Synopsis - Volt Guard Lite: AI-Enabled Offline Voltage Stabiliser

India's household appliances are designed for 230 V ±10% (≈207–253 V), yet semi-urban and rural regions frequently experience extreme voltage swings of ±30–40%, transient spikes, and prolonged brownouts. These anomalies accelerate appliance wear, waste energy, and cause costly failures. Existing stabilisers are often reactive, with mechanical relay response times of 20–40 ms—too slow for sub-10 ms spikes—and many depend on cloud connectivity, which is unreliable in low-network areas. Volt Guard Lite addresses this gap as an offline, AI-enabled, solid-state voltage stabiliser engineered for Indian households, particularly in low-connectivity zones. It combines TinyML-based voltage forecasting, local data logging, and ultra-fast solid-state switching to protect appliances from both predictable and sudden anomalies.

Key Innovation Pillars:

- Predictive AI Protection: On-device TinyML model forecasts instability, enabling pre-emptive switching before harmful events occur.
- Offline Smart Operation: Functions entirely without internet; Bluetooth app offers real-time monitoring and manual control.
- Solid-State Speed: SSR/IGBT modules deliver microsecond-level switching with no mechanical wear or noise.
- Technology Stack: ESP32 with TinyML: Executes real-time voltage prediction using locally trained models.
- PostgreSQL Database: Stores historical voltage/current data for pattern analysis and model refinement. Solid-State Switching: SSR/IGBTs ensure fast, silent, and durable operation. Bluetooth Mobile App: Built with MIT App Inventor or Flutter for intuitive control and live monitoring.

By integrating predictive intelligence, offline resilience, and high-speed protection, Volt Guard Lite offers a scalable, affordable, and future-ready solution to India's voltage instability challenge-extending appliance life, reducing downtime, and safeguarding consumer investments.

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1. **Problem Statement (What & Why)**

In India, household appliances are rated for 230 V ±10% (≈207–253 V), yet semi-urban and rural regions often face swings of ±30–40%, transient spikes, and brownouts. These anomalies shorten appliance lifespan, increase energy waste, and cause costly failures. Existing stabilisers are reactive, slow (mechanical relay response times of 20–40 ms), and often rely on internet/cloud connectivity — impractical where connectivity is unreliable.

There is a pressing need for an affordable, locally intelligent stabiliser that can:

1. Predict voltage fluctuations using on-device learning.
2. Operate entirely offline without cloud dependency.
3. Provide real-time monitoring and control to the user.
4. Deliver sub-millisecond switching to protect sensitive electronics.
5. Scale from small devices (TVs, routers) to heavy loads (ACs, refrigerators).

2. **Brief Description of the Idea/Solution**

Volt Guard - Lite is an offline, AI-enabled, solid-state voltage stabiliser designed for Indian households, especially in low-connectivity regions. It combines TinyML-based voltage forecasting, local data logging, and fast solid-state switching to safeguard appliances from both predictable and sudden anomalies.

Innovation Pillars:

- Predictive AI Protection – On-device TinyML model forecasts instability, enabling pre-emptive switching before harmful events occur.
- Offline Smart Operation – Works entirely without internet; Bluetooth app provides monitoring and manual control.

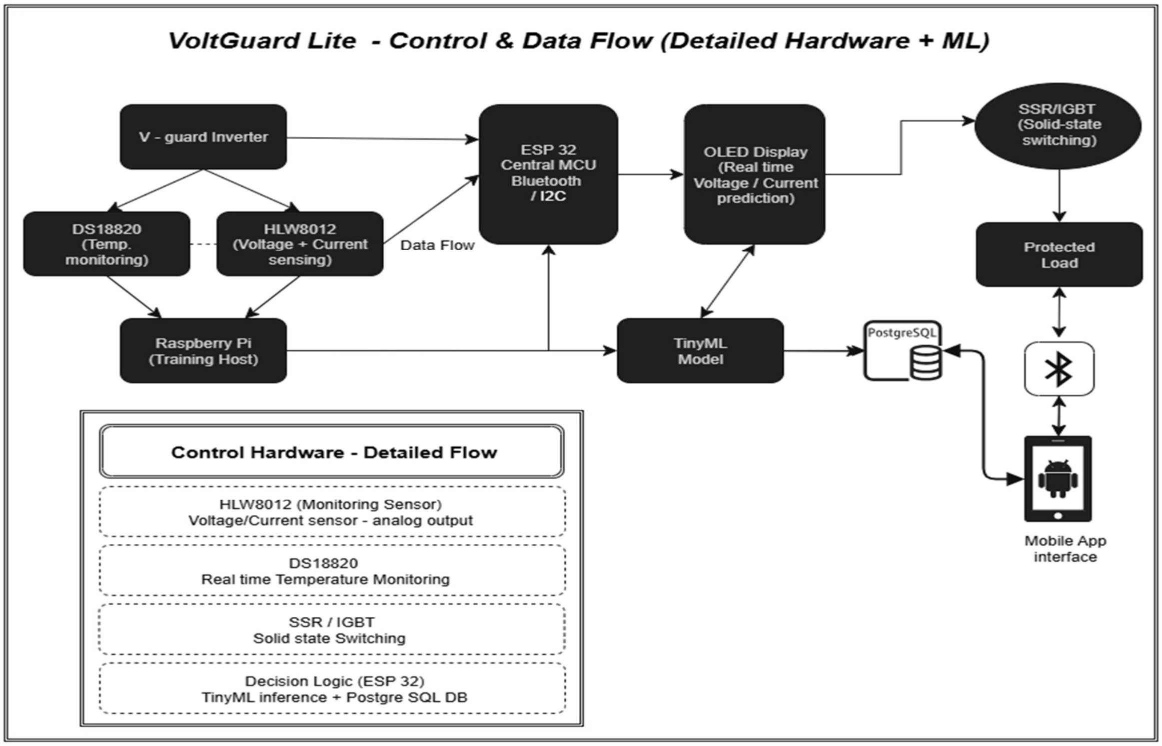
Solid-State Speed – SSR/IGBT modules ensure microsecond-level switching with no mechanical wear or noise.

