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Original Article

Monitoring and Prediction of Hass Avocado Conditions Using Support Vector Machines on an Embedded Device

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Abstract *- This article presents an innovative monitoring and prediction system for the conditions of Hass avocado crops, aiming to manage resources better and achieve greater productivity. It is designed to address the technological limitations of Peruvian agriculture. The project focused on integrating sensors that collect a large amount of environmental data, including temperature, humidity, pressure, light, soil moisture, and rain/snow, which are processed in real time on an ESP32 microcontroller. A dataset of 900 instances was used; the system was categorized into three groups: "Requires Attention," "Optimal," and "Critical Range." A historical and georeferenced database was used; the Support Vector Machine (SVM) model identified temporal and spatial patterns, providing key perspectives for optimal irrigation schedules and the long-term effects of weather on plant health. By having an SVM model with a linear kernel, the system achieved an accuracy of 97.78%. The robustness of the model allows for identifying crop conditions, highlighting the transformative potential of machine learning in Peruvian agriculture, in addition to contributing to smarter agricultural practices.*

Keywords *- Agricultural management, Embedded system, Hass avocado, Machine Learning, Smart agriculture.*

1. Introduction

Hass avocado (Persea americana) is currently the most important avocado variety worldwide, dominating nearly 80% of the international market due to its resistance, flavor, versatility, and postharvest quality [1]. According to Comisión de Promoción del Perú para la Exportación y el Turismo (Commission for the Promotion of Peru for Exports and Tourism), global avocado consumption is growing at a rate of 5% annually, highlighting its high nutritional value due to its significant content of proteins, healthy vegetable oils, and antioxidant properties. However, climatic anomalies such as the "El Niño" phenomenon cause an average reduction of 20% in fruit size, which negatively impacts both the harvested volumes and the quantities destined for export [2]. Despite this adverse context, Peru's dynamism and competitive potential have positioned it as the second-largest avocado exporter in the world in 2020, only behind Mexico (which accounts for approximately 50% of global exports), with the regions of Lima, La Libertad, and Ica leading the country's exports [1]. In 2023, exports reached 570,000 metric tons, reflecting a 3% growth compared to 2022. However, this growth did not reach the initially projected 12.5%, which was later revised to 8% [2]. While expansion into new cultivation areas in the highlands aims to mitigate these risks, progress has been slow, and significant structural limitations persist in the agricultural innovation system. According to [3], the Comisión Técnica Regional de Innovación Agraria (Regional Technical Commission for Agricultural Innovation) identifies producers' low level of technological adoption as the main obstacle. Among the causes cited are the sector's high socioeconomic vulnerability, weak institutional coordination, limitations in research and development, reduced technology transfer, poor digitalization, and the lack of a clear identification of agricultural demands. Therefore, one of its priorities is to develop strategies for efficient crop management. Projections for 2024 showed a lower fruit yield per tree, with final quality and size still largely depending on climatic factors [2]. Nevertheless, the increase in exportable supply should not be based solely on the expansion of planted areas, but rather on continuous improvement in yield per hectare through the optimization of technical management of this crop and the analysis of production seasonality, so that opportunities arising when other countries, such as Mexico, reduce their supply can be exploited to cover counter-seasonal market niches. The integration of technologies such as machine learning significantly drives agricultural management, optimizing resource utilization. Likewise, Peru is not the only country seeking technological innovations for the agricultural sector. Data shows that agriculture represents between 65% and 70% of India's economy, therefore, studies [4, 5] have been conducted, which highlight those annual losses in agricultural production can reach up to 19% due to factors such as climate and the weak implementation of adequate technologies such as the use of Internet of Things (IoT) and machine learning. For this reason, it is important to analyze studies that address this type of implementation. In [6], the Random Forest algorithm achieved 99% accuracy in predicting suitable crops for specific terrains, while YOLO techniques have reached 34.83% accuracy in detecting the ripeness of cocoa pods [7]. These innovations align with the sustainable development goals by minimizing waste and maximizing productivity [8, 9].

