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An Intelligent Fertilizer Dosing System Using a Random Forest Model for Precision Agriculture

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***Abstract*—The inefficient application of fertilizers in horticultural crops, particularly in rural areas of Peru, leads to significant economic losses, soil degradation, and environmental risks. In response to this issue, this paper proposes an intelligent fertilizer dosing system that integrates solid and liquid fertilization applications through a predictive machine learning model. The main contribution of this research is the development and partial validation of an embedded system that dynamically adapts nutrient (NPK) doses based on real-time soil conditions, crop type, and phenological stage. The predictive model, based on Random Forest (RF), was trained using 10000 synthetic data points generated via Sobol-LHS sampling and validated with 1000 real field measurements. The method incorporates thirteen agronomic variables, including soil moisture, pH, temperature, and nutrient content, enabling adaptive control of the dosing mechanisms. The system achieved promising results, with root mean square errors (RMSE) of 2.81 kg/ha for nitrogen, 1.42 kg/ha for phosphorus, and 0.94 kg/ha for potassium. These results demonstrate the model's ability to deliver accurate crop-specific fertilization recommendations, reducing input waste and improving nutrient use efficiency. Although full field trials are planned for future phases, the proposed system offers a scalable and low-cost solution for precision agriculture in resource-constrained settings, promoting more sustainable farming practices and enhancing the productivity of smallholder farmers.**

Keywords—Random Forest; Intelligent Fertilizer Dosing; Precision Agriculture; Soil Sensing; Embedded Agricultural Systems.

I. INTRODUCTION

The sustainability and productivity of horticultural crops face serious challenges due to the inefficient application of fertilizers in Peru [1]-[4]. In this country, 44% of the 2.26 million farmers use chemical fertilizers, and more than 80% of them cultivate plots smaller than 5 hectares [5], where nutrient application is still carried out manually [6]-[12]. A high external dependency compounds this low level of mechanization; in 2022, Peru imported over one million tons of mineral fertilizers, while domestic guano production in 2021 covered barely 2% of total national demand [5]. This situation results in significant economic losses, soil degradation, and environmental risks associated with uncontrolled nutrient application [13]-[15].

In recent decades, precision agriculture has promoted the use of sensors, controllers, and digital platforms to optimize the management of inputs such as water and fertilizers [16]-[18]. However, many existing solutions have critical limitations; they often focus on a single type of fertilization (liquid or solid), involve high costs, or rely on deterministic algorithms poorly suited to environmental variability. Furthermore, artificial intelligence (AI) models developed for agriculture are often difficult to deploy in the field due to overfitting, high computational requirements, or incompatibility with low-power embedded hardware such as microcontrollers [19]-[22].

A critical review of the state of the art reveals a persistent gap between the intelligent mechanical design of dosing mechanisms and the practical implementation of AI models [23]-[26]. Some developments allow for monitoring variables such as soil moisture, pH, or nutrient levels but do not automatically adjust dosing according to crop type, phenological stage, or agroclimatic conditions [27]-[31]. Predictive models that achieve promising results in simulated environments, such as neural networks or regression algorithms, often require high-capacity platforms, making them incompatible with low-power microcontrollers like the ESP32, which are essential for field-embedded applications [32]-[37].

To address these limitations, this study proposes an intelligent dosing system that integrates the mechanical design of a dual module for solid and liquid fertilizers, real-time multiparameter sensing, and a Random Forest machine learning model embedded in an ESP32 microcontroller. The model was trained with 10000 synthetic data points generated through Sobol-LHS sampling and validated with 1000 real field measurements, enabling the precise prediction of optimal nitrogen, phosphorus, and potassium (NPK) doses based on thirteen agronomic variables, including soil moisture, pH, temperature, and crop type.

The main contribution of this research is the design, partial validation, and embedded implementation of an autonomous adaptive nutrient dosing system for horticultural crops, utilizing robust artificial intelligence and low-cost hardware. This development represents a significant advance in precision agriculture by enabling contextualized, efficient, and scalable fertilization, particularly in rural environments with limited resources, promoting more sustainable and data-driven agricultural practices.

II. THEORETICAL FRAMEWORK

A. Horticultural Crops and Nutritional Requirements

Horticultural crops such as tomato, broccoli, and lettuce exhibit high physiological and agronomic variability, leading to specific nutritional demands that change according to the crop type, phenological stage, and edaphoclimatic conditions

[38], [39]. This variability requires more precise fertilization strategies compared to extensive crops, as an imbalance in the application of nitrogen (N), phosphorus (P), or potassium (K) can directly affect yield, quality, and input use efficiency [40]-[43].

Nutrient management in horticultural crops must dynamically adapt to multiple factors, including soil pH, moisture content, texture, initial nutrient levels, and local climate conditions [44], [45]. Consequently, traditional approaches based on fixed doses or empirical rules have proven insufficient. In this context, machine learning models offer the ability to predict optimal nutrient doses by processing multiple input variables, thus facilitating decision-making in embedded systems for precision agriculture.

An adaptive fertilization strategy must not only consider the type and quantity of nutrients but also determine the optimal timing and method of application according to the crop's phenological stage. Table I summarizes the typical fertilization phases, their associated key nutrients, and the expected functioning of the proposed intelligent dosing system.

