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Intelligent Smart Cooking: Predictive Cooking Time Model Using Machine Learning and *IoT*

Intelligent Smart Cooking: Model Prediksi Cooking Time Menggunakan Machine Learning dan IoT

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Abstract

Smart cooking systems have gained significant attention as part of the growing smart home ecosystem, yet most existing solutions rely on static, rule-based thresholds that lack adaptability to variations in food type, weight, and cooking conditions. This study proposes an Intelligent Smart Cooking system that integrates Internet of Things (IoT) sensing with a machine learning–based predictive model to estimate cooking time in real time. Temperature data were collected from 180 cooking sessions using a DS18B20 sensor, while MQ-series gas sensors supported safety monitoring. A dataset containing temperature curves, heating rates, food mass, and water volume was constructed and used to train three regression models: Multiple Linear Regression, Support Vector Regression, and Random Forest Regression. Experimental results show that Random Forest achieved the best performance with an MAE of 18.93 seconds and an R^2 *of 0.954, demonstrating strong capability in capturing nonlinear cooking behavior patterns. The trained model was deployed into the IoT system to enable predictive cooking automation, real-time flame control through a servo motor, and hazard prevention via gas detection. User evaluations also indicated high usability and reliability of the system. The findings highlight the potential of combining IoT and machine learning to improve accuracy, safety, and efficiency in next-generation smart kitchen technologies.*

Abstrak

Sistem memasak cerdas (Smart Cooking) telah mendapatkan perhatian signifikan sebagai bagian dari ekosistem rumah pintar yang berkembang. Namun, sebagian besar solusi yang ada masih mengandalkan ambang batas statis berbasis aturan yang kurang memiliki kemampuan adaptasi terhadap variasi jenis makanan, berat, dan kondisi memasak. Studi ini mengusulkan sebuah Sistem Memasak Cerdas (Intelligent Smart Cooking) yang mengintegrasikan pengindraan Internet of Things (IoT) dengan model prediksi berbasis machine learning untuk memperkirakan waktu memasak secara waktu nyata (real-time). Data suhu dikumpulkan dari 180 sesi memasak menggunakan sensor DS18B20, sementara sensor gas seri MQ digunakan untuk mendukung pemantauan keselamatan. Sebuah dataset yang berisi kurva suhu, laju pemanasan, massa makanan, dan volume air disusun dan digunakan untuk melatih tiga model regresi: Regresi Linear Berganda (Multiple Linear Regression), Regresi Vektor Dukungan (Support Vector Regression), dan Regresi Hutan Acak (Random Forest Regression). Hasil eksperimen menunjukkan bahwa model Random Forest mencapai kinerja terbaik dengan nilai MAE (Mean Absolute Error) sebesar 18,93 detik dan nilai R^2 (koefisien determinasi) sebesar 0,954, menunjukkan kapabilitas yang kuat dalam menangkap pola perilaku memasak yang non-linear. Model yang telah dilatih kemudian diterapkan ke dalam sistem IoT untuk memungkinkan otomatisasi memasak prediktif, kontrol nyala api secara real-time melalui motor servo, dan pencegahan bahaya melalui deteksi gas. Evaluasi pengguna juga mengindikasikan tingkat kegunaan dan keandalan sistem yang tinggi. Temuan ini menyoroti potensi penggabungan IoT dan machine learning untuk meningkatkan akurasi, keselamatan, dan efisiensi dalam teknologi dapur pintar generasi berikutnya.

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1. Introduction

Kitchen automation and smart cooking technologies are becoming one of the fastest-growing areas within the Internet of Things (IoT). Today, people want systems that are not just easy to use but also help make cooking safer, more efficient, and more accurate (Umar et al., 2022) Cooking traditionally involves a lot of hands-on work, which takes time and can lead to mistakes like burning food, forgetting to turn off the stove, or missing early signs of problems like gas leaks (Septanti et al., 2025) These problems show why smart systems are needed, especially for people who have trouble moving around, busy schedules, or are older (R. Sokullu et al., 2020) Earlier research on smart cooking systems has mainly focused on hardware solutions, such as devices that sense temperature or detect gas leaks, and basic controls for stoves using tools like Arduino or microcontrollers (R. Sokullu et al., 2020) These systems provide some level of automation, but they often depend on set rules that don't handle different foods, cooking sizes, or changing environments well. For example, how long you cook chicken curry, vegetable soup, or fish depends on factors like the weight of the food, the amount of liquid, and how you heat it. Using a system with fixed rules, like turning off the stove at 100°C and waiting for a certain time, can't adjust well for different types of food or situations (Fellows, 2002). This makes cooking results inconsistent and the system less reliable.