In [10], the usefulness of IoT devices in collecting data on pH, humidity, and nutrients has been demonstrated, enabling informed decision-making to optimize nutrient absorption and reduce environmental impact. Monitoring soil fertility and water quality is essential for healthy crop growth. Machine learning algorithms such as SVM have proven particularly effective, achieving 99% accuracy in predicting the most suitable crops to plant [11]. On the other hand, techniques such as K-Nearest Neighbors (KNN) have shown 98.3% accuracy in predicting irrigation needs, optimizing water usage [12]. Similarly, drip irrigation systems have increased crop yield by up to 157% while reducing water consumption by 13.89% in avocado plantations [13]. Additionally, the implementation of automatic weather stations run by ESP32 microcontrollers, through continuous monitoring of environmental variables such as temperature and humidity, has achieved a 98% acceptance rate in cloud data transmission, which promotes sustainability through better decision-making [14-18].

The use of techniques such as KNN has proven to be economically viable in precision agriculture, optimizing water use and improving yield through recommendations on the type of crop according to the soil. For their part, SVM models have achieved an accuracy of up to 98.34% in disease detection, which suggests their potential in monitoring Hass avocado to improve plant health and profitability. Although CNNs can offer similar performance, they usually require more resources; in contrast, SVMs represent an efficient and practical alternative [19-22]. In [23], the implementation of SVM is reviewed, which has proven to be highly effective, achieving accuracy rates of up to 98.01% in the identification of crop diseases. Likewise, it is estimated that these diseases could cause yield losses of around 13%. Monitoring parameters such as temperature, humidity, and pH in hydroponic systems allows resource optimization and proper plant growth [24]. In addition, implementing low-cost automatic weather stations proves to be effective in real-time atmospheric data collection, supporting better decision-making in crop management [25]. Traditional methods lack precision and efficiency, which is why machine learning systems allow real-time monitoring, providing accurate recommendations for fertilization and crop management [5, 16]. These technologies promote the transition toward more sustainable agriculture, facilitating the efficient control of variables such as soil moisture, temperature, and nutrient levels [10]. Deep Learning (DL) and Machine Learning (ML) provide solutions by processing large volumes of data, allowing precise classification and prediction. Among these, SVMs stand out in binary and multiclass classification [26]. Despite these advances, establishing smart technologies introduces challenges in practices that protect digital data against unauthorized access, loss, corruption, or theft. As more IoT devices integrate into agricultural systems, ensuring data security becomes essential [24]. In [25], the use of the SD bus in 4-bit mode resulted in higher transfer rates and significantly lower power consumption, which translated into lower battery drain during write operations, despite the higher current flow. Likewise, the temperature monitoring system developed in [26] demonstrated that ESP technology with a 20,000 mAh battery makes it possible to operate for approximately one month with the deep sleep function between data transmission intervals.

Low-cost machine learning technologies have transformed traditional agricultural environments into semi-controlled systems. In [27], DHT22 sensors were used to measure temperature and humidity, and industrial-grade instruments were used for actuator management with the objective of preserving an adequate environment for the crop under study using control logic governed by the ESP32. Although projections suggest a decrease in the yield of agricultural production, the integration of advanced technologies such as machine learning is presented as a promising solution, since it not only optimizes resource use but also enables precise monitoring of critical parameters such as temperature and humidity, which are essential for avocado growth.

The implementation of machine learning models, such as SVM and KNN, has demonstrated their effectiveness in disease detection and irrigation optimization, offering a path toward more sustainable and productive agriculture. Therefore, it is necessary to apply solutions that improve the resilience of Hass avocado production against adverse climatic conditions, while promoting more efficient and sustainable agriculture. Conventional methods, which rely primarily on manual observations and data recording, are imprecise and cannot provide real-time information. In addition, they lack the capacity to process large volumes of data from various sources, such as climate conditions, humidity, temperature, and soil parameters. Therefore, they are insufficient to address the growing challenges posed by climatic anomalies, increase the risk of errors, and reduce decision-making effectiveness. In this context, there is limited literature on real field implementations. Nevertheless, the developed project allows the generation of historical data records, which are analyzed to optimize real-time decision making, anticipate future conditions and improve agronomic planning.

2. Methodology

An agile development strategy was adopted to integrate SVM into an embedded system for monitoring Hass avocado crop conditions. This strategy promotes constant iteration and the presentation of concrete results at each stage of development. Sensors were carefully selected and calibrated for precise measurements, and electronic circuits were designed for data collection and analysis. A software system was also developed to gather data and execute optimization algorithms.