TABLE I. RELATIONSHIP BETWEEN CROP GROWTH STAGES AND AUTOMATED DOSING STRATEGIES

Phenological Stage	Application Timing	Main Nutrient	System Action
Establishment	Before planting	P, K	Initial RF estimation
Active Growth	Vegetative phase	N	Adaptive solid and liquid dosing
Maturation	Final stage	N, K	Real-time adjustment

This phenology-based approach enables more efficient nutrient dosing throughout the crop growth cycle, maximizing input utilization and reducing risks associated with nutrient leaching or critical nutritional deficiencies.

B. *Soil Preparation and Fertilization Efficiency*

Proper soil preparation is a fundamental requirement to ensure the effectiveness of any fertilization strategy, particularly in horticultural crops. The physical and chemical properties of the soil directly influence moisture retention, aeration, and nutrient availability to plant roots [46]-[50]. In particular, soil texture, structure, and organic matter content significantly affect the mobility and absorption of essential macronutrients such as nitrogen (N), phosphorus (P), and potassium (K).

Common agronomic practices such as tillage, leveling, and organic matter incorporation aim to improve soil structure, facilitate root development, and optimize soil-plant interactions [51]-[53]. However, these practices are not always accompanied by dosing systems capable of dynamically responding to soil changes throughout the crop cycle. Most traditional fertilization schemes apply nutrients uniformly, without considering spatial variability or temporal evolution of soil properties. This approach often leads to overfertilization in some areas and deficiencies in others, decreasing nutrient use efficiency and increasing environmental risks such as leaching and salt accumulation [54], [55].

In this context, the integration of multiparameter sensors capable of measuring soil pH, electrical conductivity, moisture, and temperature enables a more precise characterization of soil conditions and allows real-time adjustment of fertilization doses. This principle is essential in the design of the proposed dosing system, where real-time soil measurements are used as input variables for a predictive model that calculates the optimal fertilizer application rates.

C. *Fertilizer Strategies and Phenological Adaptation*

Fertilizers used in horticultural agriculture are commonly divided into two main types: solid and liquid. Solid fertilizers, such as granular urea, diammonium phosphate, or ammonium nitrate, are characterized by their gradual release into the soil, making them suitable for long-cycle crops and basal applications [56]-[58]. In contrast, liquid fertilizers are concentrated nutrient solutions that allow for immediate absorption either through the roots or foliage and are particularly utilized during critical stages of crop development [59]-[65].

The method of fertilizer application varies depending on its properties. Solid fertilizers are typically distributed mechanically into the soil using systems such as helical screws, allowing relatively precise control of the applied mass flow [66], [67]. Meanwhile, liquid fertilizers are dosed through fertigation systems employing peristaltic pumps, which enable flow regulation based on the crop's needs and soil conditions. The coordinated combination of both fertilization types takes advantage of the persistence of solids and the rapid responsiveness of liquids [68], [70].

To maximize agronomic efficiency and minimize input waste, fertilizer applications must align with the crop's phenological stage, a strategy known as phenological adaptation [71], [72]. During establishment, phosphorus and potassium are prioritized to support root development; in active growth, nitrogen dosage is increased; and in maturation, nitrogen and potassium ratios are adjusted to enhance harvest quality [73], [74].

The intelligent system proposed in this study incorporates this phenological adaptation logic into its machine learning model. The phenological stage is introduced as a categorical variable, along with thirteen other agro-environmental variables captured in real time. Based on these inputs, the model automatically adjusts the dosing of solid fertilizers (via helical screw) and liquid fertilizers (via peristaltic pump), synchronizing applications with the crop's specific nutritional requirements at each developmental stage. This adaptive integration enables precise, sustainable, and technically feasible nutrient management in rural settings, reducing leaching losses and maximizing nutrient use efficiency.

III. MATERIALS AND METHODS

A. *Mechanical Design of the Dosing System*

The proposed system for fertilizer dosing in horticultural crops was designed with the integration of mechatronic technologies and machine learning algorithms, which allowed for precise and adaptable application of solid and liquid fertilizers. The structure of the system consisted of sensors for monitoring soil conditions, an actuator-driven dosing mechanism, and an artificial intelligence model aimed at optimizing nutrient application in real time [75]. The design was developed in SolidWorks, defining both the component architecture and the dosing mechanism configuration. Materials with high corrosion resistance and durability were selected to ensure efficient operation in harsh agricultural environments [76], [77].

Three main components were selected for accurate fertilizer dosing:

1) Storage hopper: It was designed with a volume of 0.35 m^3 and a capacity of 300 kg for solid or granular fertilizers. The conical structure, with an angle of 40° and an outlet diameter of 20 cm, allowed a controlled flow to the dosing mechanism.

2) Helical screw: Responsible for the dosing of solid fertilizers. It was made of wear and corrosion-resistant materials. Its rotation speed was controlled by an electric motor, which adjusted the amount of fertilizer applied based on the real-time data provided by the sensors.

3) Fertigation system: Composed of peristaltic pumps used to dose liquid fertilizers in the form of NPK solutions diluted in irrigation water. This system allowed for precise and efficient application through a drip system.

B. Sensor Integration and Calibration

The proposed system integrated a multi-parameter soil sensor with RS485 protocol (model RBD-2300, IP68 rating), designed for agricultural applications in the open field. This sensor allowed the simultaneous measurement of key variables such as soil moisture, temperature, pH, electrical conductivity (EC), and estimated concentrations of nitrogen, phosphorus, and potassium (NPK). Its corrosion-resistant package, along with its ability to operate submerged or buried, made it suitable for continuous monitoring in harsh weather conditions. The communication under the Modbus RTU protocol was managed by a TTL-RS485 converter connected to the ESP32 microcontroller, ensuring robust and interference-free data transmission.

