INTEGRATED SMART WATER-FOCUSED IRRIGATION SYSTEM USING IOT AND AI/ML

Project ID: 25-26J-520

Project Proposal Report

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DECLARATION

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We declare that this is our own work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of our knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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Table 1: Declaration Table

The supervisor/s should certify the proposal report with the following declaration.

The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

.... 27/08/2025

Signature of the supervisor **Date**

ABSTRACT

This project addresses the persistent problem of water-stressed irrigation planning in Sri Lanka’s Udawalawe scheme (RBMC/LBMC), where seasonal quotas, heterogeneous soils, and volatile crop prices lead to suboptimal “paddy-by-default” choices and low water productivity. The gap is the absence of an integrated, explainable decision service that couples field sensing, hydrologic budgets, agronomic suitability, market expectations, and optimization under uncertainty usable by both farmers and scheme managers. We propose an Adaptive Crop & Area Optimization (ACA-O) module that ingests IoT sensor streams (soil moisture, water level, pH, EC), hydro-climate and ETo/Kc data, soils/land-use layers, reservoir/canal allocations, and price/cost signals; computes FAO-style water budgets; ranks candidate crops via fuzzy-TOPSIS for transparent field-level suitability; predicts yield with tabular ML (e.g., XGBoost/LightGBM) and short-horizon prices (e.g., TFT/LSTM/baseline); and solves a quota-aware linear/MIP to allocate hectares by crop at farmer/canal levels, with a mid-season “Plan-B” re-optimization on allocation or market shocks. Expected results include feasible Top-3 crop shortlists with rationales and risk bands, hectare plans consistent with water and soil constraints, and water-requirement envelopes for the scheduler, all published as signed snapshots to the Irrigation Department dashboard. Significance lies in improving profit per hectare and $kg\cdot m^{-3}$ water productivity while preserving auditability, policy compliance, and user trust through explainability providing a scalable template for climate-resilient, market-aware irrigation management across Maha (Sep Mar) and Yala (May Aug) seasons.

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LIST OF ABBREVIATION

Abbreviation	Full Form
AI	Artificial Intelligence
API	Application Programming Interface
ASVS	Application Security Verification Standard
CBSL	Central Bank of Sri Lanka
DCS	Department of Census & Statistics
DSSAT	Decision Support System for Agrotechnology Transfer
EC	Electrical Conductivity
FAO	Food and Agriculture Organization
HARTI	Hector Kobbekaduwa Agrarian Research & Training Institute
IoT	Internet of Things
IVR	Interactive Voice Response
LBMC	Left Bank Main Canal
LKR	Sri Lankan Rupees
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MCDM	Multi-Criteria Decision-Making
ML	Machine Learning
MLflow	Machine Learning Workflow (tool for ML model tracking)
MQTT	Message Queuing Telemetry Transport
ONNX	Open Neural Network Exchange
OWASP	Open Worldwide Application Security Project
P95	95th Percentile (latency measure)
PDPA	Personal Data Protection Act (Sri Lanka)
Pi	Raspberry Pi
PWA	Progressive Web Application
RBMC	Right Bank Main Canal
REST	Representational State Transfer
RMSE	Root Mean Square Error

SLO	Service Level Objective
SMS	Short Message Service
SUS	System Usability Scale
TLS	Transport Layer Security
WCAG	Web Content Accessibility Guidelines
WUE	Water Use Efficiency
XAI	Explainable Artificial Intelligence
XGB	XGBoost (Extreme Gradient Boosting)

1 INTRODUCTION

Irrigated agriculture in large surface-water schemes must continually balance agronomic feasibility, infrastructure constraints, and farmer livelihoods against finite and seasonally variable water supplies. In Udawalawe (RBMC/LBMC), the challenge is amplified by heterogeneous soils and land-use, canal delivery limits, and the strong seasonality of Maha (Sep-Mar) and Yala (May-Aug). Crop choice and area planning are hard because decisions must jointly satisfy water quotas, soil/pH/EC thresholds, rotation and policy rules, and risk preferences while pursuing economic returns an inherently multi-objective problem where improvements in one objective (e.g., profit) may degrade another (e.g., water productivity or equity) [1]. Market uncertainty further complicates planning: short-horizon price fluctuations can erode margins if farmers default to traditional choices (e.g., paddy) without considering expected water use, suitability, or price dynamics. Consequently, planners need a systematic way to integrate hydrologic budgets, agronomic suitability, and price expectations into allocations that remain feasible under quota and delivery constraints.

Recent evidence indicates that machine learning can extract actionable cropping-pattern signals from mixed feature sets-combining land, soil, and climate variables-supporting predictive decision support at scheme scale [2]. Such models handle heterogeneous data types, capture non-linear interactions (e.g., between soil texture and rainfall), and generalize to new seasons or locales when appropriately validated. This body of work motivates using tabular ML for yield components and crop likelihoods, then embedding those predictions into transparent ranking and optimization workflows for field-to-canal planning.

Project scope. This proposal develops Function 4 - Adaptive Crop & Area Optimization (ACA-O) within an integrated IoT-AI irrigation platform. ACA-O delivers (i) a DL-assisted Top 3 crop recommendation per field (with rationales and risk bands) and (ii) quota-aware hectare planning across farmer and canal aggregates. Inputs include IoT sensor streams (soil moisture, water level, pH, EC), hydro-climate/Eto-Kc, soils/land-use layers, reservoir/canal allocations, and market price/cost signals. Methods combine FAO-style water budgets, fuzzy-TOPSIS suitability, tabular ML for yield, short-horizon price forecasting, and a linear/MIP optimizer that honors land, water, soil/rotation, and policy constraints. A mid-season "Plan-B" re-optimization responds to allocation and market shocks within defined service levels.

1.1 Background Literature Survey

A) Domain Overview

Cropping pattern refers to the spatial and temporal arrangement of crops on a given land area within and across seasons (e.g., Maha and Yala). In canal-command schemes, patterns emerge from farmers' crop choices under hydro-climatic variability, soil heterogeneity, and infrastructure constraints. Market dynamics add another layer: short-horizon price swings and input costs shift expected margins, often pushing "default" choices that may not align with water productivity objectives. Machine-learning studies show that cropping patterns and choices can be predicted from mixed agro-environmental features combining land, soil, and climate variables supporting data-driven decision services in such settings [1].

