Edge computing in Smart Agriculture scenario based on TinyML for irrigation control

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***Abstract*—Various regions around the world are encountering substantial difficulties as a result of arid conditions, vulnerability to climate change, and water shortages. These factors present significant obstacles to maintaining agricultural practices. Water stress resulting from limited water availability adversely affects crop growth and productivity. To tackle this pressing issue, the application of *Tiny Machine Learning* (TinyML) models for optimizing crop irrigation is proposed.**

TinyML involves implementing machine learning algorithms on resource-constrained devices, such as microcontrollers. By collecting and processing meteorological and crop data, a TinyML model has been trained to optimize irrigation practices and detect crop anomalies in real-time. This approach has the potential to revolutionize agricultural practices by enabling precise and efficient water management, even in remote environments.

This work tackles the first steps to implementing TinyML algorithms for irrigation. We have computed the relationship between humidity and temperature changes with NDVI (Normalized Difference Vegetation Index) anomalies in crops to make predictions and make intelligent decisions toward water usage.

***Index Terms*—TinyML, smart agriculture, irrigation**

I. Introduction

Around half of the world's population is experiencing severe water shortages at least part of the year and only 5% of the water on Earth is potable and usable.
Unfortunately, estimations lead us to believe that these numbers will be worst in the near future due to climate change, pollution, and population growth [1].

Over the last 30 years, food production has increased by more than 100 %, and it is estimated that 60 % more food will be needed to meet the nutritional needs of the population by 2050 [1]. It is therefore crucial to manage the water used for agriculture correctly, as it accounts for such a high percentage of total water consumption.

The Region of Murcia is one of the driest areas in Spain, making it highly vulnerable to climate change and water scarcity. Agriculture is an important economic activity in the region, and the intensive use of water for irrigation has led to a situation of water stress. Given this scenario, optimizing irrigation in crops becomes a key measure to save water and ensure the sustainability of agricultural production in the region. Therefore, the main objective of this work is to obtain and process meteorological and crop data from Murcia to develop and subsequently train a Tiny Machine Learning model that can optimize crop irrigation and detect anomalies in real time.

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Agriculture is continually evolving through technological advances. Precision agriculture comprises a series of techniques and tools to increase the quality and productivity of soil and crops. The aim is to produce more with fewer resources while maintaining high quality in the process.

In precision agriculture the comprehensive collection of data and information helps in making the right decisions and corrections to optimize production, energy [2] and water usage [3]. For this, sensors, actuators and satellite images are essential in order to precisely control relevant parameters such as vegetation indexes and their relation with other parameters such as humidity, temperature, and radiation.

Smart agriculture is the evolution of precision agriculture and includes not only gathering data but also analyzing it by means of Artificial Intelligence.

In that sense, we can separate the technologies into two: the ones to gather data and the ones to analyze it.

A. Data gathering: Internet of Things, sensors and green indexes

Sensors, drones and satellites, among others, are used for accurate data collection. Those technologies are part of the paradigm known as Internet of Things (IoT). IoT consists of the gathering and exchange of information between sensors and actuators and, in the case of agriculture, can help to improve decision-making by the automatic gathering of data about weather, soil quality and other environmental factors like evapotranspiration and green indexes, which can affect crop growth [4]. Those concepts can help in deciding how to make the agriculture process, such as crop irrigation [5]. Satellites allow us to obtain up-to-date images of crops with high precision. Amongst the many possibilities that can be understood through satellites, green indexes are derived from these images and are widely used in smart agriculture to monitor crop growth, detect stress conditions, and optimize farming practices. One of the most commonly used green indexes is the Normalized Difference Vegetation Index (NDVI). NDVI is calculated based on the principle that healthy vegetation absorbs most of the visible light (mainly red) for photosynthesis and reflects a significant portion of the near-infrared (NIR) light. The formula for NDVI is as follows:

$$NDVI = (NIR - Red)/(NIR + Red)$$

The result of the calculation is a value that ranges from -1 to +1. High positive NDVI values (close to +1) indicate dense, healthy vegetation, while low or negative values indicate sparse or stressed vegetation.