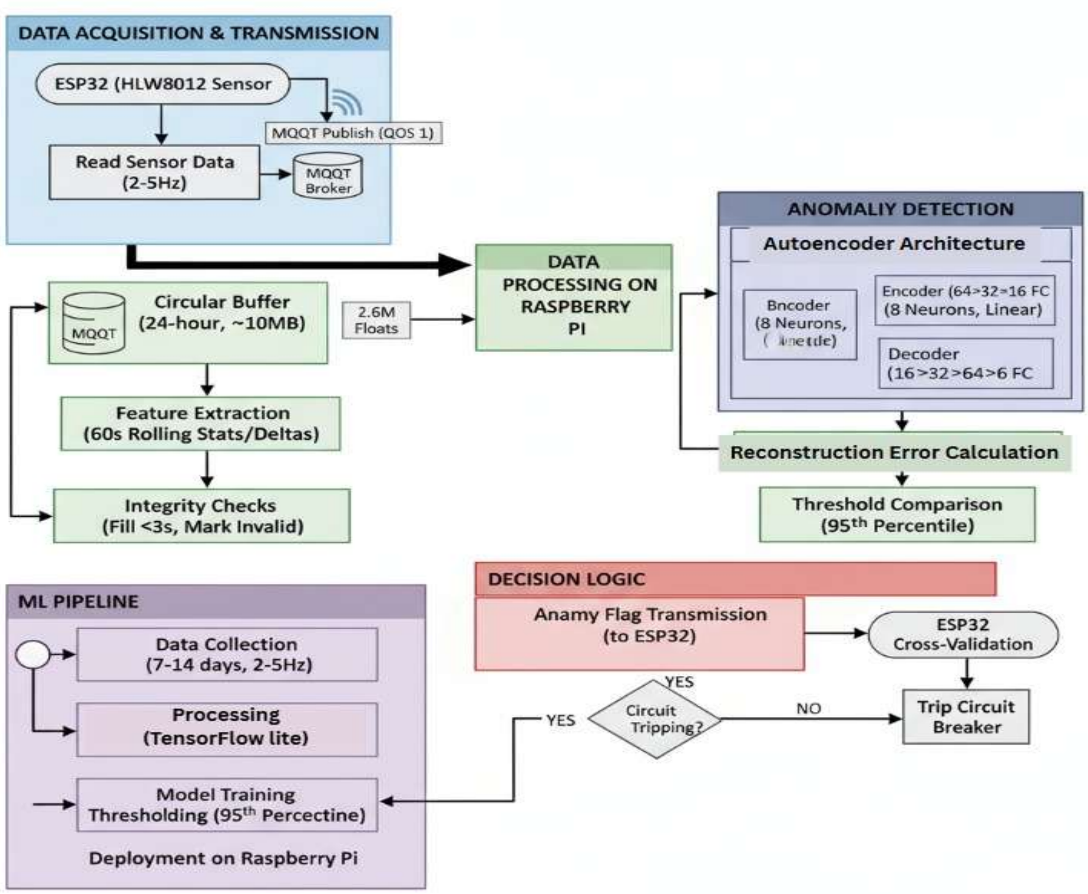
3. **Technology Proposed**

- **TinyML on ESP32:** Enables real-time voltage prediction using locally trained models.
- **PostgreSQL Database:** Stores historical voltage and current data for pattern analysis and model training.
- **Solid-State Switching:** Uses SSR/IGBTs for fast, silent, and durable operation.
- **Offline Bluetooth mobile app:** Built with MIT App Inventor or Flutter—for intuitive control and live monitoring.
- **Smart Safety Features:** Includes automatic cutoff and appliance delay timers for protection.

Modular Design: Scalable architecture suitable for various appliances, from TVs to ACs.

4. System architecture and Operational workflow





4.1 Core Components

- **Sensing Module:** HWL8012 voltage and current sensor to provide continuous, time-stamped measurements of supply voltage and load current.
- **Edge Controller & Compute Node:** ESP32 microcontroller for sensor sampling, TinyML inference, control logic execution, and local communications. Raspberry Pi for heavier data processing, model training
- **Local Database:** PostgreSQL instance for structured storage of historical voltage/current logs used for model training and diagnostic analysis. The database may be hosted on the Raspberry Pi or on compact, embedded storage, dependent on system capacity.
- **Switching Hardware:** Switching is performed via solid-state devices to ensure microsecond responsiveness and eliminate mechanical wear. Protection circuits and snubbers are implemented to manage switching transients and to ensure the long-term reliability of power semiconductors.
- **User Interface:** Offline Bluetooth mobile application (e.g., Flutter) providing visualisation, alerting, and manual override capabilities.

4.2 Sensing and Data Logging

The sensing pipeline continuously samples voltage and current at fixed intervals appropriate to the selected prediction window. Raw samples are timestamped and aggregated into short windows for immediate inference and into longer series for storage. The ESP32 performs primary acquisition and short-term buffering. For deployments with greater logging requirements, the Raspberry Pi hosts a PostgreSQL database that stores structured records and supports exploration of patterns.

4.3 TinyML Training and Inference

Volt Guard-Lite employs a TinyML workflow to perform prediction on resource-constrained hardware. Historical voltage and current logs are used to train compact models—such as pruned decision trees, lightweight ensemble regressors, or small neural networks—that capture premonitory data of sags, swells, spikes, and prolonged burnouts.

Trained models are converted into a format suitable for the ESP32 (e.g., TensorFlow Lite for Microcontrollers). Inference produces a discrete state label (for example: Stable, Warning, Critical). Model selection and feature engineering emphasise low latency, predictable memory usage, and robustness to sensor noise. Periodic retraining is supported using accumulated local logs to adapt to site-specific electrical profiles.

4.4 Control Logic and Actuation

- **Pre-emptive Switching:** When the prediction engine indicates a high likelihood of instability, the controller transitions connected loads to safe states (e.g., disconnect noncritical loads, engage staged power limits).
- **Immediate Cutoff:** If measured voltage/current exceeds hard safety thresholds, the system performs an immediate disconnection via SSR/IGBT to prevent equipment damage.

- **Staged Recovery and Delay Timers:** After an adverse event, the controller enforces configurable delay timers and staged reconnection logic to avoid damage from rapid oscillation on restoration.
- **Manual Override:** Authorised users may override automatic behaviour through the Bluetooth interface; however, the system enforces safety interlocks that prevent manual operations when thresholds are critically breached.

4.5 User Interface and Offline Operation

A Bluetooth mobile application provides a direct link to the ESP32, offering real-time telemetry (voltage/current graphs), alert notifications, configuration panels, and manual control. The application also displays diagnostic logs and the most recent model status. All user interactions and configuration changes take effect locally; optional features for exporting logs or model updates may use a local USB or Raspberry Pi interface when network connectivity is available.