Seasonality structures both water availability and agronomic windows. Quota announcements, reservoir status, and canal delivery capacities bound feasible irrigation schedules, while soils (texture, depth, pH, EC) and land-use constraints filter crop suitability. Planning must therefore balance multiple objectives (profitability, water productivity, equity/compliance) under resource limits and agronomic thresholds. Fuzzy and multi-criteria formulations explicitly recognize these trade-offs and encode expert or rule-based knowledge to maintain feasibility when information is imprecise or uncertain [2]. In operational terms, robust crop-area plans must respect land/soil constraints, rotation and policy rules, and quota-aware water budgets, while remaining responsive to mid-season shocks in allocations or market conditions.

Scope of this project. Within this context, our system develops a DL-assisted Top 3 crop recommendation per field and a quota-aware hectare plan across farmer/canal levels. The pipeline integrates IoT sensing (soil moisture, water level, pH, EC), hydroclimate and ETo/Kc budgets, soils/land-use layers, and price/cost signals, aligning predictive models with multi-objective, constraint-aware optimization. The intent is to move from descriptive pattern mapping to prescriptive, explainable recommendations and plan updates that remain feasible under water limits and market uncertainty—an approach consistent with evidence on ML over mixed features [1] and with fuzzy, multi-objective planning principles for cropping-pattern design [2].

B) Related Work Comparison

Fuzzy-TOPSIS for crop selection. Studies applying fuzzy-TOPSIS rank candidate crops against criteria such as soil suitability (including pH/EC), temperature windows, water availability, and land type, handling linguistic/uncertain judgments via fuzzy sets. The method computes a close coefficient to an ideal solution, yielding transparent rankings and sensitivity to criterion weights. This supports explainable field-level shortlists that can be surfaced to farmers and planners [3]. While strong for ranking, TOPSIS does not by itself allocate area or enforce inter-field water coupling, motivating its integration with downstream optimization.

ML classification of cropping patterns. Work on cropping-pattern prediction with mixed features (land, soil, climate) demonstrates that tree-based learners (e.g., gradient boosting) and other classifiers can learn non-linear interactions and deliver competitive accuracy at scheme or regional scales [1]. Complementary efforts propose ML pipelines and tooling for major pattern prediction and decision support, underscoring practicality for operational deployments and offering baselines for feature engineering and validation strategies [4]. These strands validate the feasibility of learning crop tendencies and yield components from heterogeneous tabular inputs but typically stop short of coupling predictions to water-quota-aware hectare optimization.

Remote sensing for mapping patterns/phenology. Phenology-based approaches use time-series vegetation indices to map cropping patterns and temporal dynamics, aiding rotation detection, season delineation, and anomaly flags (e.g., late sowing). Such products can augment ground features with spatial continuity and historical context, improving suitability and yield features while informing rotation/sequence constraints [5]. However, these studies focus on mapping and monitoring; they rarely integrate market expectations or translate maps into prescriptive, quota-constrained area decisions.

Fuzzy multi-objective planning. Fuzzy systems have been used to formalize multi-objective, multi-constraint cropping-pattern problems where water, agronomy, and policy targets must be balanced under uncertainty. These frameworks provide a principled way to handle imprecision and trade-offs, shaping feasible, interpretable decisions [2]. Yet, most formulations do not ingest real-time sensor/market signals nor connect to short-horizon price/yield forecasts, limiting responsiveness to mid-season allocation changes or market shocks.

Synthesis. Across strands, we find: (i) fuzzy-TOPSIS offers explainable crop ranking but not quota-aware area allocation; (ii) ML classifiers learn cropping tendencies from mixed features but often lack prescriptive coupling to water budgets and market risk; (iii) remote-sensing phenology enriches features and rotation context but remains descriptive; and (iv) fuzzy multi-objective planning encodes trade-offs but rarely fuses live IoT/market data or mid-season re-optimization. The missing piece is an integrated, predict-then-optimize service that combines explainable suitability (fuzzy-TOPSIS), tabular yield and short-horizon price forecasts, and quota-aware hectare optimization with Plan-B re-optimization—precisely the role targeted by our ACA-O module.

1.2 Research Gap

Fuzzy methods excel at transparent ranking but stop short of prescriptive, quota-aware allocation. In crop selection, fuzzy-TOPSIS and related fuzzy multi-objective systems provide explainable scores over criteria such as soil pH/EC, temperature windows, and water suitability; however, they neither fuse full-lifecycle rainfall/irrigation demand with short-horizon price signals nor decide how many hectares to assign per crop across coupled fields under scheme-level quotas and policy bounds [1], [4].

Supervised ML work on cropping-pattern prediction shows that labels can be learned from mixed land–soil–climate features, yet these classifiers (and tool-style pipelines) output “what pattern” rather than a quota-aware area plan that respects rotation, canal delivery, and water envelopes [2], [5]. Remote-sensing phenology adds valuable, spatially complete maps of past or current patterns, but remains descriptive: it does not integrate prices or allocate hectares forward in time [3].

Therefore, the gap is a unified, forward-looking service that (i) learns predictive signals (yield/price) from heterogeneous data, (ii) produces explainable Top-3 field recommendations, and (iii) allocates hectares via an optimizer that enforces land, soil/rotation, policy, and water-quota constraints—plus mid-season re-optimization when allocations or markets shift. Our DL-assisted recommender + allocator is designed to fill exactly this gap by coupling explainable fuzzy ranking with data-driven forecasts and quota-aware optimization into a single, operational module (ACA-O).

1.3 Research Problem

Design and evaluate an operational module that generates explainable Top 3 crop recommendations per field and a quota-feasible hectare plan for the Udawalawe scheme by fusing stage-wise crop water needs (Kc–ETo), reservoir/canal availability, lifecycle rainfall forecasts, soil/pH/EC and land-use constraints, and market price/cost signals. The system must preserve feasibility with respect to land, water envelopes, soil/rotation, and policy rules; produce signed water-requirement envelopes for the scheduler; and support mid-season Plan-B re-optimization when allocations or prices shift. Success will be demonstrated through constraint feasibility, improvements over baseline practices in profit per hectare and water productivity, timely re-optimization, and farmer adherence to recommended plans-without specifying numeric thresholds at proposal stage.