NDVI is a quantitative measure of vegetation health. By regularly assessing NDVI values, farmers can identify areas of the field that exhibit abnormal or declining vegetation growth that is indicative of nutrient deficiencies, diseases, pests, or water stress; yield estimation since NDVI values correlate with crop productivity; and irrigation management since NDVI values indicate water stress, farmers can adjust irrigation schedules accordingly, ensuring water is applied when needed, thus reducing water wastage and improving water use efficiency.

Edge computing provides significant advantages in irrigation control for smart agriculture:

- Real-time Decision Making: Through local data processing on edge devices, prompt analysis and decision-making regarding irrigation scheduling and water distribution can be achieved.
- Reduced Latency: By eliminating the need to transmit data to a central server, edge computing ensures faster response times, enabling timely actions for efficient irrigation.
- Optimized Bandwidth Usage: Local data preprocessing and selective transmission of relevant or aggregated information reduce the data volume, optimizing the utilization of limited network resources.
- Enhanced Data Privacy and Security: Processing sensitive agricultural data on edge devices mitigate risks associated with transmitting data to a remote server, ensuring enhanced data privacy and security.
- Offline Capability: Edge computing enables the irrigation control system to function autonomously even in areas with limited or no internet connectivity, guaranteeing uninterrupted operation.
- Scalability and Flexibility: Deploying multiple edge devices across the agricultural field forms a distributed network for data processing, allowing for effortless scalability and flexible deployment tailored to specific irrigation requirements.

B. Data analysis: Artificial Intelligence, Big Data and Tiny Machine Learning

In recent years, the application of Big Data and Artificial Intelligence (AI) has introduced innovative ways to revolutionize the agricultural sector [6]. In agriculture, Big Data can significantly enhance productivity and sustainability by revealing patterns and trends through the analysis of large datasets, providing crucial information for informed decision-making [7]. The implementation of AI in agriculture involves utilizing machine learning algorithms and expert systems to assess crop conditions and make immediate, precise decisions, akin to those of an expert. AI and machine learning improve crop performance prediction by leveraging real-time sensor data and visual analysis from drones and satellite imagery. By combining sensor data on moisture levels, fertilizers, and nutrients, the growth patterns of individual crops can be analyzed over time. Ultimately, machine learning enables predictions to optimize crop performance [8]. Traditional smart agriculture systems often rely on cloud computing and require a stable internet connection, posing challenges in remote locations or areas with limited connectivity, a very common scenario in the frame of agriculture. These challenges could be solved by following a TinyML approach. Communication activities can consume more energy than moderate processing tasks on these devices. Therefore, local computation for making intelligent decisions can be more suitable than relying on remote processing. This is particularly important considering that many IoT devices are powered by batteries. Additionally, reducing the transmission of raw data helps to minimize cybersecurity risks and decreases the computational burden of cryptographic operations, resulting in lower energy consumption [9]. TinyML, a machine learning technique focused on extremely compact devices with limited storage capacity, holds immense potential despite their low computational power and storage. Their characteristics, such as low power consumption and low cost, make them attractive for machine learning applications. Real-life IoT applications call for coordinated efforts from different entities aiming at widening the cognitive capabilities of the complete system, although the integration of intelligent decision-making mechanisms within constrained end devices is a great advance. Considering the individual circumstances of the elements deployed in highly distributed environments is crucial. However, there is still a gap in this regard as this kind of solution has not been deeply investigated in the literature yet [10]. The field of TinyML presents significant obstacles, including the constrained computational resources of microcontrollers, the absence of a cohesive framework, and the scarcity of open-source TinyML datasets. Nevertheless, TinyML holds immense potential due to the widespread availability and affordability of microcontrollers. By leveraging TinyML, it is conceivable to reduce energy consumption, lifetime costs, and inference latency in IoT devices while enhancing data privacy and intelligence [11].

When considering the implementation of edge computing in IoT devices, it becomes evident that the limited computational resources of microcontrollers pose a considerable challenge. This challenge is further compounded when employing standard neural network-based machine learning (ML) algorithms. To address this issue, lightweight software frameworks, tools, and libraries have been recently developed, specifically tailored for microcontrollers, facilitating the creation of TinyML models. Once the model is constructed, it can be integrated into the source code of IoT devices to enable ML capabilities

[11].

