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Edge AI-Based Intelligent Controller for Energy and Water Efficient Smart Washing Machines

Preet Thakur[1], Dr. Sukanya Kulkarni[2], Dr. Reena Sonkurse[3], Dr. Prashant Kasambe[4]

PG Student, Dept. of Electronics and Telecommunication Engineering, Mumbai University[1]

Assistant Professor, Dept. of Electronics and Telecommunication Engineering, Mumbai University[2]

Assistant Professor, Dept. of Electronics and Telecommunication Engineering, Mumbai University[3]

Assistant Professor, Dept. of Electronics and Telecommunication Engineering, Mumbai University[4]

Abstract: Conventional washing machines rely on rigid, pre-programmed cycles that ignore the actual physical state of the laundry load, leading to substantial and unnecessary water and energy waste [1]. To tackle this everyday inefficiency, this paper presents a practical, smart washing machine controller powered by Edge AI and Internet of Things (IoT) technologies [2], [3]. The proposed system utilizes an ESP32 microcontroller outfitted with a comprehensive sensor suite, continuously monitoring load weight, multi-axis vibration, real-time water flow, temperature, and power consumption [4]. Rather than relying solely on high-latency cloud processing, the device performs local data acquisition and preprocessing at the edge, securely transmitting refined metrics to a Flask server via a REST API [5]. A Random Forest machine learning model utilizing an ensemble of 200 decision trees dynamically analyzes these variables to predict the optimal water volume, wash duration, and spin speed for each unique load. Live system metrics and operational states are continuously visualized using the ThingSpeak IoT platform. Experimental validation confirms that this adaptive, real-time approach significantly outperforms conventional fixed-cycle methods. The proposed Edge AI controller achieved a 24% reduction in water usage, an 18% drop in overall energy consumption, and shortened wash durations by 25%. Furthermore, the Random Forest model demonstrated robust predictive accuracy, achieving an R^2score of 0.87. Ultimately, this framework offers a highly practical, retrofit-friendly solution for transforming standard household appliances into sustainable, genuinely intelligent systems.

Keywords: Edge AI, Internet of Things (IoT), Random Forest Regression, Smart Home Appliances, Resource Optimization, Real-Time Data Acquisition, Sensor Integration, Predictive Modeling, Cloud Data Visualization

I. INTRODUCTION

Washing machines have become one of the most essential household appliances in modern daily life. However, conventional washing machines typically operate on fixed washing cycles that blindly follow a pre-programmed timer, regardless of the actual load size or condition. Consequently, unnecessary water and electricity are wasted during almost every wash. As the global push for energy efficiency, water conservation, and sustainable home technologies accelerates, this inherent inefficiency must be addressed. To solve this, there is a rapidly growing need for intelligent systems capable of adapting to real-time physical conditions. Recent advancements in the Internet of Things (IoT) and edge computing offer a robust framework for upgrading such smart appliances. By moving data processing closer to the hardware source rather than relying entirely on remote cloud servers Edge AI provides faster, more dependable localized decision-making. Researchers have already begun exploring predictive maintenance for home appliances like washing machines to continuously monitor their health and operating conditions [6].

Furthermore, deploying machine learning directly within edge computing environments has proven highly effective for real-time applications and resource optimization [7]. In the context of laundry systems, several recent studies have attempted to integrate intelligent automation. Approaches range from AI-assisted one-touch input mechanisms capable of adapting to load conditions [8] and sensor-driven automatic drying frameworks [9], to comprehensive IoT-enabled smart washing machine models [10].

