

A Smart IOT-Driven Digital Platform for Sustainable Dry Fish Processing in Sri Lanka

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Project Proposal Report

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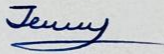
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DECLARATION

I declare that this is my own work, and this proposal does not knowingly incorporate any material previously submitted for a degree or diploma at any other university or higher education institution, nor does it contain any material that has been previously published or written by another person apart from where proper acknowledgment is given in the text.

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ABSTRACT

The dry fish industry in Sri Lanka plays an important role in food preservation, household income generation, and coastal livelihoods. However, the industry is informal and largely manual, with drying taking place in open or semi-open environments that expose the fish to spoilage, unstable weather conditions, and inconsistent temperatures. These challenges result in significant losses in dried fish yields, poor product quality, and reduced producer income. This research focuses on the design and development of an IoT-driven smart drying quality monitoring and automatic control module as one component of a comprehensive digital platform for dried fish processing in Sri Lanka. The proposed module addresses a clear gap in the existing literature, where most solutions focus on physical drying hardware or on traceability and market systems separately, with limited attention paid to real-time automated environmental control tailored to Sri Lankan coastal conditions. Before the drying process begins, the module collects fish-specific input data, including fish variety, initial weight, and ambient humidity. Using this data, the system calculates the optimal drying temperature and estimated drying time. An ESP32-class microcontroller with temperature, humidity, and weight sensors forms the hardware foundation. The system automatically controls a heater and a humidity controller to maintain the calculated drying environment. A load sensor continuously monitors the weight of the batch, and the system triggers a drying completion notification when the fish reaches one-third of its original weight, which is the standard indicator of complete dryness in use in Sri Lanka. Additionally, Gunasekara's visual module communicates with this IoT unit via real-time API calls to adjust heat and humidity based on visual quality assessments. The result is a closed, vision-guided, automated drying control system that eliminates human guesswork, standardizes product quality, and aims to minimize losses from dried fish harvest for small-scale dried fish producers in Sri Lanka.

Keywords: IoT, dry fish, automated control, ESP32, humidity monitoring, Sri Lanka, weight sensor, food quality, drying completion detection, API integration

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
ESP32	Espressif Systems Microcontroller
API	Application Programming Interface
CNN	Convolutional Neural Network
IoT	Internet of Things
DHT	Digital Humidity and Temperature (Sensor)
RH	Relative Humidity
ML	Machine Learning
SDG	Sustainable Development Goal
UI	User Interface
WBS	Work Breakdown Structure

Table 1 -- list abbreviation

1 INTRODUCTION

1.1 Background and Context

Sri Lanka has a long history of fish processing, and dried fish, locally known as "karawala", is one of the most important preserved seafood products in the country. It serves as an affordable source of protein for millions of households, especially in rural and coastal communities. The dried fish industry supports a large number of small-scale fishers, processors and traders, who rely on it as their main source of income. According to the Food and Agriculture Organization of the United Nations (FAO), artisanal and small-scale fish processing plays a crucial role in food security in developing countries, including Sri Lanka [1]. Despite its economic and nutritional importance, the dried fish processing industry in Sri Lanka is largely informal and manual. Drying is usually carried out in open or semi-open outdoor environments, where fish are spread out on mats, racks or roofs and left to dry in the sun. This traditional approach exposes fish to a wide range of environmental hazards, including dust, insects, rodents, stray animals, smoke from nearby activities, and unexpected weather changes such as sudden rainfall. When dried fish become partially wet from unexpected rain, the reabsorption of moisture creates ideal conditions for microbial growth, spoilage, and contamination, significantly reducing both product quality and shelf life.

The consequences of these challenges are multifaceted. From a food safety perspective, poor handling and processing conditions of fish products can lead to the formation of harmful substances such as histamine and other biogenic amines, which pose public health risks to consumers [4]. From an economic perspective, producers frequently suffer revenue losses due to spoilage, inconsistent quality, and limited access to fair markets. They are often forced to sell their products through intermediaries at exploitative prices due to a lack of market information and direct buyer contacts. From an environmental perspective, unmanaged fish waste and inefficient energy use in processing contribute to coastal pollution and local greenhouse gas emissions.

The primary technical problem is that the drying environment is currently managed entirely by human experience and visual judgment. There is no objective method for determining the ideal drying temperature for a type or weight of fish, no real-time monitoring of dangerous humidity conditions that indicate the risk of spoilage, and no automated system to stop or adjust the drying process when conditions become unsafe. This leads to inconsistent product quality across batches and a high reliance on the knowledge and presence of experienced workers.

Stakeholders directly affected by this problem include small-scale dried fish producers and processors, particularly women who manage drying operations in coastal communities; buyers and traders who require consistent product quality; consumers who rely on safe, affordable dried fish as a dietary staple; Regulatory bodies responsible for food safety compliance; and platform administrators managing digital infrastructure. Each of these groups benefits from a system that can automatically and in real time monitor and control drying conditions..