Scalability and Modularity

The architecture is intentionally modular. The sensing and inference stack is decoupled from the power stage so that power electronics (SSR/IGBT modules) can be re-specified for different load classes without altering the prediction or control algorithms. The same firmware and model framework can be reused across product variants by changing sampling rates, model thresholds, and power stage ratings.

5 Hardware Design

5.1 Power Module

AC mains pass through a fuse & surge protection (MOV, TVS diode, NTC) to guard against inrush and line surges, feeding a power module that delivers isolated, stable 5 V and 3.3 V rails for the ESP32, sensors, and drivers.

- **AC–DC Conversion:** The HLK-PM01 module converts 230V AC to 5V DC.
- **Filtering:** Capacitors and inductors form a low-ripple power rail.
- **3.3V Regulation:** The AMS1117-3.3 regulator steps down 5V to 3.3V, powering the ESP32 and HLW8012.
- **Protection: A** TVS diode absorbs transients, while fuses isolate in case of sustained faults.

5.2 Sensing Circuit – HLW8012

The sensing block's HLW8012 IC provides the ESP32 with clean, calibrated, real-time voltage and current data for precise decision-making.

- **Current Measurement:** Achieved through a diverter (R5–R8 network) feeding into HLW8012.
- **Voltage Measurement:** A resistive divider (R1, R2) scales down the AC mains to safe levels.
- **Accuracy:** HLW8012 outputs digital pulses proportional to instantaneous power, voltage RMS, and current RMS.
- **Noise Handling:** Capacitors (C2, C3) provide filtering to reject harmonics and high-frequency noise typical in the Indian grid.

5.3 Control Unit – ESP32 and Raspberry Pi 3B

- The HLW8012 pulse outputs via optocouplers, and the Temperature sensor signals come from the SSR thermal monitoring for instant switching.
- GPIO control of SSR via NPN transistor driver stages and buzzer (BZ1) activation for audible fault alerts.

Core Features:

- Dual-core MCU with integrated Wi-Fi and Bluetooth.
- Runs TinyML inference for predictive fault detection in sync with Raspberry Pi 3B.

Raspberry Pi Collaboration:

- Executes over-voltage/undervoltage protection, delay timers, and safety logic.
- Combined ESP32 + Raspberry Pi ensures connectivity, predictive analytics, and real-time protection.

5.4 Switching Stage – SSR

- The ESP32 drives an opto-isolated SSR via an NPN transistor driver. This ensures safe low-voltage control of the AC Load.
- Snubber circuits suppress switching transients.
- Combined ESP32 + Raspberry Pi ensures connectivity, predictive analytics, and real-time protection.

Safety Features: Circuit integrates multi-layer safety mechanisms

- **Over/Under Voltage:**
  If the sensed voltage is >270V or <180V, the ESP32 immediately disconnects the load via SSR.
- **Configurable Delay:**
  For motor appliances (like refrigerators and ACs), the ESP32 introduces programmable delays before reconnection to prevent compressor damage.
- **Thermal Monitoring:**
  A temperature sensor near the SSR ensures that if switching devices overheat, the ESP32 shuts down the output.
- **Audible Alerts:**
  The buzzer is triggered during abnormal events (faults, restarts, and overheating).

Together, these features provide **robust protection against electrical faults, surges, and unsafe operating conditions**

