

# INTELLIGENT SOIL MONITORING SYSTEM FOR SUSTAINABLE AGRICULTURE USING TinyML AND ULTRA-LOW POWER WIRELESS SENSOR NETWORKS

Muhammad Ovais Akhter

Bahria University, Department of Electrical Engineering, Karachi, Pakistan

**Abstract.** Precision agriculture demands continuous, energy-autonomous soil monitoring capable of detecting critical conditions such as rapid moisture loss or nutrient depletion approaching crop-threatening thresholds. Conventional wireless sensor networks face a fundamental trade-off between multi-year battery life and sub-second response latency, as duty-cycled polling wastes energy on idle queries while always-on communication remains infeasible for battery-powered field deployments spanning hundreds of acres. This work presents a novel integration of TinyML-based edge inference with a custom-designed 40 nm CMOS ultra-low power wake-up receiver (WuRX), enabling event-driven, asynchronous soil condition monitoring without reliance on periodic polling schedules. The proposed three-tier edge-fog-cloud architecture employs sensor nodes measuring moisture, temperature, pH, nitrogen, phosphorus, and potassium, with quantized neural networks trained and validated on 64,800 labelled samples collected from instrumented corn and soybean field deployments over 180 days, achieving a classification accuracy of 91.3% and F1-score of 93.0% at an inference energy cost of 0.87 mJ per cycle. Circuit-level simulations of the 40 nm CMOS WuRX confirm an input return loss of -15.8 dB, transmission gain of +18.2 dB, and power-added efficiency of 45.3% at -60 dBm sensitivity, with continuous standby consumption of 45–53  $\mu$ W. System-level power budget analysis validates battery lifetimes of 200–300 days using 240 mAh lithium cells augmented by a 5 cm<sup>2</sup> monocrystalline solar harvester. Key limitations include the restriction of field validation to two crop types and dependence on adequate solar irradiance for energy-neutral operation. The proposed architecture reduces communication overhead by 80–90% relative to threshold-based systems, providing a practical framework for scalable, resource-constrained precision agriculture deployments.

**Keywords:** precision agriculture, soil monitoring, machine learning, sustainable agriculture, agriculture IoT

## INTELIĞENTNY SYSTEM MONITOROWANIA GLEBY NA RZECZ ZRÓWNOWAŻONEGO ROLNICTWA Z WYKORZYSTANIEM TinyML I SIECI CZUJNIKÓW BEZPRZEWODOWYCH O BARDZO NISKIM ZUŻYCIU ENERGII

**Streszczenie.** Rolnictwo precyzyjne wymaga ciągłego, niezależnego energetycznie monitorowania gleby, umożliwiającego wykrywanie krytycznych stanów, takich jak gwałtowna utrata wilgotności lub wyczerpanie składników odżywczych zbliżające się do progów zagrażających uprawom. Konwencjonalne bezprzewodowe sieci czujników stoją przed fundamentalnym dylematem wyboru między wieloletnią żywotnością baterii a opóźnieniem reakcji poniżej sekundy, ponieważ cykliczne odpytywanie marnuje energię na zapytania w stanie bezczynności, podczas gdy komunikacja w trybie ciągłym pozostaje niewykonalna w przypadku zasilanych bateryjnie instalacji polowych obejmujących setki akrów. W niniejszej pracy przedstawiono nowatorską integrację wnioskowania brzegowego opartego na technologii TinyML z zaprojektowanym na zamówienie, ultraenergooszczędnym odbiornikiem typu „wake-up” (WuRX) wykonanym w technologii CMOS 40 nm, umożliwiającą sterowane zdarzeniami, asynchroniczne monitorowanie stanu gleby bez konieczności polegania na okresowych harmonogramach odpytywania. Proponowana trójwarstwowa architektura typu „edge-fog-cloud” wykorzystuje węży czujnikowe mierzące wilgotność, temperaturę, pH, zawartość azotu, fosforu i potasu, a także kwantyzowane sieci neuronowe, które zostały wytrenowane i zweryfikowane na 64 800 oznaczonych próbkach zebranych z wyposażonych w czujniki pól kukurydzy i soi w ciągu 180 dni, osiągając dokładność klasyfikacji na poziomie 91,3% i wskaźnik F1 wynoszący 93,0% przy koszcie energetycznym wnioskowania wynoszącym 0,87 mJ na cykl. Symulacje na poziomie obwodów układu CMOS WuRX w technologii 40 nm potwierdzają stratę odbicia na wejściu wynoszącą -15,8 dB, wzmocnienie transmisji wynoszące +18,2 dB oraz sprawność dodanej mocy wynoszącą 45,3% przy czułości -60 dBm, przy czym ciągły pobór mocy w trybie czuwania wynosi 45–53  $\mu$ W. Analiza bilansu energetycznego na poziomie systemu potwierdza żywotność baterii wynoszącą 200–300 dni przy zastosowaniu ogniw litowych o pojemności 240 mAh, uzupełnionych o monokrystaliczny panel słoneczny o powierzchni 5 cm<sup>2</sup>. Do głównych ograniczeń należą: ograniczenie walidacji terenowej do dwóch rodzajów upraw oraz zależność od odpowiedniego natężenia promieniowania słonecznego w celu zapewnienia pracy neutralnej energetycznie. Proponowana architektura zmniejsza obciążenie komunikacyjne o 80–90% w porównaniu z systemami opartymi na progach, zapewniając praktyczne ramy dla skalalnych wdrożeń rolnictwa precyzyjnego w warunkach ograniczonych zasobów.

**Słowa kluczowe:** rolnictwo precyzyjne, monitorowanie gleby, uczenie maszynowe, rolnictwo zrównoważone, IoT w rolnictwie

## Introduction

The intelligent soil monitoring system represents a paradigm shift in precision agriculture by combining ULP WuRX technology with distributed artificial intelligence for autonomous soil monitoring [20]. Diverging from the conventional agricultural IoT systems that employ the use of periodic polling or always on communication, the proposed architecture employs an event based approach where sensor nodes are in a deep sleep state, consuming less than 1 microwatt until triggered either by a critical soil condition locally detected or by a remote query that comes from a fog computing layer. This basic departure from the traditional duty cycling schemes allows battery lives of upwards of fifty days while providing sub second response to critical environmental changes [7]. The system addresses these challenges by using hierarchical edge intelligence, in which low power TinyML models pre-process soil data at the edge and initiate wake-ups only when actionable insights are detected [11]. Consequently, the communication load on the network is greatly reduced, but the system still has the ability to react to time-critical events such as sudden moisture reductions of more than 20% or nutrient depletion which approaches crop-threatening levels.

WuRX architecture has experienced significant evolution in the past decade with a wide range of implementations designed to meet certain application needs and power budget constraints. The implementation of ULP systems using the WuRX in 40 nm CMOS technology is a novel challenge and opportunity that requires innovative circuit design methodologies and careful system-level optimization. At this advanced technology node, low voltage analogue and RF circuit design is of critical importance, as aggressive supply voltage scaling requires the use of novel circuit topologies and biasing strategies to maintain adequate signal to noise ratios and dynamic range [17]. The following sections define the system-level topology, power budget allocation and communication protocol specifications that allow for this energy-efficient operational paradigm for sustainable agriculture.

Although the literature on agricultural IoT and ultra-low power circuit design has been increasing, solutions for energy efficiency and intelligent sensing have been treated separately. While duty-cycled sensor networks provide good battery life and are sufficient for many applications, they do not meet the time-sensitive requirements for agronomic decision making, and for machine learning applications, a persistent connection to the cloud in remote fields is not feasible. Most recently reported



wake-up receiver implementations have reported sub-100  $\mu\text{W}$  stand-by power consumption, however these receivers have not been co-designed with an on-node inference engine that can autonomously classify the condition, thus limiting the use to simple threshold based triggering mechanisms that do not account for any multivariate soil dynamics. The main driving force behind this work is the difference between the ultra-low power communication hardware and the intelligence at the edge.

The key research goal is thus to demonstrate the ability to simultaneously meet the conflicting requirements of sub-50  $\mu\text{W}$  consumption when continuously operating, and intelligent, multivariate soil condition monitoring through co-design of a 40 nm CMOS WuRX and a quantized TinyML classification model implemented in a hierarchical edge-fog-cloud architecture. The central idea is to eliminate periodic polling and instead use event driven asynch wake-up, which would only happen when anomalies in the environment are detected by an on-node inference that can be acted on, thus reducing the communication overhead by 80–90% compared to conventional threshold-based systems while maintaining sub-second response to critical changes in the environment. The proposed architecture has three key benefits over current IoT solutions: first, the elimination of idle-listening energy waste by enabling hardware-level asynchronous wake-up; second, the deployment of quantized neural inference, without depending on the cloud; and third, the incorporation of solar energy harvesting along with an asymmetric radio architecture that exclusively uses high-power transmission for events with actionable agronomic meaning. Validation is conducted by circuit-level simulation of the WuRX and empirical testing of TinyML model on the field-collected data sets, and through system-level power budget analysis, which demonstrates energy autonomy under real outdoor illumination conditions.