1.1.1 Analysis of Existing Solutions and Their Limitations

Existing approaches to fish quality assessment in Sri Lanka are exclusively manual. Processors rely on visual cues including colour, surface appearance, texture, and smell, with outcomes that vary significantly between individuals, across lighting conditions, and with changes in processor fatigue or experience. There are no standardised grading criteria applied consistently across the industry.

At the international level, computer vision and deep learning approaches to food quality grading are well established in industrialiser markets. Automated inspection systems exist for fruit grading, grain sorting, and seafood processing in high-income settings. However, these systems are designed for large-scale operations with controlled laboratory environments, expensive high-resolution industrial cameras, and training datasets that bear no resemblance to Sri Lankan fish species, processing methods, or environmental conditions. Their cost and design assumptions make them entirely inaccessible and inapplicable for small-scale Sri Lankan coastal processors.

No existing system provides an automated, locally contextualised quality grading solution for Sri Lankan dry fish that operates within a real-world processing environment, accounts for the

practical constraints of small producers, and improves continuously over time through professional verification.

This research directly addresses this gap by developing a CNN-based computer vision module with a self-learning verification station, trained on locally collected data from Sri Lankan processing contexts and integrated within an enclosed, hygienically controlled drying prototype.

1.1.2 SDG Alignment

- SDG 2 - Zero Hunger: Reducing post-harvest losses through controlled drying environments and automated completion detection, improving food safety and extending the safe usable period of dry fish for Sri Lankan consumers.
- SDG 9 - Industry, Innovation and Infrastructure: Introducing IoT-driven automated processing control to a traditional informal industry with no existing instrumentation or digital infrastructure.
- SDG 12 - Responsible Consumption and Production: Minimising food waste and batch spoilage through real-time humidity monitoring, automated threshold alerts, and consistent drying outcomes that reduce over-processing and under-processing losses.
- SDG 14 - Life Below Water: Supporting sustainable and responsible fisheries through traceability-linked processing records and quality-assured drying practices that improve the long-term viability of Sri Lanka's coastal fishing communities.

1.2 Literature Review

The following review examines eleven scholarly sources relevant to the IoT monitoring and automated control module, identifying key findings and limitations that contextualise and justify the technical approach and novelty of this research

1.2.1 IoT-Based Environmental Monitoring in Food Processing

Mishra et al. demonstrated that IoT-based environmental monitoring using ESP32-class microcontrollers and standard DHT sensors can improve drying process consistency in food processing applications and provide early warning of unsafe humidity and temperature conditions [1]. Their work establishes the technical feasibility of low-cost sensor deployments for real-time environmental monitoring in food processing contexts directly comparable to the dry fish drying environment targeted by this research. A key limitation of their work is the absence of automated actuator control: their system monitors and alerts but does not automatically respond to detected unsafe conditions. This research addresses this limitation by implementing closed-loop automated control through relay-driven actuators directly connected to the ESP32.

1.2.2 Weight-Based Moisture Content Estimation in Food Drying

Babalis et al. investigated continuous weight monitoring as a method for tracking moisture content reduction in food drying applications, demonstrating that weight loss over time provides a reliable and low-cost proxy for moisture content without requiring laboratory-grade moisture meters [2]. Their findings validate the use of load cell-based continuous weight monitoring as the primary drying completion detection mechanism in this research, where the one-third weight threshold represents the traditional Sri Lankan indicator of commercially acceptable dryness, validated through field consultation with the external supervisor

1.2.3 Fungal Contamination in Dried Fish

Riba et al. investigated fungal spoilage in dried and salted fish products, identifying *Aspergillus flavus*, *Aspergillus parasiticus*, *Penicillium citrinum*, and *Cladosporium* species as the dominant fungal contaminants in dried fish processed under humid open-air conditions [3]. Their findings confirmed that sustained relative humidity above 70 to 85 percent is required for fungal growth initiation. Maintaining processing environment humidity below this threshold effectively prevents fungal colonisation, directly establishing and validating the humidity control target and threshold alert settings used in the automated control logic of this research.

1.2.4 ESP32 Microcontroller in Agricultural and Food IoT Applications

Kassim and Harun reviewed the application of ESP32-class microcontrollers in agricultural IoT systems, confirming that ESP32 devices provide sufficient computational capacity for concurrent sensor reading, threshold evaluation, actuator control, and Wi-Fi data transmission within a single firmware deployment [4]. Their review establishes the technical suitability of the ESP32 as the central processing unit for the monitoring and control module in this research.

supporting both the real-time sensor processing loop and the REST API endpoint for vision module integration without requiring separate hardware for different functions

1.2.5 Relay-Based Actuator Control in IoT Systems

Islam et al. demonstrated reliable relay-based actuator control using ESP32 microcontrollers for environmental management applications including temperature control and humidity regulation, confirming that relay modules can be driven directly from ESP32 GPIO pins with sufficient switching reliability for sustained processing applications [5]. This work directly supports the actuator control architecture of this research, in which the heater relay and humidity fan relay are both managed through ESP32 GPIO outputs in response to sensor readings and API commands.