2 OBJECTIVES

2.1 Main Objectives

Design, implement, and evaluate ACA-O to produce Top-3 crops per field with rationales and a quota-feasible hectare plan at farmer/canal levels by fusing stage-wise crop water need (Kc–ETo), reservoir/canal availability, lifecycle rainfall forecasts, market price signals, and historical data maximizing profit/ha while respecting soil/pH/EC, rotation, and seasonal water constraints.

2.2 Specific Objectives

1. SO1 - Explainable field recommendations. Generate Top-3 per field with one-line rationales and risk bands; ensure full field coverage and responsive API delivery; ties to FR-Top3, FR-API and F4.6 latency metrics.
2. SO2 - Forecasting quality. Deliver rolling-origin-validated yield and short-horizon price forecasts, including predictive uncertainty for risk; ties to FR-Forecasts and F4.6 error metrics (MAE/RMSE/MAPE).
3. SO3 - Quota-feasible optimization. Produce hectare plans that pass water-envelope, soil/pH/EC, rotation, and policy checks; respect announced quotas; ties to FR-HectOpt, FR-Env and feasibility metric in F4.6.
4. SO4 - Outcome improvement. Demonstrate uplift in profit/ha versus paddy-by-default and heuristic baselines and increase water productivity ($kg \cdot m^{-3}$); ties to outcome metrics in F4.6.
5. SO5 - Mid-season resilience (Plan-B). When allocations/prices change, recompute and publish a delta plan promptly with minimal disruption to already-planted areas; ties to FR-PlanB and F4.6 re-optimization SLOs.
6. SO6 - Adoption & usability. Achieve positive usability (SUS) and farmer adherence to recommended hectare plans in pilot; ties to F4.6 adoption metrics.

2.3 SMART Check

Objective	S (Specific)	M (Measurable)	A (Achievable)	R (Relevant)	T (Time-bound)
Main Objective	Recommender + optimizer maximizing profit/ha under constraints	Profit/ha, feasibility rate, latency, adherence	Uses platform data + solver stack	Central to LO1–LO5	By pilot end [TBD date]
SO1	Top-3 with rationale/risk per field; responsive APIs	% fields covered; API P95 latency [TBD]	Model + API in FastAPI/K8s	Enables trust & usage (FR-Top3/FR-API)	Live by [TBD date]
SO2	Yield & price forecasts with uncertainty	Rolling-origin MAE/RMSE/MAPE ≤ [TBD]	Data pipelines + baselines in place	Feeds profit/risk & Plan-B (FR-Forecasts)	Backtested by [TBD date]
SO3	Quota-feasible hectare plan	Feasibility ≥ [TBD]%; envelope ≤ quota	Linear/MIP with rule packs	Satisfies constraints (FR-HectOpt/Env)	First cut [TBD date]
SO4	Outcome gains	Profit/ha ↑ [TBD]%; WP ($kg \cdot m^{-3}$) ↑ [TBD]%	Pilot A/B against baselines	Direct impact to farmers & scheme	Pilot read-out [TBD date]
SO5	Mid-season Plan-B	Re-opt E2E ≤ [TBD]; publish ≤ [TBD]	Pre-warmed models + cached features	Operational resilience (FR-PlanB)	SLA live [TBD date]
SO6	Usability & adherence	SUS ≥ [TBD]; adherence ≥ [TBD]%	PWA + training	Ensures real uptake	Survey window [TBD date]

Table 2.1: Smart Check Table

3 METHODOLOGY

3.1 System Overview

The ACA-O pipeline ingests multi-source data, engineers crop–water and market features, learns predictive models, then solves a quota-constrained hectare allocation and serves results to both farmers and scheme managers. Field telemetry (soil moisture, water level, pH, EC) is sent from edge nodes via MQTT v5 publish/subscribe to a broker and streamed into Apache Kafka topics for durable, replicated storage and fan-out to consumers [1], [2]. Hydroclimate (rainfall, ETo), reservoir allocations, soils/land-use, and price feeds join the stream; a feature service applies FAO-56 procedures (Kc–ETo) to compute field-resolved ETc and water budgets that underpin feasibility and water-productivity analysis [3].

Model layer.

- Environmental suitability & explainability. Candidate crops are scored with fuzzy-TOPSIS (an MCDM method) using criteria such as soil pH/EC, water availability, temperature window, and land type; outputs include the closeness coefficient and a human-readable rationale [4].
- Yield (tabular). Field/season features feed gradient-boosted trees—XGBoost [5] and LightGBM [6]—chosen for accuracy and efficiency on structured agronomic data.
  Short-horizon prices (time series). We forecast weekly price signals with Temporal Fusion Transformers (TFT) [7]; where series are short/sparse, we fall back to LSTM [8] or a classical baseline.
- Profit under uncertainty. We combine yield × price − cost to estimate profit distributions (Monte Carlo) and pass expected value and risk bands to optimization.
- Optimization. A linear/mixed-integer program maximizes expected profit while penalizing water use/volatility; constraints enforce reservoir/canal quotas, pH/EC feasibility, rotation, and policy bounds. Fuzzy optimization literature supports multi-objective trade-offs and shows area shares should shift materially under water/ecology goals [9].

APIs & UI. A FastAPI service exposes: POST /f4/recommendations (field/canal context → Top-3 crops + hectare plan + water envelope), POST /f4/planB (mid-season re-optimization when allocations change), and GET /f4/national-supply (aggregate area/demand). Responses are signed and published to the Irrigation Department dashboard for RBMC/LBMC operations [10].

MLOps & deploy. Models are tracked in MLflow Model Registry (lineage, versioning, stage transitions) [11]. Services are containerized with Docker and orchestrated on Kubernetes Deployments to enable rolling updates/rollbacks with near-zero downtime during season windows [12]. Stream ingestion and model services scale independently via horizontal pod autoscaling.