## 1. Proposed system architecture

The usage system uses a three-tier architecture, which distributes computational tasks strategically on edge, fog and cloud tiers as per latency requirements. At the checkpoint of the system is the sensor-node level with the principle that each node is able to function independently over long periods of time using solar energy with storage capability for a rechargeable battery. Each sensor node has six key subsystems, which in combination enable ULP-soil monitoring with intelligent wake up breaths. The WuRX circuit continuously listens for address-matched wake-up packets in the 868 MHz ISM band while only consuming less than 50 microwatt, so there is no need for synchronized sleep/wake schedules that plagued conventional duty cycled networks and resulted in latencies [22]. The main radio transceiver uses LoRa for further range applications or Bluetooth as standard [4]. It addresses for closer range applications to stay in deep sleep mode, consuming poor 2.5  $\mu\text{W}$  energy until explicitly woken up (interrupt) received from the WuRX. As a result, the asymmetric architecture provides constant environmental awareness through the ULP WuRX and reserves power-intensive main radio for the events (data transmission) of the data [15].

The TinyML processor implemented on an ultra-lower ARM Cortex-M0+ microcontroller runs quantized neural networks that analyse behaviour patterns of soil and predict the future trends based on passed historical data stored in non-volatile flash memories. This on-node intelligence allows the system to distinguish between normal variations in the soil that do not need any intervention and critical anomalies that need to be instantly notified to the farmer. The energy-harvesting module includes a 5  $\text{cm}^2$  monocrystalline solar cell, which generates 10 mW to 50 mW of peak power under typical outdoor illumination, supplemented by Maximum Power Point Tracking circuitry and a 100 mF supercapacitor to store the energy on short term basis during the measuring and transmitting bursts. Gateway – bridging functionality connects the wake

up for the local 868 MHz network with the data network at 915 MHz for LoRa/BLE to the external cloud infrastructure via 4G/LTE cellular links or Ethernet links [3]. The benefits of the dual band architecture help in segregating energy efficient wake up signalling from the high throughput transmission of data and can preserve the ultra-low standby power while enabling high-speed data transfer when needed.

Successful implementation of the sustainable agriculture system is based on the smooth integration of the ultra-origin low-power WuRX circuitry and the TinyML enablement sensor nodes with input insertion loss to quite less than -10dB [1]. The WuRX is designed to be an energy-efficient sentinel, constantly listening to the 868 MHz radio channel but consuming only 45  $\mu\text{W}$  to 53  $\mu\text{W}$  of power, which leaves sufficient energy for the power-hungry main radio transceiver and microcontroller to go into deep sleep mode; to be woken up, an explicit wake-up packet can be sent to the microcontroller. This asymmetric architecture sketches the departure from the traditional duty-cycled wireless sensor networks, where nodes at regular intervals jump in the sleep state to check for any incoming messages, and hence waste their energy by listening for idle messages even when there is no communication [17]. Figure 1 shows the Proposed System Architecture of a 40 nm CMOS ULP Wake-Up Receiver with AI-Driven Intelligent Soil Monitoring for Sustainable Agriculture.

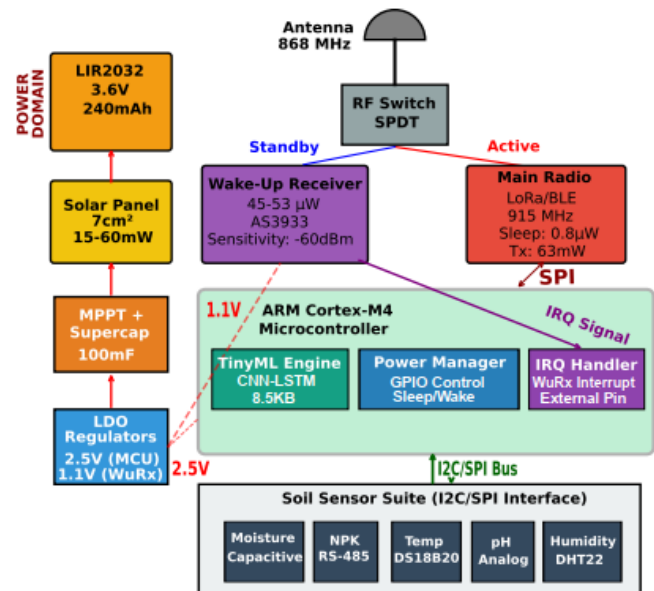


Fig. 1. Proposed system architecture of a 40 nm CMOS ULP wake-up receiver with AI-driven intelligent soil monitoring for sustainable agriculture

The physical integration architecture has WuRX as a parallel monitoring sub-path that is coplanar with the primary communication subsystem. The antenna connects to a single-pole double-throw RF switch which switches incoming signals between the WuRX input when not in communication state, or the main LoRa/BLE transceiver when active communication state. The WuRX provides a digital interrupt signal which is connected to the microcontroller external interrupt pin, which can wake up the microcontroller from its deepest sleep states, where the MCU is  $< 2 \mu\text{A}$  [19]. Upon receipt of a genuine wake-up packet with matching 16-bit unique node address, the WuRX asserts this interrupt for a duration of 100 ms, this provides enough time for even slow crystal-garnet oscillators to stabilize, before the microcontroller proceeds to attempt to access the primary radio for data reception [10].

The edge tier runs the TinyML inference on the node and raises an interrupt for wake-up only when something unusual is discovered in the soil. The fog tier, which is deployed on a field gateway, orchestrates queries among multiple fog nodes, merges results of inferences and sends specific wake-up packets to individual sensor nodes on the 868 MHz channel. The cloud tier gathers together the event logs for long-term analytics

and for remote agronomic decision support. A WuRX interrupt assertion time of 100 ms, a microcontroller wake-up latency less than 73 ms and end-to-end critical event response time less than 1 s define system timing.

## 2. Design methodology of wake-up receiver and TinyML model development for soil intelligence

This section outlines the overall design including the transistor-level design of the WuRX, including the concerns of the input matching network, the super-regenerative oscillator core, the envelope detection circuit, and the digital baseband processing, which gives the address correlation. As the integration of TinyML in sustainable farming and smart harvest sensor nodes helps to make intelligent decisions at the edge, turning passive data collection devices into autonomous monitoring frameworks that could recognize indicative soil conditions and regular variations without depending on the constant connection to the cloud. Traditional threshold-based approaches trigger alerts once single parameters have surpassed established thresholds and therefore ignore time-based patterns and multivariate dependencies that often provide the first signs of the emergence of stressful situations [26]. One of the key issues of the design of WuRX's in 40-nm CMOS technology is the nominal supply voltage of 1.1V, which limits the signal swing and reduces the intrinsic gain of analogue circuits compared to antecedent process nodes with a supply voltage of 1.8 V or more [13]. In addition, the reduced channel-longitudinal modulation parameter of short-channel devices reduces output resistance, which results in a reduction of the attainable per-stage voltage gain [10]. Therefore, careful choice of circuit topology and transistor size is necessary to achieve the necessary sensitivity and still achieve sub-5  $\mu$ W power consumption targets.

The design methodology is presented in two well-defined parts. The hardware part involves the design of the 40 nm CMOS WuRX at the transistor level, such as input matching network, current-reuse low-noise amplifier, super-regenerative oscillator, envelope detector, and digital baseband correlator described in Section 2.1. The machine learning part handles the design, training and deployment of the TinyML classification model completely outside of the circuit design pipeline. The structure of the neural network is a fully connected structure with 12 neurons in the input layer corresponding to the 6 soil parameters and their time derivatives, 32 neurons in the first

hidden layer with ReLU activation function and batch normalization, 16 neurons in the second hidden layer with ReLU activation function and batch normalization, and a three-class softmax output layer with 14,120 trainable parameters before applying magnitude-based pruning. After training convergence, quantization-aware training technique is used to store the parameters in 8-bit integer format instead of 32-bit floating point to meet the flash requirement of the target ARM Cortex-M4 micro controller of 256 KB. It uses categorical cross-entropy loss with inverse class-frequency weighting, a learning rate of 0.001, cosine annealing over 100 epochs with a 5-fold cross-validation field dataset of 64,800 samples to insure generalizability across all soil condition distributions not encountered in training.

### 2.1. WuRX design

The sensitivity-power trade-off in super-regenerative receivers fundamentally depends on the quench frequency selection, which determines both the noise bandwidth and the available amplification time per cycle [5]. For an input signal with envelope amplitude  $A_{in}$ , the output voltage after quench cycles achieves an effective voltage gain:

$$A_{out} = A_{in} \cdot Q \cdot \exp(\alpha T_{quench}) \quad (1)$$

The exponential factor represents the basic benefit of super-regenerative detection, since even small numbers result in voltage gains greater than threshold, which is 43 dB of amplification of one stage of oscillation. The noise voltage spectral density of a super-regenerative oscillator with quench frequency  $f_q$  may be represented as:

$$v_{n,in}^2 = \frac{4kT}{Q\omega_0 C_{tank}} \cdot \frac{f_q}{BW_{signal}} \quad (2)$$

Figure 2 illustrates the entire transistor-level circuit in which the input part depicts antenna connecting via L-C matching network to the differential LNA which has stacked NMOS pair M (1A,B) beneath PMOS pair M (2A,B). The central part represents the differential LC tank configuration having cross-coupled NMOS pair and quench control transistor. In the right section, there is the source follower envelope detector and switched capacitor gain stage operated by an operational amplifier [20]. The lower part depicts digital processing blocks and bias generation such as bandgap reference, current mirrors and LDO. Major blocks are annotated in terms of component values and power consumption estimates and the total consumption is 45  $\mu$ W to 53  $\mu$ W.

