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Nurturing Agribusiness: A Sustainable Farming System for Tomato Crop Management Leveraging Machine Learning

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Abstract— The agriculture industry is undergoing a transformative shift with the introduction of IoT technology, enabling global connectivity for farmers. This technology offers a plethora of advantages, ranging from precise seed selection based on soil analysis to efficient crop maintenance, water management, and enhanced marketing support for improved profitability. To further enhance tomato farming practices, we propose the implementation of a smart farmer marketing assistant that streamlines the process of segregating yield based on its growth stage, reducing labor and time requirements.Further, the frame work is capable of early-disease management system that can detect diseases like early blight,light blight, buck eye rot and anthranose and suggest remedy. By adopting this innovative approach, financial losses associated with traditional methods are minimized.The traditional practice of combining all categories of vegetables (ripened, unripened, and partially rotten) in a single container often results in reduced shelf life for the produce. In our framework, we employ color sorting to categorize the vegetables, ensuring proper packing into their respective bins. This valuable data is made accessible through a cloud environment, providing potential buyers with comprehensive information about the yield, its category, and pricing. This increased visibility empowers farmers to reach a global market and sell their produce at competitive prices.

In this context, we present a case study focused on the tomato crop, where we have successfully developed a prototype utilizing ESP32, a color sensor, and Google Firebase. This comprehensive framework effectively harnesses the power of IoT, Machine Learning, and potential marketing strategies, transforming the way farmers manage their crops and connect with buyers on a global scale with highly accurate 87.9% experimental results.

Keywords- TCS 3200 Color sensor, ESP32, Firebase, Kodular, Disease Management,Machine Learning.

I. INTRODUCTION

Technology has a significant and successful impact on society in today's world. Advancements in technology have profoundly transformed human life. Banking, communication, business, and health care are some of the domains where it might be used [1]. However, the agriculture industry is not yet fully explored the available power of Technology. Farming, crop production and Marketing place significant role in strengthening economic power of farmer. In this aspect the technology usage will definitely stabilize the agriculture industry as well as financial status of farmer and boost countries economic power of our country which is primarily depend on agriculture. Authors [2] successfully employed IoT based approach for soil nutrient analysis for groundnut crop.

Despite of fruit and vegetable production is high, the farming industry is always deprived supporting prices as they are not properly marketed within their shelf life [3]. Enzymatic activities influence the color parameters a*, b* of tomatoes [4]. For example, if tomato crop is not marketed within 5 days of the yield, they are useless. In various instances, farmers are forced to discard tomatoes onto the streets as they fail to recoup their initial investments. The agricultural supply chain shows a significant disparity: consumers face higher prices due to intermediaries and transportation costs, while farmers struggle to meet their minimum investment requirements. Factors

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include multiple intermediaries adding to the retail price and transportation costs impacting farmers, especially in remote areas. Fluctuating market prices and unpredictable weather add to farmers' challenges. To address this, transparent supply chain practices like direct-to-consumer models and technology-driven platforms can reduce intermediaries, benefiting both farmers and consumers. Government support and improved access to resources and markets can empower farmers. A collaborative effort from stakeholders is needed for a fair and sustainable agricultural ecosystem. In this regard we proposed IoT based frame work for farming community which addresses above problems. As a case study we considered tomato crop in which acknowledge is used for sorting and packing the crop as well as communicating with potential buyer. If ripe and unripe vegetables or fruits are combined, the half-ripened vegetables or fruits will be harmed due to the ripe vegetables or fruits' rapid rotting properties. The technology-based sorting avoids the problems associated with manual sorting such as subjectivity, unreliability of human judgment, worker tiredness and time taking process.

Our framework uses the ESP32 (32-bit Micro controller), TCS3200 color sensor, Supervised machine learning prediction technique and Google cloud environment – Firebase. The TCS3200 sensor is used to collect the sample information, which can convert the color of a sample in R, G, and B values. These R, G and B values are used to train the machine learning algorithm and generate the model which will be implemented using ESP32. Firebase is used for remote communication and maintaining the real-time databases between farmer and potential buyers. Tendolkar [5] proposed "Care Bro" IoT based environment that ensured seamless farming and support ethical Pest management for the agriculture. In a study by Arko Chatterjee [6], a smart assistant for farmers was proposed, utilizing IoT and deep learning techniques. The main focus of their research was on plant disease classification, using leaf images as the basis for identification. Emerson Navarro [7] proposed" PRISMA" (preferred reporting items for systematic reviews) which enable a review process that use the data so that crop problems are reduced and improve the accuracy associated with crop diagnosis. Ritika Srivastava [8] proposed arduino based solution for analyzing soil properties and controlling water management for the Agriculture fields. Partha Pratim Ray [9] proposed emphasizing on Technologies, practices and future direction of IoT in smart agriculture. Authors [10] emphasized cloud-based solution for smart agriculture management. Yang [11] proposed a case study using machine learning for strawberries to diagnose ontogeny status of the crop and predicting harvesting time.

This comprehensive discussion explores the challenges associated with crop health monitoring, as well as the critical task of disease detection and classification in agriculture[12]. The analysis highlights the integration of advanced machine learning and deep learning techniques to provide effective solutions. Additionally, the transformative potential of the Internet of Things (IoT) framework is emphasized by authors [13,14,15,16] for collectively support the remarkable progress in developing IoT frameworks to agricultural applications.

