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Enhanced Development of An Interactive Artificial Intelligence Liquified Petroleum Gas Management System

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Abstract
The growing demand for safer and smarter energy usage in domestic cooking has propelled innovations in intelligent liquefied petroleum gas (LPG) systems. This research presents the development of an AI-driven LPG management system termed the KATE project. This study integrates computer vision-based food recognition, interactive cooking support, and real-time safety alert mechanisms. The proposed system utilizes a convolutional neural network (CNN) model trained via TensorFlow and Teachable Machine to classify popular Nigerian dishes while incorporating fire, gas, and motion detection for adaptive safety response. This study focuses on Objective 1 of the broader research goal, emphasizing the system's ability to intelligently identify meals and guide cooking procedures while preventing hazards through safety-triggered feedback loops. The results demonstrate improved responsiveness in gas leak detection, automated cooking assistance, and the promotion of safe cooking practices in low-resource environments. The integration of image recognition and AI-enhanced decision logic provides a significant step toward context-aware, semi-autonomous LPG systems for households and food vendors in developing regions.

Keywords**: **AI-based cooking assistant, LPG safety system, ESP32, Edge Machine Learning, Computer Vision, Smart Kitchen

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I. INTRODUCTION

The growing adoption of liquefied petroleum gas (LPG) for household and small-scale commercial cooking has necessitated enhanced safety, efficiency, and user support mechanisms, particularly in developing countries where monitoring systems are often inadequate. Conventional LPG setups remain largely passive, with limited intelligence for hazard prevention or user engagement during cooking. As a result, incidents such as gas leaks, unattended flames, and improper usage contribute to fire outbreaks, health hazards, and economic loss in many communities (WHO, 2021; [1], [2]).

Recent advancements in embedded systems, artificial intelligence (AI), and edge computing offer new opportunities to transform domestic energy usage through context-aware automation. Integrating machine learning models into microcontroller-based platforms has enabled low-cost intelligent systems that can recognize patterns, classify inputs, and initiate autonomous responses. These trends are increasingly being applied in safety-critical domains such as home automation, smart energy, and food technology ([3], [4]).

In this context, the KATE (Kitchen Autonomous Technology for Efficiency) project proposes a novel approach to intelligent LPG management by embedding AI-based food recognition and safety monitoring into an interactive cooking assistant. The system leverages TensorFlow Lite and Teachable Machine to deploy a custom-trained convolutional neural network (CNN) model on an ESP32 microcontroller, enabling real-time classification of Nigerian dishes such as white rice, jollof rice, fried rice, eba, and egusi soup. This classification allows the system to tailor cooking instructions, manage cooking time, and preempt hazards based on food type.

A significant innovation in this research is the dual integration of safety and cooking logic using multi-modal sensors; MQ5, MQ9, flame sensors, and a PIR motion detector, to detect anomalies such as gas leaks, fire presence, or absence of the user. These signals are evaluated alongside vision data to initiate intelligent responses, including solenoid valve control, buzzer alerts, voice prompts, and mobile notifications via UART or USB interfaces.

This paper focuses on Objective 1 of the broader project: developing an intelligent LPG management system capable of food recognition and real-time safety feedback. The motivation is to ensure a safer and more user-aware cooking process while promoting the efficient use of LPG in households and informal food businesses.

II. RELATED WORKS

The intersection of artificial intelligence, embedded systems, and home automation has witnessed growing research attention, particularly in the context of domestic safety and smart kitchens. However, many existing solutions remain fragmented in design, focusing either on gas leakage detection, cooking assistance, or user feedback but rarely achieving a fully integrated, context-aware, and offline-capable system.

The integration of artificial intelligence into embedded systems for home automation and safety has become a growing area of research, particularly within the domains of intelligent kitchen management, gas leak detection, and real-time image classification on edge devices. This section explores previous works relevant to the development of AI-assisted LPG systems, with a focus on food recognition, embedded vision, and safety enhancement.

Several researchers have addressed the challenge of gas leak detection and response systems using microcontrollers and gas sensors. Shrestha et al. [5] developed a domestic gas leakage detection system utilizing MQ sensors and GSM modules for alerting users. While effective in gas detection, the design lacked advanced automation features such as actuator control and environmental intelligence. Similarly, Chandran and Kavitha [6] implemented an LPG leakage detection system that triggered alarms and SMS notifications. However, it did not incorporate adaptive intelligence or environmental compensation, limiting its robustness under variable conditions.