1.2.6 REST API Design for IoT Command Integration

Patel et al. examined REST API design patterns for IoT command and control applications, establishing that stateless HTTP-based APIs provide the most practical and scalable communication mechanism for integrating IoT hardware control endpoints with web-based application modules [6]. Their design recommendations, including stateless request design, structured JSON command and response payloads, bearer token authentication, and sub-second response time targets, directly inform the API specification for the vision-to-IoT command integration implemented in this research.

1.2.7 Digital Traceability in Fish Supply Chains

Cromwell et al. conducted a systematic review of digital technologies for traceability in global fish supply chains, identifying that integrated platforms combining sensor-based processing condition records with quality grading data represent a critical emerging priority for small-scale processing contexts in low-income settings [7]. Their review identified that the majority of existing traceability solutions address supply chain logistics and cold chain management rather than the processing environment itself, leaving a significant gap that this research addresses through sensor log integration with the batch traceability record.

1.2.8 MQTT Protocol for Lightweight IoT Data Transmission

Al-Fuqaha et al. reviewed the MQTT protocol as a lightweight publish-subscribe messaging standard for IoT sensor data transmission, demonstrating that MQTT provides significantly lower bandwidth overhead and better reliability under intermittent network conditions compared to HTTP polling for continuous sensor data streams [8]. This finding is relevant to the data transmission architecture of this research, where sensor readings must be transmitted continuously from the ESP32 to the cloud backend under the variable network conditions typical of Sri Lankan coastal processing environments.

1.2.9 MongoDB for Time-Series Sensor Data Storage

Cattell reviewed NoSQL database systems for IoT time-series data applications, finding that document-oriented databases such as MongoDB offer practical advantages for sensor log storage including flexible schema design, efficient time-range querying with compound indexes, and horizontal scaling appropriate for multi-device deployments [9]. These properties directly support the database design of this research, where sensor time-series records, API command logs, and completion event records are stored as MongoDB documents indexed by batch ID, device ID, and timestamp.

1.2.10 Node.js for Real-Time IoT Backend Services

evaluated Node.js as a backend runtime for real-time IoT data ingestion and API routing applications, demonstrating that Node.js's event-driven, non-blocking I/O model provides efficient concurrent handling of multiple device data streams and API requests without the thread-per-connection overhead of traditional synchronous server architectures [10]. This directly supports the technology choice of Node.js as the cloud backend for the IoT monitoring module, which must handle concurrent sensor data streams from multiple ESP32 devices alongside real-time API commands from the computer vision module.

1.2.11 Food Loss and Waste in Low-Income Fishing Communities

Gustavsson et al. reported that post-harvest losses in fish processing in low-income settings account for a disproportionate share of economic loss and environmental impact across food supply chains [11]. Their findings confirm that the highest-impact intervention point for reducing fish waste is the processing stage itself, where environmental control failures, over-drying, and undetected spoilage cause preventable losses before the product reaches the market. This finding reinforces the importance of automated drying condition monitoring and completion detection as the primary mechanism for reducing post-harvest losses in the Sri Lankan dry fish processing sector.

Technologies / Methods	Paper [1]	Paper [2]	Paper [3]	Paper [4]	Paper [5]	Proposed System
Automated Drying Parameter Calculation	✗	✗	✗	✗	✗	✓
Real-Time Sensor Monitoring (Temp / Humidity)	✗	✓	✗	✓	✗	✓
Automated Actuator Control (Heater / Fan)	✗	✗	✗	✗	✗	✓
Weight-Based Completion Detection	✗	✗	✗	✗	✗	✓
Vision-Guided IoT Control (Closed-Loop API)	✗	✗	✗	✗	✗	✓
Real-Time Alert Notifications	✗	✗	✗	✗	✗	✓
Batch Traceability Integration	✗	✗	✗	✗	✓	✓
Predictive Analytics Integration	✗	✗	✗	✗	✗	✓
Low-Cost Hardware (ESP32 / DHT22)	✗	✗	✗	✗	✓	✓
Small-Scale / Coastal Producer Applicable	✗	✗	✗	✓	✗	✓
Works in Controlled Drying Environment	✗	✗	✗	✗	✗	✓
Mobile Dashboard & Notification App	✗	✗	✗	✗	✗	✓

Table 2 - Comparison of Existing Research Methods and Proposed System (IoT Monitoring & Automated Control Component)

1.3 Research Gap

The literature review reveals a clear and significant research gap at the intersection of IoT-based environmental control, fish-specific drying parameter calculation, visual quality feedback integration, and weight-based completion detection, especially in the context of small-scale dried fish processing in Sri Lanka.

First, while IoT monitoring systems for food drying exist in the literature, they are mainly designed as passive monitoring tools. They collect and display sensor data and can generate threshold-based alerts, but they do not automatically control heating or humidity equipment in response to detected conditions. The transition from monitoring to automated closed-loop control has largely not been addressed in low-resource, small-scale food processing contexts.

Second, no existing research addresses the calculation of optimal drying parameters based on fish-specific inputs such as variety and initial weight. Current systems treat all batches equally, applying the same temperature and duration regardless of the specific characteristics of the fish being processed. In reality, different fish varieties and batch sizes require different drying conditions, and failure to account for these differences results in inconsistent quality results.