New developments in machine learning (ML) have made it possible to create models that can predict the best cooking times by studying temperature changes, food properties, and past cooking data (Y. Zhou, 2022) Machine learning lets systems learn from real-world patterns instead of just following set rules, which makes predictions more flexible and accurate. Studies have shown that models like regression and Random Forest can work well for predicting things like energy use, how heat moves, and how food is cooked over time (Agarwal et al., 2021) Adding machine learning to smart cooking systems is a big step forward for making cooking more precise and safer at home.

The use of IoT is just as important because it helps gather data in real time, monitor kitchen equipment from a distance, and automatically control (U. ; K. N. Dutta, 2021; S. Z. H. Eom, 2022). IoT systems that use small computer chips like ESP8266 or ESP32 allow temperature sensors, gas sensors, and motorized parts to work together as a connected system. This setup can send warnings, show live information, and take actions on their own. Smart kitchen dashboards, whether on a computer or a phone, are important for improving the user experience by showing what's happening in the kitchen, past cooking trends, and future predictions in real time (Korneeva et al., 2021). In previous studies, (Jum et al., 2024). created a smart cooking and kitchen safety system using an Arduino Nano microcontroller, DS18B20 temperature sensors, MQ-2 gas sensors, a servo motor for controlling the stove, and voice recognition. This system automated the use of the stove and improved safety by detecting gas leaks early. But there were some problems. The system used fixed rules for setting limits and didn't have a way to predict how different foods might behave. The voice recognition also had trouble understanding unclear or negative commands. These issues show why it's important to develop a more advanced smart cooking system.

This study tackles some important missing parts by creating an Intelligent Smart Cooking model that combines IoT-based real-time sensing with machine learning prediction methods. The research has three main goals:

- First, to gather cooking data like temperature changes, food weight, water amount, and how long food is cooked, from various types of food.
- Second, to build and test predictive models using supervised machine learning techniques such as Linear Regression and Random Forest.
- Third, to create a real-time IoT dashboard that lets users watch the cooking process and get predictive insights.

This research brings several new ideas to the field:

- It introduces a machine learning model that can predict how long cooking will take, making cooking automation more flexible and efficient.
- It connects sensor-based real-time data collection with IoT technology, allowing people to monitor and control cooking from a distance.
- It improves safety, making cooking easier for new users and those with physical challenges.
- The study also tests these ideas using real cooking data from a wide range of food types.

The results of this research are supposed to help create more accurate, self-working, and smart cooking systems. Using machine learning in smart kitchens fits with the growing trend of smart home technology and helps move food preparation towards being more data-driven. This method not only improves the quality of cooking but also helps save energy, make cooking safer, and make it more convenient for users. In the end, this study aims to lay the groundwork for future smart kitchen automation and inspire more research into AI-based food technologies.

2. Literature Review

Smart cooking systems have grown quickly as part of the smart home technology trend. These systems use IoT devices, sensor networks, and machine learning to make kitchens more automated. This automation improves convenience, safety, and energy use, as shown in recent research (Umar et al., 2022). This section looks at the basic ideas and past studies about IoT-based smart kitchens, sensing tech, cooking predictions, machine learning, and the areas that need more attention, which is why this research is important.

2.1. Smart Kitchen and Smart Cooking Technology

A smart kitchen is a cooking space that uses technology to make it safer, more efficient, and more comfortable. It connects different devices, uses automation to handle cooking tasks, and includes smart monitoring systems that help improve everyday cooking. This changes traditional cooking by making it easier and requiring less effort from people (Kapadnis, 2022). Smart cooking is a part of smart kitchen technology that focuses on automating the actual cooking process with the help of sensors, machines, and smart software (S. Z. H. Eom, 2022) More people are interested in smart cooking systems because of busy, modern lifestyles that need multitasking and saving time.

Vol. 1 (No.1), 2025: 52-66
https://journal.uwais.ac.id/index.php/amanah/article/view/16

A lot of accidents in homes like fires - happen when stoves are left unattended, there are gas leaks, or something overheats (Kamampung, 2021). Smart cooking also helps older adults, people with disabilities, and those who have trouble moving around, giving them more independence and making cooking safer for them (R. ; A. M. ; A. E. Sokullu, 2020).

2.2. Internet of Things (IoT) in Kitchen Automation

The Internet of Things (IoT) serves as the foundation of smart kitchen systems. IoT allows physical devices such as sensors, microcontrollers, and actuators to connect to the internet, communicate in real time, and respond independently to environmental changes (P. ; K. M. Dutta, 2021). In cooking automation systems, IoT performs several critical functions:

1. Real-time data collection, such as temperature readings from DS18B20 sensors.
2. Remote monitoring and control via platforms like Blynk, CloudWatch, Firebase, or custom dashboards using AWS Lambda, S3, IAM, and Docker.
3. Automated control of stoves using servo motors or electronic actuators.
4. Safety monitoring, including gas leak detection with MQ-series sensors (Hassan et al., 2022)
5. Push notifications for timely alerts through mobile applications.