3.1.1 System Overview Diagram (Overall)

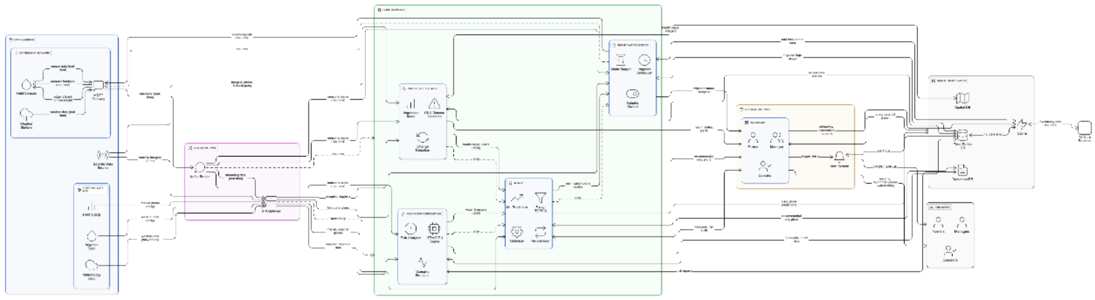

Figure 3.1: System Overview Diagram

3.1.2 Approach and Workplan

3.1.3 Data and Instruments

Datasets (sources & access).

- Market prices. Daily/weekly farm-gate & wholesale bulletins from HARTI (CSV/PDF), used for short-horizon price features and validation.
- Retail prices. Weekly retail dashboards and historical tables from the Department of Census & Statistics (DCS) for consumer-side signals.
- Hydro-climate & forecasts. Official Sri Lanka Department of Meteorology advisories/forecasts for 7–14-day inputs; FAO CROPWAT and CLIMWAT for crop water requirement calculations and station climatologies.

- Remote sensing. Sentinel-2 L2A (surface reflectance) for crop/soil context, Landsat 8/9 L2 access via USGS, and MODIS MOD13Q1 NDVI (16-day, 250 m) for phenology features.
- Spatial context. GeoGoviya national agri/parcel portal for farmer and paddy-land registries used in ground truthing and scheme-level aggregates.
- Sensors / instruments (field telemetry).
- Soil moisture (VWC). *METER Group TEROS-10* probes for volumetric water content; rugged, frequency-domain, field-ready.
- Water level (canal/field). *JSN-SR04T* waterproof ultrasonic ranging module (20–600 cm) for low-cost level sensing in lined channels.
- Soil/irrigation water pH. *Atlas Scientific EZO-pH* circuit + probe for continuous pH telemetry.
- Electrical conductivity (EC/salinity). *Atlas Scientific EZO-EC* circuit for µS/cm measurements and temperature-compensated salinity/TDS.
- Rain (optional station). *OTT Pluvio²-S* weighing precipitation gauge for reference rainfall at scheme office (WMO practice).
- Measurement standards. Instrument siting/QA aligned to WMO No. 8 (Guide to Instruments and Methods of Observation).

Software & tooling.

- IoT transport. MQTT v5.0 (OASIS standard) via Eclipse Mosquitto broker.
- Streaming/ingest. Apache Kafka for durable event log and fan-out.
- Feature/DB. Feast (feature store) and TimescaleDB (Postgres extension) for time-series telemetry/hypertables.
- APIs & MLOps. FastAPI for REST endpoints; MLflow Model Registry for lineage/versioning; Kubernetes Deployments for rolling updates.
- Models (canonical). XGBoost / LightGBM for tabular yield; Temporal Fusion Transformer (TFT) and Prophet as price-forecast baselines

3.1.4 Anticipated Results and Evaluation

Metrics (what we will measure)

- **Decision outcomes**
  - **Profit/ha (LKR/ha)** vs. baselines (paddy-by-default; heuristic splits).
  - **Water productivity (kg m^{-3})** = yield ÷ crop water use (ETc), per FAO/AquaCrop; reported by crop, canal, and scheme.
  - **Oversupply/shortage alerts**: **precision**, **recall**, **F1** of alerting at canal/district level (ground truth from realized prices/volumes). Definitions follow IR evaluation (F1 = harmonic mean of precision & recall).
- **Forecasting quality**
  - **Price (1–4-week horizon): MAE**, **RMSE**, **MAPE** under **rolling-origin** evaluation; canonical accuracy measures per Hyndman. Competing models compared with the **Diebold–Mariano (DM) test** for equal predictive accuracy.
  - **Yield: RMSE/MAE** against harvest labels; stratified by crop/season/soil.
- **Feasibility & usability**
  - **Feasibility rate:** % of recommended hectares that satisfy **water quota + pH/EC + rotation** constraints.
  - **Usability: System Usability Scale (SUS)** for farmer/manager UIs (10-item, 0–100).
- **Operations (SRE-style)**
  - **Latency SLOs:** P95 **≤2 s** (/recommendations), **≤5 s** (/area-optimize).
  - **Availability SLO: ≥99.5%** monthly; tracked via SLOs/error budgets per Google SRE workbook.

- **Validation plan (how we will test)**
- **Blocked field pilot (Udawalawe RBMC/LBMC):** A/B across distributaries to compare **profit/ha** and **water productivity** against baselines over one season.
- **Rolling-origin backtesting (prices):** multi-horizon evaluation with MAE/RMSE/MAPE; model comparisons via **DM test** (α=0.05).
- **Spatial/temporal CV (yield):** leave-canal/leave-season-out folds; report RMSE/MAE with confidence intervals.
- **Alert evaluation:** compute **precision/recall/F1** of oversupply/shortage flags using realized outcomes.
- **Plan-B stress tests:** simulate −10/−20% mid-season allocation cuts; measure **re-opt latency**, **feasibility rate**, and **profit shortfall** vs proportional-cut baseline.
- **Usability study:** SUS with ≥10 users (farmers/managers); qualitative feedback logged.
- **Operational SLO monitoring:** latency/uptime tracked with SLOs and **error budgets**; alerting on SLO burn rate.
- **Reporting & baselines**
- **Baselines:** paddy-by-default area; heuristic 50/50 splits; **seasonal-naïve/last-value** price forecasts; simple linear yield model—per forecasting practice.
- **Dashboards:** per-canal metrics (profit/ha, kg m^{-3}), forecast error tables, and SLO status; all results versioned and auditable.