Third, integrating a computer vision quality grading module with a real-time IoT control unit via API-based communication represents a novel architectural approach that has not been utilized in dried fish processing. This cross-module feedback loop, where visual inspection directly drives operator adjustments, creates a more intelligent and responsive processing environment than either system could achieve independently.

Fourth, the use of a load cell-based weight monitoring system to automatically detect drying completion based on the traditional one-third weight loss criterion has not been implemented in any existing digital platform for dried fish processing. This bridges the gap between local processing knowledge and modern sensor technology in a culturally appropriate and technically robust manner.

This research directly addresses these gaps by proposing a locally contextualized, software-centric, IoT-enabled drying module that integrates automatic control, fish-specific parameter calculation, visual feedback integration, and weight-based completion detection into a single integrated system..

2 OBJECTIVE

2.1 Main Objective

Design, development and evaluation of a smart IoT-driven drying quality monitoring and automatic control module that calculates optimal drying parameters based on fish-specific inputs, automatically controls the drying environment using actuators, detects drying completion through weight-based sensing, and integrates with a display module via real-time API communication to ensure consistent dried fish quality and reduce post-harvest losses in small-scale processing settings in Sri Lanka..

2.2 Specific Objectives

2.2.1 Fish-Specific Drying Parameter Calculation

To develop a parameter calculation engine that accepts fish variety, initial batch weight, and ambient humidity as inputs and computes the optimal drying temperature and estimated drying duration for that specific batch, using rule-based logic validated against domain knowledge from the external supervisor

2.2.2 IoT Hardware Prototype Development

Build a low-cost IoT prototype using an ESP32-class microcontroller integrated with temperature sensors, humidity sensors, and a load cell load sensor, capable of regularly capturing drying ambient conditions and batch weight and transmitting the data to the platform in real-time.

2.2.3 Automated Drying Environmental Control

Implementation of software-controlled actuator management that automatically adjusts the heater to maintain calculated target temperatures and controls the humidity controller to keep moisture levels within safe drying ranges, with simulation-first development and physical prototype validation.

2.2.4 Weight-based Drying Completion Detection

To implement a real-time weight monitoring system that continuously compares live batch weight readings against a calculated completion threshold of one-third of the original weight, automatically triggers a drying completion notification and records the event in the batch tracking report.

2.2.5 Real-time API integration with Vision module

Develop and expose a RESTful API endpoint that receives real-time control commands from Gunasekara's AI Vision module every few seconds, performs visual quality assessments and automatically adjusts operators accordingly, and returns current sensor readings and operator status as confirmation responses.

2.2.6 Dashboard development and evaluation

Develop a real-time monitoring dashboard that displays live sensor readings, calculated parameters, batch weight progress, operator status, and integration logs, and evaluate the system through alarm accuracy and recall measurements, as well as quality feedback from users or test operators

3 METHODOLOGY

This research follows a design-and-build methodology with iterative development and practical validation. The module is developed in two phases. In the first phase, the drying parameter calculation, actuator control logic, load-based completion detection, and API integration are developed and tested entirely in a software simulation environment. In the second phase, a physical IoT prototype is assembled and evaluated in a controlled drying environment. This simulation-first approach reduces risk, allows for early identification of design issues, and enables validation of the logic before committing to hardware procurement and assembly.

3.1 Data Collection Methods

Primary data will be collected from a small-scale drying setup that logs temperature, humidity, and weight over time. Drying trials will be conducted using common Sri Lankan dry fish varieties such as karawala (Seer fish or Trevally). For each trial, the initial fish weight, variety, and ambient humidity will be recorded at the start. Sensor readings will be captured at fixed intervals throughout the drying process, and the final weight and quality outcome will be recorded at completion.

A pilot dataset of 30 to 60 drying batches will be created to validate the parameter calculation engine and weight-based completion detection logic. Where real-world data is limited, controlled simulations and synthetic datasets based on established food science principles will be used to supplement the training and validation process.

For the sustainability and traceability components, waste generation and handling data will be captured through short interviews with processors in coastal communities, supported by the domain expertise of the external supervisor

3.2 Technical Methods and Tools

The hardware layer will be built using an ESP32 class microcontroller as the central processing unit. A DHT22 or similar sensor will capture temperature and relative humidity readings at one-minute intervals. A load cell paired with an HX711 amplifier module will provide continuous load monitoring. A relay module will act as the software-controlled switch for the heater, and a fan-based humidity control mechanism will regulate humidity levels.

The software layer will be developed using Node.js or Python for the back-end services. A RESTful API will be implemented to handle commands coming from the visual module and expose current sensor readings and actuator status. The dashboard will be developed as a mobile app using Flutter, displaying live data via WebSocket connections for real-time updates.

The drying parameter calculation engine will initially use a rule-based lookup table, mapping fish variety and weight categories to recommended temperature ranges and drying times. This lookup table will be validated and refined using data from pilot drying trials and guidance from an external supervisor. If sufficient data is available, a simple regression model can be applied in subsequent iterations.