Circuit Schematic

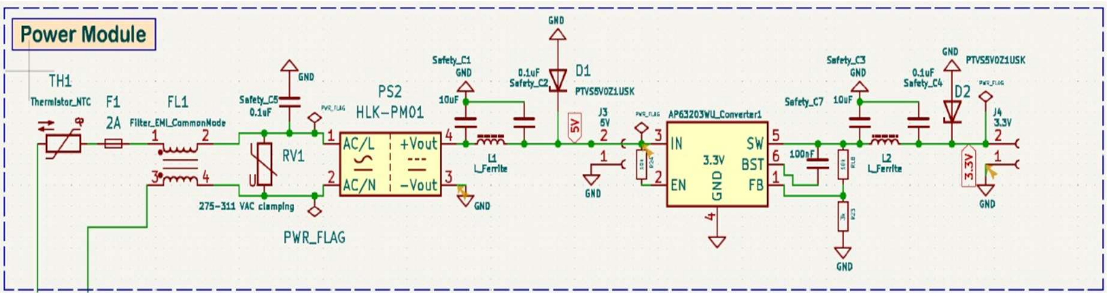


Figure 3.1. Power Module

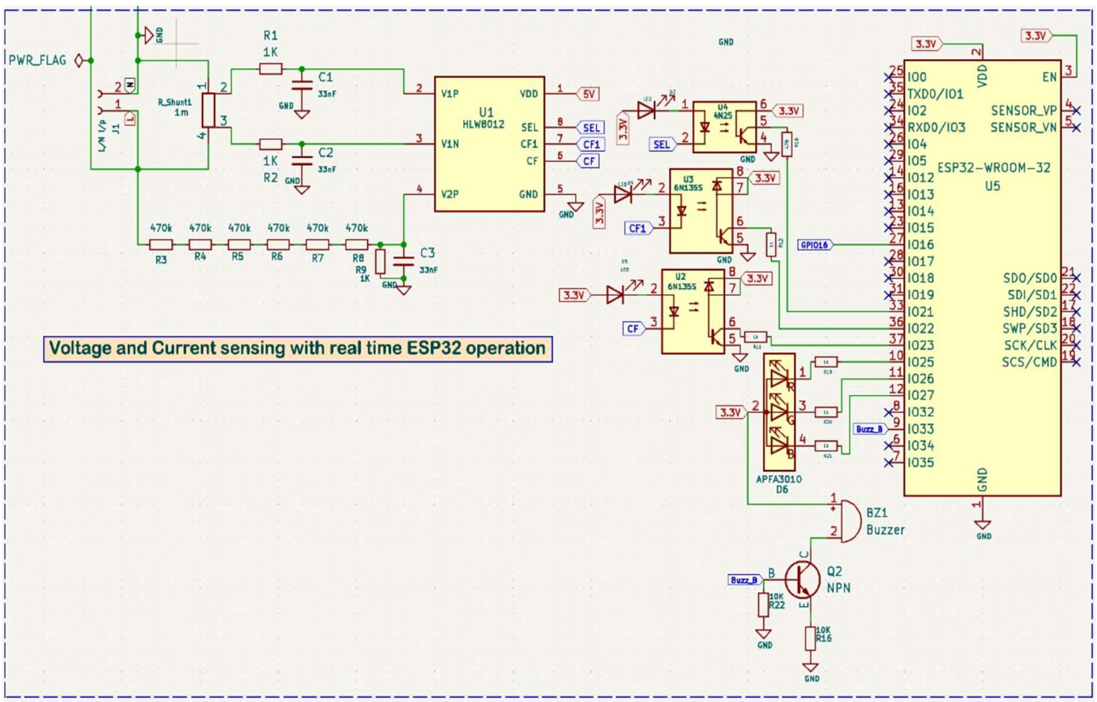


Figure 3.2. Voltage & Current sensing with real time ESP32 Operation

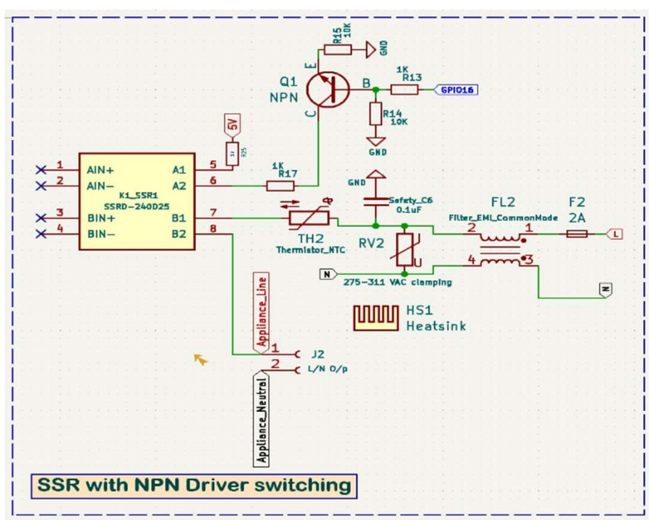


Figure 3.3. SSR with NPN Driver switching

3D PCB Layout

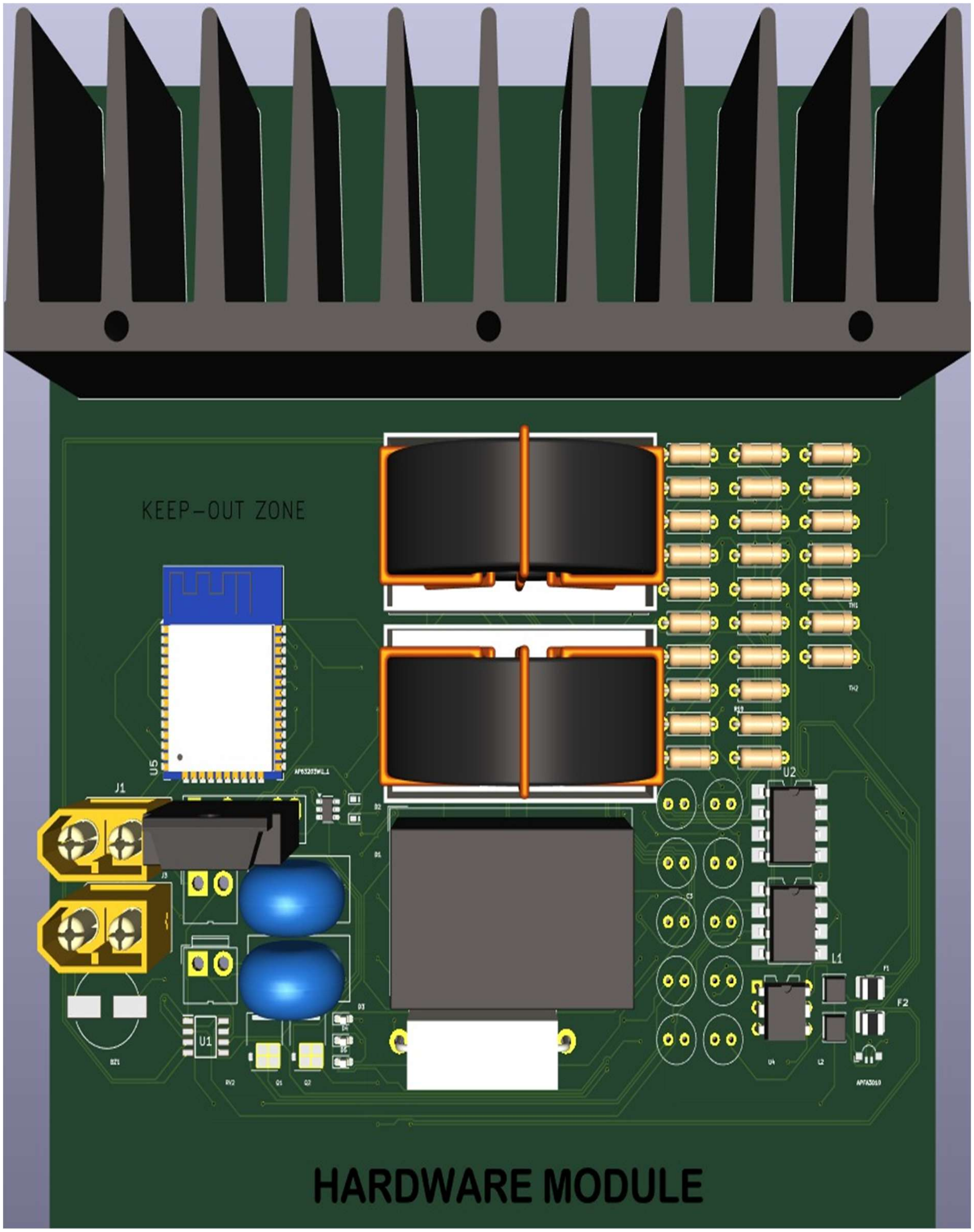
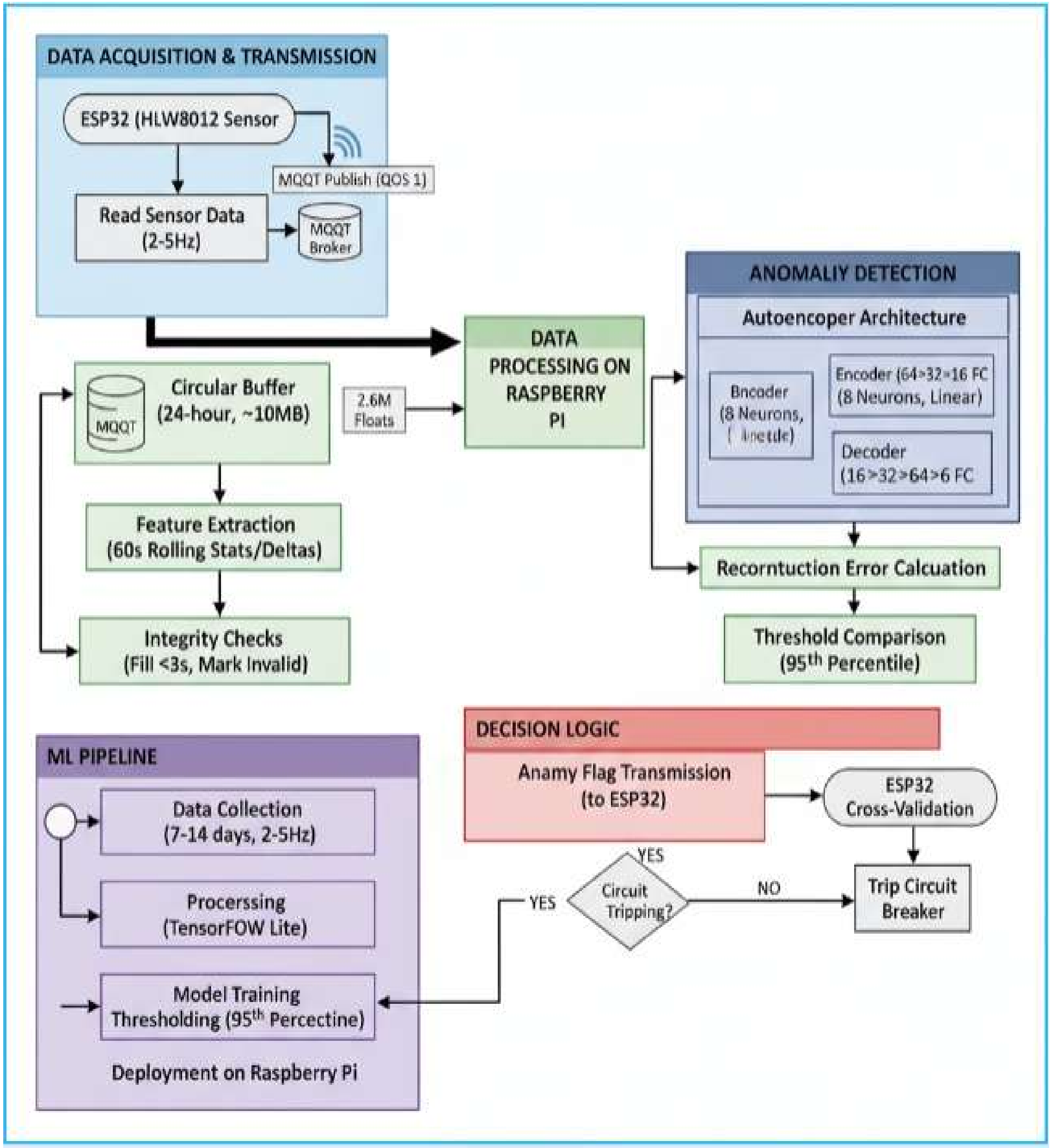