While these contributions are significant, many existing solutions remain limited by cloud latency dependencies or require consumers to purchase entirely new hardware. To bridge this gap, this paper introduces a highly practical, Edge AI-based intelligent controller designed to optimize washing machine efficiency. The proposed architecture centers around an ESP32 microcontroller equipped with a suite of five sensors that continuously monitor load weight, multi-axis drum vibration, water flow, temperature, and real-time power consumption. By executing initial data preprocessing locally at the edge, the system securely transmits refined metrics to a Flask server. There, a Random Forest machine learning model

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predicts the optimal water level, wash duration, and spin speed tailored precisely to that exact load. Experimental validation of this setup demonstrates a 24% reduction in water usage, an 18% drop in energy consumption, and a 25% decrease in wash duration, proving that continuous sensing and Edge AI can transform an ordinary appliance into a highly adaptive, resource-efficient system.

II. PROBLEM STATEMENT

Washing machines are among the most heavily used appliances in modern households, yet their standard operation remains surprisingly inefficient. The fundamental flaw lies in their reliance on fixed, pre-programmed washing cycles. When a user selects a cycle, the conventional machine blindly executes it using a fixed volume of water and a set timer, regardless of whether the drum is packed with heavy denim or lightly loaded with a few shirts. Because these traditional systems cannot adapt to varying load conditions, they consistently trigger unnecessary and excessive consumption of both water and electrical energy during almost every wash.

While recent research has heavily advocated for the integration of intelligent technologies to combat resource waste, a practical gap remains at the individual appliance level. For instance, although broad frameworks utilizing IoT and Machine Learning have been proposed to monitor and improve overall smart home energy efficiency [11], and modern power electronics have been investigated to physically enhance machine hardware [12], these solutions rarely address dynamic, real-time adaptability during the active wash cycle itself. Researchers have successfully developed virtual models to analyze how washing machines utilize resources under different conditions [13], and have presented smart home management strategies specifically aimed at optimizing energy consumption and reducing operational costs [14]. Furthermore, the vital role of Artificial Intelligence and Machine Learning in achieving sustainable energy management is widely recognized in the academic community [15].

However, translating this high-level energy research into a localized, real-time decision-making system for an everyday washing machine remains a significant challenge. Standard machines lack the on-board sensory awareness to detect the actual physical state of the laundry such as its exact weight or mid-cycle drum vibrations and lack the localized edge-processing capabilities required to instantly adjust parameters like water flow, heat, and spin speed on the spot. Therefore, the core problem addressed by this project is the absence of an adaptive, continuous-monitoring controller that can dynamically adjust to real-time physical conditions, thereby eliminating the resource waste caused by fixed timers and blind operational cycles.

III. LITERATURE SURVEY

The domain of smart appliance automation and household energy management has commanded immense focus from the global research community, driven primarily by the urgent need for resource conservation and sustainable technologies. To combat operational inefficiencies, researchers have aggressively investigated a wide spectrum of machine learning frameworks and intelligent control architectures aimed at optimizing resource utilization and system reliability.

[16] In 2024, Tekin et al. engineered a comprehensive review focused on on-device machine learning for IoT applications from an energy perspective. While their investigation showcased the clear benefits of keeping AI processing local to ensure speed and dependability, the study exposed the persistent challenges of model compression on resource-constrained microcontrollers. Ultimately, their findings underscored the critical necessity of balancing hardware constraints with advanced edge computing capabilities to achieve truly sustainable smart devices.

[17] Addressing the limitations of rigid, pre-programmed control systems, Ai-zhen and Guo-feng (2012) constructed a neural network fuzzy controller designed specifically for washing machines. Their architecture improved upon baseline models regarding adaptive washing parameters based on predefined inputs. However, the architecture's reliance on older, isolated network paradigms meant it lacked the modern IoT connectivity required for real-time remote monitoring, continuous data logging, and dynamic updates.

[18] Wu (2016) conducted an investigation evaluating the micro-interactive interface design of intelligent washing machines operating within an IoT environment. The study's conclusions emphasized that seamless user interaction and continuous environmental sensing play a pivotal role in overall appliance efficiency. Even with optimal interface design, achieving true hardware-level resource optimization without continuous, multi-sensor feedback throughout the active wash cycle remained a persistent, unresolved hurdle for these systems. [19] In an attempt to optimize automated decision-making, Wang et al. (2010) deployed a Fuzzy-Neural Network based on a Hybrid Genetic Algorithm (HGA)

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within a washing machine control system. While their system managed to secure a moderate degree of adaptability in controlled or simulated environments, it lacked the edge-processing capabilities required to instantly parse and react to the complex, noisy sensor data generated during real-world physical operations. This failure highlighted an urgent requirement to transition toward much more responsive, localized data acquisition strategies.