The weight-based completion detection logic will operate as follows: The system records the initial batch weight entered by the operator at the start of drying, calculates the target completion weight as one-third of the initial weight, and continuously monitors the live weight reading from the load cell. When the live weight equals or falls below the target completion weight, the system triggers a completion event, sends a notification, reduces or stops the heater, and records the completion time in the batch traceability report.

3.3 Ethical Considerations

All data collection involving human participants, including interviews with processors and feedback from test operators, is done with informed consent. Participants are clearly informed about the purpose of the research, the right to withdraw at any time, and how their data will be used. No personally identifiable information is collected beyond what is necessary for the research. Data is stored securely with role-based access control.

The domain knowledge of the external supervisor is used only with his consent and due acknowledgement. All sensor data collected during the drying experiments is anonymized before being used for model training or validation.

3.4 Validation Strategy

The module is evaluated using both quantitative measurements and qualitative feedback. To calculate the drying parameters, the estimated drying time is compared with the actual recorded durations using the mean absolute error (MAE). For the automatic control system, the temperature deviation from the target setting is measured during the drying experiments. To identify the completion of drying, the completion time detected by the system is compared with the manual expert assessment. For API integration, the response latency and the accuracy of command execution are measured. For the dashboard, the usability is assessed through structured feedback from the test operators using a short questionnaire.