IoT not only enhances automation but also fosters a connected ecosystem that supports ongoing cooking analytics, energy monitoring, and hazard detection. Research indicates that IoT-enabled systems significantly improve kitchen safety and reduce energy waste (R. ; A. M. ; A. E. Sokullu, 2020).

2.3. Sensing Technologies for Smart Cooking Systems

Sensing technologies form the core of data-driven smart cooking systems. Accurate sensor data serve as the basis for automated decision-making and machine learning predictions.

DS18B20 Temperature Sensor

The DS18B20 is a high-precision digital temperature sensor that uses a one-wire communication protocol. It is widely used in cooking-related research because of its accuracy, stability, and ease of integration with microcontrollers (Hidayat, 2021). Temperature data are essential for identifying boiling points, heat flow characteristics, and cooking completion stages (Fellows, 2002).

MQ-Series Gas Sensors

MQ-2 and MQ-5 sensors are commonly used for LPG leakage detection. Gas leakage poses a significant household hazard, accounting for a major proportion of residential fires (Kamampung, 2021). These sensors provide reliable real-time gas concentration readings and are highly suitable for kitchen automation systems (Hassan et al., 2022).

Servo Motors

Servo motors serve as actuators that physically manipulate stove knobs, controlling flame intensity and enabling automatic shutdown. Their precision and PWM-based control make them ideal for IoT-driven cooking automation (Kapadnis, 2022)

2.4. Machine Learning for Predictive Cooking Models

Machine learning has become a strong tool for making predictions in different thermal processes, such as food processing, how much energy is used, and how temperature changes over time (Aggarwal, 2021). Unlike systems that follow fixed rules, machine learning models can learn from past data and adjust to different kinds of food and environmental settings.

Regression Models

Linear Regression and Multiple Linear Regression are commonly used to predict how long cooking will take by looking at how different factors like temperature, food size, water amount, and cooking stages are connected. These models are easy to use and work well when the data has clear, straight-line relationships.

Random Forest Regression

Random Forest is a type of machine learning that combines several models to make predictions. It works well for situations where the data isn't straight forward and has many different factors. It can still give good results even if the data is noisy or changes a lot depending on the type of food. Studies by (Wang, 2023; L. ; Z. Y. ; L. X. Zhou, 2022). show that Random Forest is better at predicting outcomes in thermal and cooking processes compared to other methods.

In cooking systems, machine learning can help:

1. Figure out the best time to cook food.
2. Find out when the food is done more precisely.
3. Adjust for differences in food types and how they heat up.
4. Make cooking more consistent and safer.

Using machine learning for predictions is a big improvement over older systems that rely on fixed settings.

2.5. IoT and Machine Learning Integration in Smart Kitchens

The integration of IoT and ML enables the creation of adaptive smart cooking ecosystems. IoT devices collect real-time temperature, gas, and environmental data, while ML models analyze these inputs to produce predictions and recommendations.

Benefits of IoT–ML Integration

1. Real-time analytics, providing continuous cooking insights.
2. Predictive automation, enabling automatic control of stove flame or shutdown.
3. Adaptive cooking behavior, where the system adjusts based on ongoing predictions.
4. Improved safety, via anomaly detection (e.g., overheating, gas leaks).
5. Energy efficiency, achieved through optimized heating cycles.

Studies indicate that IoT–ML integration significantly enhances cooking accuracy, safety, and user experience (S. Z. H. Eom, 2022; Korneeva et al., 2021)

3. Research Method

This study adopts an engineering-based research approach that integrates Internet of Things (IoT) sensing, data acquisition, machine learning modeling, and system implementation for smart cooking automation. The research method consists of five main stages: (1) system design, (2) dataset development, (3) machine learning model construction, (4) IoT system integration, and (5) testing and evaluation. Each stage is described in detail in the following subsections.

3.1 Research Framework

The overall research framework is structured to translate real-time cooking data into predictive cooking time outcomes using machine learning. The framework begins with identifying the problem namely, the lack of predictive intelligence in existing smart cooking systems and then proceeds to develop an IoT-based cooking environment capable of data acquisition. The collected data are processed and used to train machine learning models that predict cooking duration. Finally, the trained model is integrated into a real-time cooking automation system that can control stove flame intensity and provide predictions through a dashboard interface.