[20] Taking a broader structural approach, Ding et al. (2011) introduced foundational research on an automatic washing machine control system aimed at improving baseline mechanical operations. This heuristic approach proved highly capable of executing fundamental, sequenced automated tasks. Unfortunately, the rigidity of early automation heavily restricted its adaptability, causing it to fail when confronted with varying load weights, mid-cycle vibrations, and real-time fluctuations in water flow.

A comprehensive review of the existing academic literature consistently indicates a clear technological trade-off. Traditional automated control systems deliver operational simplicity but routinely fail to map the complex physical realities and real-time variations of individual laundry loads. In contrast, heavy cloud-based AI architectures provide deep analytical capabilities, but they frequently introduce prohibitive latency, strict connectivity dependencies, and high computational overhead. Consequently, constructing a hybrid implementation that carefully integrates the low-latency, localized data preprocessing of an ESP32 edge microcontroller with the robust predictive capabilities of a Random Forest machine learning model represents a highly promising architectural solution. This combined framework successfully bridges the gap, offering the computational efficiency, real-time responsiveness, and deep resource optimization required to execute genuinely intelligent, adaptive washing machine control in real-world scenarios.

IV. PROPOSED METHODOLOGY

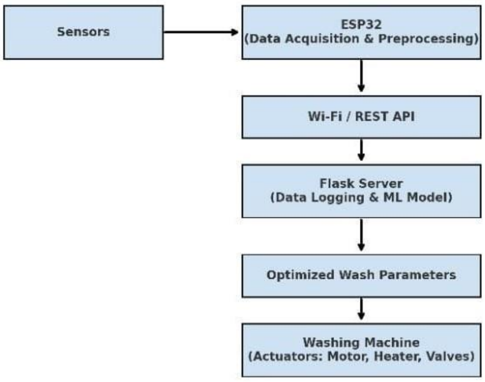

Fig 1. Proposed Methodology

Designing a genuinely intelligent washing machine requires moving away from static, pre-programmed timers and instead building a system that actively "listens" to its physical environment. The proposed architecture achieves this by distributing the operational workload across a local sensing layer, an edge-processing microcontroller, and a cloud-based machine learning server. This layered approach ensures that immediate, urgent decisions happen right on the device, while heavy computational analysis takes place on the server.

The Hardware and Sensing Layer

To fully understand what is happening inside the drum during a wash, the machine is retrofitted with five distinct sensors:

- **Weight Detection:** A load cell paired with an HX711 amplifier accurately calculates the exact mass of the laundry load before the cycle begins.
- **Vibration Monitoring:** An MPU6050 sensor tracks 3-axis movements, acting as a mechanical safeguard to detect dangerous imbalances especially during high-speed spins.
- **Water Management:** A YF-S201 flow sensor precisely counts incoming water pulses, translating them into actual volume to prevent wasteful overfilling.
- **Thermal Tracking:** A DS18B20 temperature sensor monitors the water heating process in real-time.

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- **Energy Auditing:** A PZEM-004T module keeps a continuous, live log of voltage, current, power, and overall energy consumption.

Edge Processing via ESP32 Raw sensor data straight from the hardware is inherently messy, often filled with minor errors, jumps, or voltage spikes. Instead of flooding the server with this noisy data, the ESP32 microcontroller acts as an edge processor. It locally filters the readings, smooths out vibration metrics using RMS calculations, and stabilizes the load weight values before any transmission occurs.