To ensure representative measurements, the sensor was installed at a depth of 15 cm with vertical orientation, ensuring uniform contact of its electrodes with the soil array. Moisture was estimated using the dielectric constant of the soil, with a reading range of 0 to 100 % VWC. The calibration was carried out using the gravimetric method, correlating the mass of water in samples with the values obtained by the sensor [78]. A polynomial curve was generated with R^2 = 0.976, and an estimated error of ±3 % under normal field conditions.

The temperature was measured in a range of −40 °C to 80 °C with an accuracy of ±0.5 °C. In the range of 15-35 °C, the mean deviation was less than ±0.4 °C. This variable was used for thermal compensation of other readings. The pH measurement was calibrated using the two-point method with standard buffer solutions (pH 4.0 and 7.0), obtaining a maximum error of ±0.15 units and good stability after 8 h of continuous operation [79].

EC was used as an indirect parameter to detect salinity and fertilizer accumulation. Although the sensor does not include explicit internal calibration, it was validated with NaCl solutions (0.1 M, 0.5 M, 1 M), observing a stable linear response. For NPK, a comparative validation was carried out with laboratory analysis: nitrogen (Kjeldahl method), phosphorus (colorimetry with molybdate) and potassium (flame photometry), obtaining average errors of ±6.2 mg/kg (N), ±3.9 mg/kg (P) and ±5.7 mg/kg (K), considered acceptable for field applications [80].

The sample rate was set to 5 s. The data was processed using an exponential moving average filter to smooth out high-frequency noise without losing the dynamics of change. In addition, a recalibration protocol based on time drift was implemented: every 72 h of continuous operation or every 10 h of intermittent use, with automatic alerts from the ESP32 firmware. Finally, the corrected values were normalized and sent as inputs to the artificial intelligence model in charge of estimating the optimal dosage of fertilizers. Fig. 1 shows the functional flow of the process of acquisition, calibration, and normalization of data from the multiparameter sensor, before being used by the artificial intelligence model for dosing decisions.

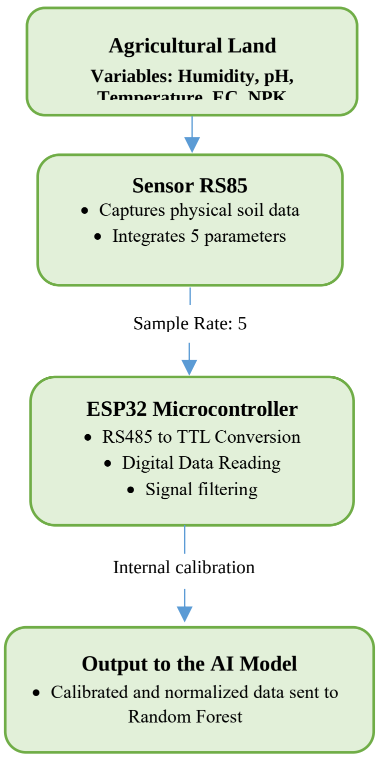

Fig. 1. Functional diagram of the soil data acquisition system, integrating moisture, pH, temperature, electrical conductivity, and nutrient (NPK) measurements

C. Mathematical Models for Adaptive Fertilizer Dosing

The ferti-dosing module was developed in this study with the aim of modeling the dynamics of the soil-plant-atmosphere system (SPAC) and adjusting the nutrient application in real time. The system used the data captured by the multi-parameter sensor, which was processed using machine learning algorithms. Unlike simplified approaches, this model considered nutrient availability and efficiency, integrating variables measured in situ such as humidity, temperature, pH, and electrical conductivity.

The evolution of nitrogen available in the soil was represented by a dynamic balance shown in (1), which included root uptake, leaching loss and microbial mineralization:

$$\dot{N}\ disp(t) = Ucrop(t) - L(t) + M(t) \tag{1}$$

Where $Ucrop(t)$ corresponded to the rate of absorption by the plant, $L(t)$ represented the leached fraction as a function of soil moisture and electrical conductivity, and $M(t)$ described microbial mineralization. This formulation allowed to capture more accurately the dynamics of the soil in the face of environmental disturbances.

Root absorption was modeled with a Michaelis-Menten kinetics modified to the agricultural environment [81], [82] shown in (2), which considered both the concentration of the nutrient in solution and the combined effect of humidity and temperature:

$$Ucrop(t) = \frac{Umax \cdot C(t)}{Km + C(t)} \cdot f(\theta(t), T(t)) \tag{2}$$

Where $C(t)$ was the concentration of the available nutrient, $Umax = 4.5\, mg \cdot d^{-1}$ the maximum absorption rate, $Km = 20\, mg \cdot kg^{-1}$ is the semi-saturation constant, and $f(\theta, T)$ a function that integrated the volumetric moisture of the soil $\theta(t)$ and the temperature of the profile $T(t)$, both measured by the RS485 multi-parameter sensor [83], [84].

1) Solid fertilizer dosage: The solid fertilizer application rate was calculated using (3) as a mass flow delivered by the helical screw, dynamically adjusted by the AI model based on the crop's absorption efficiency:

$$D(t) = \frac{nAN}{60S} \cdot \eta c(t) \cdot [1 + L(t)]^{-1} \tag{3}$$

In this equation, n represented the filling coefficient (related to the density of the fertilizer), A the cross-sectional area of the screw, N its rotation speed, S the helical pitch, and $\eta c(t)$ the crop-specific absorption efficiency, estimated by a Random Forest model trained with thirteen agronomic variables. The term $[1 + L(t)]^{-1}$ it acted as a corrective factor for leaching losses, integrating real-time readings of moisture and EC [85].