Nonetheless, the lack of a unified framework capable of supporting a diverse range of hardware poses a significant hurdle in the field of TinyML. Notably, the process of developing TinyML models differs from traditional ML approaches, as the model is typically created on a more efficient computer and subsequently transferred to a microcontroller for inference operations [11].

Enabling microcontrollers on these devices to execute machine learning models can unlock new frontiers in machine learning. Currently, only approximately 1% of generated data worldwide is utilized daily due to the staggering volume of information produced every second by integrated systems (around 250 billion), which cannot be processed entirely on a server for predictive purposes. The limitation of connecting all sensors to a network or the excessive energy and resource consumption required to constantly load information, often due to low power and memory capacities, results in missed opportunities for real-time responses to received data and information. Traditional application of machine learning algorithms typically necessitates several days to obtain meaningful results.

This is where the potential of TinyML becomes evident: making real-time decisions and predictions by executing machine learning algorithms directly on devices or sensors, considering their low energy (mW) and memory (KB) consumption. The key lies in avoiding the computationally expensive training of machine learning models within the tiny sensors or devices. Instead, the training is conducted separately, and once the model is obtained, it is inserted into the sensor as hexadecimal code. As a result, the device only needs to perform inference or prediction using real-time data and make decisions based on these predictions. The goal is to employ these applications to power integrated devices, enabling them to operate for extended periods, ranging from weeks to months or even years. Thus, the key lies in employing techniques such as quantization to reduce the time and memory required by these algorithms, focusing on making inferences rather than conducting training. In agriculture and crop irrigation, this technology opens up new possibilities for real-time decision-making using sensors and devices to obtain more precise and localized measurements and parameters, such as temperature and humidity [12]. TinyML models represent compact machine learning models tailored for devices with constrained resources. They conduct on-device data processing for swift predictions using streamlined inference methods. These models employ quantization to economize memory, execute feature extraction, and encode information with efficiency. By utilizing low-power hardware, TinyML facilitates instantaneous, privacy-aware, and highly responsive applications. Its adaptability allows the integration of sensor data and applications across diverse domains, tackling scalability and customization challenges. The integration of TinyML in smart agriculture presents a compelling prospect for leveraging sensor technology to enable real-time predictive capabilities over extended durations in agricultural settings characterized by inadequate internet connectivity or limited network infrastructure, a prevalent scenario within the domain.

The main contributions of this paper are summarised as follows:

- Creation of a dataset that relates NDVI, humidity, and temperature.
- Definition of NDVI anomalies in a scenario with multiple sensors.
- Development of a TinyML methodology able to relate NDVI anomalies to temperature and humidity measurements in real time.
- A TinyML model that achieves high precision in the prediction of NDVI anomalies while being able to run in constrained hardware due to the optimization and quantization done to this model.
- Lay the groundwork for the creation of a smart irrigation system based on TinyML, therefore able to run in remote smart agriculture locations with constrained hardware.

II. Background

The development of an anomaly detection system for crop irrigation adheres to a customary approach employed in constructing Tiny Machine Learning (TinyML) applications and systems. The construction of a TinyML system involves a series of indispensable steps and methodologies. The collection and preprocessing of data play a crucial role in the construction of a TinyML system, significantly impacting the accuracy and efficiency of the machine-learning model. Given the limitations of low-power devices, it is vital to define pertinent features for the model's input. To this end, preprocessing techniques such as normalization, noise removal, sampling, and feature selection are employed to amplify data quality and ensure compatibility with the model.

The selection of an appropriate machine learning model and its effective training are of paramount importance in attaining accuracy and efficiency in a TinyML system. Considering the limitations of such systems, the selected model must be lightweight, computationally efficient, and capable of delivering satisfactory performance. Decision trees, support vector machines (SVM), k-nearest neighbors (KNN), and neural networks are popular models well-suited for TinyML applications, providing intriguing options for our study.

Upon training the model to meet the desired performance criteria, it is deployed onto the target TinyML device. This deployment process involves transforming the model into an executable format, such as TensorFlow Lite. During this stage, the constraints of the target device, including memory, processing power, and energy efficiency, are taken into account. Model optimization techniques, including quantization, pruning, and compression, are employed to reduce the model's size and enhance its efficiency without causing significant performance degradation. In our optimization endeavors, we will leverage the TensorFlow Python library.