The previously mentioned methodology addresses the complexity of sustainable and technological agriculture in a practical and flexible way, which allows continuous development that adapts to changing needs, achieving effective results gradually. Based on the above, the development of a monitoring solution to contribute to agricultural development is described. Data acquisition and subsequent processing allow for the creation of models, describing these processes in the research and construction of the prototype based on the ESP32 microcontroller. Finally, results related to weather prediction and crop recommendations are described.

2.1. Hardware

2.1.1. Sensor Selection and Evaluation

At this stage, sensors adapted for environmental monitoring in agricultural fields are used. Due to the need to capture information on heat and humidity perception, a DHT22 sensor is used, allowing efficient integration with the ESP32 microcontroller. Furthermore, it is necessary to acquire information on the existing light in the fields where, according to the literature review, the BH1750 digital sensor is widely used. This parameter is relevant because it allows inferring events related to crop photosynthesis. Furthermore, the BMP180 sensor complements the previous ones due to the need to perform validations on atmospheric pressure measurements.

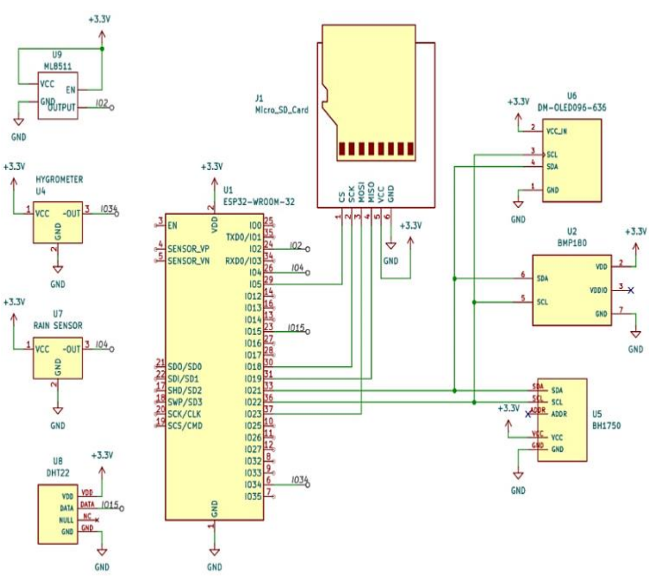

Fig. 1 Electronic circuit of the system

Additionally, a sensor for rain/snow detects precipitation, allowing for real-time adjustments in irrigation strategies. The soil moisture sensor ensures adequate irrigation, preventing issues such as waterlogging or drought, which could compromise root health. Finally, as a complement, an Ultraviolet (UV) sensor is integrated to evaluate radiation exposure. The ESP32 microcontroller serves as the central unit for managing data acquisition from all sensors. Figure 1 shows the electrical schematic of the environmental monitoring and data logging system. The system integrates analog and digital sensors that communicate via I2C and GPIO protocols to enable real-time data acquisition in agricultural environments.

2.1.2. Sensor Calibration

The reliability of environmental monitoring systems depends on sensor calibration using reference patterns suitable for agronomical applications. For the DHT22 temperature sensor, readings were adjusted using a thermocouple measured with a digital multimeter to provide a temperature reference. The sensor readings were compared with those obtained from the thermocouple under controlled conditions, and a correction factor was derived to adjust the sensor output. In the case of humidity, the gravimetric method was employed to adjust the DHT22 humidity sensor readings.

The soil moisture was determined based on the mass loss of a previously weighed sample after being subjected to a controlled drying process. Subsequently, the results obtained were compared with the readings provided by the sensor, and the discrepancy between both values allowed for calibration adjustment. The BMP180 readings were adjusted by comparing their values with data from a local weather station. The atmospheric pressure values recorded by the BMP180 were contrasted with the reference data, and an adjustment factor was applied to minimize discrepancies, with the objective of aligning the pressure measurements with recognized atmospheric information.

For the light intensity measurements, the readings from the BH1750 were adjusted using a reference based on lux measures. Meanwhile, the humidity sensor readings were adjusted using a hygrometer, which had been previously calibrated through the salt saturation method. This procedure employed a saline solution in equilibrium with a known relative humidity level (75% RH using sodium chloride) to establish a stable humidity environment.