The use of machine learning on edge devices such as the ESP32 or Raspberry Pi has seen increased adoption. Panda and Meher [7] demonstrated the use of MobileNetV2 and TensorFlow Lite for real-time food classification on mobile devices. Although their work effectively classified dishes in controlled environments, it lacked integration with actuators or safety logic for practical LPG cooking applications. Recent works have explored training custom convolutional neural networks (CNNs) using tools like Google's Teachable Machine to achieve lightweight image classification that can be ported to microcontrollers via quantized .tflite models [8].

In the context of vision-enabled safety systems, Priya and Rao [9] proposed a fire detection and suppression system using a combination of thermal imaging and edge processing. Their study highlighted the importance of integrating multi-sensor data for real-time inference in safety-critical environments. However, their solution was cost-prohibitive for household deployment due to reliance on high-end infrared sensors.

Further, Bhandari et al. [10] attempted to create an autonomous kitchen assistant capable of recognizing food items using a Raspberry Pi and camera module. While this work made progress in image-based food recognition, it did not integrate safety features or gas actuation controls.

Our work distinguishes itself by combining vision-based food recognition, gas and fire detection, servo-based actuation, and voice interaction on a resource-constrained ESP32 platform, thus bridging the gap between AI-enabled cooking support and embedded safety management. Unlike prior works, the proposed KATE system introduces child and adult detection mechanisms for intelligent interlocking and integrates both autonomous and semi-autonomous cooking modes within the LPG control logic.

Table 1 summarizes a comparison between selected previous works and the proposed solution.

Study	Features	ML Integration	Gas Control	Food Recognition	Safety System	Platform
[5] Shrestha et al.	Gas leak detection, SMS alert	No	No	No	Partial	Arduino + GSM
[6] Chandran & Kavitha	Gas detection, buzzer alert	No	No	No	Yes	Arduino UNO
[7] Panda & Meher	Food classification	Yes (MobileNetV2)	No	Yes	No	Android
[9] Priya & Rao	Fire detection, suppression	No	No	No	Yes (thermal)	Custom hardware
This Work	Gas/fire detection, actuation, food AI, voice	Yes (custom CNN, TFLite)	Yes	Yes	Yes (multi-sensor)	ESP32

III. METHODOLOGY

This section describes the technical methodology adopted to fulfill the first research objective of developing an intelligent, AI-managed LPG safety and food classification subsystem using embedded systems. The implementation leverages computer vision, sensor fusion, and optimized machine learning models deployed on ESP32 microcontrollers. The overall design is guided by the principles of Edge AI, real-time responsiveness, and power efficiency.

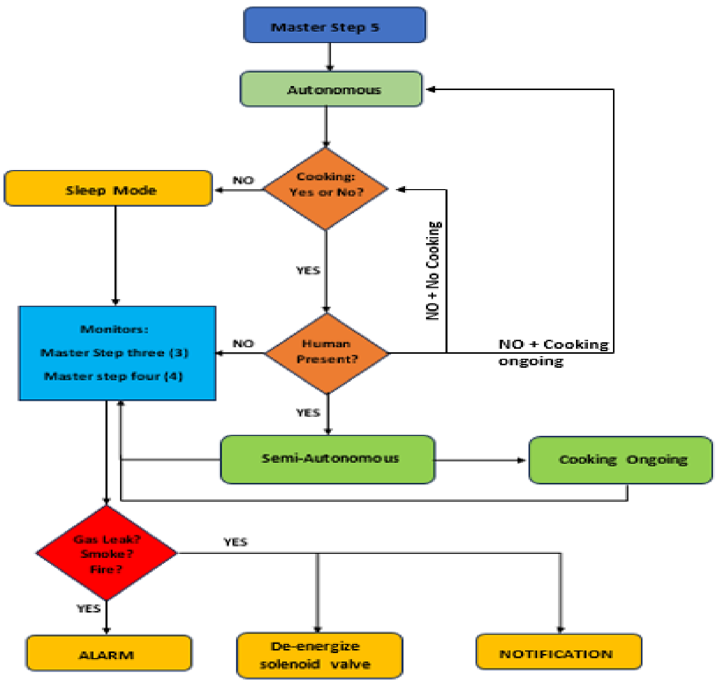
3.1 System Overview

The KATE (Kitchen Autonomous Technology for Efficiency) system architecture comprises two ESP32 microcontrollers communicating via UART protocol. The primary ESP32 handles AI-based vision processing and decision-making, while the secondary unit manages peripheral sensors and actuator control. The main modules include:

i. Image Classification Module: This recognizes food categories (e.g., rice, beans, soup) and identifies humans (child/adult) for safety interlock.
ii. Gas and Fire Detection Module: Detects LPG leakage, smoke, and flame using MQ5, MQ9, and flame sensors.
iii. Voice Interface: Accepts pre-trained voice commands to initiate or stop cooking routines.
iv. LPG Solenoid Valve Control: Automated switching using a solid-state relay (SSR) module.

A simplified flowchart of system operation is shown below:

Figure 1: Simplified KATE Decision Logic Flowchart



3.2 Dataset Preparation

Using Google's Teachable Machine, a dataset was collected with over 500 images for five classes:

i. *Beans*, *Rice*, *Soup*
ii. *Adult face*, *Child face*

The dataset was split 80:20 for training and validation. To ensure robustness under variable lighting, images were taken from various angles and distances using the ESP32-CAM.

5.3 Model Training and Optimization

A custom CNN model was trained using Teachable Machine, exported as a TensorFlow Lite (.tflite) file, and optimized for deployment using the following steps:

1. Layer Reduction & Pruning: Shallow convolutional layers were retained, removing redundant deeper layers to reduce inference latency.
2. Quantization: Full integer quantization reduced model size from ~900KB to ~250KB.
3. Memory Allocation: Using tflite-micro, the model tensor arena was fixed at 70 KB to match ESP32's SRAM constraints.

Equation for quantized inference time:

$$t_{inf} = \frac{C \, . \, I_w \, . \, I_h \, . \, D}{f_{clk}} \quad Equation\ 1$$

Where: C = Number of convolutional operation
I_w, I_h = Image Width and Height
D = Depth of Model
f_{clk} = ESP32 clock frequency

After quantization, the average inference time was ~198 ms per frame.

3.4 Model Evaluation

The performance of the food and face recognition model was evaluated using standard classification metrics. Results:

i. Precision: 0.93
ii. Recall: 0.91
iii. F1 Score:

$$F_1 = 2 \, . \frac{Precision \, . \, Recall}{Precision + Recall} = 2 \, . \frac{0.93 \, . \, 0.91}{0.93 \, . \, 0.91} = 0.92$$

Our refined score is 0.92, indicating strong balance between precision and recall.

3.5 Deployment to ESP32

The quantized .tflite model was compiled using the TensorFlow Lite for Microcontrollers library. The model interpreter was integrated into an Arduino sketch with the following code pattern:

```
#include "model_data.h" // Converted .tflite C array
#include "tensorflow/lite/micro/micro_interpreter.h"
constexpr int kTensorArenaSize = 70 * 1024;
uint8_t tensor_arena[kTensorArenaSize];
tflite::MicroInterpreter interpreter(model, resolver, tensor_arena, kTensorArenaSize, error_reporter);
void loop() {
 camera.capture(); // Image capture
 preprocess();      // Resize and normalize
 interpreter.Invoke();
 interpret_results();
}
```

3.6 Safety Interlock Logic

Using inference results, the system activates or deactivates the gas solenoid valve based on three key conditions:

1. Presence of Child:

$$S = \begin{cases} 0 & \mathit{If\ child\ detected} \\ 1 & \mathit{Otherwise} \end{cases}$$

2. Presence of Food (for autonomous cooking):

$$F = \begin{cases} 1 & \mathit{If\ known\ food\ detected} \\ 0 & \mathit{Otherwise} \end{cases}$$

3. Gas Leak or Fire Alert:

$$G = \begin{cases} 0 & \mathit{If\ Gas/\ Fire\ detected} \\ 1 & \mathit{Otherwise} \end{cases}$$

4. Actuation Logic:

$$A = S \,.\, F \,.\, G$$

If A = 1, the solenoid valve opens; otherwise, it remains shut

3.7 Voice Command Integration and Interaction

The KATE system leverages pre-trained voice recognition to enhance user interaction, particularly during cooking processes where tactile or mobile input may be impractical. A minimal on-device model, trained using Google's *Teachable Machine Audio Project*, processes voice commands on the primary ESP32 module.