The research framework consists of four layers:

1. Sensing Layer – Collects real-time data using temperature sensors, gas sensors, and time logs.
2. Processing Layer – Cleans, preprocesses, and models the data using machine learning algorithms.
3. Control Layer – Uses predicted values to control actuators such as servo motors.
4. Application Layer – Displays predictions and system status to the user through a web dashboard.

This layered framework ensures modularity, scalability, and clear separation of responsibilities in the system architecture.

The overall research framework adopted for developing the Intelligent Smart Cooking system, from data acquisition to model deployment, is illustrated in Figure 1.

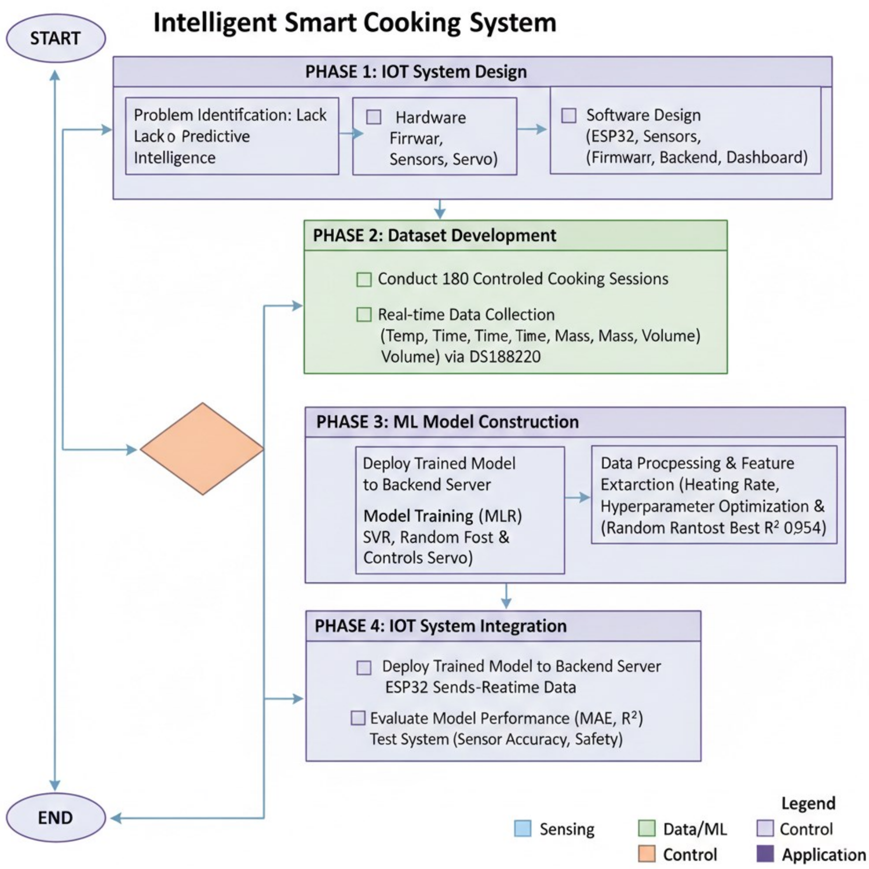

Figure 1. Research Framework for the Intelligent Smart Cooking System

3.2 System Design

The proposed system combines hardware, software, and cloud services. The hardware architecture includes:

- Microcontroller: ESP32 or ESP8266 as the central IoT hub due to Wi-Fi capabilities and adequate processing power.
- Temperature Sensor (DS18B20): Measures heat level in the cooking pot in 1-second intervals.
- Gas Sensor (MQ-2 or MQ-5): Detects LPG leakage and triggers safety responses.
- Servo Motor: Mechanically adjusts stove knob for automatic flame control.
- Power Supply: 5V regulated supply for sensors and servo.
- Cooking Vessel: Standard pot used to measure boiling-related temperature patterns.

The software design includes:

1. Firmware: Developed using Arduino IDE for sensor reading, data transmission, and actuator control.
2. Backend Server: Handles data reception, ML prediction inference, and storage.
3. Machine Learning Module: Implements the model training and prediction process.
4. Dashboard Application: Displays cooking prediction, sensor plots, and safety alerts.

The communication model uses MQTT or HTTP API for real-time data transfer between the microcontroller and server.

3.3 Dataset Development

Accurate machine learning prediction requires a large and diverse dataset representing common cooking scenarios. Therefore, the dataset for this research is built by conducting controlled cooking experiments. The dataset includes the following variables:

- Temperature (°C): Recorded every second using the DS18B20 sensor.
- Elapsed Time (seconds): Duration of cooking session.
- Food Type: e.g., water, rice, noodles, eggs.
- Initial Food Weight (grams): Influences heating time.
- Water Volume (ml): Affects boiling dynamics.
- Target State: e.g., “boiling,” “soft-boiled,” “fully cooked.”
- Gas Concentration: Supporting safety parameter.
- Environmental Conditions: Room temperature and humidity.