2.2. Firmware

The control algorithm, written in C language for the ESP32, manages the real-time acquisition, visualization, and storage of data from multiple environmental sensors. The system utilizes sensors to measure air temperature and humidity (DHT22), atmospheric pressure (BMP180), light intensity (BH1750), soil moisture (capacitive sensor and hygrometer), UV radiation (GY-ML8511), and rain/snow presence (FC-37). Together with the signal conditioning, processing, storage, and machine learning modules, these sensors are organized within a modular embedded architecture, as Figure 2 illustrates the end-to-end flow from data acquisition to intelligent prediction. Code execution begins with pin configuration and the initialization of communication interfaces (I2C and SPI). Data acquisition is performed at 1-second intervals, while structured logging to a microSD card in CSV format occurs every 15 minutes. Simultaneously, sensor values are alternately displayed on the OLED screen every 5 seconds and transmitted through the serial port to enable real-time monitoring. Data flow is managed using non-blocking timers to maintain system responsiveness. Multiple validation routines ensure proper initialization of all sensors and the microSD card. Moreover, error-handling mechanisms are embedded to detect disconnections or malfunctions, triggering automatic reconnection attempts when necessary. The system also allows safe microSD card ejection and reinsertion via serial monitor interaction, without interrupting program execution.

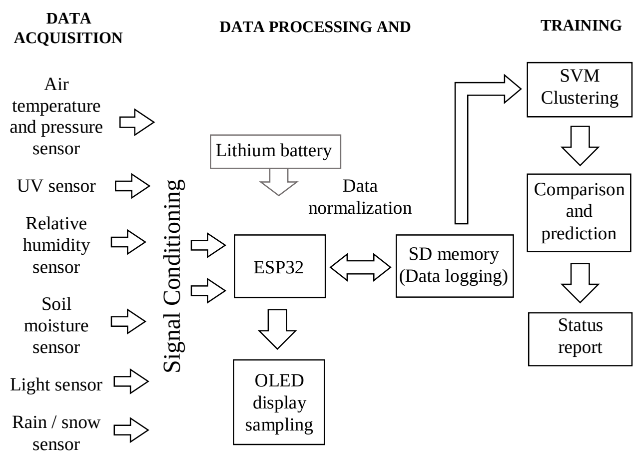

Fig. 2 Block diagram of the control algorithm

2.3. Machine Learning

This section describes the methodological process followed for the development of the prediction system based on SVMs. It covers sensor data processing, including data loading, filtering, and normalization. Subsequently, the SVM model training process is explained, detailing the parameter configuration and the data partitioning strategy for validation.

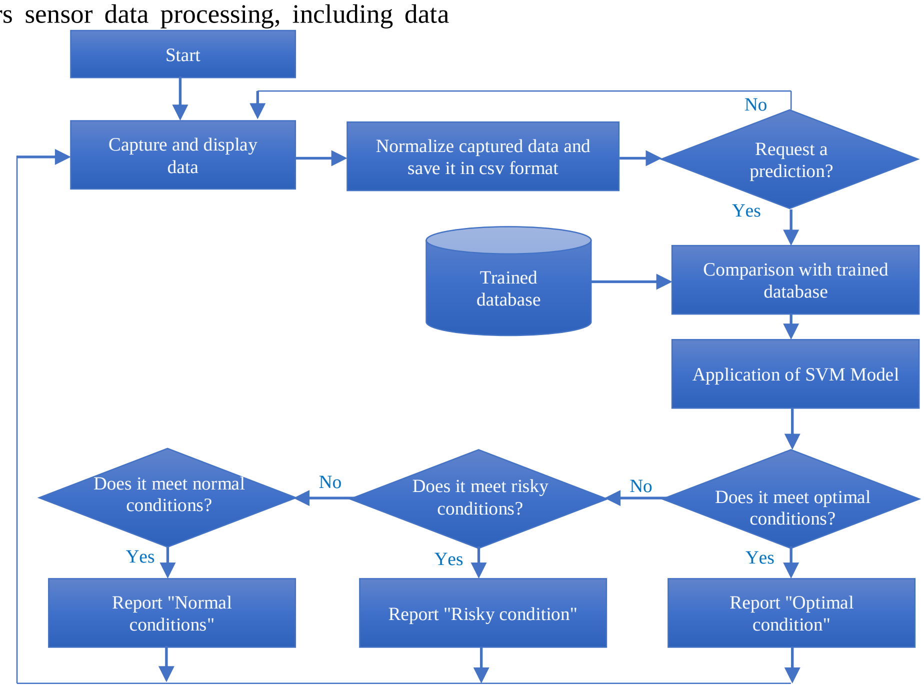

Fig. 3 Workflow of avocado crop monitoring and prediction system

The procedure for exporting the trained model into ESP32-compatible code and its integration into the microcontroller for real-time classification of monitored conditions is presented.