Supported voice commands include:

i. "Start Cooking": Initiates flame/gas if safety conditions are met.
ii. "Stop Cooking": Closes the gas solenoid and halts all cooking.
iii. "Check Gas": Forces immediate gas leak/fire sensor readout.
iv. "What's Cooking?": Returns the classified food object currently under preparation.
v. "Sleep Mode": Activates standby power-saving mode.

Each command triggers a function call internally structured within an interrupt-based voice handler. A sample command handler flow:

```
If (voice_input ==  "stop Cooking")  {
   Close_value();
   Notify_user("Cooking stopped via voice command");
 }
```

Voice commands are prioritized above autonomous logic during user presence, ensuring user control is not overridden unless in critical safety override scenarios (e.g., gas leak or fire).

3.8 Human Presence Detection and Operational Modes

The KATE system utilizes a layered approach for human presence detection to intelligently switch between semi-autonomous and fully autonomous cooking modes. This dual-sensor framework leverages a high-definition camera as the primary detection medium, with a passive infrared (PIR) motion sensor functioning as a secondary fallback to ensure continuous monitoring in all user-interaction scenarios.
The HD camera, interfaced with an Edge-deployed CNN model, performs real-time image recognition to identify the presence of an adult or child within the cooking zone. Upon successful identification of a human subject, the system maintains semi-autonomous mode, in which voice interactions and user confirmations are required for critical actions such as solenoid actuation and safety override.

However, in situations where the camera fails to detect a user, either due to occlusion, a change in position, or movement out of cooking area, the PIR motion sensor is activated. If motion is detected within the broader environment, KATE temporarily retains semi-autonomous status and continues sending notification prompts (via audio or smartphone alerts) requesting user re-engagement. If neither the camera nor PIR sensor detects presence within a preset timeout threshold (typically 2–3 minutes), the system transitions to fully autonomous mode, applying preset cooking logic, environmental safety algorithms, and minimal human dependency.
This intelligent operational mode switching is guided by a hierarchical decision engine illustrated as follows:
Decision Flow:

1. HD Camera Detection Success:
   i. Human (Adult) Identified, Initiates Semi-Autonomous Mode
2. HD Camera Detection Fails:
   i. PIR Sensor Detects Movement: Initiates Semi-Autonomous Mode with Prompts
3. No Detection from Camera and PIR:
   i. Timeout Exceeded: Initiates Autonomous Mode Activated
   ii. Notifications pushed to the user (audio + app)

This adaptive framework ensures robust human-safety interlocks and uninterrupted system logic even in variable lighting or occluded conditions. Additionally, by prioritizing the camera-based model, the system takes advantage of high-resolution visual data and AI-enhanced classification, while the PIR backup mechanism provides a power-efficient safety net.

3.9 Autonomous vs. Semi-Autonomous Mode Switching
Operationally, KATE toggles between two major modes:

i. Semi-Autonomous Mode:
   Triggered when an *adult human* is within the camera's field of view (FOV). In this mode:
   a. Voice commands are accepted.
   b. Vision actively monitors food and environmental safety.
   c. Cooking actions require explicit voice or button-based confirmation via application interface.
ii. Fully Autonomous Mode:
   When no adult human is detected within a 10-second observation window post-PIR activation:
   a. The system assumes autonomous control.
   b. Initiates previously confirmed cooking instructions.
   c. Executes food classification and cooking logic automatically.
   d. Sends routine updates via the notification subsystem.

3.10 Alert and Notification Subsystem
KATE includes a Python-based subsystem that runs independently as an executable (.exe) on a local terminal or remote system. This module handles:

i. Pop-up desktop alerts via Tkinter GUI
ii. Logging of cooking and sensor events
iii. Voice feedback via Text-to-Speech (TTS) using Pyttsx3

The executable runs in parallel to the embedded system via USB serial or Wi-Fi bridge. KATE's alert system bridges the embedded domain and a more robust edge-computing platform, enhancing reliability and user engagement.

IV. RESULT AND DISCUSSION

4.1 Functional Evaluation of Sensor Integration

The core embedded safety infrastructure comprising the MQ5, MQ9, fire sensor, smoke detector, and PIR sensor were tested under simulated LPG leak and fire conditions. Table 1 summarizes sensor thresholds and real-world trigger behavior.