Figure 3.4. PCB Layout of Hardware

* Circuit parameters might change depending upon component requirements and ratings.

6 Software & Intelligence Layer



6.1 Data Flow

1. Acquisition – ESP32 reads HLW8012 data at 2–5 Hz.
2. Transmission—Data sent via MQTT (QoS 1) to Pi 3 B.
3. Buffering – Pi stores data in a fixed-size circular buffer covering exactly 24 hours.
4. Feature Extraction – Rolling statistics and deltas computed every 60 seconds.
5. Anomaly Detection—The autoencoder processes the 24-hour window and outputs reconstruction error.
6. Decision Logic – ESP32 trips the circuit based on ML flag and real-time validation or direct threshold breach.

Before the system is put into active protection mode, it undergoes a learning period in the actual household environment. This ensures the model understands the inverter's unique "normal" behaviour.

6.2 Process

- Setup: HLW8012, ESP32, and Pi 3 B are connected; trip function disabled during data logging.
- Data Logging: Collect 7–14 days of V/I data at 2–5 Hz with rolling stats; store in local DB.
- Model Training on an autoencoder on Pi using TensorFlow Lite or export data for external training.
- Thresholding: Analyse reconstruction error to set 95th percentile anomaly cutoff.
- Activation: Enable trip function; system enters real-time protection mode.

6.3 Edge ML Pipeline

- MQTT over TCP/IP ensures reliable delivery; Pi 3 B runs a Python (paho-mqtt) client to subscribe, ACK, and validate timestamps.
- **24-Hour Circular Buffer**: Stores ~2.6M floats (5 Hz × 24 h × 6 features ≈ 10 MB); auto-overwrites oldest data.
- Integrity checks fill short gaps (<3s), mark longer ones invalid, and exclude them from inference.
- Every 60s, Pi computes mean, std dev, and deltas for V/I, combining them with raw data to form the model input.

6.4 Autoencoder-Based Anomaly Detector

An **autoencoder** is a type of neural network designed to learn a compressed representation of input data and then reconstruct it as accurately as possible.

In our inverter system, this unsupervised model becomes a powerful tool for **detecting anomalies** in voltage and current behaviour by learning what "normal" looks like — and flagging deviations through **reconstruction error**.

<u>Architecture of Autoencoder-Based Anomaly Detector</u>

The autoencoder is split into two main components:

- **Encoder**: Compresses input data into a low-dimensional latent space.
- **Decoder**: Attempts to reconstruct the original input from this compressed representation.

The **bottleneck layer** between them forces the network to retain only the most critical features of the data, discarding noise and redundancy. This compression is key to anomaly detection: if the input is abnormal, the decoder struggles to reconstruct it accurately, resulting in a high reconstruction error.

- The input layer processes a 24-hour window of six features per time step: raw voltage/current, 60-second rolling means, and standard deviations of both signals.
- The encoder consists of 3 fully connected layers: the 1st with 64 neurons and ReLU (Rectified Linear Unit) activation to capture broad patterns, the 2nd with 32 neurons for refinement, & the 3rd with 16 neurons to extract the most essential features.
- Bottleneck Layer: Latent Embedding dense Layer with 8 neurons and linear Activation

This layer serves as the **latent space** or **embedding vector**, encoding the essential dynamics of a full day's inverter behaviour. It acts as a compressed signature of normal operation, minimising redundancy while retaining reconstructive fidelity.