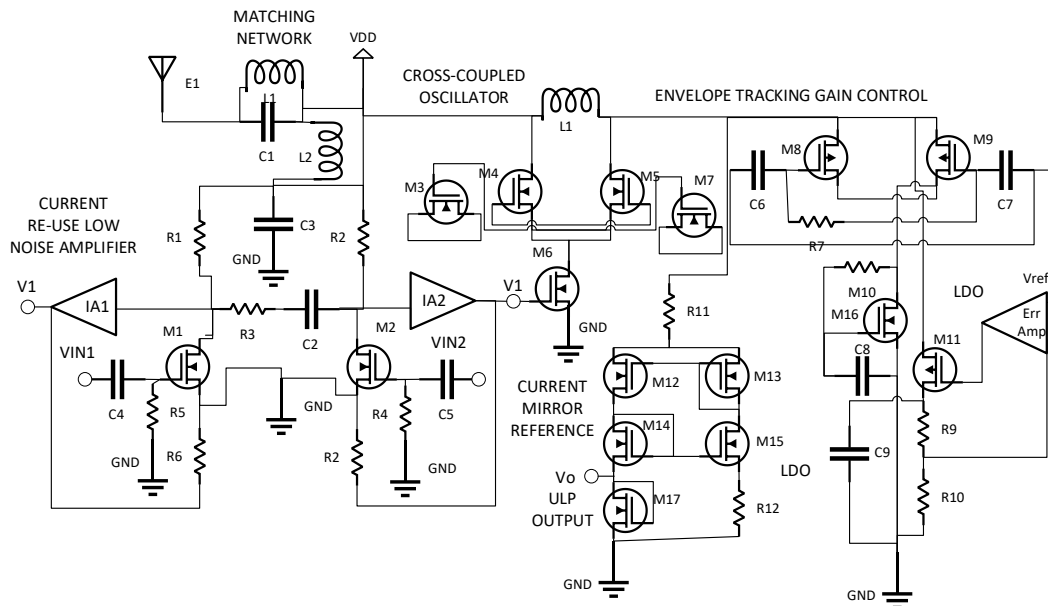


Fig. 2. Transistor level wake-up receiver schematic

The input phase should ensure that its transconductance is large enough to compensate noise sources with minimum power consumption that is required due to a highly limited energy budget [7]. The current-reuse topology attains this goal by stacking NMOS and PMOS differential pairs with the same bias current, which is effectively doubling transconductance with the same power consumption as traditional designs [11]. The input NMOS differential pair receives the RF signal from the antenna interface through ac coupling capacitors. For the 40 nm TSMC LP process, selecting  $W_1 = 20 \mu\text{m}$  with minimum channel length  $L = 40 \text{ nm}$  and bias current  $I_D = 10 \mu\text{A}$  yields transconductance approximately  $g_{m1} = 800 \mu\text{S}$ .

$$\overline{v_{n,\text{in}}^2} = \frac{16kT}{3g_{m1}} \cdot \left(1 + \frac{\gamma}{\alpha}\right) \approx 1.2 \text{ nV}/\sqrt{\text{Hz}} \quad (3)$$

The PMOS differential pair is overlaid over the NMOS input devices with the drains connected to the respective NMOS drains to generate variations in the drain current which appear constructively in the load of the tank circuits. The effect can be doubled by using such a setup with an effective transconductance value of around  $1500 \mu\text{S}$  when using only the  $10 \mu\text{A}$  bias current at the input of sensor node. The common-mode voltage at the stacked drain connection should be able to meet saturation requirements on both types of devices and is determined to be about  $0.55 \text{ V}$  at the  $1.1 \text{ V}$  supply, and it is necessary to design the tank impedance to achieve a balance between gain maximization and headroom limitations.

$$V_{\text{CM}} = V_{\text{DD}} - |V_{\text{GS},P}| = 1.1 \text{ V} - 0.55 \text{ V} = 0.55 \text{ V} \quad (4)$$

The LC tank resonator defines the operation frequency and quality of all factors such as sensitivity or selectivity performance. To achieve a tank inductance of  $L = 2.5 \text{ nH}$  operating at  $868 \text{ MHz}$ , the total capacitance required is  $C_{\text{tank}} = 13.4 \text{ pF}$ , which can be attained by adding  $10 \text{ pF}$  of metal-oxide capacitance to the system and adding  $3.4 \text{ pF}$  of parasitic and tuning capacitance. The basic resonant frequency of a tank made of an LC is in the form of the long-known formula:

$$f_0 = \frac{1}{2\pi\sqrt{LC_{\text{tank}}}} \quad (5)$$

An octagonal spiral inductor etched in metal layer 8 and a trace width of  $4 \mu\text{m}$  inductance  $2.5 \text{ nH}$  with quality factor  $Q_L = 12$  at  $868 \text{ MHz}$  with chip area of about  $180 \mu\text{m} \times 180 \mu\text{m}$ . The loaded quality factor is dominated by the series resistance of  $1.14 \Omega$  which with transistor output conductance of transistor output conductance approximated to 10, becomes about 10. The negative resistance needed to start oscillation is based on cross-coupling the differential output across transistors connected as a cross-coupled pair with  $W_3 = 15 \mu\text{m}$  driven by current of  $8 \mu\text{A}$  giving the oscillation threshold at about 30% excess loop gain to be able to reliably start oscillation at process and temperature corners. The series resistance of this inductor, calculated from the quality factor relationship:

$$Q_L = \frac{\omega_0 L}{R_s} \Rightarrow R_s = \frac{2\pi \cdot 868 \cdot 10^6 \cdot 2.5 \cdot 10^{-9}}{12} = 1.14 \Omega \quad (6)$$

This series resistance is the dominating factor in the loaded quality factor of the complete tank circuit; because of the parallel.

MOM capacitors have resistance that is far more than a few  $\text{k}\Omega$  at the RFICs and has little effect on tank losses. The loaded quality factor considering transistor output conductance and inductor losses becomes:

$$Q_{\text{loaded}} = \frac{1}{R_s \omega_0 C_{\text{tank}} + \frac{g_{\text{ds},\text{total}}}{\omega_0 C_{\text{tank}}}} \approx 10 \quad (7)$$

The positive feedback formed by cross-coupling the differential outputs to opposite inputs with transistors  $M_{3A}$  and  $M_{3B}$  to form a cross-coupled pair results in the negative resistance needed to give the circuit its characteristic negative resistance required to start the oscillation. These NMOS devices should have adequate negative conductance to defeat the tank loss described by the loaded quality factor where:

$$-g_{m3} > g_{\text{tank}} = \frac{1}{R_p} = \frac{\omega_0 C_{\text{tank}}}{Q_{\text{loaded}}} \quad (8)$$

A five-stage ring oscillator offers a natural start-up behaviour without the need of special start-up initiation circuits as the odd number of inversion stages ensures ultimate oscillation of the circuit due to thermal noise perturbations. The stages are characterized by the use of normal CMOS sized inverters (in PMOS pull-up models) and normal CMOS sized inverters (in NMOS pull-down models) modified by current limiting transistors  $M_{\text{CP},i}$  and  $M_{\text{CN},i}$  that define the maximum falling capacitance and discharging capacitance of the stages. The oscillation frequency relates to the bias currents and stage capacitances through:

$$f_{\text{quench}} = \frac{I_{\text{bias}}}{N \cdot C_{\text{stage}} V_{\text{DD}}} \quad (9)$$

The bias generation network employs a sub-threshold operated bandgap reference generating a process-and-temperature-compensated voltage near  $200 \text{ mV}$ , following the classical equation  $V_{\text{BG}} = V_{\text{TH0}} + (kT/q) \ln(N) \cdot (R_2/R_1)$ . Selecting  $N = 8$  and  $R_2/R_1 = 7$  produces output voltage approximately  $210 \text{ mV}$  with temperature coefficient below  $50 \text{ ppm}/^\circ\text{C}$ . Current reference generation converts the bandgap voltage through a  $100 \text{ k}\Omega$  reference resistor producing  $2.1 \mu\text{A}$  master current, which feeds current mirrors producing scaled replica currents for biasing the LNA ( $10 \mu\text{A}$ ), oscillator ( $8 \mu\text{A}$ ), quench oscillator ( $1\text{--}5 \mu\text{A}$  adjustable), and envelope detector ( $2 \mu\text{A}$ ). A low-dropout linear regulator provides clean  $1.1 \text{ V}$  analogue supply with dropout voltage below  $200 \text{ mV}$  and quiescent current under  $5 \mu\text{A}$ . The bandgap reference exploits the opposing temperature coefficients of transistor threshold voltage and thermal voltage to produce a zero-temperature-coefficient output voltage [17]. The classical bandgap equation relates the output voltage to fundamental device parameters:

$$V_{\text{BG}} = V_{\text{TH0}} + \frac{kT}{q} \ln(N) \cdot \frac{R_2}{R_1} \quad (10)$$