4 HIGH-LEVEL SYSTEM ARCHITECTURE

4.1 Overview of the Computer Vision Component

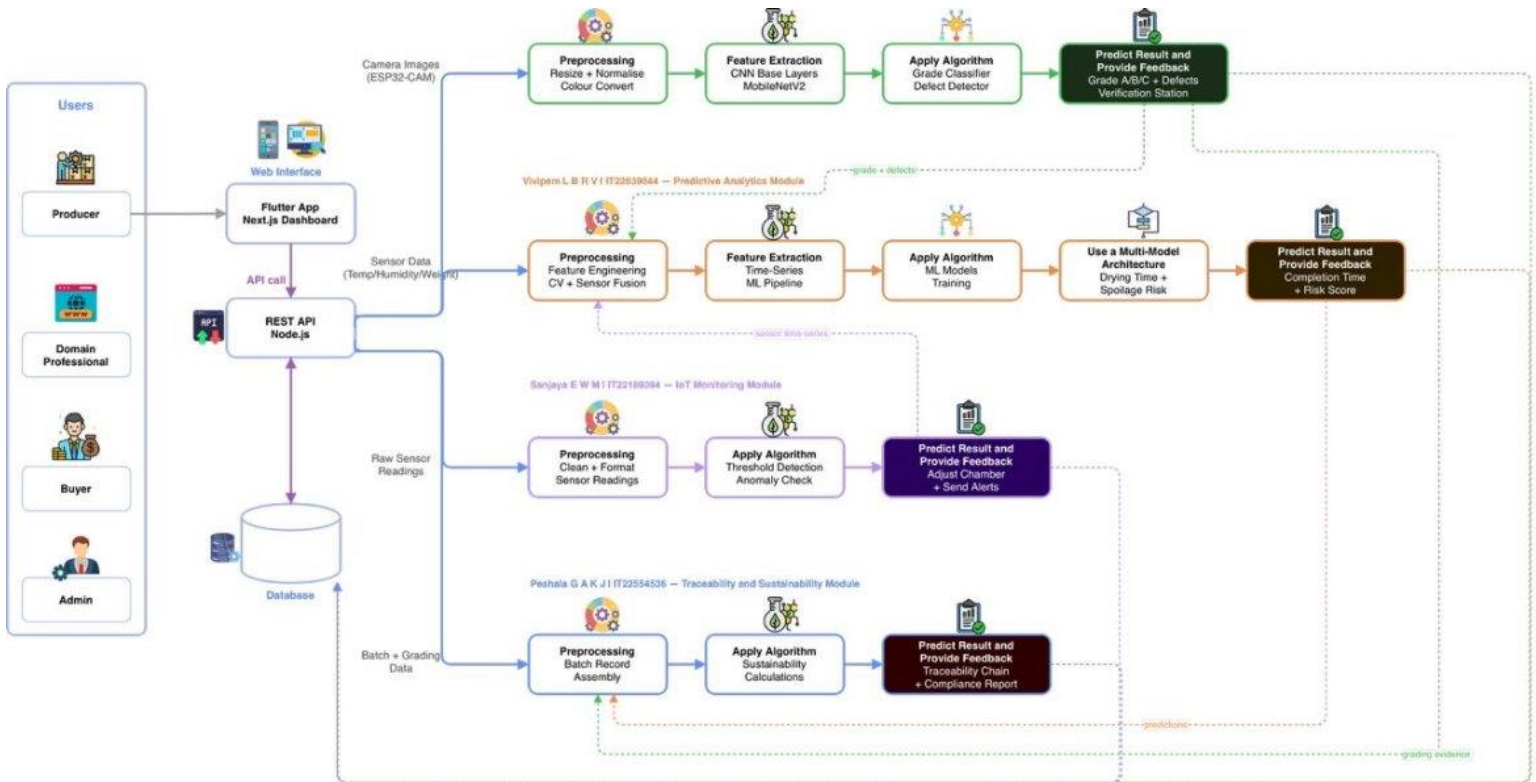


Figure 1 -- Overview of the Computer Vision Component

4.2 Data Flow — IoT Drying Condition Monitoring & Automated Control Module

The following table provides a comprehensive step-by-step description of the data flow through the IoT drying condition monitoring and automated control module. Each step identifies the responsible actor, the action performed, and the resulting output, covering the complete processing lifecycle from initial operator input through sensor-driven drying control, vision-guided actuator adjustment, weight-based completion detection, and final platform integration.

Step	Actor	Action	Output
1	Operator (Input Form)	Enters fish variety (species and type), initial batch weight in kilograms, and ambient humidity percentage into the platform input form before drying begins.	Input parameters stored; batch record initialised
2	Parameter Calculation Engine	Processes the fish variety and ambient humidity inputs through the fish-type lookup table to calculate the optimal target drying temperature in degrees Celsius and the estimated drying duration in hours.	Target temperature (°C) and duration (hours) output; sent to ESP32 as setpoints
3	ESP32 Microcontroller	Receives calculated setpoints from the backend; activates the heater relay to begin warming the chamber to the target temperature; activates the humidity fan if ambient humidity exceeds the safe threshold.	Heater and fan actuators activated; drying environment conditions begin adjusting toward target
4	DHT22 Sensor Array	Captures temperature and humidity readings from inside the drying chamber at one-minute intervals throughout the active drying session.	Sensor time-series data stream begins; readings written to MongoDB with timestamp and batch ID
5	Load Cell + HX711	Continuously monitors the live batch weight at frequent intervals throughout the entire drying session, transmitting readings to the ESP32 for processing.	Live weight readings available for comparison against target completion threshold

6	Threshold Rule Engine	Evaluates each incoming temperature and humidity reading against predefined safe operating ranges. If a reading exceeds the safe threshold for a sustained period, an alert is triggered immediately.	Normal operation continues (threshold safe) or alert generated (threshold breached)
6a	Alert Generator (Threshold Breached)	Generates a push notification to the Flutter mobile application and the React.js admin dashboard. Logs the alert event with timestamp, sensor type, reading value, and batch ID.	Alert notification delivered to mobile and dashboard; alert event logged in database
6b	Heater Humidity Controller (Normal Operation)	Both controllers continue operating at the setpoints calculated in Step 2. Heater maintains target temperature; humidity fan activates or deactivates based on live humidity readings.	Drying continues at target conditions; actuator states logged continuously
7	AI Vision Module (Gunasekara)	Sends a structured API command via HTTP POST to the IoT module's REST API endpoint every five seconds, based on the visual quality assessment of the fish batch currently in progress.	API command received: action field set to increase_heat, reduce_humidity, or status_ok
8	API Command Executor	Parses the incoming API command received from the vision module. If the action is increase_heat or reduce_humidity, the corresponding actuator is adjusted by the specified value. If the action is status_ok, no actuator change is made.	Actuator adjustment executed (if required); response object built with current sensor readings
9	Sensor Response Builder	Constructs a JSON response object containing the current temperature, humidity, batch weight, heater status, humidity controller status, and timestamp. Returns this response to the vision module as confirmation.	JSON response returned: current_temp, current_humidity, current_weight, heater_status, humidity_ctrl_status, timestamp
10	Target Weight Calculator	Calculates the target completion weight by dividing the initial batch weight entered by the operator in Step 1 by three. This threshold represents the traditional Sri Lankan indicator of sufficient dryness.	Target completion weight (kilograms) established and stored; used in all subsequent weight comparisons

11a	Live Weight Comparator (Drying Incomplete)	Compares the current live weight from the load cell against the calculated target completion weight. If the live weight is still above the target, drying continues without interruption.	Drying continues; dashboard updated with current weight and estimated progress percentage
11b	Completion Event Trigger (Drying Complete)	Detects that the live batch weight has reached or fallen below the target completion weight (one-third of initial weight). Fires the drying completion event automatically without requiring manual operator action.	Completion event fired; heater shutdown initiated; completion notification prepared
12	Heater Shutdown	Receives the completion event signal and deactivates the heater relay. The humidity controller continues operating briefly to allow the chamber to cool safely before it can be opened.	Heater relay deactivated; chamber begins cooling; humidity fan continues on cool-down cycle
13	Push Notification (Completion Alert)	Delivers a completion notification to the Flutter mobile application and the React.js dashboard, informing the operator that the batch has reached its target dryness level and is ready for inspection or packaging.	Completion notification delivered to all registered devices for this batch
14	MongoDB Database	All sensor time-series logs, API command logs, actuator state logs, alert event logs, and the completion event record are written to persistent storage with full batch identification, device identification, and timestamps.	Complete batch processing record stored in database; all logs linked by batch ID

Table 3 - Data Flow: IoT Drying Condition Monitoring & Automated Control Module

4.3 Scalability and Security

The modular architecture allows the system to scale from a single drying unit to multiple units operating simultaneously. Each ESP32 unit communicates with the cloud backend through a unique device identifier, and the backend can manage multiple device streams concurrently. The API integration with the vision module is stateless, meaning each request carries all necessary information, which simplifies scaling.