3.1.5 System Overview Diagram (Individual)

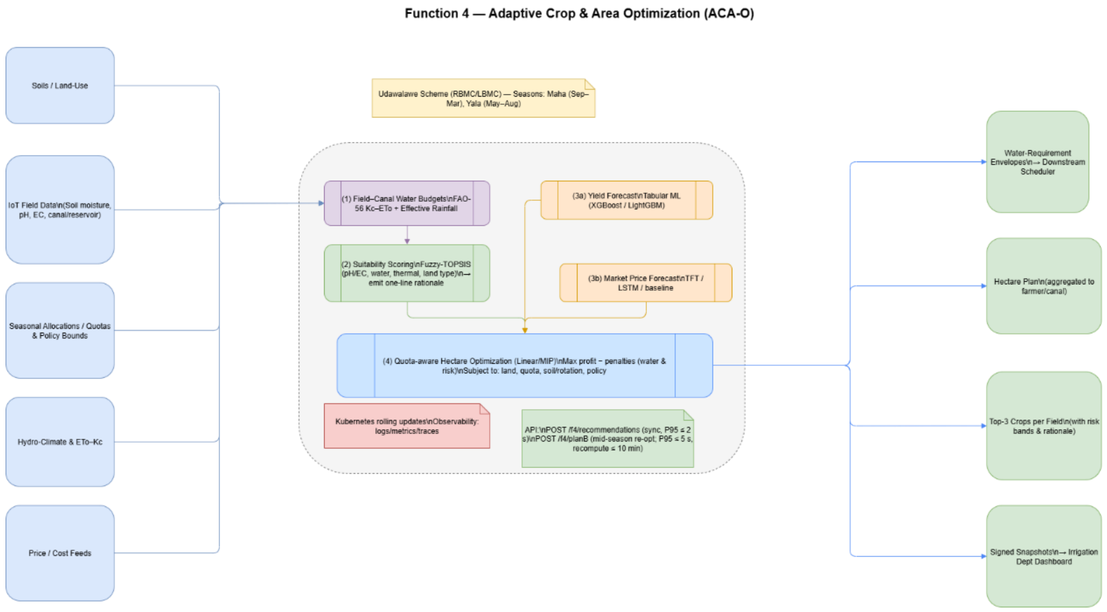

Figure 3.2: System Overview Induvial Component

3.2 Requirement Analysis

3.2.1 Functional Requirements

- **Ingest telemetry (Edge→Broker).** Edge gateway publishes soil-moisture, water-level, pH, EC via **MQTT v5** topics; messages accepted and acknowledged by broker. (Conformance: OASIS **MQTT 5.0**).
- **Stream processing (Platform).** Normalize and persist telemetry and price/allocation feeds to a durable log (**Kafka** topics) with partitioning & replication. (Conformance: Apache **Kafka** docs).
- **Water budget features (Service).** Compute per-field **ETc** and deficits using **FAO-56** Kc–ETo procedures; store to feature/analytics store. (Method: FAO-56).
- **Suitability scoring (Service).** For each field, produce **Top-3** crops with fuzzy-TOPSIS scores and human-readable rationales. (Method: fuzzy-TOPSIS).
- **Yield & price signals (Service).** Train tabular yield models (XGBoost/LightGBM) and short-horizon price models (TFT; fallback LSTM); expose prediction endpoints. (Canonical methods).

- **Hectare optimization (Service).** Solve **quota-constrained** crop–area allocation (profit↑, water use↓, risk↓) subject to pH/EC/rotation and policy bounds; return **hectares per crop** (farmer & canal). (Grounded in fuzzy multi-objective literature).
- **Plan-B re-optimization (Service).** On allocation/advisory change, recompute plan and publish delta within SLA (see NFRs).
- **Water envelope publication (Service).** Convert area plans to **water-requirement envelopes** and publish to the scheme dashboard for scheduling.
- **APIs (Backend).** Provide POST /f4/recommendations, POST /f4/planB, GET /f4/national-supply with OpenAPI docs (**FastAPI**).
- **Access control & security (Platform).** Enforce authn/authz and secure coding checks per **OWASP ASVS**; map platform controls to **NIST SP 800-53** families.
- **Accessibility (Frontend).** Farmer PWA & manager dashboard meet **WCAG 2.1 Level AA** for critical user flows.
- **Privacy compliance (Data).** Process personal data in line with **Sri Lanka PDPA No. 9 of 2022** (e.g., lawful basis, cross-border provisions).

3.2.2 Non-functional Requirements

- **Performance & availability**
  NFR-1: **Latency** P95 ≤ **2 s** for `/recommendations`; P95 ≤ **5 s** for `/planB`.
  NFR-2: **Availability** ≥ **99.5%/month** using rolling updates (Kubernetes **Deployments**).
- **Security & privacy**
  NFR-3: Meet **OWASP ASVS** L2 coverage for auth, session, input validation, crypto, logging.
  NFR-4: Implement platform controls mapped to **NIST SP 800-53 r5** (e.g., AC, AU, CM, SC families); document assessments per **800-53A**.
  NFR-5: **PDPA** alignment—data minimization, purpose limitation, retention, DPO contact where applicable.

- **Usability & accessibility**
  NFR-6: **SUS ≥ 75** with target users; apply **Nielsen's 10 heuristics** during UX reviews.
  NFR-7: **WCAG 2.1 AA** success criteria for navigation, color contrast, keyboard use, alt text.
- **Reliability & auditability**
  NFR-8: **Exactly-once** processing semantics for critical streams or compensating logic documented; Kafka topic retention ≥ 30 days for audit.
  NFR-9: **Model lineage/versioning** via **MLflow Model Registry**; only "Production" models may serve.
- **Maintainability & portability**
  NFR-10: Services containerized; **rolling updates/rollbacks** supported; infra-as-code stored in VCS.

3.2.3 User Requirements

Personas & roles

- Farmer (primary). Receives Top 3 crop choices with profit bands, Plan-B, disease diagnosis; can confirm a choice and see water-requirement envelope. *Maps: FR-1, FR-2, FR-4, FR-7.*

- Scheme Manager (RBMC/LBMC). Sets seasonal quotas/weights, views oversupply/shortage signals, exports reports. *Maps: FR-3, FR-9, FR-10, FR-12.*

- Analyst/Planner. Audits rationale, monitors data quality and model drift; runs exports. *Maps: FR-10, FR-11.*

- MLOps/Admin. Manages access (OAuth2/OIDC), release channels, and alerts. *Maps: FR-8, FR-11.*

Accessibility & inclusion (WCAG-aligned)

- The web/mobile UI shall **conform to WCAG 2.1 Level AA** (perceivable, operable, understandable, robust) with keyboard navigation, sufficient contrast, alt text, form error cues, and focus order [1]. WCAG 2.x is backwardscompatible, and WAI recommends using the most recent version; targeting **2.2 compatibility** is acceptable for AA conformance [2].