2) Liquid fertilizer dosage: For fertigation, the volumetric flow applied by the peristaltic pumps was dynamically adjusted using (4), considering leaf evaporation induced by microclimatic conditions:

$$Q(t) = v \cdot \frac{\pi D2}{4} \cdot \eta c(t) \cdot [1 + E(t)]^{-1} \tag{4}$$

Where v was the speed of the fluid, D the internal diameter of the duct, and $E(t)$ the fraction of leaf evaporation estimated using a simplified energy balance model that included temperature, relative humidity, and solar radiation. This approach made it possible to avoid losses of liquid fertilizer due to surface evaporation and to adjust the doses precisely [86].

3) Integration with sensors and adaptive control: All environmental variables were preprocessed using a discrete Kalman filter, which allowed for the reduction of noise and variability of measurements. These calibrated readings were used as inputs to both the mathematical model and the machine learning model. The control system combined feed-forward, based on equations (1)-(4), with a closed-loop PID control, which was responsible for correcting the residual deviations between the estimated dose and the desired agronomic response. The controller parameters were adjusted using iterative simulations in MATLAB/Simulink, using the modified Ziegler-Nichols method as a starting point. The final tuned values were: *Kp*=1.2, *Ki*=0.08, and *Kd*=0.01, which allowed maintaining a stable and oscillation-free response under different simulated scenarios. Absorption efficiency $\eta c(t)$, generated by the Random Forest model, presented a dynamic range between 0.65 and 0.91, the latter in high humidity and neutral pH scenarios. This value was updated in real time by the system, which allowed the dosage to be adjusted without the need to retrain the model when changing crops or agroecological zones.

D. Development of the Artificial Intelligence Model

The proposed innovative dosing system incorporated a predictive module based on machine learning, aimed at estimating in real time the optimal doses of nitrogen (N), phosphorus (P), and potassium (K). To this end, a multi-output Random Forest model was developed, which uses thirteen agro-environmental variables obtained through field sensorization as input, including data on soil moisture, temperature, pH, electrical conductivity, phenological state of the crop, soil type, and predominant climate [87]-[90].

The model was trained using a synthetic set of 10000 records generated by quasi-uniform Sobol-LHS sampling, with the aim of representatively covering the hyperspace of possible agricultural conditions. Continuous variables were distributed within agronomically relevant ranges: air temperature (5-35 °C), soil moisture (5-45 %), pH (5.0-8.0), electrical conductivity (20-1200 µS/cm), and initial NPK concentrations (0-250 kg/ha). In addition, categorical variables such as cultivation (10 species), phenological stage (3 phases), soil type (3 textural classes), and climate (3 agroecological scenarios) were incorporated.

To increase the realism of the synthetic assembly, controlled Gaussian noise was introduced in the continuous variables, based on the precision tolerances of the RS485 multiparameter sensor (±0.05 pH, ±2% humidity, ±5 µS/cm EC). A random factor of spatial heterogeneity of 15% was also added to nutrient concentrations, simulating typical variability in the open field. Categorical variables were encoded using one-hot encoding, and continuous variables were normalized to the interval [-1, 1].

In addition, 1000 real measurements were made using physical sensors connected to the ESP32 microcontroller, under real agricultural conditions. These measurements were used to verify the model's behavior against field data, demonstrating its practical applicability, although full integration with the physical dosing system has not yet been implemented.

The dataset was divided into 70% for training, 15% for validation, and 15% for testing, and 5-fold cross-validation was applied. Eighteen regression algorithms were compared in the MATLAB Regression Learner environment, with the Random Forest model obtaining the best overall performance, with a configuration of 120 trees, a maximum depth of 10, and a bagging method. The mean absolute errors (MAE) were: 6.8 kg/ha (N), 6.1 kg/ha (P), and 6.4 kg/ha (K), all below 5% of the operating dosing range, which validated its robustness and generalizability under nonlinear multivariate conditions. Fig. 2 shows the general flow of the Random Forest model, in which random subsets of the dataset (bagging) were generated to train multiple decision trees, whose outputs were aggregated to obtain a robust prediction that was less sensitive to overfitting [91].

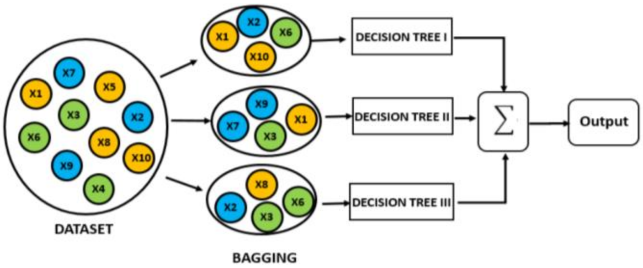

Fig. 2. Decision tree used in the Random Forest model

The generated predictions were interpreted as specific absorption efficiencies $\eta c(t)$, representing the estimated percentage of nutrients effectively absorbed by the crop under given conditions. These efficiencies fed into the mathematical equations of dosing described in the previous section. In addition, the recommendations were divided by phenological stages: 25 % during establishment, 55 % in active growth, and 20 % in maturation. Finally, the model was exported to C code using MATLAB Coder, with a view to its future implementation in low-power microcontrollers such as ESP32 operating on FreeRTOS. Preliminary testing with the 1000 actual measurements confirmed the model's compatibility with inputs from the physical environment. Although these tests do not constitute a functional validation of the integrated system, they did allow us to verify its behavior against real data, establishing a solid basis for its complete validation in later phases.