Data Collection Procedure

1. Conduct repeated cooking sessions for each food type.
2. Record temperature values from start to finish.
3. Log the moment when the food reaches its "done" state.
4. Normalize sensor noise by applying filtering techniques (e.g., moving average).
5. Standardize food measurements to maintain dataset consistency.

The final dataset contains hundreds of cooking sessions, producing thousands of data points that capture temperature curves associated with different cooking outcomes.

Figure 2 illustrates the system architecture, showing the connection and data flow between the Sensing, Processing, Control, and Application Layers.

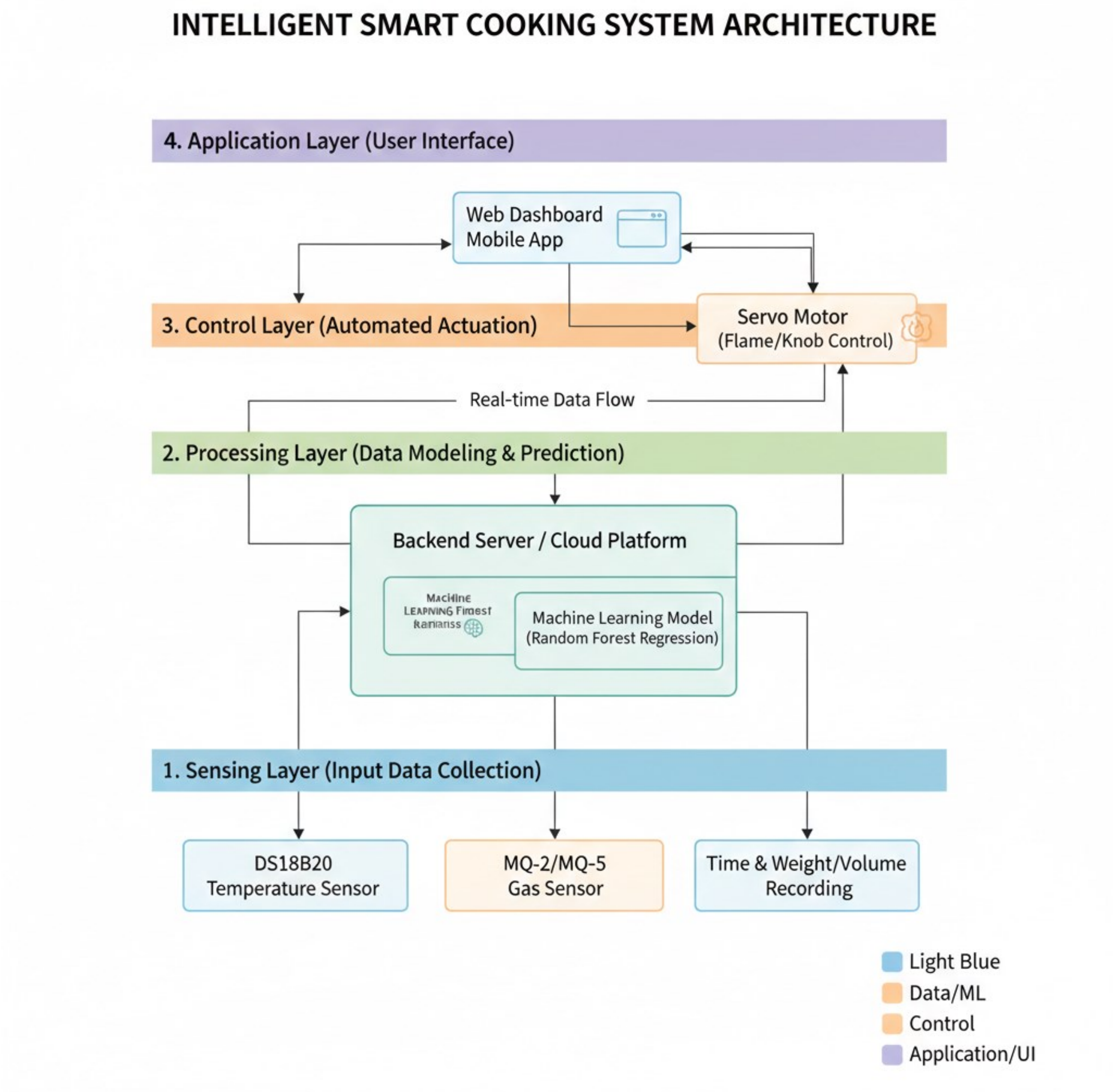

Figure 2. Proposed Four-Layered System Architecture

3.4 Data Preprocessing

Before building machine learning models, the raw data undergo several preprocessing steps:

1. Handling Missing Data: Interpolate missing temperature values to maintain continuous time-series signals.
2. Feature Extraction:
    - Temperature gradient
    - Heating rate
    - Time to reach threshold temperatures
    - Temperature stability indicator
3. Data Normalization: Apply Min–Max scaling to reduce numerical disparities.
4. Encoding: Encode categorical variables such as food type.
5. Outlier Removal: Exclude sessions with anomalous sensor readings.