- The decoder reconstructs the input through a sequence of dense layers: starting with 16 neurons and ReLU (Rectified Linear Unit) activation, followed by 32 and 64 neurons to progressively restore detail and scale, and ending with a 6-neuron output layer using linear activation to recreate the original six features.

This symmetric design forces the network to learn only the most important aspects of normal operation.

6.5 Training Process

Training teaches the autoencoder what "normal" looks like so it can spot deviations later.

- Data Collection: Capture 24-hour inverter voltage/current logs from real household settings to model normal behaviour.
- Validation Strategy: Inject synthetic faults (spikes, drifts, noise) into separate data to evaluate anomaly detection.
- Loss Function: Minimise Mean Squared Error (MSE) between input and reconstruction on normal data.
- Optimiser: Adam (LR = 0.001) for fast, stable convergence.
- Batch Size: 64 samples per batch for optimal training efficiency.
- Early Stopping: Halt training if validation MSE stagnates for 10 epochs to prevent overfitting.

Thresholding

- **Run Inference on Held-Out Normal Data**:

Use a separate validation set containing only healthy (non-anomalous) data. Pass this data through the trained autoencoder to compute reconstruction errors (typically Mean Squared Error, MSE).

- **Set Anomaly Threshold**:

Calculate the 95th percentile of the MSE distribution from the normal data. This value becomes the **cutoff threshold**: any input with reconstruction error above this is considered anomalous. This approach assumes that 95% of normal behaviour is well reconstructed, & the top 5% may contain outliers or borderline cases.

Detection Metrics (Evaluated on Fault-Injected Data)

- **Precision**: Measures how many of the flagged anomalies are true faults. High precision means fewer false alarms.
- **Recall**: Measures how many of the actual faults were successfully detected. High recall means fewer missed faults.
- **F1 Score**: Harmonic mean of precision and recall. Balances the trade-off between false positives and false negatives.

6.6 Deployment: Real-Time ML on Raspberry Pi 3 B

- **Model Conversion and Optimisation**

The trained autoencoder is exported to **TensorFlow Lite** format for compatibility with embedded systems.

- **Post-training quantisation** is applied, converting weights and activations to **8-bit integers (int8)**.

This reduces the model size to approximately **5 MB**, significantly lowering memory usage and improving inference speed.

- **Inference Performance**

The quantised model processes a full **24-hour time window** of input data in **50–80 milliseconds**. This execution time is well within the system's operational cycle of **60 seconds**, allowing for real-time anomaly detection.

- **Execution Flow on Raspberry Pi**
    - Upon boot, the Raspberry Pi loads the quantised TF Lite model into memory.
    - A rolling buffer containing the last 24 hours of voltage and current data is extracted.
    - Input features are **normalised** to match the distribution used during training.
    - The normalised data is passed through the autoencoder for **inference**.
    - **Reconstruction error** (Mean Squared Error) is computed between input and output.
    - The error is compared against a predefined **threshold** (95th percentile of healthy data).
    - If the error exceeds the threshold, an **anomaly flag** is generated and transmitted to the **ESP32 microcontroller**.

6.7 Role of Raspberry Pi 3 B in Smart Inverter System

- **ESP32 reads data** from the HLW8012 sensor at a rate of 2–5 Hz, capturing voltage and current measurements. **Each reading is packaged** into a JSON payload with relevant metadata.
- **Data is transmitted via MQTT** to the Raspberry Pi using QoS1 to ensure reliable delivery.
- **Raspberry Pi validates each message**, checks for integrity, and sends an acknowledgement (ACK) back to the ESP32.
- **Valid samples are stored** in a 24-hour circular buffer in RAM for fast access and rolling analysis.
- **Pi performs rolling statistics and delta calculations** on the buffered data to monitor trends and detect deviations.
- **An autoencoder model analyses the buffer, and if the reconstruction error exceeds a set threshold, the data is flagged. Anomaly alerts and raw data are sent** from the Pi to the ESP32 for cross-verification.
- **ESP32 confirms the anomaly**, comparing it with its own recent readings or sanity checks.
- **If confirmed, ESP32 activates a relay** to disconnect the load and turns on an LED to indicate fault status.
- **Raspberry Pi logs the event**—including raw data, anomaly details, and system state—into a PostgreSQL database for long-term storage and analysis lagged as anomalous.