Within our study, we will utilize quantization as a pivotal technique in the Tiny Machine Learning (TinyML) approach.

This technique offers an effective solution to address resource limitations encountered in microcontroller-based systems. Quantization involves reducing the numerical precision of model parameters and activations, enabling efficient computation and optimal memory utilization.

In the realm of TinyML, quantization serves as a fundamental approach to optimize machine learning models, particularly in scenarios with severely constrained computational resources. Through quantization, the continuous-valued parameters and activations are discretized into a fixed-point representation with reduced bit width. This reduction in precision significantly reduces the memory footprint and computational requirements of the model, making it well-suited for deployment on resource-constrained microcontrollers.

The quantization process involves determining an appropriate bit width to represent the parameters and activations, striking a balance between preserving model performance and achieving resource efficiency.

The advantages of quantization in the TinyML domain are substantial. By reducing the bit width of model parameters and activations, quantization leads to a significant reduction in memory usage, which is crucial for microcontroller-based systems with limited storage capacity. Furthermore, quantization enables more efficient computations, resulting in faster inference times and lower energy consumption. Although there may be some accuracy loss due to the reduced precision, the overall trade-off between resource savings and acceptable performance degradation renders quantization a valuable technique in the TinyML approach.

III. Related Work

In related literature, several studies have focused on the implementation of smart irrigation systems to conserve water in different regions. For instance, the relationship between vegetation indices (including NDVI) and atmospheric and biological factors have been investigated in [13]. The study found positive correlations between vegetation indices and temperature, solar radiation, and chlorophyll content, while negative correlations were observed with precipitation. Considering these findings, the NDVI has been identified as a crucial factor for smart irrigation since it reflects plant water stress. Although the NDVI itself cannot be used directly in the TinyML approach, studies have shown that other parameters such as temperature and humidity can be correlated with NDVI and used as inputs for the model. The main idea is to control irrigation by detecting anomalies in continuously collected sensor data and taking appropriate actions, such as regulating irrigation, making real-time decisions, and performing predictions, to achieve efficient crop management. A comprehensive review of the potential and effectiveness of implementing Tiny Machine Learning (TinyML) to enable Edge Intelligence is presented in [14]. It evaluates how TinyML can enhance the efficiency and accuracy of intelligent edge systems. The authors engage in a detailed discussion on various aspects of TinyML, including algorithm selection and resource optimization for low-power device implementation. They conclude that the implementation of TinyML can significantly improve the efficiency and precision of intelligent systems. A scientific review of anomaly detection based on Tiny Machine Learning, specifically focusing on low-power devices (TinyML) is gathered in [15]. Its aim is to analyze the techniques and machine learning algorithms used in anomaly detection and evaluate the effectiveness of implementing these techniques on low-power devices. The authors provide an in-depth discussion of machine learning techniques and algorithms employed in anomaly detection, encompassing supervised learning, unsupervised learning, and reinforcement learning. They conclude that implementing anomaly detection techniques based on Tiny Machine Learning can significantly enhance efficiency and real-time anomaly detection accuracy on low-power devices. The article [16] introduces a TinyML-based system for active and optimized microclimate control in greenhouses. The system aims to maintain optimal temperature, humidity, and light conditions in the greenhouse to maximize crop production and minimize energy consumption. It consists of a set of sensors measuring various microclimate variables such as temperature, humidity, and lighting, and a low-power microcontroller running a TinyML-based machine learning model to predict real-time optimal growing conditions. The results indicate that the system can predict optimal growing conditions with an average accuracy of 85%, demonstrating high precision in predicting optimal crop conditions. In conclusion, these articles highlight the significant potential of TinyML technology for smart agriculture applications and underscore the importance of ongoing research in this field. Implementing TinyML systems in agriculture for anomaly detection, real-time issue identification, and correction could greatly enhance water usage efficiency and crop productivity, particularly in regions like Murcia facing water scarcity challenges.