Mobile-first & offline tolerance

- UI follows **responsive layout** and adaptive panes/grids for small screens (farmers) up to desktop dashboards (managers), using Material Design responsive patterns [3][4].
- Farmer apps behave as a **PWA**: cache last recommendations, rationale, and images; provide **offline and background operation** via **service workers** for weak connectivity [5][6][7].

Localization & internationalization (i18n/L10n)

- Provide **Sinhala/Tamil/English** UI strings; ensure **Unicode end-to-end** (front-end, APIs, DB) and follow W3C i18n guidance (language metadata, text direction handling, date/number formats) [8][9][10].

3.2.4 System Requirements

Category	Requirement	Notes / Source
Edge HW	Linux-class gateway with MQTT 5 client; sensor interfaces (I^2C/analog)	Protocol conformance: **MQTT 5.0**.
Broker	**MQTT** broker (e.g., Mosquitto)	OASIS MQTT v5 standard.
Streaming	**Apache Kafka** cluster (≥3 brokers; replication ≥3)	Topics for telemetry/prices/allocations; durability & partitioning.
Feature/DB	**TimescaleDB** hypertables for time-series telemetry	Hypertables & chunking for scalable writes/queries.
Model registry	**MLflow Model Registry**	Lineage, versioning, stage transitions.

API layer	**FastAPI** services for /f4/* endpoints	Auto OpenAPI/Swagger docs.
Orchestration	**Kubernetes** (Deployments)	Rolling updates/rollbacks for zero-downtime releases.
Frontends	PWA (farmer), web dashboard (manager)	**WCAG 2.1 AA** accessibility targets.
Security & privacy	Controls mapped to **OWASP ASVS** and **NIST SP 800-53 r5**; PDPA compliance	Security verification & control catalog; national data-protection law.