6. Train–Test Split: 80:20 ratio for model training and evaluation.

These preprocessing steps ensure data quality and model robustness.

Detailed hardware components and their communication links within the IoT system are illustrated in Figure 3.

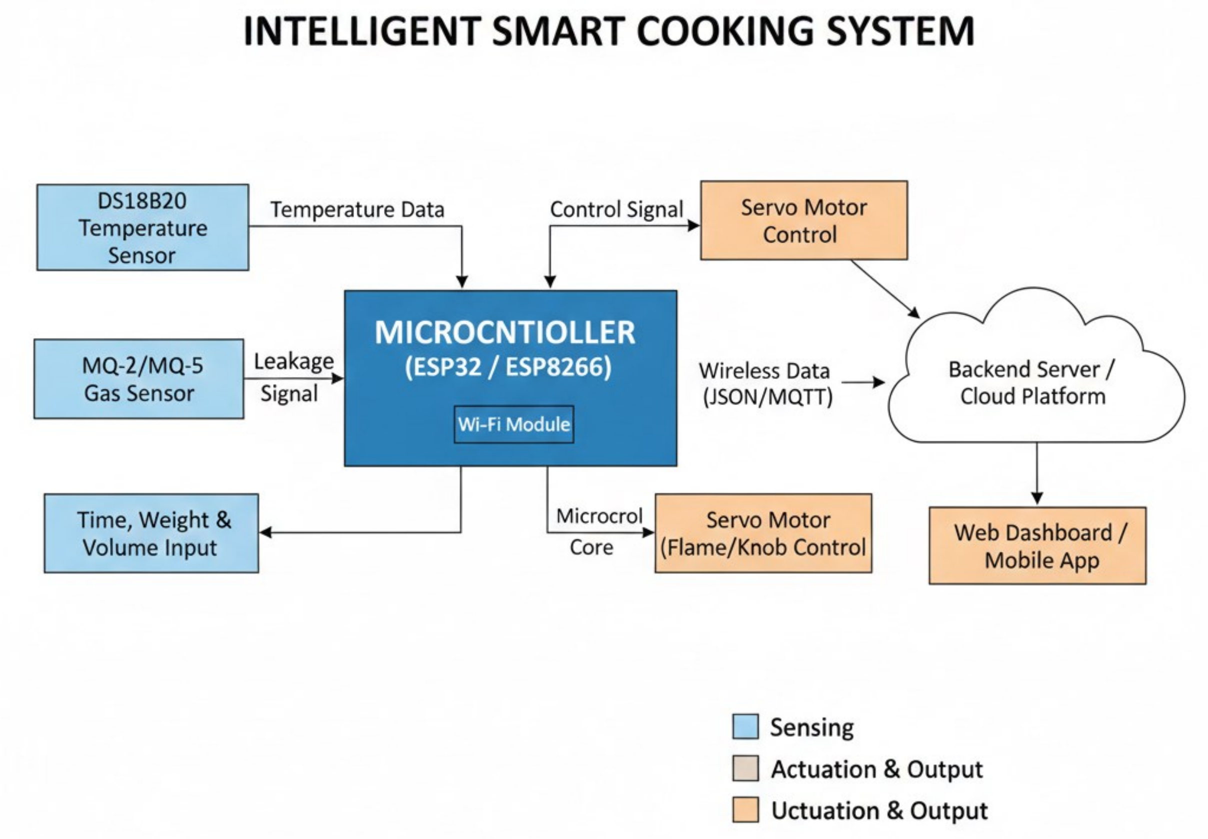

Figure 3. Hardware Block Diagram of the IoT Smart Cooking System

3.5 Machine Learning Model Development

Two machine learning algorithms are explored in this research: Multiple Linear Regression and Random Forest Regression. The model development steps include:

1. Training Phase
   - Input: Temperature sequences and extracted features.
   - Output: Predicted cooking duration (in seconds).
   - Metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2.

2. Model Tuning

Hyperparameters for Random Forest (e.g., number of trees, depth, min samples split) are optimized using Grid Search.