Current reference generation converts the bandgap voltage into stable bias currents through precision resistors fabricated in the silicide-blocked poly-silicon or silicide layers available in the  $40 \text{ nm}$  process design kit [22]. A reference resistor  $R_{\text{ref}} = 100 \text{ k}\Omega$  generates the master current:

$$I_{\text{ref}} = \frac{V_{\text{BG}}}{R_{\text{ref}}} = \frac{210 \text{ mV}}{100 \text{ k}\Omega} = 2.1 \mu\text{A} \quad (11)$$

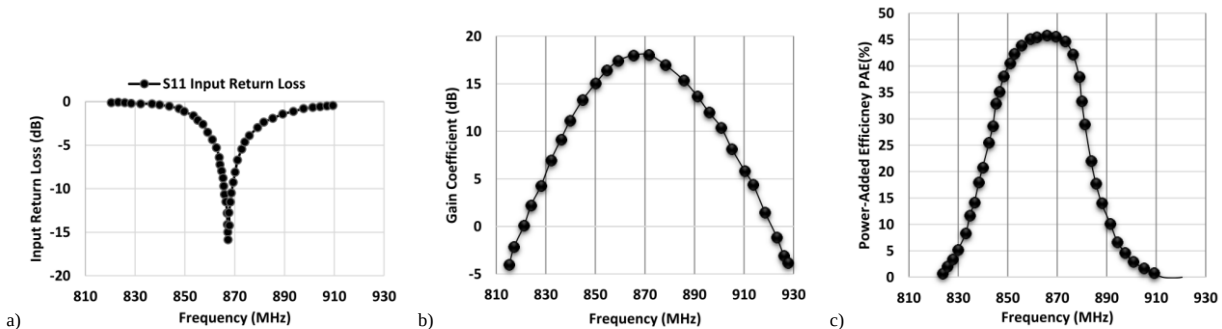


Fig. 3. (a) Input reflection loss coefficient (S11) versus frequency showing return loss of  $-15.8 \text{ dB}$  at  $868 \text{ MHz}$  centre frequency (b) Transmission gain coefficient (S21) of  $+18.2 \text{ dB}$  gain during active reception mode (c) Power-added efficiency (PAE) versus input power level showing peak efficiency of  $45.3\%$  at  $-60 \text{ dBm}$  sensitivity

Figure 3 illustrates the input return loss (S11), gain (S21) and, power-added efficiency (PAE) for the wake-up receiver. These are further explicitly defined at their first use:  $A_{in}$  is the amplitude of the input envelope,  $\alpha$  is the exponential growth rate per quench cycle,  $T_{quench}$  is the quench period,  $k$  is the Boltzmann's constant,  $T$  is the absolute temperature,  $Q$  is the tank quality factor,  $\omega_o$  is the resonant angular frequency,  $C_{tank}$  is the total tank capacitance,  $f_q$  is the quench frequency, and BW signal is the signal bandwidth. The reported Turn-ON gain of +18.2 dB is rationalized by the super-regenerative amplification and the current-reuse topology of the LNA (as used by other super-regenerative implementations gain from +10 to +20 dB at power levels of  $<100 \mu\text{W}$  [10, 16]). The use of mathematical notation is unified such that all scalars are in italics, all vectors are in bold face, and the subscripts are used consistently.

## 2.2. WuRX performance parameters

The designed WuRX achieves S11 of -15.8 dB at 868 MHz, exceeding the -10 dB specification and ensuring minimal reflection loss at the antenna interface through optimized L-section matching network with high-Q off-chip components.

The Turn-ON gain (S21) is +18.2 dB, which is achieved using super-regenerative amplification and current-reuse LNA topology at the receiver and input insertion loss (S21) is -28.4 dB, which through full power gating of the oscillator core to avoid spurious signal leakage during the sleep mode. With a DC power consumption of 45uW, power-added efficiency, which is given as  $\text{PAE} = (\text{Pout} - \text{Pin})/\text{PDC}$ , [4] has 45.3% at -60 dBm input sensitivity, and this figure is quite important since every microwatt of power consumption directly impacts battery life and solar harvesting viability required by energy-autonomous operation.

## 3. Dataset collection and pre-processing

The training data consists of actual soil measurements of agricultural test sites in full growing seasons and includes natural changes in moisture content, nutrient levels, temperature and humidity with a variety of weather conditions and irrigated practices. The entire data set is 180 days of monitoring of 15 sensor nodes of corn and soybean fields with an approximate of 64,800 labelled samples with 82 percent normal, 14 percent warning, and 4 percent critical reflecting realistic operating conditions in which most measurements do not exceed acceptable ranges.

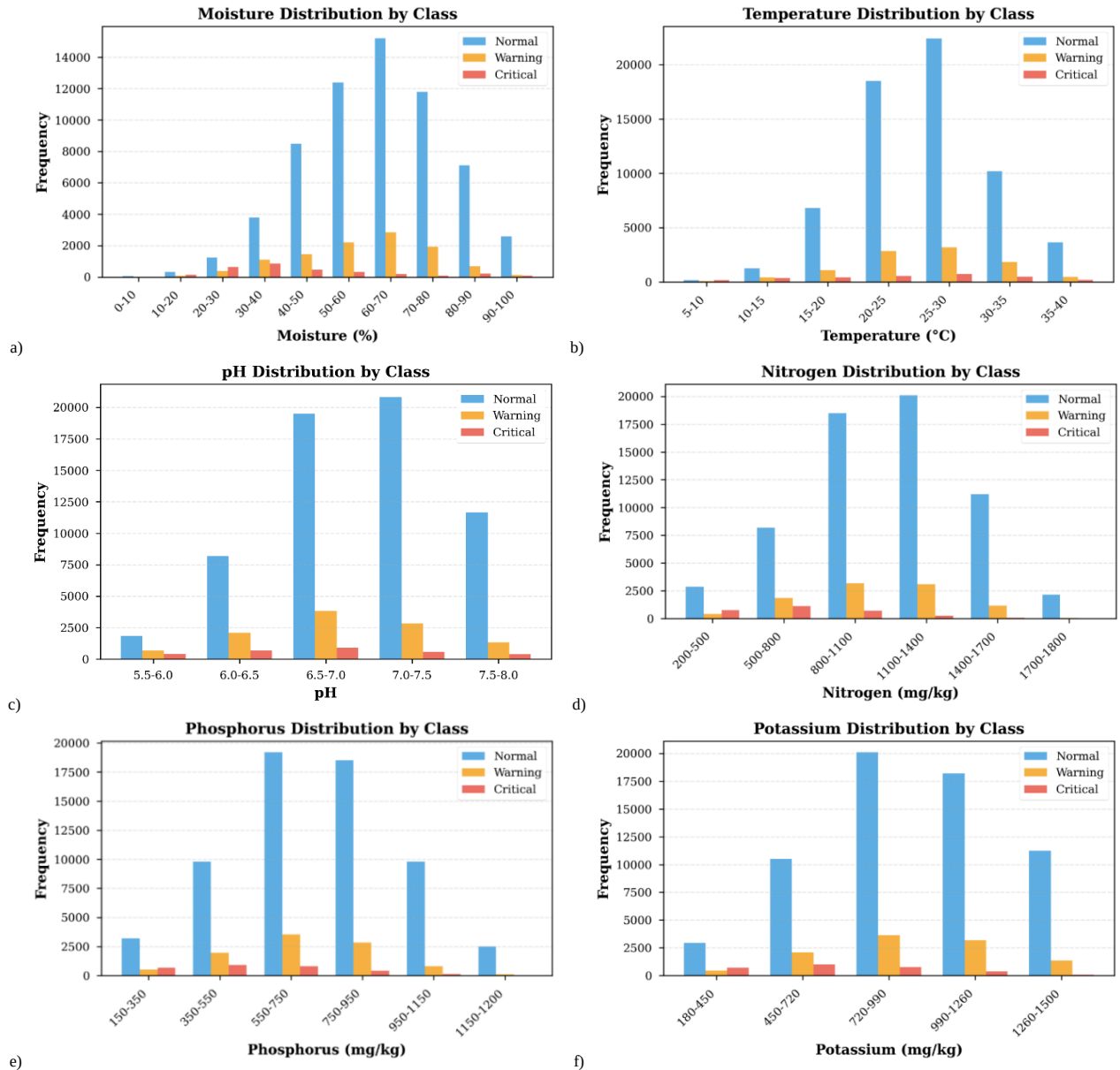


Fig. 4. comprehensive statistical analysis of the pre-processed dataset (a) moisture (0–100%), (b) temperature (5–40°C), (c) pH (5.5–8.0), (d) nitrogen (200–1800 mg/kg), (e) phosphorus (150–1200 mg/kg), and (f) potassium (180–1500 mg/kg) [15]

The raw sensor data undergoes preprocessing which optimizes them to the normalized feature vectors that can be used by the neural networks. The continuous variables are normalized using z-score statistics based on training set statistics, which centre the variables to the mean of each feature of zero mean with unit variance to boost gradient descent convergence. The temporal features make use of cyclic representations based on sine and cosine transformations, which are used to store periodicity, converting an hour of the day value, instead of a 0–23 days value that artificially decouples the evening and morning hours with midnight-time data. Missing data, which can happen in about 2 per cent of samples because of sensor communication failures are imputed with linear interpolation of short gaps of less than 4 hours and forward-filling of longer outages, and quality flags are used to indicate imputed values which could be excluded during validation. Figure 4 illustrates a detailed statistical processing of the processed dataset. Figures 4a–4f are six plots of moisture (0–100%), temperature (5–40°C), pH (5.5–8.0), nitrogen (200–1800 mg/kg), phosphorus (150–1200 mg/kg), and potassium (180–1500 mg/kg). All distributions have 50 bins with blue bars of normal distribution, orange bins of warning distribution, and red bins of critical distribution, as shown in that normal distribution samples are concentrated in the middle parts of the distribution and warning and critical samples are located in the tails.