Security is addressed through HTTPS-encrypted API communication, role-based access control on the dashboard, and device authentication tokens for ESP32 units. Sensor data is stored with timestamps and device identifiers to maintain audit trails. User consent and data minimisation principles are applied throughout data collection and storage.

5 USER REQUIREMENTS

5.1 Stakeholder Identification

The primary stakeholders for this module are the dry fish processors and producers who will operate the system on a daily basis. Secondary stakeholders include platform administrators who maintain and configure the system, the AI vision module (Gunasekara's component) which interacts with this module through API calls, and regulators who may access batch traceability records. The external supervisor, who owns a dry fish business, represents the real-world user perspective

5.2 Functional Requirements

Req. ID	Requirement	Priority	Description
FR01	Input fish details before drying	High	System shall accept fish variety, initial weight, and ambient humidity as inputs before a drying batch begins.
FR02	Calculate drying parameters	High	System shall calculate optimal target temperature and estimated drying duration based on the provided inputs.
FR03	Monitor temperature in real time	High	System shall continuously capture and display temperature readings from the drying environment at one-minute intervals.
FR04	Monitor humidity in real time	High	System shall continuously capture and display relative humidity readings at one-minute intervals.
FR05	Monitor batch weight in real time	High	System shall continuously monitor and display the live batch weight using a load cell sensor.
FR06	Control heater automatically	High	System shall automatically adjust the heater to maintain the calculated target temperature throughout drying.
FR07	Control humidity automatically	High	System shall automatically activate the humidity controller when humidity exceeds the safe drying threshold.
FR08	Detect drying completion	High	System shall trigger a completion notification when live batch weight reaches one-third of the original weight.
FR09	Receive and execute API commands	High	System shall receive real-time control commands from the AI vision module via API and execute actuator adjustments accordingly.
FR10	Send confirmation responses	Medium	System shall respond to each API command with current sensor readings and actuator status.

FR11	Generate threshold-based alerts	High	System shall send alerts when temperature or humidity exceeds defined safe ranges or when weight indicates spoilage risk.
FR12	Display live dashboard	Medium	System shall provide a real-time dashboard showing sensor readings, actuator status, completion progress, and alerts.
FR13	Log all events to batch record	High	System shall log all sensor readings, API commands, actuator changes, and completion events to the shared batch traceability record.

Table 4 - Functional Requirements

5.3 Non-Functional Requirements

ID	Requirement
NFR01	The system shall return a sensor response to the AI vision module's API command within 500 milliseconds under normal network conditions.
NFR02	The dashboard shall update live sensor readings with a display latency of no more than 5 seconds from the time of sensor reading capture.
NFR03	The alert notification shall be delivered to the mobile application within 60 seconds of the threshold breach being detected by the threshold rule engine.
NFR04	The temperature control system shall maintain the measured chamber temperature within plus or minus 2 degrees Celsius of the calculated setpoint during active drying.
NFR05	The weight-based completion detection system shall detect batch completion within 50 grams of the calculated target completion weight.
NFR06	All API communications between the ESP32, the Node.js backend, and the AI vision module shall be conducted over HTTPS with TLS encryption.
NFR07	Each registered ESP32 device shall authenticate with the backend using a unique device token; unauthenticated requests shall be rejected.
NFR08	The mobile application input interface shall be operable by producers with limited digital literacy following a brief orientation session.
NFR09	The dashboard shall be accessible on standard mobile and desktop browsers without requiring installation of additional software.
NFR10	The system shall maintain at least 99 percent sensor data collection uptime during active drying hours, defined as any drying session in progress.
NFR11	The system architecture shall support a minimum of 50 concurrent ESP32 device connections to the Node.js backend without performance degradation.

Table 5 - Non-Functional Requirements

6 COMMERCIALIZATION PLAN

6.1 Target Market

The primary target market consists of small-scale dried fish producers and processors operating in coastal communities in Sri Lanka, particularly in the Northern, Eastern, Southern and Northwestern provinces where dried fish processing is most concentrated. The secondary market includes medium-sized fish processing companies seeking to modernize their quality control processes and gain access to digital certification and traceability records for export purposes. In the long term, the platform model can be adapted for other dried seafood products across South and Southeast Asia, where similar informal processing conditions and post-harvest loss challenges exist. Target market and customer persona

6.2 Value Proposition

The Smart Dry platform, and in particular the IoT monitoring and control module, offers the following value propositions to its target users. For producers, the system removes the guesswork from the drying process, reduces spoilage losses and improves the consistency and quality of each batch. For buyers, access to digital quality grades and traceability reports increases confidence in product authenticity and safety. For regulators, standardized digital reports simplify compliance monitoring and food safety enforcement. For all stakeholders, the platform reduces reliance on intermediaries and creates a fairer, more transparent marketplace.