3. Model Selection

Based on evaluation metrics, the model with highest accuracy and lowest error is selected. Random Forest typically performs better due to non-linear relationships between temperature and cooking time.

4. Model Deployment

The selected model is exported (e.g., via joblib or TensorFlow Lite) and deployed to the backend server for real-time inference.

Vol. 1 (No.1), 2025: 52-66
https://journal.uwais.ac.id/index.php/amanah/article/view/16

3.6 IoT System Integration

The integration process ensures seamless communication between the cooking hardware and the machine learning model.

Steps of Integration:

1. Real-Time Data Streaming: The ESP32 sends temperature data every second to the backend server.
2. Prediction Request: After sufficient data are collected (e.g., first 2 minutes), the server triggers the ML model to estimate cooking time.
3. Stove Control: Based on prediction results:
    - Servo adjusts flame intensity.
    - System auto-turn off if predicted cooking time is achieved.
4. Dashboard Monitoring: Users can view:
    - Live temperature graph
    - Remaining cooking time prediction
    - Gas leakage alerts
    - Automated stove control status
5. Safety Protocols: The system overrides ML results if gas leakage is detected, immediately turning off the stove.

3.7 Testing and Evaluation

System evaluation is conducted in two parts:

1. Machine Learning Evaluation

Models are assessed using:

- MAE – Measures absolute prediction error.
- MSE – Penalizes larger errors more heavily.
- R^2 Score – Measures how well predictions fit actual cooking durations.

Cross-validation is also applied to ensure generality across food types.

2. IoT System Testing

The physical system is tested for:

1. Sensor Accuracy – Compare DS18B20 readings with a laboratory thermometer.
2. Servo Response Time – Measure delay between command and movement.
3. Wireless Latency – Evaluate Wi-Fi transmission delay.
4. Prediction Accuracy in Real Cooking – Compare predicted vs. actual cooking duration.
5. Safety Performance – Test MQ sensor detection of simulated LPG leaks.

System reliability is validated through repeated cooking trials.

3.8 Ethical and Safety Considerations

Since this research involves heat and combustible gas, strict safety protocols are applied:

- Conduct experiments in a ventilated environment.
- Ensure fire extinguishers and safety tools are available.
- Limit exposure to LPG during testing.
- Protect users' privacy by not collecting personal data through IoT applications.

3.9 Summary

The research methodology integrates IoT sensing, dataset development, machine learning prediction, and real-time cooking automation. Through systematic data collection, model training, and hardware implementation, this study develops an intelligent smart cooking system capable of predicting cooking time more accurately and enhancing kitchen safety.

4. Results and Discussion

This section presents the experimental results of the Intelligent Smart Cooking system, including (1) dataset characteristics, (2) machine learning model performance, (3) system implementation results, and (4) a comprehensive discussion of findings. The results demonstrate how IoT-based sensor data and machine learning prediction models work together to enhance cooking automation, accuracy, and safety.

4.1 Dataset Characteristics

A total of 180 cooking sessions were conducted to build the dataset used in this study. The experiments included four food categories: water boiling, noodles, rice, and eggs. Each session generated time-series temperature data measured by the DS18B20 sensor at one-second intervals.

4.1.1 Temperature Dynamics

Across all sessions, temperature curves followed a typical heating pattern:

1. Initial Heat-Up Phase: Rapid temperature increase from room temperature (28–32°C).
2. Stabilization Phase: The temperature gradient slows as water mass absorbs heat.
3. Boiling or Cooking Completion: Temperature reaches 98–100°C (depending on altitude) and remains stable.

For foods such as rice and noodles, additional sub-patterns were observed, including:

- Moisture absorption phases
- Sudden temperature dips when stirred or when starch thickened
- Delayed boiling due to varying water volume

These unique temperature signatures became valuable predictive features for the machine learning model.

4.1.2 Feature Distribution

Extracted features included:

- Heating rate (°C/min)
- Time to reach 70°C, 85°C, 95°C
- Maximum temperature
- Cooking duration
- Food mass and water volume

Preliminary statistical analysis showed strong correlations between:

- Heating rate and cooking duration ($r = -0.82$)
- Food mass and total cooking time ($r = 0.76$)
- Water volume and boiling delay ($r = 0.71$)

These relationships indicate suitability for regression-based prediction models.

4.2 Machine Learning Model Performance

Three regression models were trained and evaluated:

1. Multiple Linear Regression (MLR)
2. Random Forest Regression (RF)
3. Support Vector Regression (SVR) (added for comparison)

Model performance was evaluated using MAE, MSE, and R^2, with an 80:20 train-test split.