E. Embedded Implementation in ESP32 Microcontroller

To guarantee the operability of the system in rural environments without computational infrastructure, an embedded implementation architecture was designed on the ESP32-WROOM-32 microcontroller, which has a dual-core Xtensa LX6 architecture, 520 KB of SRAM, and support for real-time execution through FreeRTOS. The choice of this microcontroller was due to its low power consumption, local processing capacity, and compatibility with industrial communication sensors.

The system was organized into concurrent tasks, under a multitask planning scheme, separating the process of data acquisition, inference from the artificial intelligence model, and activation of actuators. To enable this integration, the predictive model was exported from MATLAB using MATLAB Coder, generating code in C language compatible with embedded systems.

Fig. 3 shows the functional diagram of this architecture, which depicts the connection between multi-parameter sensors, the ESP32 microcontroller, the AI inference module, the hybrid control system, and the actuators. The inference of the model was carried out locally, without the need for external connectivity, which allows its autonomous operation in areas without network access. The control system implemented was hybrid, combining feed-forward and PID control strategies, which were described in the hybrid control section.

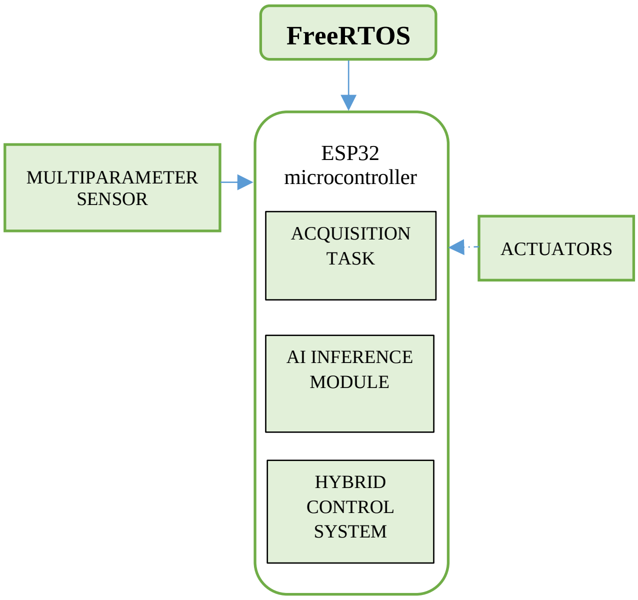

Fig. 3. Functional diagram of the ESP32 embedded system

Fig. 4 presents the physical connection diagram used during the sensing validation tests. The RS485 communication interface, the multi-parameter sensor, and an auxiliary OLED screen are observed and connected to the ESP32 microcontroller. The communication between the sensor and the ESP32 was managed by a TTL-RS485 converter module, with an independent power supply between 9 and 24 V, according to the sensor's requirements.

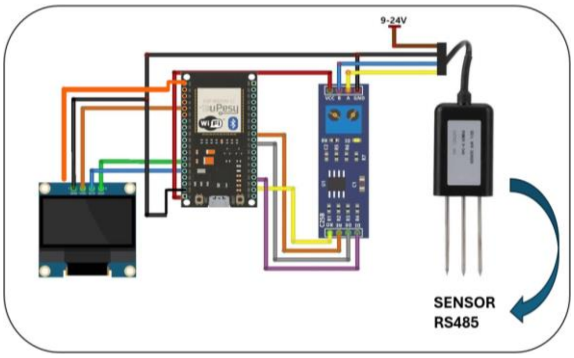

Fig. 4. Diagram of connecting sensors in the system

The architecture was designed to allow for modular scalability and accommodate configurations with multiple monitoring or application zones. In addition, its implementation in an embedded environment with local processing minimizes response latency and avoids dependence on cloud services, increasing the system's robustness in field conditions.

F. Experimental Validation

As part of the proposed system's methodological validation, a preliminary test phase was developed to verify the prediction model's behavior under real-world sensing conditions. To this end, 1000 experimental records were collected using the RS485 multi-parameter sensor in combination with the ESP32 microcontroller, replicating the complete operational flow: acquisition, calibration, preprocessing, and transmission to the artificial intelligence module. This partial validation aimed to confirm the integrity of the acquisition and normalization process for agro-environmental variables in field conditions without activating the mechanical actuators yet, as the dosing system is still under construction. The data obtained allowed for the evaluation of sensor consistency, reading stability under agricultural conditions, and proper integration with the embedded firmware.

Although these tests do not yet constitute an agronomic validation of the impact of the recommended doses, they represent a critical intermediate phase in the transition from the computational model to its functional implementation. The adopted methodology included validating the communication protocol between sensors and the ESP32, estimating background noise in key variables such as soil moisture and pH, and verifying the local inference flow within the microcontroller.

In parallel, an expanded experimental phase has been planned, which will include the integration of the complete mechanical prototype, its deployment in horticultural crop plots, and comparison against conventional fertilization methods. This stage will involve the collection of new measurements under different soil types, crop species, and agroclimatic conditions, as well as the monitoring of agronomic indicators such as yield, nutrient use efficiency, and reduction in applied inputs. The resulting data will be used to retrain the predictive model through continuous learning techniques, enhancing its adaptability and generalization capacity.