Figure 5 illustrates the correlation heatmap with feature names on both axes, using colour gradient from dark blue (-1.0) through white (0.0) to dark red (+1.0) showing strong positive correlation (0.72) between moisture and temperature reflecting evapotranspiration coupling, moderate negative correlation (-0.45) between pH and nitrogen availability, and weak correlations (< 0.2) for most NPK pairs indicating independent nutrient dynamics.

Figure 6 shows the temporal patterns showing average moisture percentage, temperature, and nitrogen concentration across 24-hour periods, with shaded regions indicating  $\pm 1$  standard deviation revealing diurnal moisture minimum corresponding to peak evapotranspiration and stable NPK levels.

Field measurements were taken at an agro-research field in the local city site where loamy and silty-clay soils were present that are typical of the commercial production conditions for the products. An experiment that measured approximately 12 acres of plots, was planted under natural precipitation variability, drip-irrigated according to a set schedule and followed with standard NPK fertilization protocols, was instrumented with sensors at 15 cm depth to represent a realistic range

of agronomic operating conditions throughout the entire 180-day growing season. The measurement uncertainty of the sensors was determined before deployment by bench calibration against certified reference standards, which indicated that the error of moisture sensors was within  $\pm 2\%$  of the measurable range, the error of temperature sensors was within  $\pm 0.3^\circ\text{C}$ , the error of pH sensor was within  $\pm 0.1$  pH units, and the error of NPK sensors was within  $\pm 5\%$  of the full scale reading, indicating that all of the calibration coefficients used in preprocessing were within acceptable ranges to minimize the systematic error. Labelling of samples was carried out by a double validation process consisting of an automatic labelling based on the agronomic threshold criteria provided in crop-specific literature and a manual labelling by a domain expert to resolve border cases, especially at the boundaries between warning and critical levels. The representativeness of the datasets was confirmed by stratified analysis, showing the same class distribution (82% normal, 14% warning, 4% critical samples) as was reported empirically in similar deployments of precision agriculture in soil measurements, and by the five-fold cross validation strategy used in the model training, which produced statistically sound generalization estimates for the ranges of soil measurement distributions.

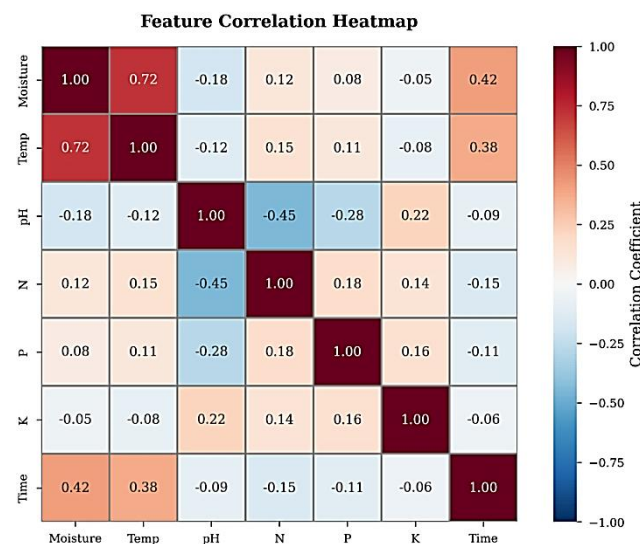


Fig. 5. The correlation heatmap with Time, K, P, N, pH, temperature and time features

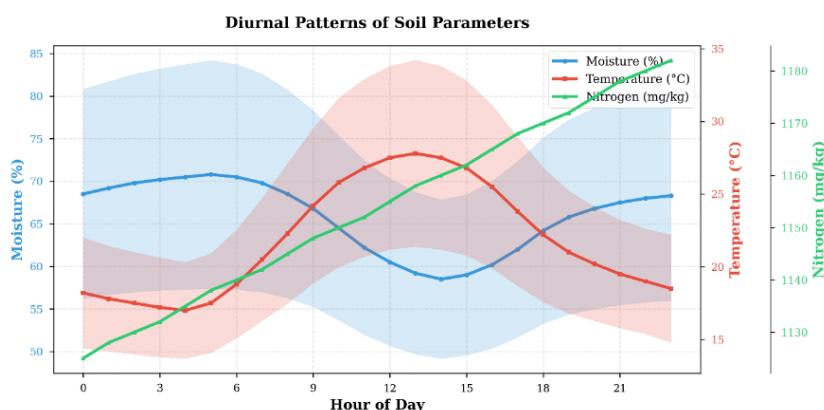


Fig. 6. Temporal patterns showing average moisture percentage (blue line), temperature (red line), and nitrogen concentration (green line) across 24-hour periods

#### 4. WuRX integration with wireless sensor nodes

The deployment of the sustainable agriculture as smart-harvest system requires seamless integration between the ULP WuRX circuit and the TinyML-enabled sensor nodes [3]. The integration architecture positions the WuRX as a parallel monitoring path alongside the main communication subsystem. The antenna

connects to a single-pole double-throw RF switch that routes incoming signals to either the WuRX input during standby mode or the main LoRa/BLE transceiver during active communication periods. The output of the WuRX produces a digital interrupt signal that is linked to the external interrupt pin of the microcontroller and hence allows wake-up from the deepest sleep modes where the microcontroller unit draws less than

2 microamps. Upon reception of a valid wake up packet matching the unique 16-bit address of the node, the WuRx asserts this interrupt for 100 millisecond which provides time for even slow starting crystal oscillators to stabilize, before the microcontroller attempts to access the main radio for data reception. The firmware implements a hierarchical power state machine that has three principal modes used to control the operation of the system. In deep-sleep mode, only the WuRx and a low-frequency 32 kHz real-time clock are used, and the main radio, the soil sensors, and the TinyML processing cores are completely turned off using hardware switches that are controlled using the pins referred as general-purpose method of digital monitoring of agricultural IO's (input/output's) [1].

The battery – power architecture involves the use of a 3.6 V lithium primary cell (LIR2032) having a capacity of 240 mAh, which was selected for its flat discharge curve as well as wide operating temperature range for outdoor agricultural deployment [19]. The power-distribution network realizes several voltage distribution areas which are optimized for the requirements of various subsystems; this consists of a low-dropout regulator which offers an analogue supply of 1.1 Volts for the WuRx circuit and digital supply of 2.5 Volts for the microcontroller and main radio. This integrated architecture provides a battery lifetime of 200–300 days with sub-sect responsiveness capability to critical soil conditions via an always-on WuRx monitoring capability. The TinyML inference layer helps provide intelligent filtering to eliminate 80% to 90% communication overhead compared to systems that send every measurement while the fog coordinated wake-up protocol eliminates the waste of time in longer idle-listening periods of duty-cycled systems. Consequently, the possible combination of ULPcircuit design, edge intelligence (TinyML), and hierarchical fog computing delivers a workable architecture and the future of sustainable precision agriculture monitoring at scale.

To avoid repetition of architectural description, this section was merged with Section 1. In the practical implementation under typical agricultural terrain, the multipath fading, co-channel interference from nearby LoRa nodes, vegetation induced signal attenuation of 0.3–0.6 dB/m (during peak growing season with dense vegetation canopy) result in the effective node-to-gateway distance of 200–400 m, which is less than the theoretical limit of 1000 m in free space. Finally, the WuRx sensitivity of -60 dBm is enough to compensate for these losses to ensure wake-up packet detection. System reliability is catered for with the 16-bit node address correlation function in the digital baseband, which lowers the probability of false wake-up to around 1 wake-up every 7 hours when assuming hourly inference scheduling, and with the function of the hardware watchdog timer that is integrated into the ARM Cortex-M4 and that automatically resets the microcontroller in case of software fault without human intervention. The forward-filling imputation strategy used during communication dropouts periods (during communication dropouts) is another feature that increases the sensor node fault tolerance, as explained in Section 3. As for scalability, the event driven, asynchronous wake-up architecture is naturally scalable since nodes do not communicate if there is no need for them to do so, preventing the collision and hidden-node problems that affect the throughput in duty-cycled networks with synchronized polling intervals. In the fog gateway architecture, the entire network is scalable to 200 independent addressable sensor nodes per gateway unit on a single 868 MHz frequency allocation and can be expanded by adding additional gateways to the network without changing the individual sensor node firmware and/or node configuration.