II. EXISTING APPROACH

Most of the current approaches in the field of crop categorization rely on image-based analysis, which often comes with significant overhead. This overhead is primarily due to various preprocessing steps, such as segmentation, thresholding, and morphological operations, which are required both during the creation of the dataset and the testing of samples. These processes can be time-consuming and resource-intensive, making real-time analysis challenging to achieve. Additionally, incorporating predictive models for accurate classification further increases the time complexity of these approaches.

In the realm of IoT-based solutions, machine learning has not been extensively explored due to the constrained environment of the controllers. Factors such as limited RAM, battery life, compatibility with communication devices, and the absence of supporting software packages have posed significant challenges in implementing machine learning algorithms in these systems. Consequently, many existing IoT-based solutions have not integrated machine learning, limiting their potential for more sophisticated and accurate crop categorization.

Moreover, cloud-based models and mobile-based approaches are not always suitable for handling crops with limited shelf life, such as tomatoes. Time-sensitive crops require immediate processing and decision-making, making it impractical to rely solely on cloud-based solutions, which may introduce delays in data transfer and processing.

In response to these challenges, our proposed framework offers a comprehensive and holistic solution. By integrating machine learning with cloud-based IoT technology, we can achieve automatic sorting, real-time cloud interaction, and even provide a marketing assistant for farmers. Our framework leverages the power of machine learning to streamline and expedite the sorting process, reducing the overhead associated with traditional image-based approaches. Furthermore, by connecting the system to the cloud, we ensure seamless and instant data transfer, allowing for real-time analysis and decision-making, even for time-sensitive crops with limited shelf life.

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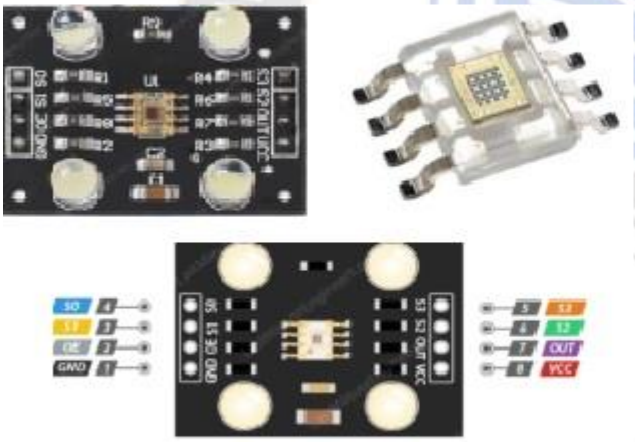
The machine learning and cloud-based IoT framework presented here offers a game-changing solution for the agriculture industry, addressing the limitations of existing approaches and paving the way for more efficient and accurate crop categorization. With the ability to perform automatic sorting, communicate with cloud servers, and provide marketing assistance, this holistic approach promises to empower farmers and enhance the overall productivity and sustainability of the agriculture sector. By overcoming the challenges posed by constrained environments and time-sensitive crops, our framework opens up new possibilities for harnessing the full potential of technology in agriculture

III. ARCHITECTURAL COMPONENTS

The proposed framework covers materials, methods, and architecture and flow process.

A. Color Sensor

For most of the automation applications in various types of industries such as food and beverages, Agriculture, Textiles, Automotive and Manufacturing, Color sensors are used to identify material, detecting color marks on objects, and validating manufacturing stages and so on. By leveraging the



TCS 3200 Color Sensor

TCS 3200 color sensor in our proposed approach, we aim to enhance the efficiency and accuracy of color-related tasks, making it a valuable addition to the field of research and application development. Its wide availability, cost-effectiveness, and user-friendly design open up new possibilities for various domains. A color sensor is classified into three kinds based on how the light is converted into photo-current, analog voltage, digital signal. We're utilizing a color sensor that converts light to digital in this approach. White light is formed by majorly with three primary red, green and blue color and distinct wavelengths. Color shades are created by collectively blending the primary colors. When white light falls on material surface, a portion of light is absorbed and the other is reflected. Exact amount of wavelength is depend on property of material surface and decides the color what we see. The color sensor module operates by exposing an object with a high-intensity white light which is generated by its four LEDs and then measuring the color reflected back and its brightness. The RGB color filters of the photo diode covert the light into current and subsequently into voltage suitable for processor reading. The color sensor in a digital camera uses a grid of photo diodes known as a Bayer filter to perceive the color of reflected light, as shown in Figure 1. The Bayer Pattern divides each pixel into four filters, namely red, blue, green, and clear. Each filter sends only one color of light to the photodiode beneath it, except for the clear filter which sends all light to the photodiode. This is particularly useful in low-light situations as the additional light passing through the clear filter is a significant benefit. The results obtained from the array of photo diodes are averaged and then provided to the processing chip. The proportionate levels of red, green, and blue light are then measured to determine the color of an object.

The TCS3200 uses an 8 × 8 array of photo diodes (totally 64) to detect color among them16 each for red filters photodiodes, green filter photo diodes, blue filter photo diodes and no filters photo diodes. In our setup, Table 1 serves as a key reference guide that outlines the specific color modes associated with different combinations of S2 and S3 pin settings. Each unique setting in the table corresponds to a distinct color mode, enabling us to precisely control which photodiode is active and ready to detect light within a particular wavelength range associated with the desired color.