IV. Results

A. Conceptual Design of the Dosing System

The conceptual design of the fertilizer dosing machine was developed using CAD software (SolidWorks), ensuring dimensional and operational precision for each subsystem. This design incorporates mechanisms for the application of both solid and liquid fertilizers, integrated into an autonomous mobile platform equipped with GPS navigation. One of the main components for solid fertilizer dosing is the helical screw, whose geometry was calculated based on fertilizer type, rotation speed, and particle size, as shown in Fig. 5.

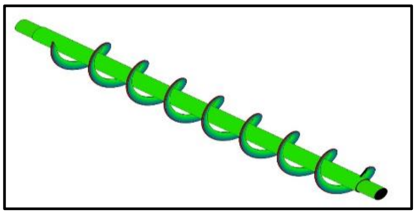

Fig. 5. Helical screw design

To maintain a constant flow towards the screw, a storage hopper was designed with the capacity to cover approximately one hectare of horticultural crops, as illustrated in Fig. 6.

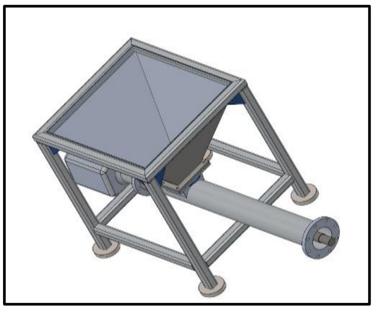

Fig. 6. Hopper design in solid fertilizer dosing system

The integration of the hopper, screw, and automated control mechanism forms the solid fertilizer dosing subsystem, shown in Fig. 7, whose simulation in SolidWorks verified the homogeneous distribution of fertilizer under different operating conditions.

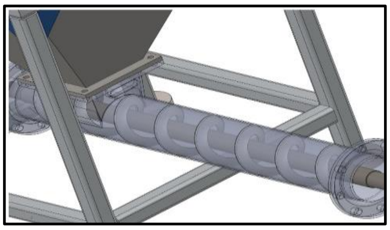

Fig. 7. Simulation of the helical screw in CAD software

For liquid fertilizer application, a fertigation module based on a peristaltic pump was developed and designed to operate synchronously with the solid dosing system and respond to recommendations generated by the artificial intelligence algorithm. Its structural design is shown in Fig. 8.

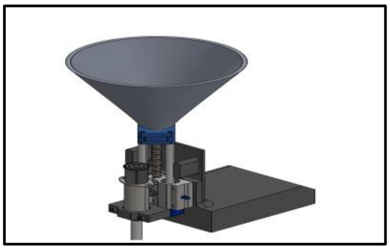

Fig. 8. Dosing system for liquid fertilizers

In addition, an autonomous chassis with traction and GPS navigation was designed to position the system according to predefined fertilization maps. The mechanical model of this locomotion system is shown in Fig. 9.

Fig. 9. Stand-alone mechanism for an intelligent dosing system

The complete integration of both dosing systems (solid and liquid) into the autonomous vehicle is presented in Fig. 10, allowing the precise and synchronized application of differentiated fertilizers.

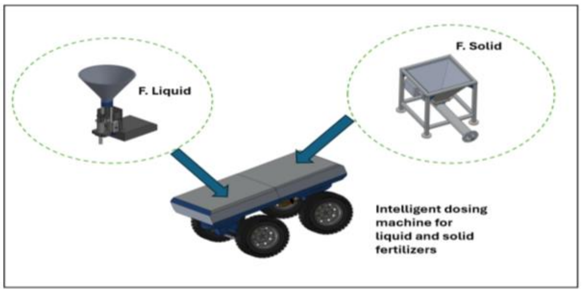

Fig. 10. Transfer mechanism for the application of organic and chemical fertilizers

B. Model Validation with Synthetic and Real Data

The predictive model was trained using a synthetic dataset of 10000 records generated through Sobol-LHS sampling. This dataset was designed to comprehensively cover diverse combinations of agro-environmental variables: temperature, soil moisture, pH, electrical conductivity, NPK concentrations, crop type, phenological stage, and soil type. This technique helped prevent sampling bias and improved the model's generalization capability across new scenarios.

A practical validation was performed using 1000 real-world measurements collected with an RS485 multiparameter sensor connected to an ESP32 microcontroller. These measurements, taken under actual field conditions, included humidity, temperature, pH, EC, and nutrient (NPK) data, and were directly processed by the embedded system, validating the complete data flow from sensor acquisition to AI model inference. During inference tests with real inputs, the system achieved an average latency of 14.6 milliseconds per sample while operating under FreeRTOS, confirming the computational feasibility of the model in a low-power embedded environment.

The prediction results obtained by the Random Forest model are shown in the following figures. Fig. 11 presents the relationship between actual and predicted values for nitrogen dosing (n_dose), showing close alignment with the perfect prediction line.