The complete process, from environmental data acquisition to predictive analytics using machine learning, is outlined in the workflow shown in Figure 3.

2.3.1. Data Acquisition

A UV radiation index between 3 and 6 is ideal, ensuring sufficient illumination for efficient photosynthesis.

However, indices above 7 are harmful, as they cause leaf and fruit burns. Wind conditions also play a significant role; while light winds promote proper ventilation, strong winds can lead to physical damage to trees, including fruit fall and structural damage.

Another critical factor is the chloride concentration, which must be kept below 4 meq/L to prevent toxicity.

Electrical Conductivity (EC) should also be maintained between 1.0 and 2.0 dS/m, as levels exceeding 2.5 dS/m hinder nutrient absorption due to excess soil salinity [28].

Table 1. Hass Avocado: productive range, dangerous ranges, and solutions

Parameter	Optimal Range	Critical Range	Solution
Temperature	20°C to 25°C during the day, 10°C at night	Less than -1.1°C and greater than 35°C	
Humidity	80% to 85%	Less than 40% and above 85% continuously	Irrigation and ventilation control, proper drainage
pH	5.6 to 6.5	Below 5: acidic Above 7: basic - alkaline	Use agricultural lime (cal). Balanced fertilization
Radiation	UV index of 3 to 6	Values above 7 (High UV index)	Paint the main branches and trunk with lime and agricultural Latex

2.3.2. Data Reading and Storage

The values collected by the embedded system are recorded and stored in a database using a microSD module. This module generates a ".csv" (Comma-Separated Values) file, selected for its simplicity and wide compatibility, ensuring the data remains accessible and easy to process. A database comprising 900 records was developed, with each entry representing sensor readings captured and stored at 15-minute intervals, facilitating the monitoring and subsequent analysis of environmental conditions based on the reference values outlined in Table 1. Additionally, the system was planned to include timestamps in each record, which allows the temporal tracking of the recorded variables and contributes to data analysis techniques, such as trend identification and predictive modeling.

2.3.3. Normalization and Standardization

Due to the variability of the data ranges generated by the sensors used in the system, a normalization process is necessary. For example, temperature sensors vary by tens of degrees Celsius (from -20°C to 45°C), atmospheric pressures range from 900 to 1100 hPa, and humidity values range from 35% to 100%. In the development of the models in this paper, the normalization process is applied to obtain data at the same scales, which is ideal for the training and prediction processes of the models, avoiding errors.

2.3.4. Model Training and Validation

The training process was performed using libraries and functions available in Python through the Scikit-learn libraries. In this case, when using a Support Vector Machine (SVM)-based algorithm, the training process used hyperparameters configured with values of C = 10 and gamma = 0.0001. Additionally, according to evaluations, the linear kernel was used, which was the most efficient for this dataset. The dataset was split for training and testing with cross-validation, considering 80% for training and 20% for validation using the train_Test_split() function. A console interface was developed to enter values and obtain predictions as part of the evaluation process. In the Python console, the tabulated data was displayed according to the classification of the output variable. The successful processing of the database was evident, reflecting how the model correctly categorized instances based on the established criteria. An example prediction using live sensor input is shown in Figure 4, where the entered environmental conditions were classified as "Optimal".