TABLE I. TCS 3200 FUNCTION & OUTPUT FREQUENCY

Photo Diode Switch Function			
S2	S3	Photodiode type	Output Frrequency %
LOW	LOW	Red	Power down
LOW	HIGH	Blue	2%
HIGH	LOW	Clear (No filter)	20%
HIGH	HIGH	Green	100%

The table typically includes a list of color modes and their corresponding S2 and S3 pin configurations. For instance, a specific row in the table might indicate that setting S2 to High and S3 to Low will activate the photodiode dedicated to detecting red light, while another row might indicate that setting S2 to Low and S3 to High will activate the photodiode designated for blue light detection.By referring to Table I and configuring the S2 and S3 pins accordingly, we can easily switch between different color modes. Table II shows pin functionality of TCS3200. This flexibility in color selection allows us to tailor our sensing process to match the specific needs of our project or experiment. Inbuilt C-F-C (current to

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Frequency converter) of the sensor will provide input to the micro controller which will be in the range of 2HZ to 500KHZ. The output frequency is scaled using control pins S0 and S1. The frequency is then scaled into one of the three pre defined levels (2%,20% and 100%). Most of the applications use a 20 percent scaling factor.

TABLE II. TCS3200 PIN FUNCTIONALITY

Pin No	Pin Name	I/O	Description
4	GND		Ground
3	OE	I	Enable Output Frequency
6	OUT	O	Output Frequency
1,2	S0,S1	I	Scaling selection inputs for O/P frequency
7,8	S2,S3	I	Selection I/P for photodiode type
5	VDD		Voltage Supply

B. ESP 32

The ESP32 is a versatile 32-bit microcontroller, as depicted in Figure 2, that comes equipped with built-in Bluetooth and Wi-Fi capabilities. This combination of features makes it an ideal choice for developing applications that require seamless connectivity and communication with other devices or networks. The built-in Bluetooth functionality allows for easy integration with Bluetooth-enabled devices, while the Wi-Fi capabilities enable wireless data transfer and internet connectivity. One of the key advantages of the ESP32 is its suitability for projects with specific constraints, such as low cost and low power requirements. Due to its efficient design and energy-saving features, the ESP32 is well-suited for battery-operated or power-sensitive systems. This makes it a popular choice for Internet of Things (IoT) devices, wearables, smart home applications, and various other embedded systems where power consumption and cost considerations are critical.

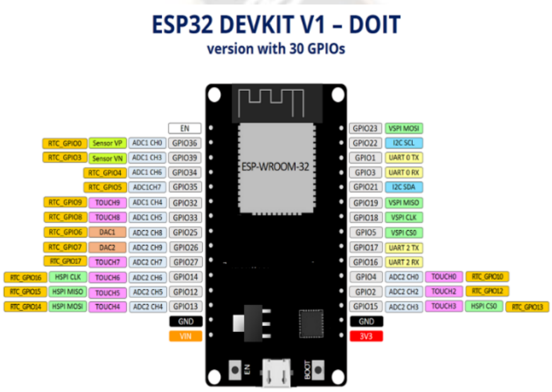

Figure 1. ESP 32 Pin Functionality

Moreover, the ESP32 offers a rich set of peripherals and interfaces, providing developers with a wide range of options for incorporating additional sensors, displays, and communication modules into their projects. This flexibility allows for the creation of complex and feature-rich applications without the need for extensive external components.

Additionally, the ESP32 is supported by a robust and active community, which means that developers have access to a wealth of resources, tutorials, and libraries to aid in their projects. This support network contributes to the popularity and widespread adoption of the ESP32 in various industries and domains.

C. Random Forest Algorithm

Random Forest stands as a powerful and widely used classification algorithm, distinguished by its ability to construct a diverse ensemble, aptly referred to as a "forest," comprised of multiple Decision Tree models. This unique approach engenders enhanced predictive capabilities and robustness, as predictions are obtained by aggregating the outputs of all constituent trees in the forest. The construction of each individual Decision Tree within the Random Forest follows a cleverly orchestrated process. Specifically, it commences by selecting a random subset, or sample, from the training dataset to serve as the input for the tree's creation. This deliberate randomness introduces an element of diversity and variability in the data leveraged by the different trees, thereby mitigating the risk of overfitting and fostering generalization prowess.

As each node of the Decision Tree is scrutinized, an additional layer of randomness is deftly woven into the mix. Herein, only a random subset of predictors is considered when determining the optimal split point. By doing so, the model acquires a unique ability to focus on diverse sets of features during each decision-making juncture, culminating in a more robust and adaptive ensemble.

The efficacy and adaptability of the Random Forest are further augmented through the skillful manipulation of two crucial parameters: RFOR_SAMPLING_RATIO and RFOR_MTRY. The former allows the user to specify the sample size used during tree construction, affording fine-grained control over the variance in the ensemble. The latter parameter, RFOR_MTRY, enables the specification of the number of predictors to be sampled at each node, contributing to the diversification of individual tree behaviors.

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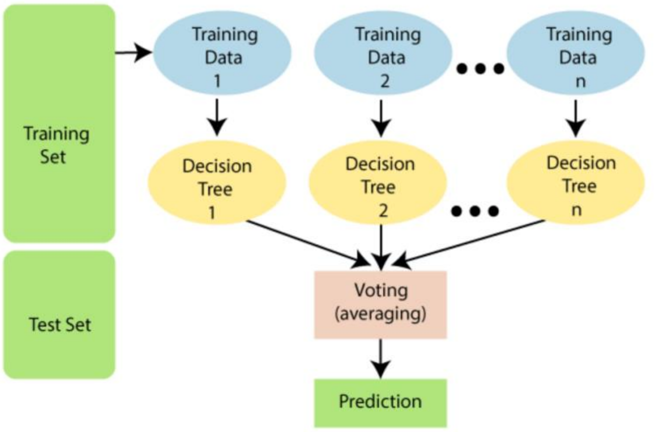

Figure 2. Random Forest Algorithm Structure

The Gini index plays a pivotal role in decision tree algorithms and other machine learning models, facilitating the evaluation of data partition purity and impurity during feature selection and data splitting processes. Through Gini index analysis, we can precisely quantify the level of homogeneity within each data partition, where a lower Gini index indicates higher purity, while a higher Gini index denotes greater impurity.