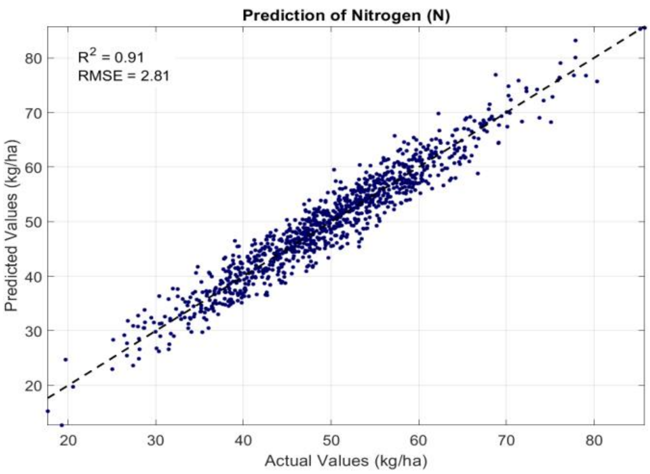

Fig. 11. Prediction of nitrogen (N) dose vs. actual values using random forest model

Fig. 12 displays the prediction results for phosphorus (p_dose). It demonstrates minimal dispersion of points from the ideal line, which indicates high predictive precision.

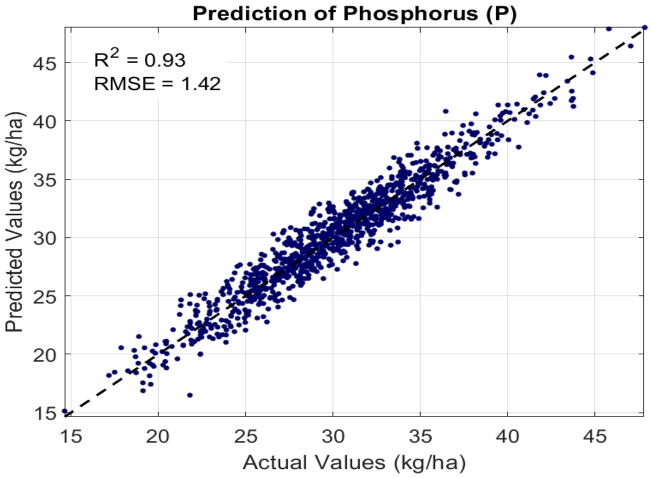

Fig. 12. Prediction of phosphorus (P) dose vs. actual values using random forest model

Finally, Fig. 13 shows the potassium (k_dose) results, with a highly aligned pattern, highlighting the model's ability to capture complex absorption and availability dynamics.

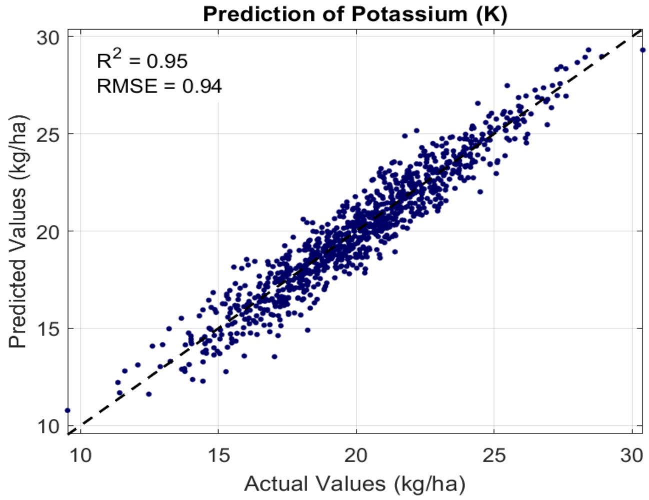

Fig. 13. Prediction of potassium (K) dose vs. actual values using random forest model

C. Predictive Model Performance and Accuracy Metrics

The Random Forest model exhibited high accuracy in predicting nitrogen, phosphorus, and potassium fertilization doses, both on synthetic and real sensor-processed data. The RMSE metric was used to quantify this precision, and the results are summarized in Table II.

TABLE II. RMSE VALUES FOR FERTILIZER DOSE PREDICTIONS BASED ON COMBINED SYNTHETIC AND REAL DATA

Nutrient	RMSE (kg/ha)	Data Source
Nitrogen (N)	2.81	Synthetic + Real
Phosphorus (P)	1.42	Synthetic + Real
Potassium (K)	0.94	Synthetic + Real

These values reflect accurate predictions in all cases. In particular, the model achieved an error below 3 kg/ha for nitrogen and below 1 kg/ha for potassium, which is highly relevant for large-scale agricultural applications. The low dispersion observed in Fig. 11, Fig. 12, and Fig. 13 further confirms the model's robustness against typical variations in agricultural environments.

From an agronomic perspective, these error levels translate into concrete benefits. Specifically, an RMSE of 0.94 kg/ha for potassium corresponds to a deviation of less than 5% in the field, potentially reducing input overuse by 10-15%. This leads to significant economic savings and mitigates the environmental impact associated with nutrient leaching. Moreover, the system's ability to dynamically adjust solid and liquid fertilizer doses based on real-time soil and phenological conditions enhances nutrient use efficiency. It promotes a more sustainable and profitable agricultural production.

D. Correlation Between Variables and Fertilization Doses

To complement the model's precision analysis, a Pearson correlation map was constructed to identify the relationships between input variables and the recommended fertilizer doses. Fig. 14 presents the correlation matrix generated from the 10000 synthetic records and the 1000 real measurements used during the model’s training and validation phases.