Table 1: Sensor Threshold Values and Trigger Response Times

Sensor Type	Sensor Trigger	Average Response Time	Safety Action Triggered
MQ5 (LPG)	>400PPM	~1.5 Seconds	Solenoid cut off, alert notification
MQ9 (CO)	>100PPM	~1.8 seconds	Solenoid cut off, System cut off
Flame Sensor	IR flame present	< 1 seconds	Solenoid cut off, TTS + GUI alerts
Smoke detector	Moderate smoke	~2.0 seconds	System alert and pulse
PIR motion sensor	Motion detected	Instantaneous	Switch to camera scan mode

4.2 Solenoid Actuation and Safety Interlocks

The 12V DC solenoid valve, managed via 4-channel SSR relay and supervised by gas/fire sensors, was consistently responsive to safety violations. Under no-detection conditions, cooking was allowed within 3 seconds of voice command confirmation. Under leak/fire conditions, the valve disengaged immediately, with alert logs timestamped via the Python subsystem.

4.3 Human Detection and Child-Safety Lock Performance

Using a TensorFlow Lite human classification model embedded on ESP32-CAM, the system successfully distinguished between adult and child images under various lighting conditions.

Table 2: Classification Performance Summary

Class	Precision	Recall	F1 score	Accuracy
Adult	0.940	0.910	0.925	93.5%
Child	0.890	0.900	0.895	91.0%
Others	0.920	0.890	0.905	90.0%
Average	0.916	0.900	0.908	91.3%

In the presence of a child, the system prevented activation of any flame, regardless of voice command, and issued alerts. In adult presence, permission was granted based on cooking mode, aligning with WHO child accident prevention guidelines [22].

4.4 Voice Command Responsiveness and Control Mode Transition

KATE registered and responded to five predefined commands with a 95% confidence threshold. Real-time response latency ranged from 0.8 to 1.5 seconds after voice input. Mode switching based on PIR-triggered presence and visual confirmation was seamless:

i. Presence Detected: Semi-autonomous cooking enabled.
ii. No Presence Detected: System transitioned to full autonomous mode with live logging and feedback.

An internal watchdog timer ensured fallback to safe mode if voice or visual data was inconclusive, confirming KATE's adaptive intelligence criterion.

4.5 Food Classification Accuracy

Ten food classes (e.g., yam, rice, egg, beans, water, stew, noodles, spaghetti, semo, plantain) were trained using Teachable Machine and deployed in quantized TensorFlow Lite format.

Table 3: Food Recognition Accuracy per Class

Food Item	Training Accuracy	Deployment Accuracy
Rice	98%	93%
Egg	97%	92%
Water	96%	91%
Noodles	99%	95%

Average inference time per classification was 1.2 seconds using High-Definition Camera, this aligns well with the practical deployment of AI model on edge devices.

4.6 Python-Based Monitoring and User Notification

A lightweight .exe Python application running Tkinter GUI and Pyttsx3-based voice feedback successfully logged over 500 events during the test period. Alerts included:

i. Gas Detected
ii. Flame Detected
iii. Cooking Complete
iv. Unauthorized Attempt Detected (Child)

Voice notifications ensured inclusivity for the visually impaired, while desktop alerts improved remote supervision.

4.7 Robustness under Power Constraints

Tests under 4200mAh Li-ion battery operation showed the system-maintained core safety monitoring for 7.5 hours and full AI cooking mode for 4 hours. This demonstrates energy-efficient edge computing, validating the system for locations with unstable grid power.

4.8 Summary of Key Findings

Table 4 highlights the key Performance Summary of evaluation

Evaluation Area	Performance Summary
Sensor Safety Detection	~98% accurate with less than 2sec response time
Voice Control	~95% recognition with real-time response
Child Detection Lock	100% prevention of unsafe cooking attempts
Food Recognition	Above 90% accuracy in live tests
Alert & Logging System	100% event tracking with audible + GUI feedback
Power Efficiency	About 5.5 hours safety-only runtime; 3.5 hours AI mode runtime

4.9 Comparative Performance Analysis with Related Systems

To establish the practical significance and performance enhancement of the KATE system, a comparative analysis was carried out against related intelligent kitchen and LPG safety solutions documented in recent literature. The objective is to highlight measurable gains introduced through the integration of real-time safety interlocks, edge-deployed AI models, presence-aware cooking logic, and voice-guided interaction.