A perfectly split dataset, with distinct "Yes" or "No" categories, is considered pure, yielding a Gini index of 0. Conversely, when data is evenly distributed across multiple classes, it is regarded as highly impure, resulting in a Gini index of 0.5 (applicable for binary classification).

In the decision-making process, we select the feature with the lowest Gini index (or highest purity) to serve as the root node in the decision tree. This decision tree recursively partitions the data based on the chosen feature, aiming to maximize homogeneity within each resulting subset.

The mathematical calculation of the Gini index involves summing the squared probabilities of each class' occurrence in a given data partition, subtracted from 1. The formula for the Gini index is represented as:

$$GI(x) = 1 - \sum_{x=1}^{n}(p_x)^2 \quad (1)$$

$$= 1- [(P_+)^2 + (P_-)^2] \quad (2)$$

Where P_+ and P_- are positive class and negative class probabilities. Adjusted Gini index which is overall Gini index of this split is calculated as

$$\text{Adjustted Gini Index} = \sum_{x=0}^{n} \frac{nx}{n} GI(x) \quad (3)$$

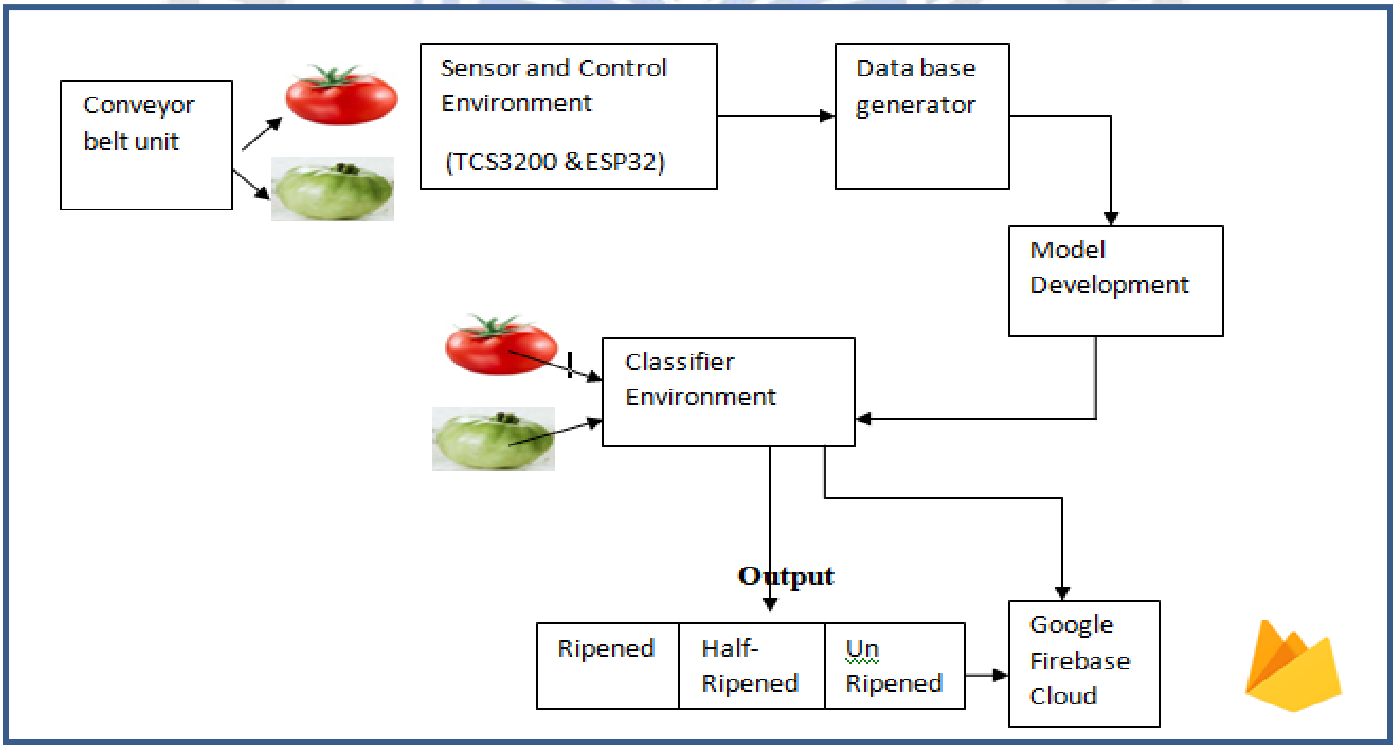

Figure 3. Architectural Framework

D. Model Generation using Micro ML

Micro ML is a transformative approach that aims to democratize machine learning techniques and make them accessible to microcontrollers, revolutionizing the way these tiny embedded devices can handle sophisticated tasks. It achieves this by converting complex machine learning algorithms into optimized C code, allowing them to be seamlessly deployed and executed on microcontrollers. The significance of Micro ML lies in its ability to bring the power of machine learning to resource-constrained devices, which

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typically have limited processing capabilities, memory, and energy constraints. By converting the machine learning algorithms into optimized C code, Micro ML ensures efficient execution and resource utilization on these microcontrollers.