Cloud Communication and Machine Learning Once the data is cleaned at the edge, the ESP32 utilizes its built-in Wi-Fi to push the metrics via a REST API to a Flask-based server and a ThingSpeak dashboard for live user visualization. The core intelligence of the system resides on this Flask server, which runs a Random Forest Regression model.

By continuously evaluating the incoming weight, vibration, and temperature features, this model leverages an ensemble of decision trees to predict the ideal parameters for the wash. Instead of following a

$$= \frac{1}{N}\sum_{i=1}^{N} T_{i}(x)$$

rigid script, it calculates the perfect settings by averaging the outputs of all individual trees: $\hat{y}$ total number$\hat{y}$ of decision trees in the model,N $Ti(x)$ where is the predicted output parameter, is the represents the specific prediction from the th tree, and x denotes the input sensor features. i

Actuation and Dynamic Control Finally, the server sends these highly optimized parameters specifically the exact required water volume, wash duration, and spin speed back down to the ESP32. The edge controller then drives the washing machine's internal actuators, intelligently operating the motor, heater, and valves to execute a cycle customized perfectly for that specific load.

V. WORKING

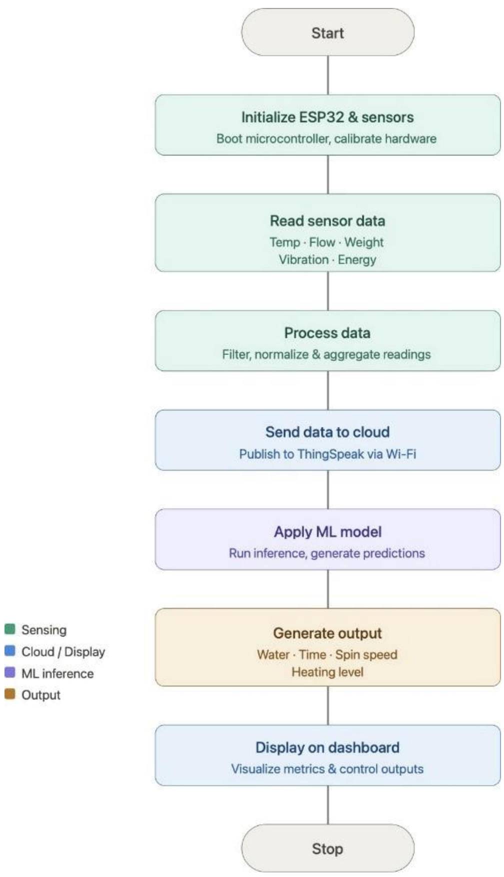

Fig 2. Flowchart

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The proposed system transforms the traditional washing cycle into a continuous, dynamic loop encompassing five main stages: sensing, preprocessing, communication, decision-making, and actuation. Rather than relying on fixed settings, this continuous operation allows the machine to constantly adapt to real-world conditions.

1. Initialization and Active Sensing

When the system first powers on, the ESP32 microcontroller does not simply start filling the drum. Instead, it runs a critical startup diagnostic to ensure every single sensor is securely connected and reading accurately. This step is vital, as faulty initial readings would throw off the entire process. Once the hardware is cleared, the board continuously pulls live data from its environment gauging the exact weight of the clothes, feeling the drum's vibrations, tracking the water flow, monitoring the heat, and measuring real-time power consumption. Together, these metrics paint a complete picture of what is happening inside the machine.

2. Local Edge Preprocessing and Safety

Raw sensor data straight from the hardware is inherently messy, often containing minor errors, voltage jumps, or odd outlier values. Before transmitting anything, the ESP32 steps in to clean it up. It smooths out the noise, calculates RMS values for the vibration data, and groups the readings so they actually make sense to work with. Crucially, this edge-processing layer acts as a local safety net: if the sensors detect severe, abnormal vibrations during a spin cycle, the ESP32 can immediately correct the issue locally to prevent mechanical damage, entirely bypassing the need to wait for a server response.