Table 3.1: System Requirements

3.3 Gantt Chart

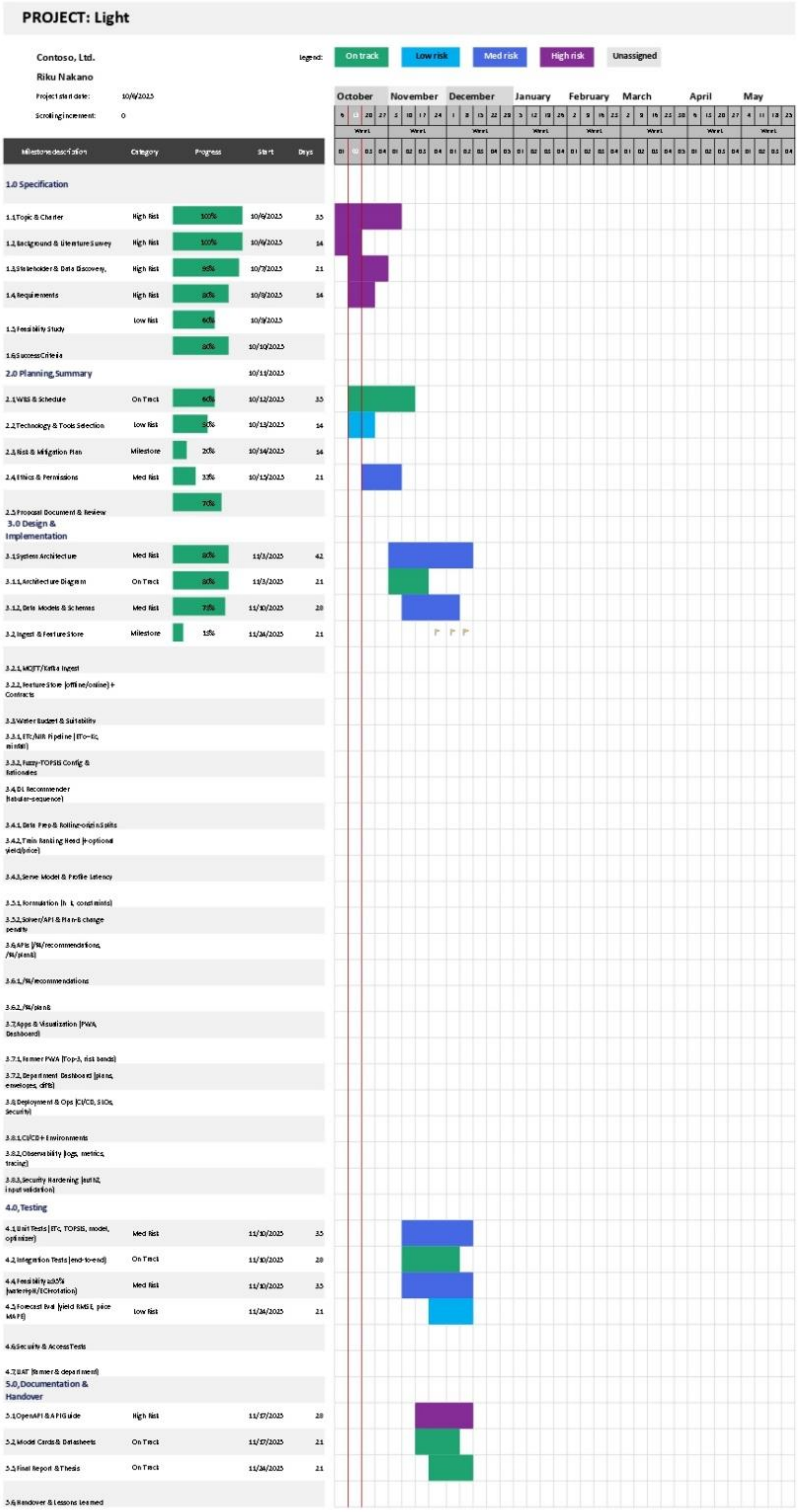

Figure 3.3: Gantt Chart

3.4 Work Breakdown Structure

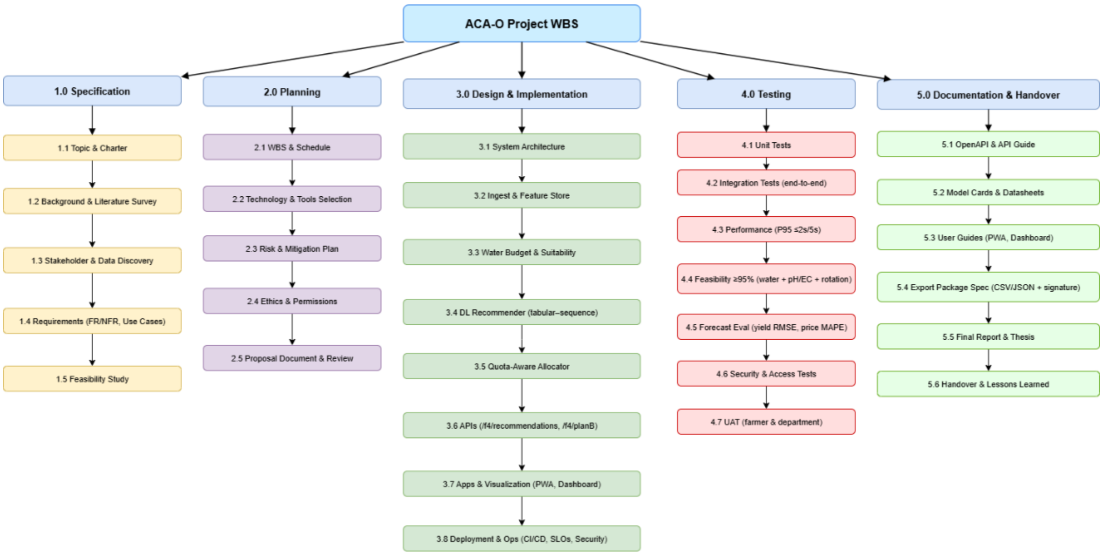

Figure 3.4: Work Breakdown

4 BUDGET AND BUDGET JUSTIFICATION

Item	Qty	Unit Cost (LKR)	Total (LKR)	Justification
Soil moisture sensor (capacitive)	5	290	1,450	Per-field soil moisture input; capacitive type is low-noise vs resistive. Price ref. duino/Alphatronic. (alphatronic.lk)
pH sensor with probe (module + BNC)	5	4,650	23,250	Field pH screening to enforce crop thresholds. Local module pricing. (tronic.lk)
TDS/EC analog sensor (conductivity)	5	2,850	14,250	EC proxy for salinity; board-level kit suitable for MCU. (tronic.lk)
Waterproof ultrasonic level sensor (JSN-SR04T)	2	1,050	2,100	Canal/reservoir level telemetry; IP-rated ultrasonic. (tronic.lk)
ESP32 DevKit (Wi-Fi/BT)	5	1,850	9,250	Edge compute & comms for each node; widely available. (tronic.lk)
3/4″ 12 V DC solenoid valve (NC, brass)	5	6,215	31,075	Actuation for laterals; common 3/4″ size. Local marketplace pricing. (Daraz)
IP65 ABS enclosure (≈200×200×80 mm)	5	2,450	12,250	Weatherproof housing for node + wiring. (General Power Electric)
20 W, 12 V solar panel	5	4,290	21,450	Off-grid power per node (sensor+ESP32+valve duty). (Duino)
12 V 7 Ah sealed lead-acid battery	5	4,790	23,950	Energy buffer for night/overcast operation. (Duino)
10 A PWM solar charge controller	5	6,790	33,950	Simple charging & panel/battery protection. (Duino)
DC-DC buck converter 12 V→5 V (5 A)	5	1,350	6,750	Regulated 5 V rail for MCU/sensors. (alphatronic.lk)
Cloud VPS (Lightsail $5/mo × 6 mo)	6 mo	1,514	9,081	API + DB hosting. $5 plan × USD→LKR ≈ 302.7 on 2025-09-29 ⇒ ~LKR 1,514/mo. (Amazon Web Services, Inc.)
Subtotal (hardware + cloud)			188,806	
Contingency (~10%)			18,881	Coverage for cables, glands, mounts, spares.
Grand Total			207,687	

Table 4.1: Estimatted Budget & Justification

5 COMMERCIALIZATION AND ENTREPRENEURSHIP POTENTIAL

5.1 Market need

Irrigated farming in Sri Lanka dominates freshwater use and faces tightening allocation constraints; FAO notes agriculture accounts for ~70% of global withdrawals and up to 95% in many developing countries, underscoring the need to raise "crop per drop" productivity in canal schemes like Udawalawe (RBMC/LBMC). In Sri Lanka specifically, FAO's country profile reported agriculture at ~87% of total withdrawals (albeit an older snapshot), while agriculture still contributes ~8.3% of GDP—a sizable productivity lever given water scarcity and quota seasons. Within the Udawalawe system, two main canals (RBMC/LBMC) supply a command area on the order of 18–20k ha from the Uda Walawe reservoir, highlighting the scale at which better crop choice and area planning can shift outcomes. Regionally, investment interest is rising: the Asia–Pacific smart irrigation market is projected to grow at ~17–18% CAGR through 2031–2033, reflecting demand for sensing-plus-software decision systems.

5.2 Competitors / Alternatives

Hardware-first irrigation vendors (drip/micro) such as Rivulis and Jain Irrigation dominate hardware supply and dealer networks, often bundling basic scheduling tools. Remote pivot management suites like Lindsay FieldNET offer telemetry, automation, and "Advisor" recommendations, but are oriented to center-pivots rather than canal-command smallholder mosaics. Sensor-platforms (e.g., Arable) combine in-field weather/plant/soil signals with analytics, yet typically stop at field-level insights rather than quota-aware, scheme-level hectare optimization. Locally, distribution partnerships (e.g., DIMO × Rivulis/Eurodrip) indicate channel depth for micro-irrigation rollouts, which we can partner with rather than replace.