The implementation of Micro ML enables the porting of various classifiers, such as Decision Tree, Random Forest, SEFR, PCA, and more, to the C language. This enables developers and engineers to harness the capabilities of these sophisticated classifiers directly within the Arduino IDE environment, creating a seamless integration of machine learning capabilities with their microcontroller-based projects.

This groundbreaking advancement in Micro ML opens up a realm of possibilities for creating intelligent and data-driven embedded systems. For instance, an ESP32-based weather monitoring system can now leverage machine learning algorithms to predict weather patterns and optimize energy consumption based on real-time sensor data. Arduino-based robotics projects can implement decision-making algorithms using Decision Trees or Random Forests, enhancing their autonomy and adaptability.

The widespread adoption of Micro ML has paved the way for a new era of smart and efficient embedded systems that can perform tasks once considered beyond the reach of microcontrollers. Its ease of implementation and compatibility with popular microcontroller platforms have garnered significant interest from hobbyists, researchers, and industry professionals alike

E. Kodular- Mobile App Development

Kodular is a popular code-free online suite for mobile app development. It empowers users with its intuitive Blocks editor and plug-and-play components, making it ideal for beginners in app development. The platform offers a comprehensive set of features, including Project Management, GUI design, and Work Flow Management, streamlining the app creation process.

Kodular's advantage lies in its compatibility with various Android devices, ensuring wide audience reach. Additionally, it supports connectivity and database components, making it suitable for IoT app development.

Overall, Kodular's user-friendly interface, code-free approach, and extensive functionality make it a valuable tool for app development, catering to both beginners and experienced developers.

F. Google Firebase

This advanced data management system leverages the power of cloud computing, enabling real-time data management with its efficient NO SQL data handling capability. With a focus on tag and value-based organization, it streamlines the process of storing and retrieving information, making data handling a seamless experience for users.

One of the standout features of this system is the robust security it offers. Users can rest assured that their data is protected with state-of-the-art encryption and access controls. Additionally, the system ensures global accessibility, allowing users to access and manage their projects from anywhere in the world, further enhancing collaboration and convenience.

For users seeking even more capabilities, the premium version takes things to the next level by supporting advanced data analytics on remotely sensed information. This empowers users to gain valuable insights and make data-driven decisions based on their datasets.To get started, the first step for a user is to create a new project. During project creation, they can define the necessary tags to categorize and organize their data efficiently. The system then generates a unique and secure database key, acting as a safeguard for their project's sensitive information. To aid users in exploring the platform's capabilities without incurring costs right away, the system offers a Test mode. This allows users to deploy their projects in a controlled environment, making use of the Google Cloud infrastructure without any charges during this phase.

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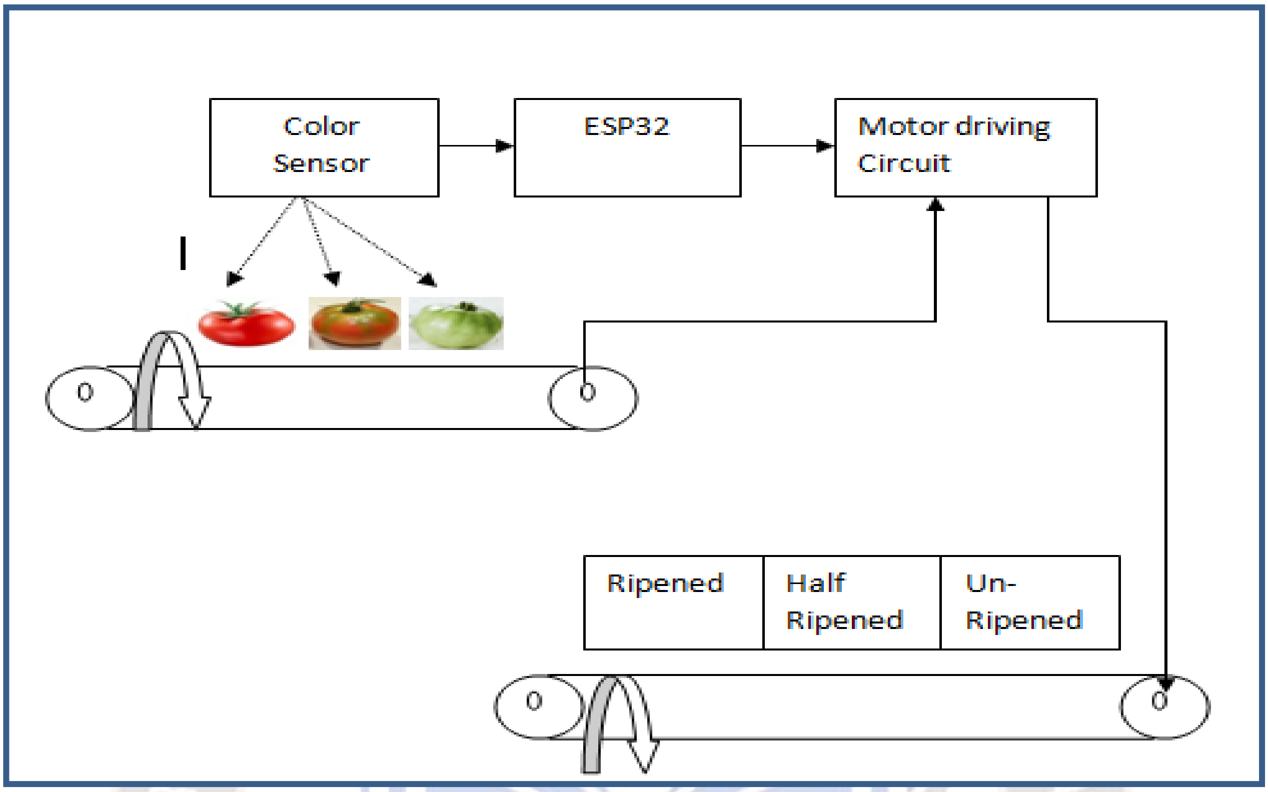