3. Cloud Transmission and Intelligent Decision-Making

Once the data is cleaned and formatted, the ESP32 utilizes Wi-Fi to push it to a Flask-based server and the ThingSpeak cloud platform. This is where the heavy computational lifting happens. Instead of relying on a rigid, pre-programmed script, a Random Forest machine learning model takes over. Having been trained on historical wash cycles, this model evaluates the fresh incoming data and calculates the best possible settings for that specific load.

4. Actuation and Live Monitoring

The ML model outputs highly optimized instructions dictating exactly how much water to use, the ideal wash duration, target temperature, and optimal spin speed. These exact commands are instantly sent back down to the ESP32. Using relays and motor drivers, the microcontroller then physically actuates the washing machine's valves, heater, and motor to execute the customized cycle. Throughout this entire process, every reading and automated decision is broadcast live to a user-friendly ThingSpeak dashboard. This allows users to effortlessly monitor their appliance's behaviour in real-time and manually tweak the settings if something needs changing.

VI. MATHEMATICAL MODEL

While the underlying machine learning architecture relies on the Random Forest algorithm, the complete mathematical modelling of the proposed washing machine system can be broken down into three distinct phases: data preprocessing, feature mapping, and ensemble regression.

1. Data Preprocessing (Edge Layer)

Before the data reaches the machine learning model, the ESP32 microcontroller processes the raw hardware signals to ensure stability. Specifically, the raw, multi-axis vibration signals generated by the MPU6050 sensor fluctuate rapidly. To create a stable mathematical input, the system applies Root Mean Square (RMS) calculations to the vibration data.

2. Feature Vector Formulation (Input Space)

The Random Forest model requires a structured input vector. Based on the active sensors utilized for predictive modelling, we can define the input feature vector $x \in R^3$ as follows:

$x = [w \; vrms \; t\,]$

Where:

w

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- = Load weight measured by the load cell.
- $vrms$ = Processed RMS vibration data.
- t = Water temperature.

3. Random Forest Regression (The Predictive Engine)

to the optimized wash parameters. Because it is an$x$ The predictive model maps the input feature vector ensemble model, it does not rely on a single decision independent decision trees. The final mathematical$N$ path but instead aggregates the results of prediction is the arithmetic mean of all individual tree outputs: $\hat{y}$

$$= \frac{1}{N}\sum_{i=1}^{N} T_i(x)$$

Where:

- $\hat{y}$ is the final averaged prediction output.

  proposed$N$ system is configured with ● is the total number of estimators (the N = 200 trees).
- T is the specific output prediction of the

  $ithi($ decision$x)$ tree given the input vector x.

4. Target Vector Formulation (Output Space)

multi-variable vector representing the optimized$\hat{y}$ The output of the regression equation, , is a washing parameters. We can define the target output space as $\hat{y} \in R^3$:

$$\hat{y} = [Vwater\ Dwash\ Sspin\ ]$$

Where the model simultaneously predicts:

- $Vwater$ = Optimal water volume.
- $Dwash$ = Total wash duration.
- $Sspin$ = Required spin speed.

5. Model Evaluation Metrics

To mathematically quantify the error and accuracy of system's performance was evaluated$x$ over a dataset$\hat{y}$ the mapping between the inputs and outputs , the of 800 training samples and 200 testing samples.

- **Mean Absolute Error (MAE):** Defines the average magnitude of errors in a set of predictions, measured as 10. 75.
- **Coefficient of Determination (R^2 Score):** Defines the proportion of the variance in the dependent variables that is predictable from the independent variables, achieved at 0. 87.

VII. RESULTS

The proposed system was evaluated using real-time sensor measurements collected during operation. The corresponding results and observations are presented in Figures 3–10.

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Fig. 3. Weight Analysis

Fig. 3 illustrates the variation in weight recorded during the washing cycle. At the beginning, the sensor showed a small reading close to 1.9 kg and then remained nearly constant for most of the monitoring period. Around 20:25, a sudden increase in weight was observed, reaching approximately 8.5 kg before returning back to a lower value. After this point, the readings again remained stable with only minor fluctuations. The graph indicates that the sensor was able to detect changes in load conditions during operation.