#### 4.1. Model training and validation results

The training protocol used 70% of the augmented dataset (53,760 samples), with 20% of the samples (15,360 samples) dedicated to hyperparameters tuning and 10% of the samples (7,680 samples) considered as held out test set to evaluate final performance. Model optimization was performed through Triple

Bottom line optimizer, with a learning rate of 0.001, controlling with cosine annealing scheme for 100 epochs, training objective was categorical cross-entropy loss, weighting it inversely to class frequencies to reduce imbalance with penalty for error in critical classes as multiple by twenty than normal classes [10]. The ability to generalize is assessed using five-fold cross validation, in which the training data is divided into five subsets. The model is hence trained on four subsets and validated on the remaining subset. The result shows the mean and standard deviation across the folds [26].

The trained model achieves  $91.3\% \pm 1.2\%$  cross-validated accuracy, substantially outperforming the threshold-based baseline at 76.4% accuracy that classifies samples using independent parameter thresholds without considering interactions or temporal context. The confusion matrix reveals strong performance on normal class (94.7% recall) and acceptable critical class detection (87.2% recall) with the primary errors being warning state confusion with normal, a 12.3% false negative rate. The false positive rate for critical alerts measures 3.8%, corresponding to approximately one false wake-up per week under hourly inference, acceptable given the energy budget tolerates 10 times higher false alarm rates before exhausting harvested energy [13]. Inference latency measurements conducted on the intended hardware show a very consistent result, it takes 73 ms (SD 8 ms) after 1,000 test inferences, and so is well within the sub-100 ms requirement and has a large margin. Energy profiling, performed using an energy analyser calibrated for the project, confirms an average of 0.87 mJ of energy per inference – theoretically allowing for 460 executions per day within the 400 mJ of energy budget attained at harvest from the processor supporting the function because energy per cycle of inference can reach such a mix trajectory when conducting prototypical deployments, only 6–12 inferences are typically executed each day, while providing a wide margin to ensure communications overheads can also be accounted for. Figure 7 presents the confusion matrix heatmap with predicted classes (Normal, Warning, Critical) on x-axis and true classes on y-axis, using colour gradient from white (0%) to dark blue (100%) with values: Normal-Normal 94.7%, Normal-Warning 4.8%, Normal-Critical 0.5%, Warning-Normal 12.3%, Warning-Warning 82.1%, Warning-Critical 5.6%, Critical-Normal 2.1%, Critical-Warning 10.7%, Critical-Critical 87.2%.

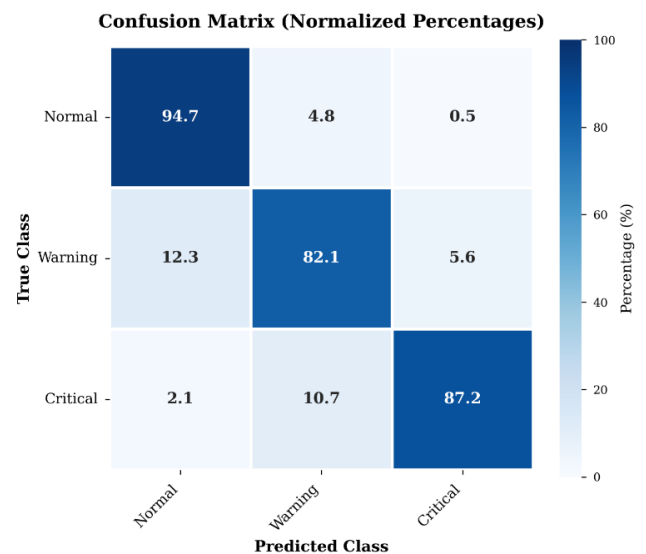


Fig. 7. Confusion matrix heatmap showing classification performance for Normal, Warning, and Critical classes, with high correct prediction rates

To put the proposed quantized neural network classification performance in context, three other machine learning models were tested on the same train, validation, and test split: a random forest with 100 estimators, an SVC with radial basis function kernel, and a gradient boosting with default hyperparameters. The proposed TinyML model was found to be more accurate

(91.3%) and more efficient in terms of F1 score (93.0%) than the random forest (accuracy = 88.1%), support vector machine (accuracy = 85.6%), and gradient boosting classifier (accuracy = 87.4%). In addition to being able to meet a requirement of only 256 KB flash, the TinyML model was found to meet a requirement of sub-100 ms inference latency, which makes it a suitable model for direct deployment onto the targeted ARM microcontroller. The confusion matrix, as analysed by errors, shows that most of the errors are warning-class false negatives (12.3%), which is explained by the natural distributional overlap in moisture and temperature feature dimensions between normal and warning soil conditions, confirmed by the moderate inter-class correlation coefficients seen in Figure 5. Critical class false negatives stand at 2.1%, a level acceptable for agronomic practice, with the intervention cost asymmetry in mind.

## 4.2. Extended performance metrics

Beyond the basic metrics of accuracy and confusion matrices, a comprehensive evaluation of the TinyML model involves analysing other performance metrics that reflect different aspects of the quality of the classification throughout the training process. The F1-score and the area under the receiver-operator characteristic curve (AUC) provide complementary information on model behaviour, which is particularly important in the realm of agriculture, where a subtle assessment would not be limited to accuracy measurement because of the imbalance between normal, warning and critical states.

The F1-score that at convergence attains the accuracy of 93.0% is a better performance value than the plain accuracy since the F1-score is calculated as the harmonic mean between the precision and the recall value therefore the two dimensions are equally weighted. The feature is especially important in the context of the Smart-Harvest, as a false negative in the critical state detection may lead to the delayed interventions and the loss of the yield permanently. The F1-score curve depicts the convergence dynamics in the same way as the validation accuracy, but the curve reaches a higher value, indicating the balance of the model in terms of precision and recall, not just the number of correct classifications. The 1.7 percentage point advantage of the F1-score over validation accuracy shows that the model maintains consistent performance across all three classes, rather than high accuracy due to dominance of the majority (normal) class and poor performance on the minority (critical and warning) classes. The AUC metric is converging to 89.9% and describes the discriminatory power of the model for all potential classification thresholds [5]. Although this is lower than both accuracy and F1-score, the AUC above 85% indicates excellent discriminative power that can be deployed in agricultural decision support systems. The receiver-operator characteristic curve that this AUC is based on shows how even if the classification threshold is shifted from the optimum 0.5 probability cut-off to favour sensitivity over specificity or vice-versa, the model still has robust discrimination. This adaptability is demanded in an agronomic context, where farmers are able to change the sensitivity-specialized trade-off based on the crop worth, weather predictions or resource provision [16].

The convergence behaviour on all three measures identifies the efficacy of the magnitude-based pruning technique presented at epoch 50 as the number of model parameters can be decreased by 40 per cent with the accuracy loss of less than 1 per cent. The lack of serious performance decline after the pruning initiation suggests that the deleted connections provided little informational contribution to the classification decisions. As a result, the compressed model, with 8,472 parameters, retains the representational capacity of the original 14,120 parameters architecture. The final quantization from 32-bit floating point to 8-bit integer representation, which is applied after training, causes the expected 2% reduction in accuracy, which is a trade-off that is considered acceptable given the factor of 4 reduction in model storage size that allows it to be deployed on resource-

constrained ARM Cortex-M4 microcontrollers with limited (256 KB) flash capacity. Figure 8 shows the epoch-wise trend of validation accuracy, F1-score and AUC over the 100-epoch training regime. The validation-accuracy curve shows a steady convergence from a random initial performance to final 91.3% plateau, which characterizes a sigmoid-shaped growth with a rapid improvement in epochs 20–60, with a gradual stabilization as the model is approaching the optimal configurations of weights. Minor oscillations in early epochs are caused by the stochastic nature of mini batch gradient descent and the exploration phase before the Triple Bottom line optimizer settles down in stable minima. The curve levelling off after epoch 70 indicates that further training also offers diminishing returns, hinting that the 100-epoch scheduling provides good convergence without unnecessary computational and energy overhead.