Figure 4. Blockschematic of sorting Process

In summary, this cutting-edge data management system redefines the way users interact with their data. It empowers them with real-time cloud-based data handling, robust security measures, and global accessibility. The premium version takes

it a step further, facilitating advanced data analytics on remotely sensed information. With user-friendly project creation and the cost-free Test mode, this system presents a compelling solution for data management and analysis needs.

IV. PROPOSED FRAMEWORK

In this section, our primary focus is to outline the architecture and IoT level necessary for the design of a sophisticated and efficient smart framework. Through the visual representation provided in Figure 4 and Figure 5, we present the proposed architecture, which incorporates a conveyor belt unit to transport tomatoes of varying ripeness levels, namely Ripened, Partially Ripened, or Not Ripened, to the TCS3200 sensor unit. By leveraging the predictive model's classification capabilities, these tomatoes are then intelligently directed to their respective bins, optimizing the sorting process and enhancing overall productivity.

V. IOT DESIGN TEMPLATE SELECTION

IoT applications are known for their versatility and scalability, thus necessitating a systematic categorization based on their components, communication protocols, and database maintenance. One of the key decisions in IoT application development is choosing the appropriate deployment environment, which can either be localized or cloud-based, depending on the specific design template employed. To ensure a cohesive and standardized approach, we adhere to the widely acknowledged Six-level design template framework.

In the context of our specific application, the system centers around a single node that is strategically deployed within an Agriculture Field, ensuring seamless integration with the agricultural operations. To cater to the requirements of potential buyers, we recognize the importance of maintaining and providing access to the classification details of the crop, in this case, tomatoes. To achieve this, we leverage the capabilities of cloud storage, which not only enables secure data retention but also facilitates convenient accessibility for authorized stakeholders [19].

After careful consideration, the level 2 design template emerges as the most suitable choice for our implementation, as elucidated in Figure 6. The level 2 template ectively accommodates the local deployment of the sensor system, specifically the single node, while effectively capitalizing on

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cloud-based storage and access solutions to manage and disseminate the essential classification data.

In summary, the amalgamation of our proposed architecture and the IoT level 2 design template represents a robust and intelligent framework, poised to revolutionize the tomato sorting process in the Agriculture Field. The effective utilization of IoT principles and cloud technology underscores our commitment to providing a seamless and accessible system for potential buyers and stakeholders, promising enhanced efficiency and convenience in the domain of crop classification and distribution.

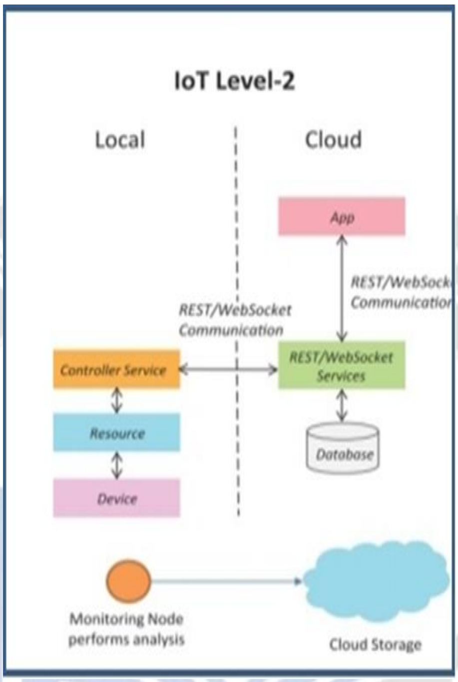

Figure 5. IoT Level 2 Template

TABLE III. R,G,B VALUES OF DIFFERENT STAGES OF TOMATO

RGB values for No object			RGB values for Ripened Tomato			RGB values for half Ripened Tomato			RGB values for Un- ripened Tomato		
R	G	B	R	G	B	R	G	B	R	G	B
175	233	215	85	111	141	197	383	359	99	172	233
158	217	209	91	117	153	171	408	388	94	165	227
175	261	259	91	117	153	129	360	337	90	156	211
213	318	308	91	117	154	114	316	291	86	149	200
222	293	256	92	119	156	113	316	292	84	147	198
166	224	205	93	120	157	113	309	289	85	150	204
160	222	218	93	120	158	114	321	298	87	153	208
194	288	289	94	120	158	115	324	299	87	152	204
221	292	256	93	120	157	114	320	294	86	151	202
164	222	208	93	120	157	113	315	291	88	155	208
161	228	226	93	119	156	112	318	294	88	156	211
197	294	294	93	120	157	113	323	300	88	156	209
231	325	289	93	119	157	114	329	304	88	154	204

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VI. EXPERIMENTATION RESULTS

In our experimentation, we have developed the dataset for classification of tomatoes using color sensor TCS3200, Controller ESP32. RGB values of the respective colors are stored as CSV files. This data in turn is segregated into Training and Testing. The predictive model based on random forest algorithm is generated 'C' file (model.h) for controller environment using Micro ML. The inference engine is used for predicting the correct class for the sample item. The cloud environment is used for interacting with potential seller for the cultivated yield. Google Firebase provided the necessary security and communication from the edge device to the cloud.