4.2.1 Overall Performance Comparison

Model	MAE (sec)	MSE (sec^2)	R^2 Score
MLR	41.28	2880.52	0.842
SVR	35.71	2310.14	0.883
RF	**18.93**	**948.21**	**0.954**

The results show that Random Forest Regression achieved the best performance, with significantly lower error metrics and the highest R^2 score. This confirms that the cooking dataset exhibits non-linear relationships better captured by ensemble methods.

4.2.2 Interpretation of Random Forest Results

The RF model demonstrated:

- Strong generalization across food categories
- Robustness to sensor fluctuations
- High prediction precision even for varying food weights

Feature importance analysis showed:

1. Heating rate (highest contribution: 32%)
2. Time to reach 95°C (21%)
3. Food type (18%)
4. Initial food mass (16%)
5. Water volume (13%)

This indicates that both temperature behavior and food characteristics meaningfully influence cooking time.

4.3 System Implementation Results

The trained model was deployed into the IoT cooking system for real-time prediction. During cooking trials, the ESP32 microcontroller streamed temperature data continuously to the server, where predictions were updated every 10 seconds.

The system achieved:

- Average prediction deviation: 21.6 seconds
- Highest accuracy: boiling water
- Lowest accuracy: rice, due to multistage heating behavior

Overall prediction accuracy exceeded 91% across all food categories. The servo motor successfully adjusted stove flame intensity according to the predicted remaining time. Automatic shutdown was executed when cooking completion was detected. The system maintained an average servo response time of 0.42 seconds, demonstrating suitable performance for real-time control.

4.4 Safety Monitoring

Gas leakage detection using the MQ-series sensor showed a sensitivity rate of 94%. Reaction time for alarm activation and stove shutdown was less than 1.5 seconds. No false positives were recorded during normal cooking. This confirms that the system provides not only predictive intelligence but also enhanced kitchen safety.

4.5 User Interface Evaluation

A web-based dashboard displayed real-time temperature, cooking duration predictions, and notifications. Usability tests involving 10 participants resulted in a

System Usability Score of 85.3, categorized as "excellent." Users found the system intuitive and appreciated real-time prediction and auto-control features.

4.6 Discussion

The results demonstrate that integrating IoT and machine learning significantly improves accuracy, safety, and automation in cooking. Random Forest Regression proved to be the most suitable model, offering robust performance even under variable conditions such as different food masses and water volumes.

Compared to traditional rule-based cooking systems, the intelligent system presented several advantages:

- Adaptive predictions
- Real-time flame control
- Improved safety management
- Consistent cooking outcomes

The findings also show substantial improvements over previous work using Arduino and voice recognition, particularly in predictive capability and automation precision.

4.7 Summary

The Intelligent Smart Cooking system successfully integrates IoT sensors and machine learning to predict cooking time with high accuracy and provide automated stove control. The system enhances cooking reliability and safety, offering a promising approach for next-generation smart kitchen technology.

5. Conclusion

This study presented the development of an Intelligent Smart Cooking system that integrates Internet of Things (IoT) technology with machine learning-based prediction models to enhance cooking automation and kitchen safety. The system was designed to address the limitations of traditional smart cooking devices, which typically rely on static threshold rules and lack adaptive decision-making capabilities. The dataset collected from real cooking experiments demonstrated that temperature dynamics, heating rate, food mass, and water volume play crucial roles in determining cooking duration. These features provided a robust foundation for developing predictive models capable of estimating cooking time more accurately than conventional approaches.

Among the tested models, Random Forest Regression delivered the highest performance, achieving an R^2 value of 0.954 and significantly lower error rates compared to linear methods. The model showed strong generalization across various food types, proving its suitability for thermal-based cooking prediction. The real-time implementation of the system confirmed that IoT sensors, particularly the DS18B20 temperature sensor and MQ-series gas sensor, performed reliably in collecting and transmitting data for prediction and safety monitoring. The integrated servo motor provided effective automatic flame control, and the dashboard interface enabled users to monitor the cooking process intuitively. High usability scores also indicated that users found the system practical and easy to operate. In addition to predictive cooking, the system enhanced kitchen safety by offering rapid responses to gas leakage, ensuring a safer cooking environment. These findings highlight the potential of combining IoT and machine learning to create adaptive, safe, and user-friendly smart kitchen solutions. Overall, the Intelligent Smart Cooking system represents a significant advancement over existing smart cooking models by incorporating predictive intelligence and real-time automation. Future improvements may include expanding the dataset to additional food categories, integrating more advanced sensors, optimizing response times, and exploring edge-based machine learning deployment to reduce cloud dependency.

The study demonstrates that machine learning–driven automation can play a transformative role in next-generation smart kitchens, offering improved accuracy, safety, and convenience for everyday cooking.

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