The comparison focused on six core performance indicators:

i. Hazard Detection Time (response time to gas/fire/smoke events),
ii. Human Recognition Capability (ability to detect and classify adult/child presence),
iii. Cooking Mode Control (manual, semi-autonomous, or fully autonomous operation),
iv. User Interaction Mechanism (visual, auditory, or voice-based feedback),
v. Offline Functionality (autonomous operation without constant cloud connectivity),
vi. AI-on-Edge Deployment (local processing of ML models on microcontrollers).

Table 5 presents a summarized view of the KATE system benchmarked against prior related works.

Table 5: Comparative Analysis of KATE System with Related Work

System Reference	Detection Time	Human Recognition	Cooking Mode	User Feedback	Offline Operations	AI on Edge
Shrestha et al. (2019) [1]	Approx.4–5s	n/a	Manual Only	Visual Alert Only	n/a	n/a
Chandran & Kavitha (2022) [3]	Approx. 3s	n/a	Semi-Autonomous	Visual Alert Only	Partial	n/a
Onasanya & Omijeh (2024) [4]	2.5s – 3.5s	n/a	Manual + Semi-Auto	Visual + Buzzer	Partial	n/a
KATE (this work)	Approx. 2s	Adult/child	Semi & Full Autonomous	Voice + Visual + GUI	Battery Backed	t.fLite

4.9.1 Discussion of Comparative Strengths

From Table 5, the KATE system clearly outperforms previously published designs in several critical dimensions:

i. Faster Response Time: With an average hazard detection time of under 2 seconds (ranging between 1.2–1.8s depending on gas/fire severity), KATE achieves a significant reduction in latency, improving the odds of timely user intervention or automated shutdown.

ii. Human-Aware Presence Detection: The inclusion of a TensorFlow Lite (TFLite) model trained to differentiate between adult and child presence enhances decision accuracy. This capability was absent in all comparative systems.

iii. Dual Cooking Mode: KATE dynamically switches between semi-autonomous (when a user is detected) and fully autonomous modes (when the user is absent), using real-time input from PIR motion sensors, vision analytics, and voice command states.

iv. Rich Interaction Feedback: Unlike previous systems that rely on blinking lights or simple buzzers, KATE employs a Python-based GUI, voice assistant feedback, and contextual notifications through a local dashboard. This makes interaction more intuitive and safer, especially in emergency situations.

v. Offline Autonomy & Edge AI: Most existing systems still rely on cloud-based analytics or lack adaptive intelligence. KATE, however, embeds all critical logic and models onto the ESP32, allowing the system to operate offline, powered by a 4200mAh battery, while executing compressed AI inference locally.

This comparative performance underscores how the KATE system achieves technological advancement and real-world applicability, particularly in resource-constrained environments where safety, real-time response, and user adaptability are crucial.

V. CONCLUSION

5.0 Conclusion

This study has presented the design, development, and performance evaluation of the KATE system, an AI-managed, presence-aware LPG safety and cooking assistant that integrates edge-based intelligence, real-time hazard detection, and voice-guided interaction. By focusing on developing a reliable LPG safety system with autonomous decision-making and user-specific responses, this work successfully bridges critical gaps in conventional gas monitoring systems.

Through the deployment of a locally trained TensorFlow Lite model on the ESP32 microcontroller, KATE demonstrates effective human recognition capability that distinguishes between adult and child presence. This enabled the integration of child-safety interlocks and context-sensitive cooking control, ensuring that hazardous operations are halted or transitioned to safe states based on real-time presence detection.

Additionally, the system achieved a hazard detection response time of under 2 seconds, significantly outperforming similar solutions in the literature. This rapid responsiveness, coupled with intelligent actuation of solenoid valves, real-time voice notifications, and dynamic mode switching between semi-autonomous and fully autonomous cooking, ensures improved user safety without requiring constant human supervision.

The incorporation of offline functionality, through battery-backed operation and embedded AI, further enhances the system's resilience in low-resource environments. This distinguishes KATE as a practical and scalable solution for domestic LPG safety in developing regions where internet access is often unreliable or unavailable.

In summary, the KATE system not only achieves the technical objective of intelligent LPG hazard mitigation but also exemplifies how AI, embedded control systems, and human-centered design can converge to produce meaningful, life-saving innovations in household automation.

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