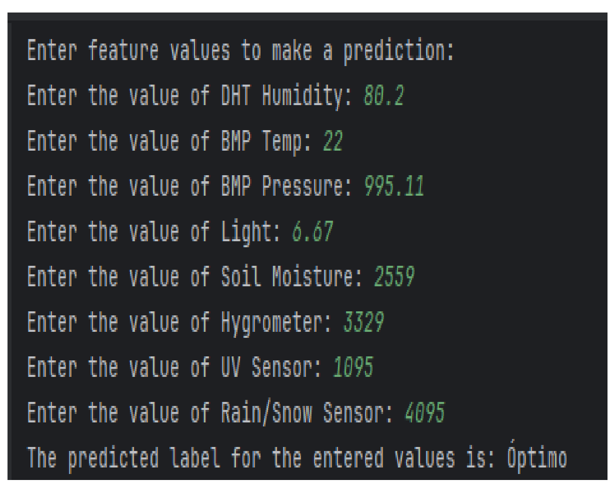

Fig. 4 Model validation in Python

The model learned to generate an optimal decision boundary based on the input data during optimisation. However, since performance on the training data does not guarantee generalization, the next stage involves evaluation and analysis of the model's performance.

The integration of Support Vector Machines (SVM) with MicroMLGen was selected for deployment on the ESP32, addressing the need for predictive analysis on resource-constrained hardware. SVMs are particularly well-suited for tasks requiring high classification accuracy, outperforming faster but slightly less precise methods such as k-NN or Naive Bayes [29].

2.3.5. Model Conversion and Adaptation

To execute the predictive system on the ESP32, it is essential to transform the trained model into a format compatible with the microcontroller. Due to the memory and processing limitations of the ESP32, machine learning models in their original format can be unsuitable, as they require external libraries and floating-point calculations that increase computational load. For this reason, the C language representation is used, allowing the model to be integrated autonomously and efficiently into the embedded system.

To perform the model conversion, it is necessary to transform the Python model into a format compatible with the ESP32 hardware using the micromlgen library. The model is exported to a file with a .h extension for import into the main program. The conversion result uses only native C++ functions, so there's no need to use external libraries.

Furthermore, considering RAM and FLASH constraints, the library optimizes the generated code to adapt its operation to the microcontroller. Code optimization considers elements such as floating-point numbers, transforming them to integers, and optimizing computation time on the device.

3. Results and Discussion

3.1. Results

The system successfully integrated the selected sensors with the ESP32 microcontroller. This validates its functionality for the development of an environmental measurement prototype. In this case, temperature and humidity sensors validated their use in low-power applications for battery-powered prototypes. Furthermore, soil temperature and humidity measurements provided direct information on the crop's status, enabling irrigation management in the event of anomalous events. The prototype demonstrated that it is possible to develop a solution with open-source hardware, tailored to specific field monitoring needs without the use of proprietary solutions, and considering IP65 environmental protection structures, ideal for outdoor conditions. As shown in Figure 5, this approach demonstrates the potential for applying low-cost, low-power technology to smart agriculture solutions.

Fig. 5 Prototype developed

The dataset used contained 900 instances, with eight features related to environmental conditions and one target variable labeled as 'quality', classified into three categories: Requires Attention, Optimal, and Critical Range. The data was split into 80% for training and 20% for testing.

The SVM model was trained using a linear kernel. Table 2 shows the reliable performance of the system with precision, recall, and F1-score above 95% in all classes according to the test sets, and a perfect performance (100%) in the classification of critical cases, demonstrating a robust capability to differentiate between agronomic conditions.

Table 2. Classification report

	Precision	Recall	F1-Score	Support
Critical Range	1	1	1	46
Optimal	0.95	0.95	0.95	37
Requires Attention	0.98	0.98	0.98	97

This choice was the most effective as it simplified the model and improved its interpretability, given that the data was linearly separable. Linear kernels are typically faster to train and less computationally intensive, particularly when handling large datasets. Figure 6 shows the results of the k-fold (k=5) cross-validation performed on the model, with an average accuracy of 96.94% and a standard deviation of 0.0055, indicating that the model maintains consistent performance across different training and testing data subsets.