IV. Methods and Materials

Our final goal is to design and build a TinyML system that is able to detect in real-time anomalies that are related to irrigation in crops in order to redefine the irrigation strategy.

Once an anomaly is detected, the network adapter of the sensor that contains the TinyML model would be activated, and the responsible farmer is notified about the need to adjust the irrigation rate at that specific moment.

The first step to achieve this objective consisted of the collection of a comprehensive dataset that includes meteorological and agricultural data from the Region of Murcia. Such a dataset is then used to train various machine-learning models. These models will be reduced and optimized to make predictions of NDVI anomalies in crops using sensors or resource-limited devices.

A. Description of Collected Data and Sources

The NDVI measurements used for anomaly detection are derived from Sentinel-2 satellite imagery from the European Space Agency (ESA). Temperature and humidity measurements were obtained from five agro-meteorological stations within the SIAM (Sistema de Información Agrario de Murcia)

tmed	hmed	NDVI_mean	Anomaly	anomaliesAgg	anomaliesAgg2
21.192	69.925	NA	NA	0.154	0.5
20.167	61.275	0.447	0	0	0
10.333	89.754	0.378	0	0.076	0.5

TABLE I
FRAGMENT NDVI ANOMALIES MO12

network, identified as "CA42", "CA91", "MO12", "MU21", and "MU62". These data were provided by the IMIDA (Instituto Murciano de Investigación y Desarrollo Agrario y Alimentario). Specifically, we utilized the average temperature, measured in degrees Celsius using a thermometer, and the average relative humidity, measured in percentage using a hygrometer. The NDVI, temperature, and humidity measurements were collected from parks and gardens in the Region of Murcia, with their geographic locations and dimensions provided by EMUASA (Empresa Municipal de Aguas y Saneamiento de Murcia).

B. Construction of the Dataset and the anomaly index

The steps carried out to create the dataset are the following:

- Data cleansing: Problematic samples, which may include outliers, missing values, or data inconsistencies, are meticulously identified and addressed. Samples with erroneous or incomplete information are either removed from the dataset or replaced with valid data points. This step ensures that the data used for analysis is of the highest quality and free from any aberrations.
- Descriptive analysis: A comprehensive understanding of the data is fundamental for making informed decisions. To achieve this, a detailed descriptive analysis is conducted. This analysis goes beyond raw data and involves the exploration of relationships among various features within the datasets.
- Datasets integration: The datasets utilized in this study are derived from various sources and may come in distinct formats. To facilitate a unified and coherent analysis, the processed datasets are merged into a single dataset. This integration process involves additional steps such as the inclusion of relevant variables that will be calculated, such as NDVI anomaly indices.
- Time-Series Preprocessing: We included past values of the same attribute. This technique enables the model to consider the temporal variations realistically. By relating these previous values to each other, the model can harness these insights for improved predictions. This step proves particularly valuable in situations where historical trends and patterns play a crucial role in understanding the data dynamics.

The objective was to obtain a dataset where the parks with measurements are grouped by meteorological station, and for each date or every 5 days given the constraints on the NDVI, we count with temperature, humidity, and NDVI measurements for each park. Figure 1 shows the location of several parks and the contour of one of them. This allowed us to determine the number of parks exhibiting anomalous NDVI values and to establish relationships between these three parameters for predictive purposes. Several R programming language scripts were developed to construct this dataset. The data were normalized, formatted, and filtered, noise and missing data were eliminated, and three NDVI anomaly indices were created as the output parameters for our machine-learning models. For the first two indices, an NDVI anomaly was considered when an NDVI measurement in a park fell within the 10th or 90th percentile of all NDVI measurements taken in that park. For the third index, an anomaly was considered if it belonged to the 20th or 80th percentile. The first NDVI anomaly index, "AnomaliesAgg", was calculated by dividing the number of NDVI anomalies occurring on a specific date by the number of park contracts in each row. This approach took into account the absence of NDVI measurements for some parks, thus achieving a balanced anomaly index. The second index, "AnomaliesAgg2", was calculated by dividing the number of anomalies by the total number of NDVI measurements. Visually, this index is easily understandable but does not consider NA values in the NDVI measurements. The third index, "AnomaliesAgg3", was calculated by dividing the number of anomalies corresponding to the 20th and 80th percentiles by the total number of park contracts. In addition to these NDVI anomaly indices, input parameters were added to the dataset for our Machine Learning models. These input data include temperatures and humidities for each date, NDVI measurements for each park, temperatures and humidities for the previous ten days, the average temperature and humidity variations over the previous ten days, and the number of valid NDVI measurements for each date. Table **??** presents a representative fragment extracted from the dataset of station MO12. This fragment includes for each NDVI measurement date, the mean temperature and humidity recorded on that date by the meteorological station, the average NDVI measurement from a specific park, binary indicators denoting anomaly (1) or non-anomaly (0) status, accompanied by two computed NDVI anomaly indices. These indices are determined based on a comprehensive aggregation of measurements acquired on the respective date.