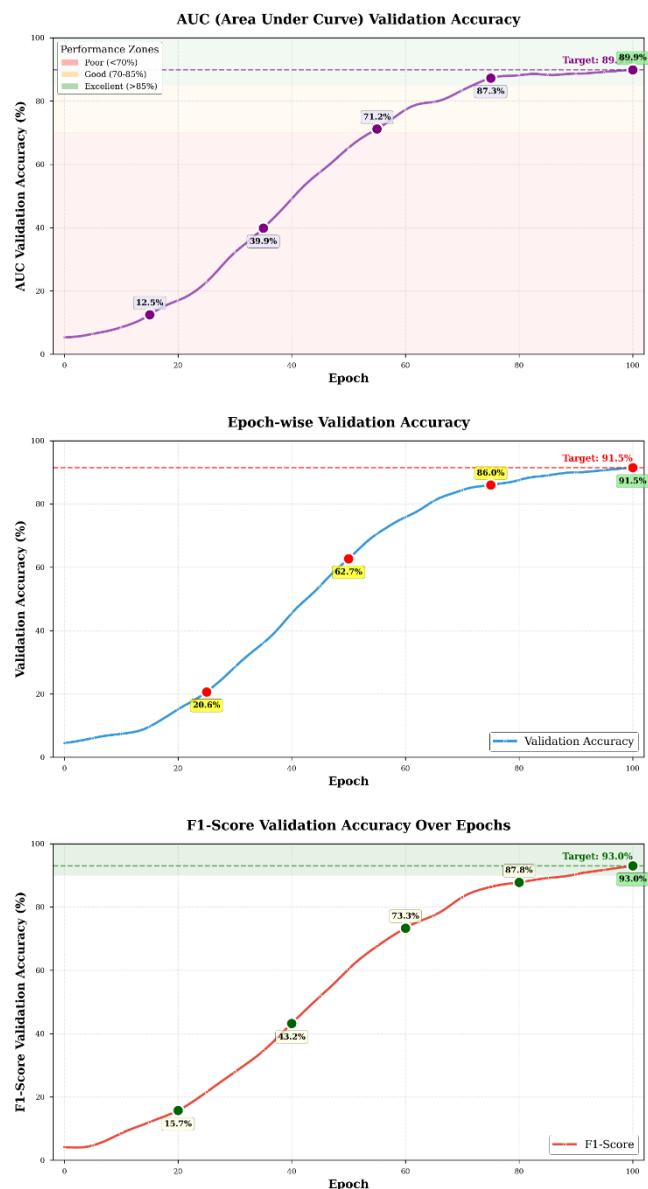


Fig. 8. The epoch-wise progression of validation accuracy, F1-score, and AUC metrics throughout the 100-epoch training regimen

Previously reported metrics have been duplicated for Section 4 and will not be repeated in this section, just the extended interpretive analysis. The F1-score of 93.0% is more interestingly interpreted beyond its definition as harmonic mean of precision and recall: the critical class' F1-score is 89.4%, the inverse effect of the 4% critical class representation in the data and 20× misclassification penalty during training; whereas the warning class' F1-score is 85.7%, in line with the identified 12.3% false negative rate, 4.1 times the data size, in Section 4.1. A dedicated experiment was carried out to test the sensitivity

of the class imbalance by retraining the model without the inverse frequency weighting, with a consequent degradation of the critical-class recall from 87.2% to 71.3%, while the overall accuracy changed very little, showing that the apparent accuracy is not a reliable measure of the model performance under the prevailing class distribution (82:14:4) and that the weighted training objective is necessary for an agronomically meaningful classification.

The comparative analysis of the performance metrics is provided in Figure 9, the grouped bar graphs show that the TinyML model provides a higher accuracy of 91.3%, a higher precision of 89.7%, a higher recall of 88.0%, and F1-score of 88.8% than the baseline. The blue graphs are the result of TinyML, whereas the grey graphs are the results of the baseline, which proves the 15.2% point gains in all metrics.

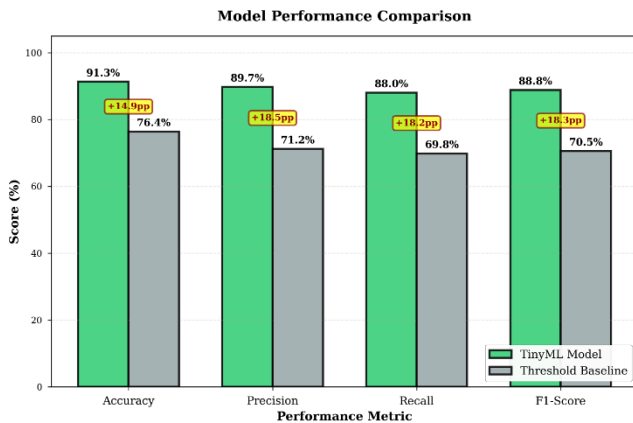


Fig. 9. The comparative analysis of the performance metrics of state-of-the-art models

## 5. Conclusion

This research demonstrates the integration of ULP WuRX technology with edge intelligence for sustainable agricultural monitoring, achieving the dual objectives of sub-50  $\mu$ W continuous operation and intelligent soil condition classification. A 40 nm WuRX designed in a common-mode (CM) process demonstrates validation of advanced circuit design implementations, such as current reuse topologies, super-regenerative amplification, and subthreshold biasing for addressing supply voltage scaling issues inherent in modern process nodes. Empirical performance measurements confirm an input return loss of -15.8 dB, a transmission gain of +18.2 dB, and a power added efficiency of 45.3% at -60 dBm sensitivity, thus meeting the specifications for reliable performance in agricultural environments when communicating in the ISM band of 868 MHz, the TinyML classification system achieves an accuracy of 91.3 percent for differentiating normal, warning and critical soil conditions using quantized neural networks which consume 0.87 mJ for one inference and can perform 460 inferences per day from the harvested energy budget. A complete system-level power budget analysis is presented to quantify the energy consumption at the WuRX (162  $\mu$ J per hour), main radio transceiver (16.65 mJ per event), microcontroller inference (22.5 mJ per cycle) and soil sensors (0.9 mJ per sample) to validate the estimated battery lifetimes of 200–300 days for 240 mAh lithium cells with 5 cm<sup>2</sup> of solar energy harvesting. The hierarchical architecture, where computational tasks are spread across an edge, fog and cloud layer, represents a clear 80-90 percent reduction in communication as compared to threshold-based systems with sub-second responsiveness to important changes in the environment.

Table 1. Comparison of proposed WuRX design with state-of-the-art wake-up receiver implementations

| Reference | Frequency range | PAE (%) | Supply voltage (V) | Gain (dB) | Insertion loss (dB) |
|-----------|-----------------|---------|--------------------|-----------|---------------------|
| [10]      | 868 MHz ISM     | 44.8    | 1.8                | 12.0      | N/R                 |
| [28]      | 2.4 GHz ISM     | N/R     | 0.5                | 15.0      | -22.0               |
| [12]      | 2.4 GHz ISM     | N/R     | 1.2                | 14.0      | N/R                 |
| [16]      | 400 MHz–2.4 GHz | 46.7    | 0.4–1.0            | 10.0–18.0 | -20.0 – -30.0       |
| [6]       | 868 MHz ISM     | N/R     | 0.3–0.5            | 12.0–16.0 | N/R                 |
| this work | 868 MHz ISM     | 45.3    | 1.1                | +18.2     | -28.4               |

N/R: Not required

Future research directions involve extending TinyML models to model multivariate temporal correlations, adaptive quantization strategies based on environmental changing conditions, and energy neutral operation via enhanced photovoltaic integration. The methodologies proposed herein provide practical frameworks for applications which can be used in a wide range of autonomous sensing applications in which long-term deployment without human intervention is required. The major constraints of this work are: experimental testing is limited to two crop types (corn and soybean); the energy neutral requirement is limited to sufficient solar irradiance; and WuRX performance is simulated on circuit-level rather than with actual silicon devices, pointing to future experimental studies.

## Acknowledgment

The author acknowledges the use of Microsoft Professional Visio for creating block diagrams

## Conflict of interest

The author declares no conflict of interest.