Fig. 4. Vibration Analysis

Fig. 4 illustrates the vibration readings measured throughout the washing process. The vibration values remained close to

10 Hz for most of the monitoring period with only small fluctuations observed in the graph. Around 20:25, a short drop in vibration to nearly 9.88 Hz was recorded, followed by a quick return to the normal range. Apart from this variation, the readings remained stable during operation. The graph shows consistent monitoring of machine vibration during the washing cycle.

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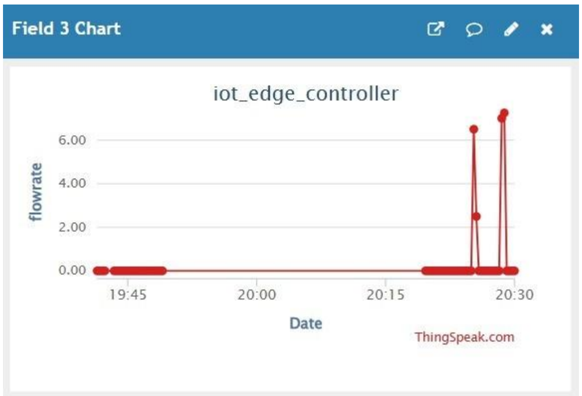

Fig. 5. Water Flow Analysis

Fig. 5 illustrates the water flow measurements recorded during system operation. For most of the monitoring period, the flow rate remained close to zero, indicating no significant water movement. Between approximately 20:25 and 20:30, the graph showed two sharp increases in flow rate, reaching nearly 6.8 L/min before returning to zero. These variations indicate short periods of water inflow during the washing process. The sensor successfully captured the changes in water flow throughout the cycle.

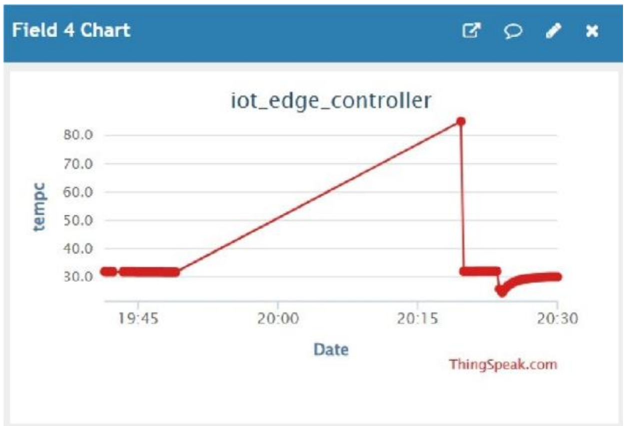

Fig. 6. Temperature Analysis

Fig. 6 illustrates the variation in water temperature during the washing cycle. Initially, the temperature remained nearly constant at around 30°C for a significant duration. After approximately 20:15, the temperature increased rapidly and reached nearly
82°C before dropping back close to the initial level. A brief decrease below 30°C was also observed before the readings stabilized again. The graph clearly shows the heating activity occurring during system operation.

Fig. 7. Voltage Analysis

Fig. 7 illustrates the voltage readings monitored during the washing process. The measurements started around 250 V and gradually increased over time, reaching values close to 254 V near the end of the monitoring period. Small fluctuations

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were observed throughout the graph, but the voltage remained within a stable operating range. No sudden drops or abnormal variations were recorded during the observation period. The graph indicates consistent voltage behavior during machine operation.

Fig. 8. Current Analysis

Fig. 8 illustrates the current consumption recorded during the washing cycle. At the beginning, the current remained close to zero for a certain duration, indicating minimal power usage. After approximately 20:15, the current increased gradually and reached nearly 0.06 A, where it remained almost constant until the end of the monitoring period. Only mi-nor fluctuations were observed after stabilization. The graph demonstrates stable current consumption during active ma-chine operation.