7 Prototype Development

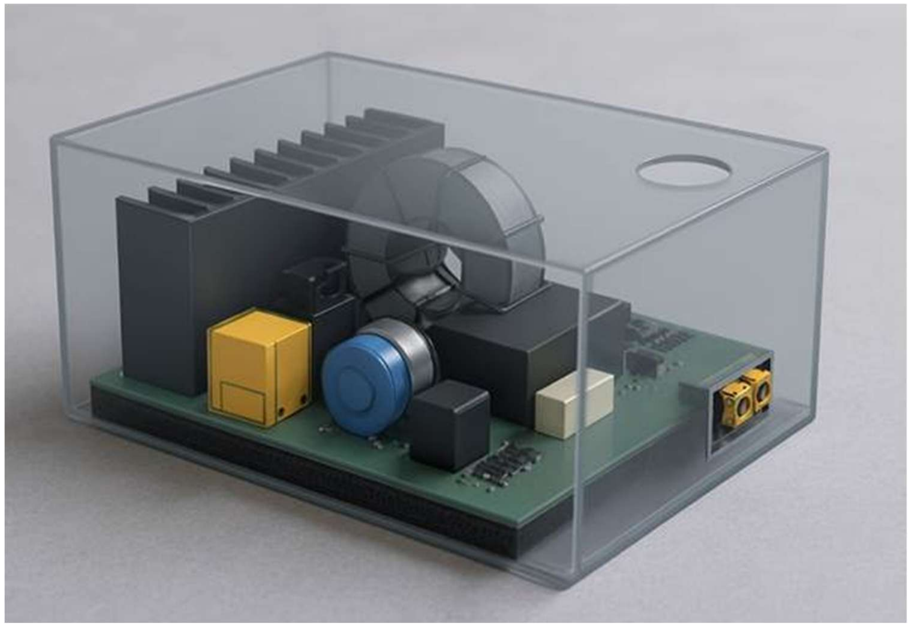
Bill of Materials

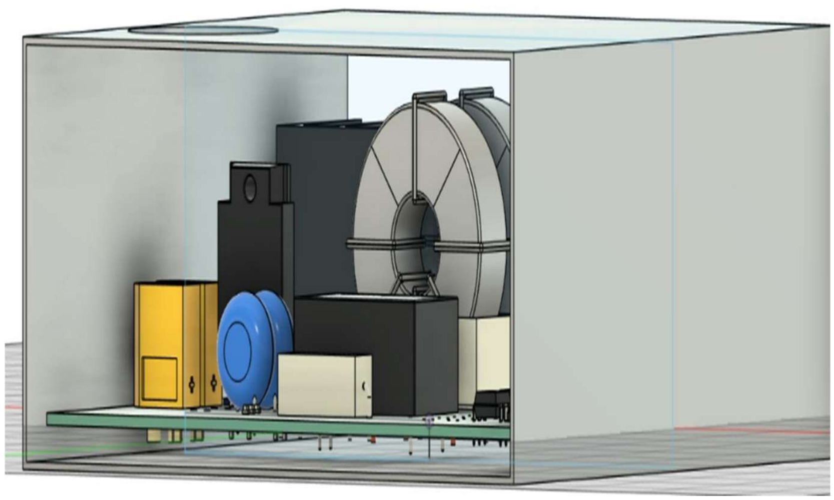
BOM			
Model No.	**Component**	**Price**	**Quantity**
NTC 10D-11(4mm, 325V rated)	Thermistor - NTC	₹10–₹15/piece	2
ESP32-WROOM-32	ESP 32 Module	₹250–₹350/piece	1
HLK-PM01	AC-DC Converter	₹150–₹200/piece	1
HLW8012	Voltage/current -sensing IC	₹40–₹60/piece	1
55RD-240025	SSR Relay	₹150–₹200/piece	1
6N135/4N25	Optocoupler	₹15–₹25/piece	3
AP63203WU	Buck Converter IC	₹30–₹50/piece	1
PTVS5VOZ1USK	TVS Diode	₹15–₹25/piece	3
APFA3010	RGB LED Strip	₹30–₹50/piece	1
Buzzer	Buzzer	₹30–₹50/piece	1
Diverter – 1mΩ	Shunt Resistor	₹10–₹15/piece	1
Ferrite Beads	Inductor	₹10–₹15/piece	2
Heatsink (Generic)	Heatsink	₹50–₹100/piece	1
Capacitors	0.1µF, 10µF, 330µF, etc.	₹2–₹5/piece	~ 10
Transistors (NPN/PNP)	Transistor	₹15–₹25/piece	~ 3
Resistors	Standard values	₹2–₹5/piece	~ 30
Connectors	Screw terminal + AMASS/Molex	₹15–₹25/piece	3 - 5
Misc Hardware	Assembly parts	₹250–₹350/piece	NA

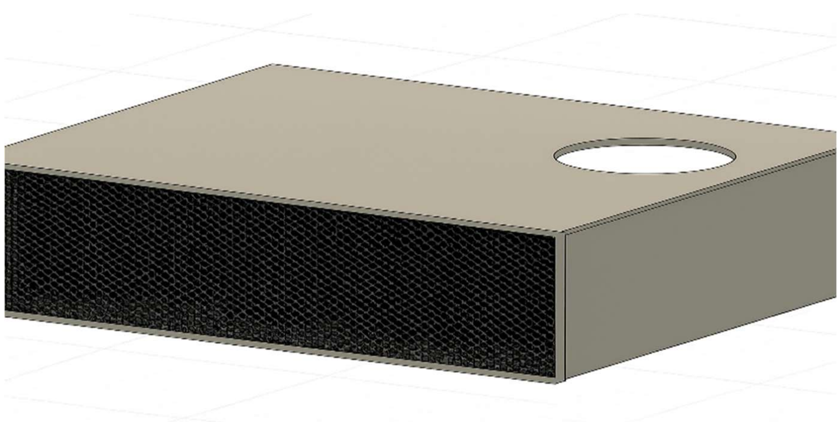
Estimated Total Cost Range

Estimated Total Cost Range Build Type	Approx. Cost (INR)	Details
Single Prototype	₹850 – ₹1,200	Includes all components, basic PCB, and connectors
Small Batch (10 pcs)	₹750 – ₹950 per unit	Bulk discounts on components and PCB fabrication
Optimised Production (100+ pcs)	₹600 – ₹800 per unit	Economies of scale, sourcing from wholesale suppliers

Enclosure Design







* A mesh-type cooling structure is given for cooling, which is done via a heat sink.

App Interface (https://volt-guard-ai.lovable.app)

A monitoring dashboard was developed using a low-code tool. This interface demonstrates the real-time visualisation, control panel, and alerting functions planned for the final Volt Guard system. While not yet fully connected to hardware, it provides a working sample configuration of the mobile/web application layer.