A. *Dataset generation:*

The Table 4 reveals that the ripened tomato maintain intensity values of in the range of 85 to 93 for RED, 117 to 120 for Green and 154 to 158 for blue. The High green and blue values denote half ripened tomato, and high RGB values indicate no object. Table III clearly depict RGB values attained for ripen, half ripen and un-ripen cases.

B. *Experimental Procedure*

Data Set Generation :Fully Ripened Tomatoes samples are placed at the fixed position near to color sensor.Color sensor Filters capture R, G, B values at regular intervals as dictated by ESP32 controller. These value records generated for 3 minutes stored as CSV file. The file name is maintained with Category Name.The above steps are repeated for other category samples.(Ripened, Half Ripened, Un Ripened).

C. *Model Generation*

I. Install MicroML generator(micromlgen) in python IDE.
II. Import port method from micromlgen.
III. Load Feature Function is used for creating the dataset.
IV. CSV Files generated in the step1 are uploaded into SAMPLE data folder.
V. CSV Files generated in the step1 are uploaded into SAMPLE data folder.
VI. Model is generated using Random Forest algorithm.
VII. The generated model.h C file is to be saved and used during the inference process.

D. *Inference Engine*

I. The inference engine is to be invoked in the arduino environment of ESP32 controller
II. Model.h of the step2 is to be included in the current Sketch folder.
III. Conveyor belt unit moves tomato vegetables that comprises Ripened, Half Ripened, Un Ripened required.
IV. Based on the predictor class the tomatoes will be moved to respective bins.

E. *Cloud Interaction*

After Registration into Google Firebase database create a new project with Real time database. Maintain the information of Host name and authentication code provided by Firebase for this project.

I. Invoke the Inference program and provide necessary information about WiFi SSID and Password.
II. Upon execution of the inference engine the category name, quantity and price are saved in Firebase database and updated in real time.
III. The potential buyer can access this information and communicate with the farmer.

F. *Mobile APP development*

I. Horizontal and vertical layout arrangements are appropriately chosen.
II. Concerned images are Positioned in the layout.
III. Lables, Buttons and text boxes are used for displaying results extracted from firebase real time database.
IV. Firebase process has been implemented in the block menu.
V. Using Kodular Companion, the app is tested on different smart phones.
VI. Project(.aia) file will be exported to mobile.

G. *Disease Management*

Short shelf life and disease magement are the major hurdles to the tomato crop management. Unless they are addressed properly huge loss to the former. Some of the diseases,as shown in Figure 7, that are managed by of frame work with color sensor are Early Blight, Buck Eye Rot, Late Blight and Anthracnose.

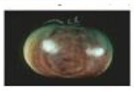
Diseage	Image	Management
Early Blight		Spraying the crop with Difolatan (0.2%), Dithane M-45 (0.2%)
Buck Eye Rot		Spraying with Difolaton (0.3%) 4 times at an interval of 10 days
Late Blight		sprayed with Captafol (2 g/litre of water) or Dithane M 45 (2 g/kg of seed) at 15 days interval
Anthracnose		well-drained soil, crop rotation

Figure 6. Disease Management using Color Sensor

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Early Blight (Alternaria solani) is a common tomato disease affecting foliage at any growth stage, characterized by small black lesions on older leaves. Effective control measures include spraying the crop with Difolatan (0.2%), Dithane M-45 (0.2%), or Bavistin (0.1%).

Buck Eye Rot, or fruit rot, poses a significant threat to tomato cultivation, primarily affecting fruits near the ground. To manage this disease, staking plants and removing foliage and fruits up to 15-30 cm from the ground level is advised. Spraying with Difolaton (0.3%) four times at 10-day intervals effectively controls the disease.

Late Blight (Phytophthora infestans) occurs during humid conditions and mild temperatures, causing rapid disease development and economic losses. Managing late blight involves spraying plants with Captafol (2 g/liter of water) or Dithane M-45 (2 g/kg of seed) at 15-day intervals, starting from 30 days after transplanting.

Anthracnose (Colletotrichum phomoides) initially appears as small, water-soaked spots on infected fruit, which later enlarge and develop concentric rings. Managing anthracnose requires well-drained soil, crop rotation, and a preventative fungicide program.

VII. CONCLUSION AN SCOPE

The proposed model is useful for all types of vegetables and fruits for which the growing stages results color variations in peripheral layer. The deployment cost of the proposed framework is affordable to the farmer due to low cost , low power with multicore controller- ESP32. Further the framework provides seamless operation on real time basis. The framework can also support for the classification of remotely collected images. The application is in tuned with the aspirations of our national government theme Athma NIrbar Bharath with digital farmer concept. This holistic frame work explore the power of IoT, Machine Learning and potential Marketing strategies. The only hindrance is wear and tear sensitivity dependence of the hardware units and required regular maintenance. Figures 8,9,10 provide implementation results of our frame work.