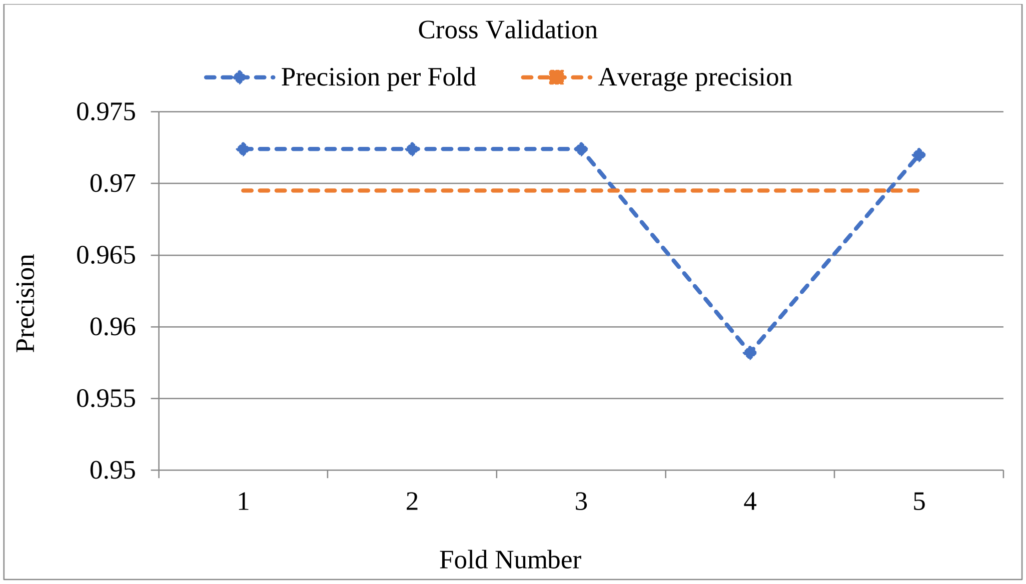

Fig. 6 Cross validation

The confusion matrix illustrates how predictions are distributed across the classification categories. The values along the main diagonal represent the number of correct predictions, while the off-diagonal values indicate misclassification errors. As shown in Figure 7, the confusion matrix for the model highlights the distribution of predictions across the three categories, with correct classifications along the diagonal and misclassifications in the off-diagonal cells. The results obtained from the implementation of the SVM machine learning model demonstrated accurate prediction of crop conditions. This model, in addition to predicting crop quality, has potential applications for optimizing irrigation decisions and resource management in other scenarios, contributing to the sustainability and productivity of agricultural systems.

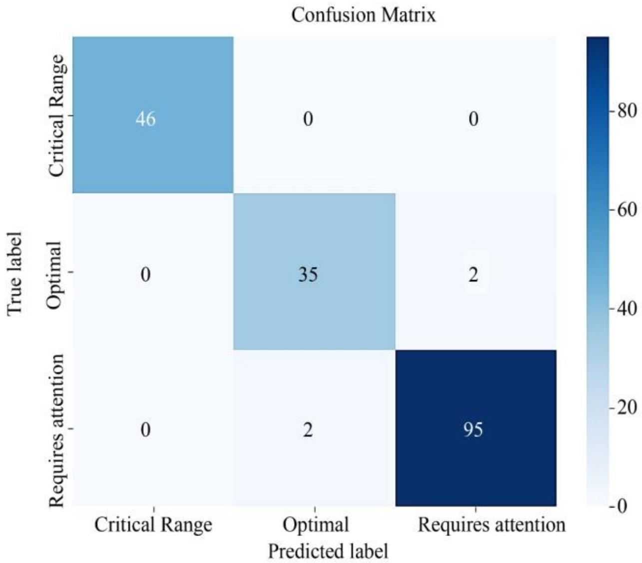

Fig. 7 Confusion matrix

Energy consumption tests conducted on the entire system, including the ESP32, sensors, and SD storage, showed an average current consumption between 80 mA and 120 mA during standard operation, highlighting its efficiency. With a 3700 mAh battery, these results demonstrate the viability of this approach in continuous monitoring environments, where autonomy and energy efficiency are crucial for the successful implementation of the system. Regarding the system interface, it was observed that it allows for reading the necessary input variables for the model, such as temperature, humidity, and solar radiation levels. Figure 8 illustrates the hardware parts of the prototype, highlighting the key components that enable parameter input and data processing. After processing these values with the SVM algorithm, the system generates a categorized output indicating that the entered conditions meet the established criteria for optimal growth of Hass avocado crops.