V. EXPERIMENTS

A. Model Selection and Training

In the development of our machine learning model, the decision was made to utilize the Python programming language due to its essential libraries, Tensorflow and Tensorflow Lite. These libraries are crucial for transforming a model with the aim of implementing it later on tiny devices with limited memory and computational capacity. For our problem, we selected a regression model based on random forest, a linear regression model from the scikit-learn library, and a neural network model from the Keras library in Python. The Random Forest model leverages a multitude of decision trees to achieve robust predictions across diverse domains while mitigating overfitting risks. The Linear Regression model, establishes a linear relationship between input features and

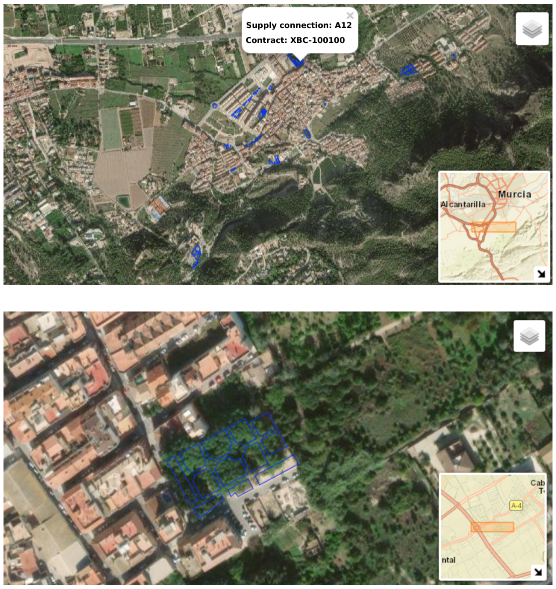

Fig. 1. Parks in Algezares, Murcia (up) and contour of one of the parks (down)

a continuous target variable, facilitating interpretation and prediction within various analytical contexts. The Neural Networks model emulates the interconnected structure of human neural networks to process complex data. Comprising layers of interconnected nodes, or neurons, it learns intricate patterns and representations from data. Various tests and experiments were conducted on these models, involving the modification of hyperparameters and the use of three distinct NDVI anomaly indices. Furthermore, multiple tests were performed to determine the minimum number of NDVI measurements required to bias the dataset. It was found that for both values below and above 70 measurements, the results worsened within a range of 20% to 30%. From these experiments, it was concluded that the best results were achieved by utilizing the NDVI anomaly index “AnomaliesAgg3” which defined an anomaly if the NDVI measurement fell within the 20th or 80th percentiles. Specifically, the best results for each model are as follows:

- For the random forest regression model, using 1000 decision trees and a randomness factor of 42, with the output variable set as “AnomaliesAgg3”, an RMSE of 0.062 and a CVRMSE of 27.4182 were obtained, as we can see in Figure 2.
- For the linear regression model, when employing the variable “AnomaliesAgg3” as the output, a CVRMSE of 30.16 and an RMSE of 0.073 was achieved, as we can see in Figure 3.
- For the sequential neural network model, 10 different runs were performed to obtain the average accuracy achieved by this model. The average RMSE was found to be 0.0644, with a mean CVRMSE of 41.423 and a standard deviation of RMSE of 0.00335, along with a standard deviation of CVRMSE of 2.4098. The best model from these 10 runs will be utilized for the subsequent phase of quantization and optimization, yielding an RMSE of 0.05891 and a CVRMSE of 36.8849, as we can see in Figure 4.