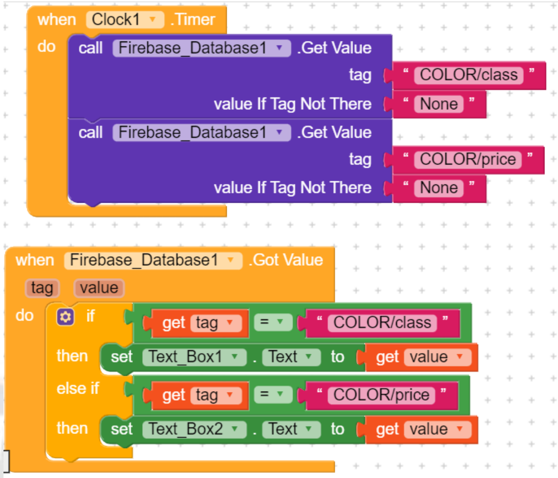

Figure 7. Kodular Blocks

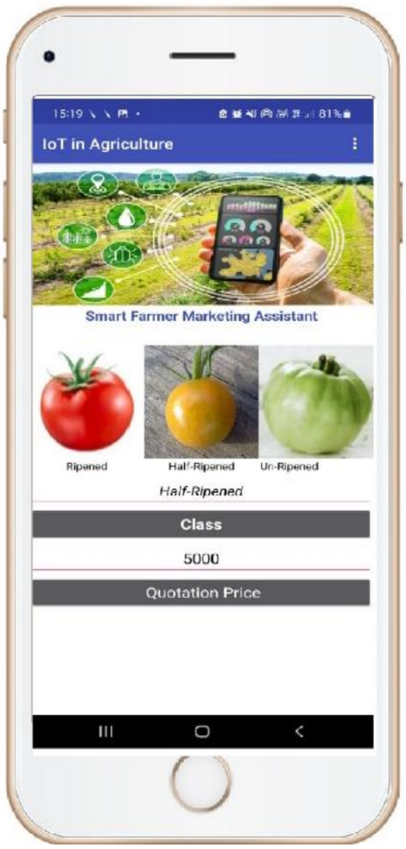

Figure 8. Mobile APP

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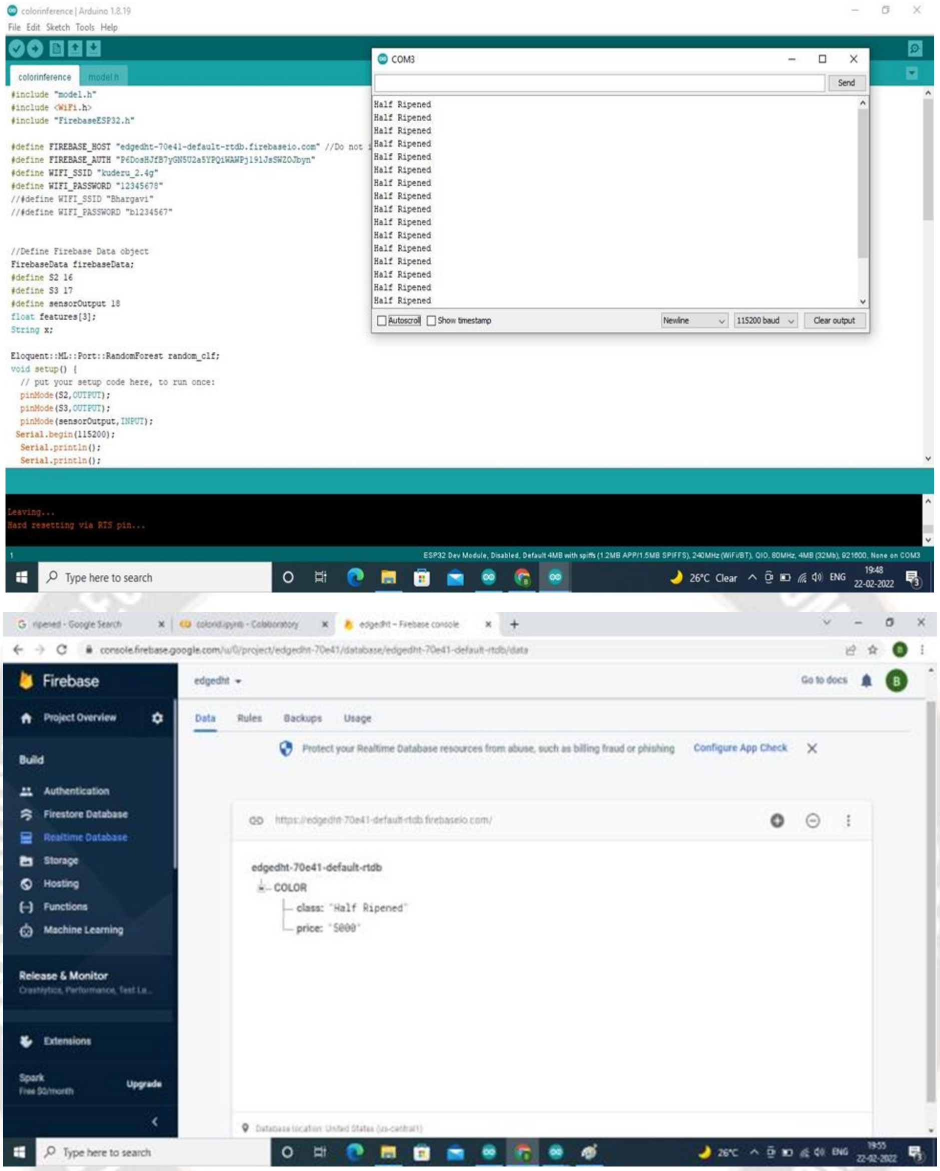

Figure 9. Half Rippen testing on Arduino IDE & Cloud Deployment

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