Substitutes today: agronomist advice, FAO-style calculators, spreadsheet planning, and ad-hoc price watching—none integrate lifecycle rainfall, live quotas, short-horizon price forecasts, and rotation rules into a single, auditable hectare plan.

5.3 **Value proposition**

ACA-O delivers (i) Top-3 explainable crop recommendations per field and (ii) a quota-feasible hectare plan that maximizes expected profit/ha while enforcing water, soil/pH/EC, rotation, and policy constraints. This goes beyond sensor dashboards by fusing forecasts (rainfall/price), scheme quotas, and agronomy into an allocation decision and by shipping signed snapshots for departmental audit. Competing tools tend to optimize at the device or field level; ACA-O optimizes across farmer/canal aggregates and provides Plan-B re-optimization when allocations change mid-season—closing a key capability gap in canal-command systems. (Market growth in smart irrigation and established hardware channels reduce adoption friction for a software-led decision layer.)

5.4 **Pricing / Unit economics**

A pragmatic model is device-light + software-first: (1) Per-hectare seasonal license for recommendations + allocator outputs (farmer tier), (2) scheme license for dashboards, archives, and exports (department tier), and (3) optional sensor bundles via partners (Rivulis/Jain/DIMO) when sites need new telemetry. Hardware is capex through channels; ACA-O monetizes the decision service. Illustrative unit economics (placeholders until procurement confirms): gross margin driven by software (hosting + support per field/canal), with acquisition via partners subsidized by existing dealer networks. Include expected payback based on profit/ha uplift and water-productivity gains from pilot evidence → [CITATION NEEDED]. For broader benchmarking, global smart-irrigation vendors price as subscriptions layered on hardware; Asia–Pacific growth signals willingness to pay where ROI is clear.

5.5 **Go-to-market & risks**

GTM: (1) Department-led pilot in Udawalawe (RBMC/LBMC) to validate feasibility, profit/ha uplift, and latency SLOs; (2) scale through dealer partnerships (e.g., DIMO/Rivulis) bundling ACA-O with micro-irrigation upgrades; (3) add-on farmer PWA for Top-3 + rationale to drive adherence.

Key risks: (a) Data/forecast gaps (price feeds, rainfall skill) → baseline fallbacks and confidence bands; (b) Change management—farmer trust and adherence → explainable rationales and field trials; (c) Channel conflict with hardware vendors →

position ACA-O as device-agnostic decision layer that increases water-use ROI; (d) Macro volatility affecting farm budgets → tiered pricing and departmental sponsorship. Macro tailwinds include rising regulatory and economic pressure to conserve water and documented growth in smart-irrigation adoption across APAC

6 DESCRIPTION OF PERSONNEL AND FACILITIES

6.1 Personnel

- **Ms. Hansi De Silva** - Supervisor, Sri Lanka Institute of Information Technology (SLIIT)
- **Ms. Karthiga Rajendran** - Co-Supervisor, Sri Lanka Institute of Information Technology (SLIIT)
- **Mr. Thilanka Bandara** - External Supervisor, Renewable Energy Consultant
- **Mr. Dilruksha A.G.C.D. (IT22561770)** - Student Researcher, Smart Water Management Component

6.2 Facilities

- Sri Lanka Institute of Information Technology (SLIIT)
- Irrigation Department
- Udawalawe Dam Authority
- Udawalawa Agricultural Office

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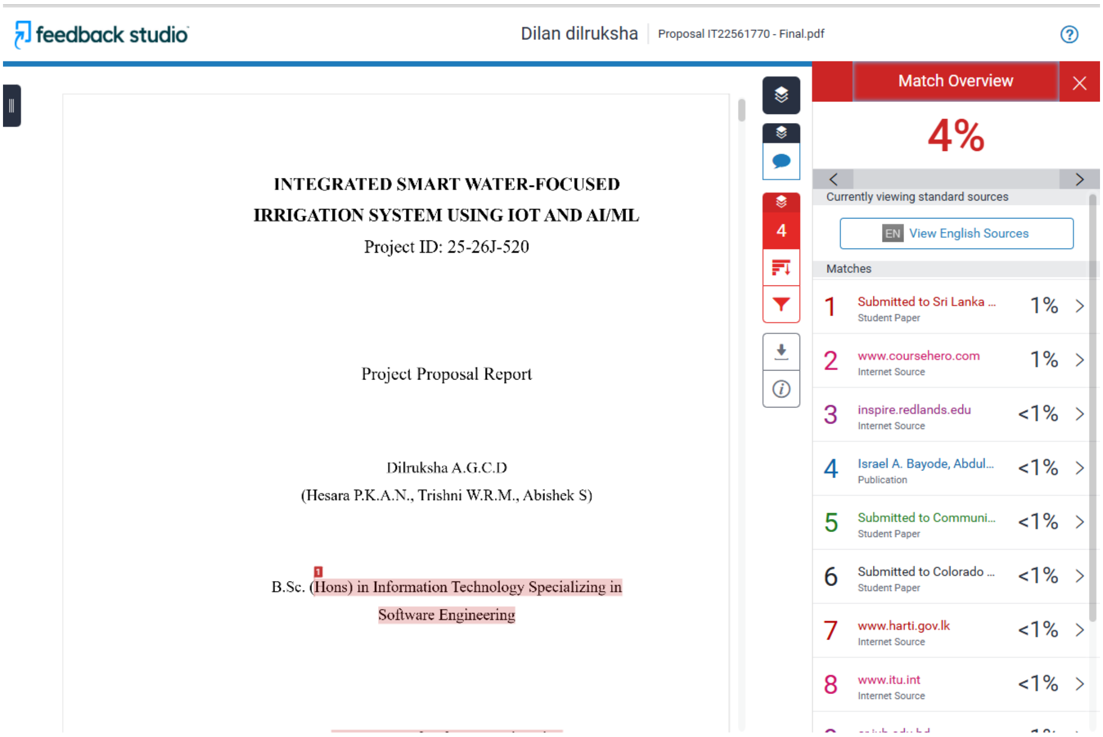
8 APPENDICES


feedback studio
Dilan dilruksha
Proposal IT22561770 - Final.pdf
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IRRIGATION SYSTEM USING IOT AND AI/ML
Project ID: 25-26J-520
Project Proposal Report
Dilruksha A.G.C.D
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