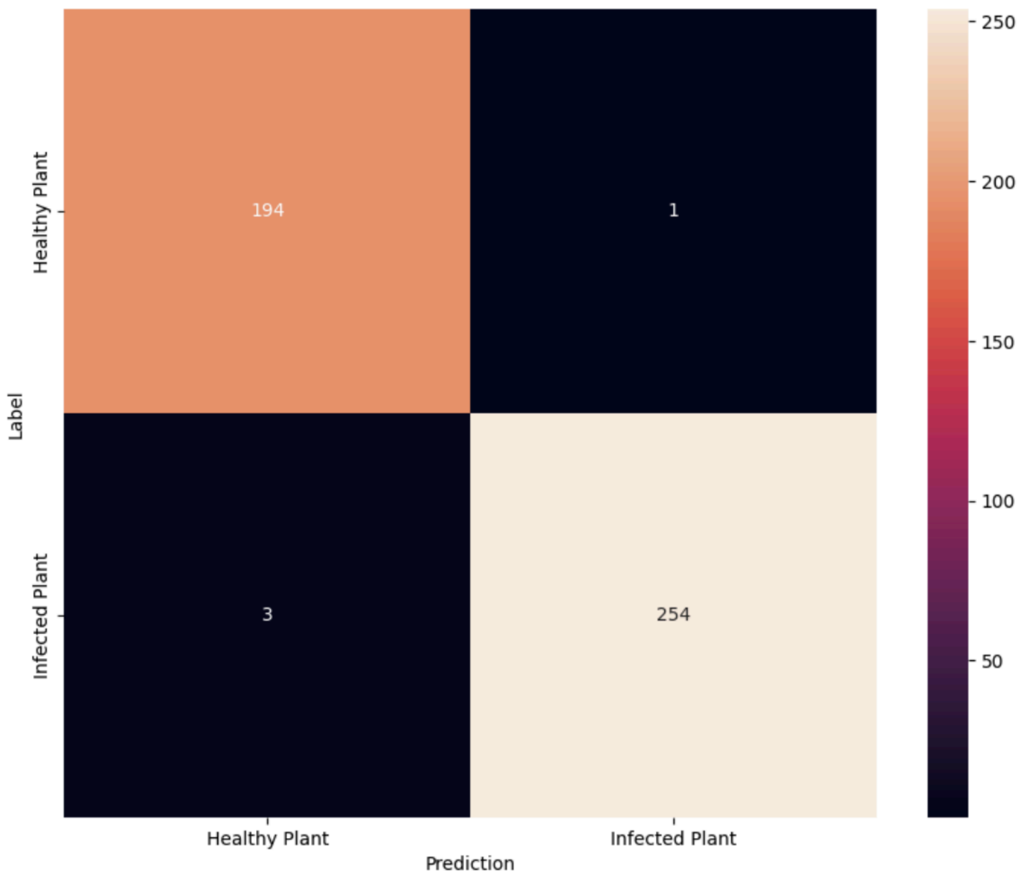

Figure 8 : Confusion matrix (accuracy) of the model on the test data

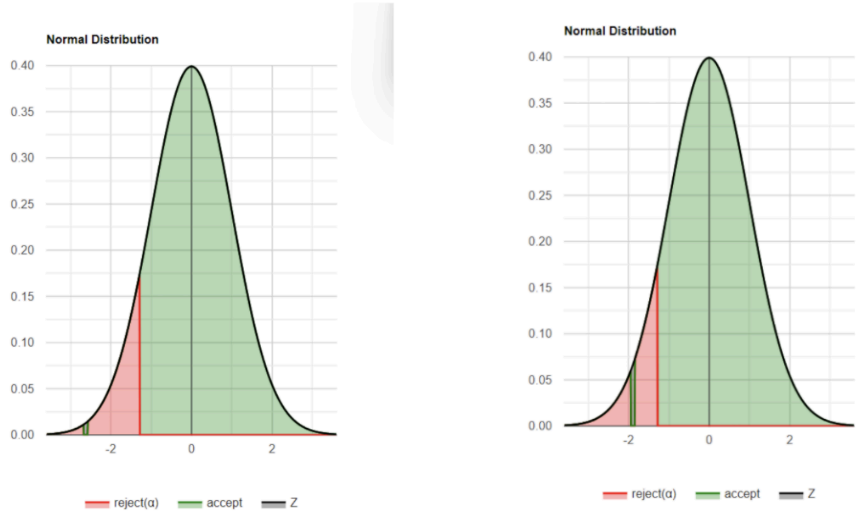

Figure 9 : Normal distribution of p-value in Test 1 and Test 2

Field-Deployable Ultrasonic Rover Prototype

For real-world use, we built a mobile rover that carries the ultrasonic sensor and does on-board inference. The hardware includes a sturdy chassis with two DC gear motors (differential drive) for navigation, powered by a rechargeable battery pack, and a Raspberry Pi 5 as the central computer. The Pi 5 (quad-core ARM, up to 8 GB RAM) was selected because recent reviews note its strong edge-ML capability and energy efficiency. A Dodotronic Ultramic 384K BLE microphone is mounted on a mast ~6-10 cm from the ground to point at plant stems (same model used in lab). An RF radio module (e.g. 2.4 GHz) provides wireless alerts to a base station.

- **Signal processing:** The Pi continuously samples ultrasound (384 kHz) and applies the same real-time filtering and threshold algorithm as in the lab (20-100 kHz bandpass, RMS thresholding). Detected pulses are formed into short spectrogram snippets.
- **Onboard inference:** A compact version of our CNN model (quantized and pruned via TensorFlow Lite) runs locally on the Pi. This "TinyML" approach allows near-real-time inference on the edge: each 30-s analysis takes only a fraction of a second on the Pi 5 CPU. The rover's autonomy allowed us to patrol a rice plot and sample multiple plants quickly. Real-time inference enabled immediate alerts whenever detected ultrasound matched the "stressed" class.

Figure 10 : Rover on field

Figure 11 : Making of the Rover

Conclusion

EchoShield offers a novel pathway for early crop stress detection by capturing and interpreting the ultrasonic emissions plants produce under stress. Unlike depending on visual symptoms, which only reveal damage after it has advanced, EchoShield provides a window into plant physiology in real time. This shift from external observation to internal monitoring addresses a critical gap in Kenyan agriculture, where smallholder farmers often lack access to advanced sensing technologies.

What sets EchoShield apart is its role as a precision agriculture instrument. By pinpointing stress at the level of individual plants or field sections, it enables interventions that are both timely and targeted. A rise in cavitation signals can trigger localized irrigation before wilting occurs, conserving water in drought-prone landscapes. Acoustic detection of pest or pathogen stress allows farmers to focus treatment on affected zones, avoiding unnecessary blanket spraying. This selective approach reduces input costs, limits chemical use, and prevents collateral damage to soils and ecosystems.

In practice, EchoShield turns passive observation into actionable intelligence, guiding farmers on when and where to act. Over time, this precision improves yields, stabilizes harvests, and strengthens food security. At the same time, it aligns with sustainability goals: water use is optimized, pesticide reliance is minimized, and ecosystem health is safeguarded.

By integrating plant bioacoustics with low-cost engineering and AI, EchoShield makes precision farming accessible to smallholders in Kenya. It is not just a monitoring system but a decision-support tool that enables farmers to shift from reactive to proactive crop management. This transformation has the potential to redefine agricultural resilience, efficiency, and sustainability in regions where every harvest counts.

References

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