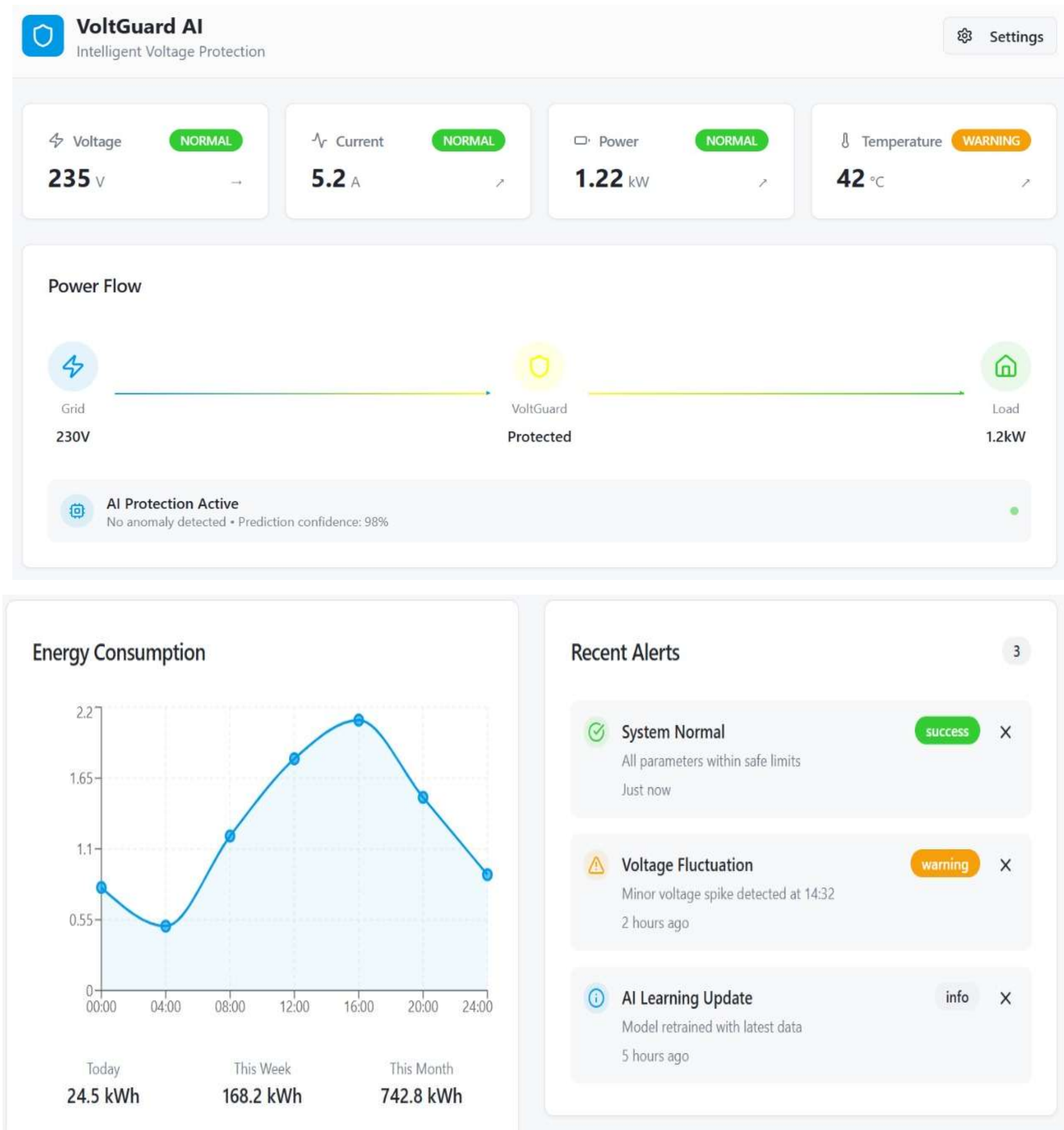


Figure 5.1. Dashboard of Web/App Interface

8 Consumer & Business Value Proposition

For Consumers

- **Longer Appliance Life:** Predictive AI monitors voltage patterns and anticipates harmful fluctuations, adjusting output to protect appliances—extending their life and reducing repair costs.
- **Uninterrupted Safety:** Unlike many smart devices that rely on cloud connectivity, this stabiliser operates entirely offline-ensuring peace of mind in all conditions.
- **Instant Awareness:** The integrated Bluetooth app empowers users with real-time live voltage readings, sends instant alerts during anomalies, & allows manual override or control-all from a smartphone. This transparency builds trust & gives users full control over their home's electrical safety.
- **Tailored Protection:** A household-specific training phase adapts the system to unique load patterns, reducing false trips and recurring cutoffs of the system.

For V-Guard (Business)

- **Market Leadership:** V Guard is blazing a trail as the first to introduce AI-powered, offline voltage stabilisers tailored for regions with limited internet connectivity. This bold move not only fills a critical gap in underserved markets but also positions V Guard as a category creator, setting the pace for future innovations in intelligent electrical protection. It's not just about being first—it's about being first with purpose.
- **Scalable Portfolio:** The product's modular design is a strategic asset. It allows seamless adaptation across a wide spectrum of appliances and power ratings. This flexibility enables V Guard to scale rapidly, customise offerings for different consumer segments, & maintain a unified technology backbone across its portfolio-driving operational efficiency and faster go-to-market cycles.
- **Cost-Optimised Design:** Uses affordable, widely available components for competitive pricing without performance compromise.

9 Future Scope & Scalability

- **Whole-Home & Industrial Integration:** Expand to protect entire circuits or industrial machinery.
- **Hybrid Connectivity:** Optional cloud sync for diagnostics, firmware updates, and aggregated analytics.
- **Enhanced ML Models:** Combine autoencoders with LSTM for deeper temporal pattern learning.
- **Renewable Energy Ready:** Integrate with solar inverter systems and PV performance monitoring.
- **Self-Adapting Intelligence: On-device** retraining to match evolving load profiles and grid conditions.
- **Compact Integration:** Miniaturised PCB versions for embedding directly into appliances.
- **High-Capacity Variants:** Scale up for SMEs, cold storage, and manufacturing facilities.

10 Conclusion

Volt Guard Lite represents a paradigm shift in inverter protection, transitioning from conventional reactive stabilisation to a predictive, adaptive, and offline-capable AI-driven architecture. Leveraging **TinyML deployment on the ESP32 microcontroller**, the system performs real-time forecasting of voltage instability, enabling **pre-emptive mitigation** rather than post-fault correction. This approach significantly enhances system resilience, particularly in environments with frequent voltage fluctuations.

The integration of **SSR mechanisms** ensures microsecond-level response times, eliminating the mechanical latency, acoustic noise, & wear associated with traditional electromechanical relays. A **household-specific learning phase**, powered by unsupervised anomaly detection and threshold-based logic, allows the system to adapt to unique load profiles, thereby minimising false positives and enhancing operational precision.

Volt Guard Lite combines:

- **High-resolution electrical sensing** via the HLW8012 module,
- A **robust edge ML pipeline** utilising 24-hour rolling data buffers,
- **Qual-layer safety logic**, merging AI-based anomaly detection with deterministic threshold checks for fail-safe operation.

The system's **offline resilience**, supported by a Bluetooth-enabled mobile interface, makes it particularly suitable for deployment in **low-connectivity regions**, including rural and semi-urban markets. Its **modular and scalable design** accommodates a wide spectrum of applications—from low-power consumer electronics to high-capacity industrial inverter systems.

Furthermore, the use of **cost-efficient, widely available components** facilitates competitive pricing, while onboard **data logging capabilities** pave the way for predictive maintenance and future integration into connected ecosystems.

In conclusion, Volt Guard Lite is not merely a voltage stabiliser—it is a **future-ready embedded AI platform**. It offers V Guard a strategic first-mover advantage in the emerging domain of intelligent inverter protection, with the potential to expand market share, reinforce brand leadership, and unlock new revenue streams across diverse geographies and product categories.

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