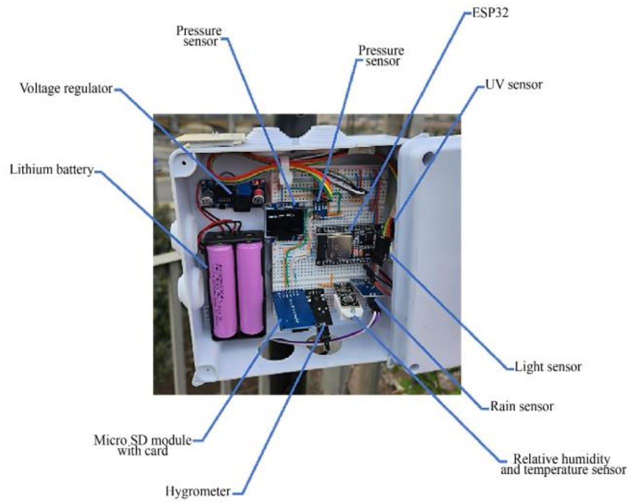

Fig. 8 Hardware parts of the prototype

The high accuracy level (97.78%) suggests that the model is highly effective in identifying crop conditions based on sensor readings. In SVM, training does not occur in epochs; instead, the optimization process happens in a single step, as the model directly fits a hyperplane to the data. Based on the detected values, the low-cost embedded system predicts three crop condition states.

3.2. Discussion

Several studies have highlighted the efficiency of smart agriculture through machine learning, technologies that also form the foundation of this project. Regarding crop prediction, algorithms such as SVM have demonstrated 99% accuracy in selecting optimal crops [11], which is directly comparable to our approach for predicting agricultural conditions using resource-constrained hardware. However, the use of heavier frameworks such as TensorFlow on devices like the ESP32 has proven inefficient due to its high energy consumption, reinforcing the decision to employ lighter and optimized models in this project [30]. Additionally, smart irrigation systems have improved crop yields by up to 157% [13], emphasizing the importance of accurate environmental variable monitoring, a key aspect of this research. Several technical challenges emerged during the implementation of the Hass avocado crop monitoring system. The connection of multiple sensors - including those for temperature, humidity, air and soil moisture, light, radiation, and pressure - caused a voltage drop, affecting their functionality. A voltage regulator powered by lithium batteries was integrated to resolve this, stabilizing the output at 3.3V. A further challenge associated with the microSD module pertained to issues with recognition, which were attributable to power instability when multiple components demanded energy concurrently. This is a critical challenge in low-power systems such as the ESP32. Compared with other studies that have utilized Support Vector Machines (SVMs) and random forest models on more advanced platforms, implementing models on low-resource hardware is subject to processing and energy constraints [6, 11]. Notwithstanding the limitations, the implementation of efficient algorithms and an energy-conscious design approach enabled the project to achieve its objectives.

The SVM-based prediction system has facilitated precise forecasting of crop conditions, thereby providing early alerts to inform decision-making processes concerning irrigation and fertilization management. The device's portability and low power consumption make it well-suited for deployment in remote agricultural contexts, where optimized resource utilization is paramount. For system upgrades, remote monitoring via Bluetooth connectivity can be used. Long-term data analysis using big data-based processing tools can also be used to optimize decision-making. The literature indicates that electrochemical sensors, such as hydrogen potential (pH) or electrical conductivity, can be added in the case of sensors. These upgrades improve more precise control of resource use, resulting in sustainable agriculture if remote control steps are added to automated irrigation or climate control processes, considering the scalability of the solution.

4. Conclusion

The use of the ESP32 microcontroller demonstrated its low power consumption for this type of application when integrated with low-cost sensors. This validates its architecture for similar deployments, considering that it can be integrated with prediction models in the field of smart agriculture. Furthermore, when the SVM model was integrated, it was possible to predict crop status, optimising resource use related to irrigation or fertiliser application.

The results showed an accuracy of 97.78% in predicting the condition of avocado crops, validating its efficiency with the hyperparameters selected during the training process. Furthermore, the integration of previous record history and the location of the readings taken allows for the identification of anomalous behavior and patterns of evolution in the monitored variables. All the information acquired contributes to decision-making regarding irrigation timing, predicting crop evolution based on long-term climate, and defining preventative crop interventions. The device demonstrated its low power consumption (using current measurements ranging from 80mA to 120mA), enabling its use in locations where conventional power is unavailable or where extended runtime is required. Furthermore, while integrating machine learning models into embedded devices requires code optimization, their use in environments close to the data source makes it a critical technique when low-latency prediction processes are required.

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