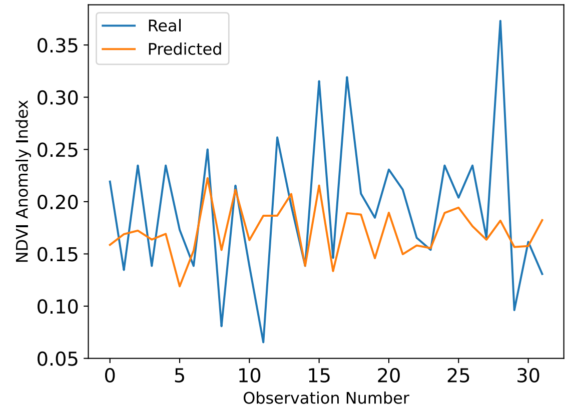

Fig. 2. Predictions from the Random Forest regressor model of AnomaliesAgg3.

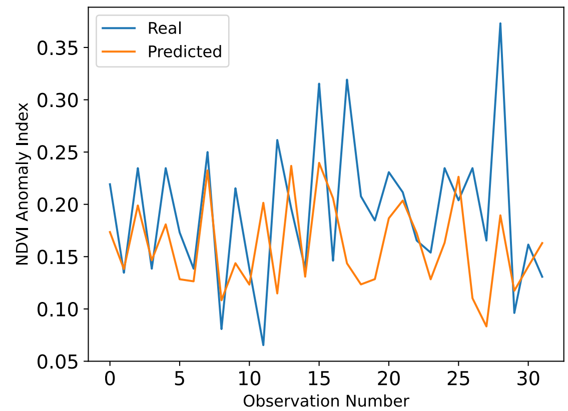

Fig. 3. Predictions from the Linear Regressor model of AnomaliesAgg3.

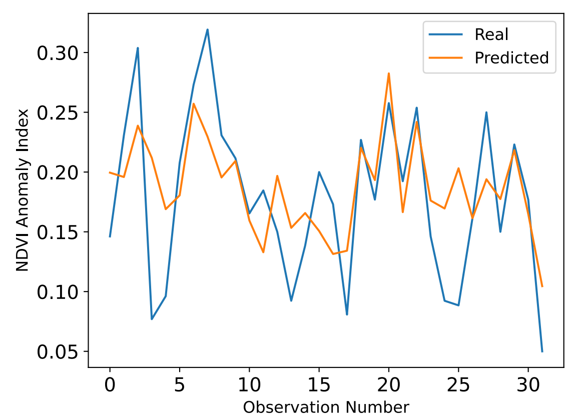

Fig. 4. Neural Network model predictions from AnomaliesAgg3, best-case scenario.

B. Model Optimization and Reduction

The optimization and adaptation of the model to reduce its size are essential for its implementation on small devices with limited resources such as memory, computation, and energy. It was concluded that the quantization technique was suitable and sufficient to reduce the size and complexity of our previously generated neural network model. The suitability of this technique lies in the fact that all the data we work with are 32-bit floating-point numbers, so reducing them to 8-bit integer data will result in improved memory usage. First, the previously generated best neural network model was transformed into a TensorFlow Lite model. This transformation was carried out using the converter provided by the TensorFlow Lite library in Python. Once we had the converted model, the default quantization of the TensorFlow Lite library was applied, resulting in a model size reduction of 82.5% and even an increase in accuracy by 10.93%. The size of the quantized model was 6208 bytes compared to the 35104 bytes of the unquantized model. The new model achieved an RMSE of 0.05878 and a CVRMSE of 32.8478, as we can see in Figure 5, compared to the previous model's RMSE of 0.05891 and CVRMSE of 36.8849. With this size reduction, it becomes feasible to continue building the TinyML system, allowing for the future implementation of the quantized model on the sensors.