6.3 Revenue Model and Pricing Strategy

Tier	Price	Features
Basic (Free)	LKR 0 / month	Up to 20 batch gradings/month, basic dashboard, limited traceability records
Producer	LKR 1,500 / month	Unlimited gradings, full dashboard, complete traceability, predictive analytics
Business	LKR 5,000 / month	All Producer features + multi-user, Verification Station access, advanced analytics, export compliance docs
Enterprise	Custom	White-label, API access, government/cooperative bulk licensing, implementation consulting

Table 6 -- Revenue Model and Pricing

6.4 Competitive Advantage and Intellectual Property

The competitive advantage of this module lies in its local contextual design. Unlike typical IoT food monitoring systems available internationally, this module is specifically calibrated for the practical limitations of Sri Lanka's dry fish species, coastal weather conditions, and small-scale processors, including low literacy, limited connectivity, and cost sensitivity. The fish-specific parameter calculation engine, weight-based completion detection, and real-time vision-to-IoT API integration are novel features not available in any existing commercial solution.

The software and system design can be protected through copyright in the code base and design documentation. Based on the outcome of a freedom-to-operate analysis, a provisional patent application for the cross-module vision-to-IoT API control architecture can be considered.

7 BUDGET AND JUSTIFICATION

7.1 Hardware Budget

Component	Quantity	Unit Cost (LKR)	Total (LKR)
ESP32 Development Board	1	1,200	1,200
DHT22 Temperature & Humidity Sensor	2	600	1,200
Load Cell (5kg) + HX711 Module	1	1,500	1,500
Relay Module (2-channel)	1	400	400
Heater Element (prototype)	1	2,500	2,500
Fan / Humidity Controller (prototype)	1	1,800	1,800
Power Supply & Cabling	1	1,000	1,000
Enclosure Box	1	800	800
Miscellaneous (connectors, resistors)	1	500	500
		Total	10,900

Table 7 -- Budget Breakdown

7.2 Software and Tools Budget

Tool / Platform	Type	Cost
Arduino IDE / ESP-IDF	Open Source	Free
Node.js / Python Backend	Open Source	Free
React.js Dashboard	Open Source	Free
Firebase / Supa base (Database)	Free Tier	Free
GitHub (Version Control)	Free Tier	Free
Postman (API Testing)	Free Tier	Free
Figma (UI Design)	Free Tier	Free

Table 8 - Software and Tools Budget

8 WORK BREAKDOWN STRUCTURE (WBS)

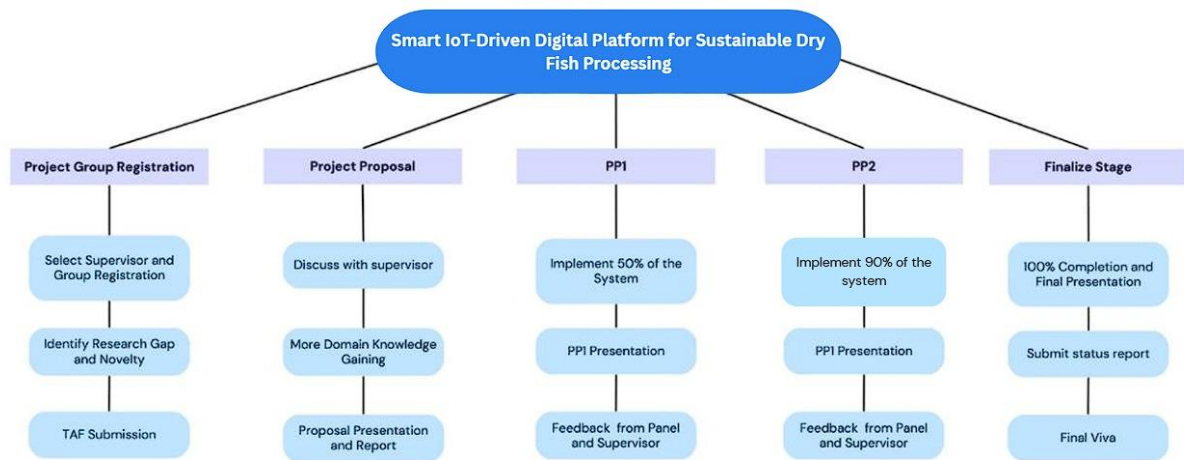


Figure 2 WORK BREAKDOWN STRUCTURE

9 GANTT CHART

Figure 3 GANTT CHART

Task	W1	W2	W3	W4	W5	W6	W7	W8	W9-12
Literature Review	■	■							
Parameter Calc. Engine		■	■						
Hardware Assembly			■	■					
SW Simulation			■	■					
Weight Monitoring				■	■				
Completion Detection					■	■			
API Development					■	■			
Dashboard Dev.						■	■		
Integration Testing							■	■	
Evaluation								■	■
Report Writing								■	■

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