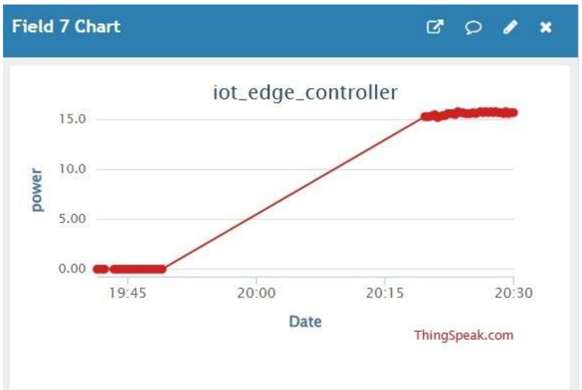

Fig. 9. Power Analysis

Fig. 9 illustrates the power consumption recorded during the washing process. The readings increased during the active stage of operation and remained relatively stable thereafter, indicating consistent power usage.

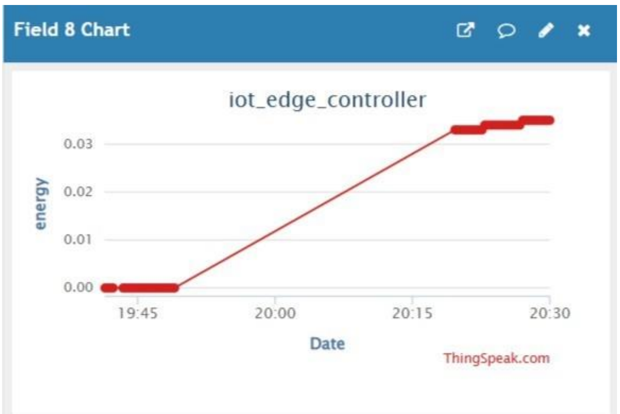

Fig. 10. Energy Analysis

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Fig. 10 illustrates the energy consumption measured during system operation. The energy value increased gradually throughout the washing cycle, reflecting continuous energy utilization.

Below are the three tables summarizing the experimental results, system comparisons, and model performance extracted from the research data.

Observed Operating Range of System Parameters

This table summarizes the range of values recorded for the monitored parameters during system operation.

Parameter	Operating Range
Weight (kg)	1.9 - 8.5
Vibration (Hz)	7.88 - 10.0
Water Flow (L/min)	0 - 6.8
Temperature (°C)	30 - 82
Voltage (V)	250 - 254
Current (A)	0 - 0.06
Power (W)	0 - 15.5
Energy (Wh)	0 - 0.033

Table 1. Observed Operating Range of System Parameters

Comparison Between Conventional and Proposed Smart Washing Machine System

This table presents a direct comparison demonstrating the improved resource management and operational efficiency of the proposed smart system versus a traditional washing approach.

Parameter	Conventional	Proposed	Improvement
Water Usage (L)	50	38	**24%** reduction
Energy Consumpti on (Wh)	1000	820	**18%** reduction
Wash Duration (min)	60	45	**25%** reduction
Load Detection	Absent	Present	Improved functionalit y
Monitorin g Capability	Basic	Real-Ti me	Enhanced monitoring
Intelligent Decision Support	Not Supported	Support ed	AI-enabled operation

Table 2. Comparison Between Conventional and Proposed Smart Washing Machine System **Random Forest Model Performance**

This table summarizes the configuration and predictive performance metrics of the Random Forest Regression model used in the proposed system.

Metric	Value
Mean Absolute Error (MAE)	10.75
R^2 Score	0.87
Training Samples	800
Testing Samples	200

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Number of Trees	200
Input Features	3
Output Parameters	3

Table 3. Random Forest Model Performance

Following image displays the real-time monitoring dashboard, which serves as the output screen of the Flask server. This web interface visualizes the live data captured by the ESP32 microcontroller and its associated sensors.