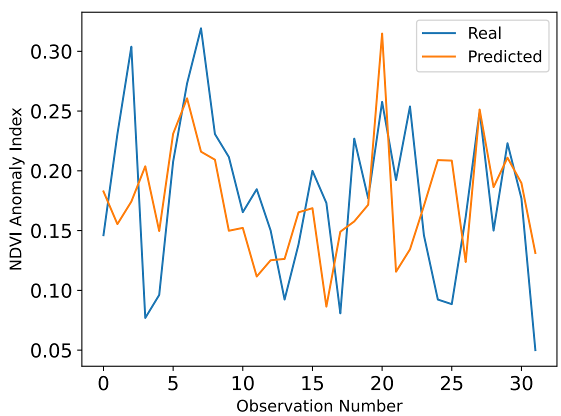

Fig. 5. Predictions from the quantized neural network model of AnomaliesAgg3.

C. Validation

The outcomes derived from this study can be subjected to validation and verification through the subsequent phase involving the application of a TinyML procedure. This stage encompasses the development of an executable program coded in Arduino. The TinyML model, procured during prior stages, is encoded in hexadecimal format and then infused into sensors situated within parks, gardens, or agricultural fields. This integration aims to discern instances of abnormal NDVI variations by concurrently considering the incessantly amassed temperature and humidity data furnished by the sensors. The initial stride entails the preliminary testing and validation of the operational efficacy of the system on one or two selected sensors. Subsequently, after confirming the accuracy and fidelity of the prognostications, the integration of the predictive model can be expanded to encompass a broader array of sensor nodes. This endeavor will facilitate an assessment of the model's scalability across a more extensive network of sensors, thereby substantiating its utility and adaptability.

VI. CONCLUSIONS

This study addressed the optimization of irrigation using a TinyML-based approach. The goal was to design and build an irrigation control system capable of real-time anomaly detection in crops and making precise irrigation decisions. Conventional machine-learning approaches were found to lack the immediacy required for predictions and decision-making. Therefore, TinyML was chosen as it can run machine learning models on devices with significant limitations in memory, energy, and computing capacity. Efficient resource utilization, including memory, energy, and time, was highlighted during the construction of the TinyML system. Algorithm and data structure selection were crucial to achieve a balance between model performance and memory usage. A comprehensive data collection and preprocessing process was conducted, utilizing the Normalized Difference Vegetation Index (NDVI) and measurements of temperature and humidity from weather stations in various parks and gardens in Murcia. A relationship between these parameters and NDVI anomalies was established, resulting in a valuable dataset for future studies in this field. The outcomes derived from this study will provide foundational insights for subsequent investigations aimed at refining and optimizing irrigation practices to achieve water conservation objectives. These insights will further be subjected to experimental implementation and validation within agricultural fields and garden environments, thus contributing to the advancement of practical methodologies in water management. The generated and optimized model will serve the purpose of prognosticating plant health, ascertaining water requirements, and identifying anomalies in NDVI through the integration of temperature and humidity data. This information will consequently enable informed irrigation decisions to be made in forthcoming contexts. Regression models based on Random Forest and linear regression were selected and trained using Python and the Scikit-Learn library. Different combinations of input and output variables were evaluated, and incorporating previous temperature and humidity measurements yielded promising results. In conclusion, a TinyML system was successfully developed, providing real-time detection of crop anomalies and enabling precise decision-making regarding irrigation systems. Including previous temperature and humidity measurements significantly improved the model's accuracy, and the "AnomaliesAgg3" anomaly index was the most effective in predicting NDVI anomalies. This study involved various tasks to apply the TinyML approach to smart irrigation, including problem definition, feasibility assessment, methodology adaptation, identification of influential factors, data acquisition and preprocessing, construction of a comprehensive dataset, model selection and training, model optimization and reduction, and evaluation and analysis of results. Although this study demonstrated the feasibility of using TinyML to optimize irrigation in the Murcia region's agriculture, there are several areas for improvement and future considerations. Potential areas for exploration include incorporating other environmental parameters and variables related to irrigation, leveraging pre-trained models from related agricultural domains, implementing the system on specific hardware devices, conducting additional tests and validations in real agricultural environments, ensuring scalability, continuous improvement of algorithms and models, considering economic aspects and farmer adoption, and promoting training and awareness activities. In summary, this study establishes the foundation for an effective TinyML-based irrigation control system. However, further research is needed to enhance accuracy, scalability, and practical viability.

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