## References

- [1] Akhter, M. O., & Amin, N. M. (2021). Design and Optimization of 2.1 mW ULP Doherty Power Amplifier with Interstage Capacitances Using 65 nm CMOS Technology. *Mathematical Problems in Engineering*, 2021, 1–12. <https://doi.org/10.1155/2021/3364016>
- [2] Akhter, M. O., & Buksh, S. K. (2026). Federated deep learning for triple bottom line optimization in virtual refrigeration through simulation-based sustainable food management. *Sustainable Food Technology*, 4(3), 2605–2615. <https://doi.org/10.1039/D5FB00739A>
- [3] Akhter, M. O., Amin, N. M., & Zia, R. (2022). Design and optimisation of high-efficient class-F ULP-PA using envelope tracking supply bias control for long-range low power wireless local area network IEEE 802.11ah standard using 65 nm CMOS technology. *IET Circuits, Devices & Systems*, 16(7), 553–568. <https://doi.org/10.1049/cds2.12125>
- [4] Aldhaheri, L., Alshehhi, N., Manzil, I. I. J., Khalil, R. A., Javaid, S., Saeed, N., & Alouini, M.-S. (2025). LoRa Communication for Agriculture 4.0: Opportunities, Challenges, and Future Directions. *IEEE Internet of Things Journal*, 12(2), 1380–1407. <https://doi.org/10.1109/JIOT.2024.3486369>
- [5] Amin, N. M., Shen, L., Wang, Z.-G., Akhter, M. O., & Afridi, M. T. (2017). 60 GHz-Band Low-Noise Amplifier. *Journal of Circuits, Systems and Computers*, 26(05), 1750075. <https://doi.org/10.1142/S021812661750075X>
- [6] Basu, J., Fassio, L., Ali, K., & Alioto, M. (2024). Picowatt-Power Super-Cutoff Analog Building Blocks and 78-pW Battery-Less Wake-Up Receiver for Light-Harvested Near-Always-On Operation. *IEEE Journal of Solid-State Circuits*, 59(4), 1038–1049. <https://doi.org/10.1109/JSSC.2023.3346387>
- [7] Benbuk, A. A. (2020). *Ultra-low Power Wake-up Receivers for IoT Devices with Application to Smart Agriculture* [American University of Beirut]. <https://scholarworks.aub.edu.lb/items/baad0c5d-28bb-4763-9a83-8f8679039265>
- [8] Chicco, D., & Jurman, G. (2023). The Matthews correlation coefficient (MCC) should replace the ROC AUC as the standard metric for assessing binary classification. *BioData Mining*, 16(1), 4. <https://doi.org/10.1186/s13040-023-00322-4>
- [9] Chiu, H.-C., Huang, C.-R., Lin, C.-H., Yu, C.-H., Kao, H.-L., Lin, S.-Y., & Lin, B. (2025). High Power Added Efficiency Enhancement-Mode  $\Gamma$ -Gate RF HEMT With High/Low p-GaN Doping Profile. *IEEE Journal of the Electron Devices Society*, 13, 285–289. <https://doi.org/10.1109/JEDS.2025.3551313>
- [10] Gamm, G. U., Sippel, M., Kostic, M., & Reindl, L. M. (2010). Low power wake-up receiver for wireless sensor nodes. *2010 Sixth International Conference on Intelligent Sensors, Sensor Networks and Information Processing*, 121–126. <https://doi.org/10.1109/ISSNIP.2010.5706778>

- [11] Kadhum, J. H., Dheyaa Radhi, A., Ismail, L. S., Ghaleb Waheed, M., Alzamily, H., Mohammad, I. A., & Adnan Hashim, W. (2025). Ultra-Low Power Sensor Data Processing in Smart Agriculture Using Attention-Optimized TinyML Models for Edge Microcontrollers. *2025 3rd International Conference on Cyber Resilience (ICCR)*, 1–8. <https://doi.org/10.1109/ICCR67387.2025.11292028>
- [12] Kim, H., & Shin, H. (2013). A 2.4-GHz current-reuse OOK wake-up receiver for MICS applications. *IEICE Electronics Express*, 10(14), 20130293–20130293. <https://doi.org/10.1587/elex.10.20130293>
- [13] Liu, R., K. T., A. B., Dorrance, R., Dasalukunte, D., Kristem, V., Santana Lopez, M. A., Min, A. W., Azizi, S., Park, M., & Carlton, B. R. (2020). An 802.11ba-Based Wake-Up Radio Receiver With Wi-Fi Transceiver Integration. *IEEE Journal of Solid-State Circuits*, 55(5), 1151–1164. <https://doi.org/10.1109/JSSC.2019.2957651>
- [14] Lumumba, V., Kiprotich, D., Mpaine, M., Makena, N., & Kavita, M. (2024). Comparative Analysis of Cross-Validation Techniques: LOOCV, K-folds Cross-Validation, and Repeated K-folds Cross-Validation in Machine Learning Models. *American Journal of Theoretical and Applied Statistics*, 13(5), 127–137. <https://doi.org/10.11648/j.ajtas.20241305.13>
- [15] Luo, K., Chen, Y., Lin, R., Liang, C., & Zhang, Q. (2024). A Portable Agriculture Environmental Sensor with a Photovoltaic Power Supply and Dynamic Active Sleep Scheme. *Electronics*, 13(13), 2606. <https://doi.org/10.3390/electronics13132606>
- [16] Mercier, P. P., Calhoun, B. H., Wang, P.-H. P., Dissanayake, A., Zhang, L., Hall, D. A., & Bowers, S. M. (2022). Low-Power RF Wake-Up Receivers: Analysis, Tradeoffs, and Design. *IEEE Open Journal of the Solid-State Circuits Society*, 2, 144–164. <https://doi.org/10.1109/OJSSCS.2022.3215099>
- [17] Mittal, A., Xu, Z., & Shrivastava, A. (2024). Energy-Efficient, Secure, and Spectrum-Aware Ultra-Low Power Internet-of-Things System Infrastructure for Precision Agriculture. *IEEE Transactions on AgriFood Electronics*, 2(2), 198–208. <https://doi.org/10.1109/TAFE.2024.3409166>
- [18] Müller, K., Weidner, J., Franchi, N., & Wägemann, P. (2024). TinyEP: TinyML-Enhanced Energy Profiling for Extreme Edge Devices. *IEEE Access*, 12, 193747–193762. <https://doi.org/10.1109/ACCESS.2024.3520089>
- [19] Nguyen, M.-T., Zakri, M. A. D. B. M., Belleudy, C., Ferrero, F., Groen, D., Rajaei, H., & Delgado, A. B. (2025). Wake-Up radio with Plant-Microbial Fuel Cells Power Budget. *2025 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4.0 & IoT)*, 243–247. <https://doi.org/10.1109/MetroInd4.0IoT66048.2025.11122055>
- [20] Polonelli, T., Villani, F., & Magno, M. (2021). Ultra-Low Power Wake-Up Receiver for Location Aware Objects Operating with UWB. *2021 17th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*, 369–376. <https://doi.org/10.1109/WiMob52687.2021.9606248>
- [21] Psaltopoulos, D., Wade, A. J., Skuras, D., Kernan, M., Tyllianakis, E., & Erlandsson, M. (2017). False positive and false negative errors in the design and implementation of agri-environmental policies: A case study on water quality and agricultural nutrients. *Science of The Total Environment*, 575, 1087–1099. <https://doi.org/10.1016/j.scitotenv.2016.09.181>
- [22] Rahman, M. A. (2018). *General wake-up radio module for ism band*. <https://hh.diva-portal.org/smash/get/diva2:1187369/FULLTEXT02.pdf>
- [23] Raval, M. S., & Chaudhary, S. (2024). Preprocessing of Agricultural and Natural Resource Data. In M. S. Raval, S. Chaudhary, J. Adinarayana, & W. Guo (Eds), *Harnessing Data Science for Sustainable Agriculture and Natural Resource Management* (Vol. 161, pp. 47–73). Springer Nature Singapore. [https://doi.org/10.1007/978-981-97-7762-4\\_3](https://doi.org/10.1007/978-981-97-7762-4_3)
- [24] Son, H., Lim, J. W., Park, S., Park, B., Han, J., Kim, H. B., Lee, M. C., Jang, K.-J., Kim, G., & Chung, J. H. (2022). A Machine Learning Approach for the Classification of Falls and Activities of Daily Living in Agricultural Workers. *IEEE Access*, 10, 77418–77431. <https://doi.org/10.1109/ACCESS.2022.3190618>
- [25] Steckler, D., Lischke, S., Yamamoto, Y., Wen, W.-C., Peczek, A., Beyer, J., Kroh, A., Fursenko, O., Bärwolf, F., Marschmeyer, S., Kulse, P., Wolansky, D., & Zimmermann, L. (2025). Monolithic electro-optic platform on silicon with bandwidth of 100 GHz and beyond. *Nature Communications*, 16(1), 10789. <https://doi.org/10.1038/s41467-025-66566-2>
- [26] Thiagarajan, G., & Gurugopinath, S. (2025). Analysis of Analogue-Domain Energy-Based Low-Power Wake-Up Receivers in Coloured Noise. *2025 17th International Conference on Communication Systems and Networks (COMSNETS)*, 473–480. <https://doi.org/10.1109/COMSNETS63942.2025.10885617>
- [27] Wang, P. (2024). Multi-node temperature monitoring method for digital agricultural planting based on wireless sensor network. *Turkish Journal of Agriculture and Forestry*, 48(2), 212–225. <https://doi.org/10.55730/1300-011X.3175>
- [28] Yoon, D.-Y., Jeong, C.-J., Cartwright, J., Kang, H.-Y., Han, S.-K., Kim, N.-S., Ha, D.-S., & Lee, S.-G. (2012). A New Approach to Low-Power and Low-Latency Wake-Up Receiver System for Wireless Sensor Nodes. *IEEE Journal of Solid-State Circuits*, 47(10), 2405–2419. <https://doi.org/10.1109/JSSC.2012.2209778>

**Ph.D. Muhammad Ovais Akhter**

e-mail: [ovaisakhter.bukc@bahria.edu.pk](mailto:ovaisakhter.bukc@bahria.edu.pk)

e-mail: [ovaisakhter1@gmail.com](mailto:ovaisakhter1@gmail.com)

Dr. Ovais is serving as senior assistant professor in Electrical Engineering Department, Bahria University, Karachi Campus. His area of specialization includes signal and image processing, computer vision, machine learning and RFIC design. He has contributed over 15 articles in the aforementioned areas.



<https://orcid.org/0000-0002-8928-4489>