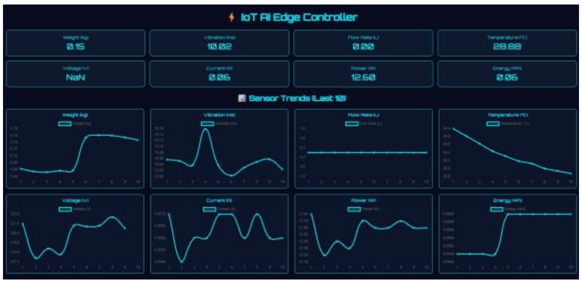

Fig. 11. Flask Dashboard

Fig. 12. Output based on ML Model

While the previous dashboard image displayed the real-time sensor inputs, this specific widget displays the final predictive outputs generated by our Random Forest machine learning model.

Here is a breakdown of the optimized parameters the AI has calculated for this specific load:

- **Water Volume (7.78 L):** The exact amount of water the model determined is necessary for the current laundry load. By dynamically calculating this volume rather than relying on a fixed fill level, the system actively prevents water waste.
- **Heating (ON):** The AI determined that the water needs to be heated for this cycle, instructing the ESP32 to activate the heating element.
- **Wash Duration (23.8 min):** The optimized runtime for the wash cycle. Instead of defaulting to a standard 45 or 60-minute timer, the AI has tailored a much shorter, highly efficient 23.8-minute cycle, directly contributing to the project's overall time and energy savings.
- **Spin Speed (790 RPM):** The dynamically calculated motor speed for the spin cycle. The model likely predicted this based on the load's weight and real-time vibration characteristics to ensure effective drying without causing mechanical imbalance.

In the context of our system's architecture, once the Flask server generates these four parameters, they are transmitted back down to the ESP32 edge controller.

The ESP32 then uses these exact values to actuate the washing machine's valves, heater, and motor, executing a perfectly customized and resource-efficient wash.

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VIII. CONCLUSION

The proposed Edge AI-based smart controller successfully bridges the gap between traditional household appliances and modern IoT capabilities. By moving away from blind, fixed-cycle operations and embracing real-time sensor monitoring, this research demonstrates that everyday machines can be taught to adapt dynamically to their physical environment. Through the integration of an ESP32 microcontroller and a comprehensive sensor suite, the system continuously tracks operational parameters including load weight, drum vibration, water flow, and temperature. Crucially, the deployment of a Random Forest machine learning model enables the system to intelligently dictate wash parameters with high precision, evidenced by an ^{2} predictive score of 0.87. The real-world experimental$R$ results clearly validate this approach: compared to conventional washing machine operations, the proposed adaptive system achieved a 24% reduction in water usage, cut electrical energy consumption by 18%, and shortened the overall wash duration by 25%. Ultimately, this project provides a highly practical, retrofit-friendly approach to sustainable appliance management. It proves that we do not necessarily need to manufacture entirely new appliances to achieve intelligent energy efficiency [21], [22]. Instead, by combining localized edge processing with machine learning, we can significantly enhance the monitoring capabilities and resource utilization of existing machines, paving the way for a genuinely sustainable smart home ecosystem [23].

IX. FUTURE SCOPE

While the current Edge AI-based controller significantly optimizes washing machine operations, several promising avenues exist for future enhancement. The proposed architecture lays a strong foundation that can be expanded by integrating a camera module with computer vision to visually identify different fabric types, allowing for more precise, material-specific washing parameters. Additionally, the continuous stream of real-time sensor data could be leveraged for predictive maintenance, enabling the system to identify abnormal machine behaviours and predict potential mechanical faults before a breakdown occurs. Future iterations could also incorporate smart scheduling algorithms that sync with dynamic local electricity pricing to run cycles during off-peak hours, alongside greywater recycling mechanisms to drastically reduce the net water footprint. As the device operates in more diverse environments, its machine learning models can be continuously retrained and enhanced using broader, real-world usage data. Finally, this versatile Edge AI and IoT framework could be seamlessly extended to improve the resource efficiency of other major household appliances, such as dishwashers and air conditioners.

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