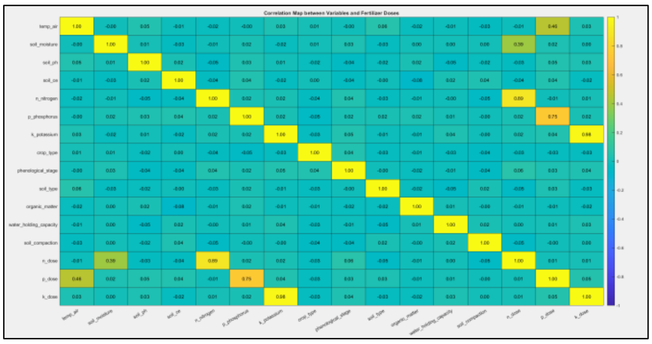

Fig. 14. Correlation map between fertilizer variables and doses

The most relevant findings include:

- Air temperature exhibited weak correlations with fertilizer doses, suggesting that thermal variations had a limited influence on nutrient requirements under the evaluated conditions.
- Soil potassium concentration showed a strong positive correlation with the potassium dose ($r = 0.98$), reinforcing the critical role of soil nutrient content in adaptive fertilization strategies.
- Extremely high correlations ($r > 0.99$) were observed among the three NPK doses, indicating a strong interrelationship modeled from the input data. This may reflect both agronomic synergistic responses and potential redundancies within the training dataset.

V. Discussion

The results obtained confirmed the technical feasibility of the proposed intelligent fertilizer dosing system. The Random Forest predictive model achieved RMSE values of 2.81 kg/ha for nitrogen, 1.42 kg/ha for phosphorus, and 0.94 kg/ha for potassium, demonstrating adequate precision for precision agriculture applications. This adaptive prediction capability, combined with its embedded implementation on low-power microcontrollers, enables autonomous execution under field conditions without the need for complex computational infrastructure. Compared to previous studies, the developed system presents substantial improvements. For example, the liquid fertilizer injection system presented in [92] was limited to a single application modality, lacking dynamic adjustment capabilities and soil sensor integration. In contrast, the present work integrates solid and liquid fertilization, multiparameter soil sensing, and adaptive control through machine learning.

The study in [88] demonstrated how proper NPK dosing impacts tuber yield, although using conventional strategies without real-time adjustment. The system proposed here overcomes this limitation by adapting fertilizer doses based on instantaneous soil and environmental conditions, increasing nutrient use efficiency and reducing the environmental impact associated with overfertilization. Regarding autonomous mobility, the vehicle presented in [93] integrated GPS navigation but lacked predictive capabilities based on intelligent soil sensing. In contrast, the system developed in this study combines autonomous locomotion with real-time adaptive decision-making for precise input dosing.

The correlation analysis revealed that soil potassium content maintained a strong positive correlation with the recommended potassium doses, while air temperature and soil moisture showed moderate correlations. Additionally, a high intercorrelation among the three NPK doses ($r > 0.98$) was identified, which may reflect both synergistic crop nutritional responses and potential redundancies that should be analyzed in future agronomic validations. Among the main agronomic implications, it is notable that an RMSE of 0.94 kg/ha for potassium represents deviations of less than 5%, resulting in input savings and increased production sustainability. Furthermore, the system’s ability to operate independently in rural environments with low connectivity provides a competitive advantage over solutions reliant on cloud-based processing.

However, the system also presents limitations. Although 1000 real measurements were used to validate the predictive model, a full agronomic validation with the final physical dosing machine has not yet been conducted. Controlled field trials are planned for future phases to evaluate agronomic responses and the independent effectiveness of nitrogen, phosphorus, and potassium recommendations. Overall, the proposed system constitutes a step forward toward the intelligent automation of plant nutrition in horticultural crops. It integrates robust predictive modeling, optimized mechatronic design, and efficient embedded processing. This solution offers a scalable, sustainable, and viable alternative to enhancing agricultural efficiency in low-resource rural contexts.

VI. Conclusion

This study proposed the development and partial validation of an intelligent fertilizer dosing system, integrating real-time multiparameter sensing and machine learning-based inference to optimize nutrient application in horticultural crops. The predictive model, based on a multi-output Random Forest, was trained with 10000 synthetic records generated through Sobol-LHS sampling and incorporated thirteen critical agro-environmental variables. Preliminary validation with 1000 real field measurements confirmed the compatibility among the sensing modules, embedded processing, and intelligent prediction, achieving RMSE of 2.81 kg/ha for nitrogen, 1.42 kg/ha for phosphorus, and 0.94 kg/ha for potassium. The main contribution of this research lies in the hybrid architecture designed, enabling the adaptive and coordinated dosing of solid and liquid fertilizers through a low-power embedded system programmed under a FreeRTOS environment. This dynamic adjustment capability, based on crop phenological stage and instantaneous soil conditions, represents a significant advance toward more efficient, sustainable, and scalable fertilization systems for precision agriculture in rural areas.

However, the system currently constitutes a proof of concept. Validation was limited to controlled agricultural conditions, without including extensive field trials across different crop types or under significant environmental variability. Additionally, the high correlation observed among the predicted doses of N, P, and K ($r > 0.98$) suggests the need to expand dataset diversity and refine training strategies to improve the independence of nutrient recommendations. Further technical factors such as long-term sensor stability, prolonged energy consumption, and end-user acceptance also require future evaluation.

Future research should conduct comparative field trials on sensitive crops such as potatoes and leafy vegetables, considering edaphoclimatic variability and water stress conditions. Moreover, exploring alternative models such as XGBoost or lightweight neural network architectures could further enhance low-power microcontrollers' predictive accuracy and computational efficiency. Addressing these aspects will enable progress toward the real and sustainable implementation of autonomous nutrient management systems in resource-constrained agricultural contexts.

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