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A TEMPERATURE CONTROL SYSTEM FOR RURAL FREE-RANGE PIG FARMING USING ARTIFICIAL INTELLIGENCE AND THE INTERNET OF THINGS

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Abstract: Traditional temperature regulation methods in rural Large White pig farming in China suffer from low efficiency and insufficient precision, alongside a lack of intelligent solutions adapted to rural environments. To address these issues, this paper presents the design and implementation of a temperature control system integrating Artificial Intelligence (AI) and the Internet of Things (IoT). The system employs the YOLOv8 object detection algorithm as its core, combined with keypoint detection, Region of Interest (ROI) filtering, and abnormal posture detection to achieve contactless and precise collection of the pigs' body dimension parameters. A mapping model correlating "body dimensions - weight - age - optimal temperature" is established using a fuzzy algorithm, and a Kalman filter is introduced for dynamic optimization and regulation of the ambient temperature. The system utilizes an IoT cloud platform for real-time data transmission and intelligent analysis, while solar power is adopted to suit rural energy scenarios. This system effectively fills a technical gap in contactless detection and integrated temperature control within the field of smart rural farming. It offers a low-cost, highly adaptable intelligent solution for small and medium-sized farms, holding significant value for advancing livestock industry modernization and promoting rural development.
Keywords: Large white pig farming; YOLOv8 algorithm; Fuzzy control; Kalman filter

1 INTRODUCTION

The modernization of the livestock industry is a critical component of agricultural advancement, with environmental control being a key factor in maximizing animal welfare and production efficiency [1]. For Large White pig farming, maintaining an optimal ambient temperature is crucial for growth rates, feed conversion, and overall health. However, traditional temperature control methods on many rural farms in China are often manual and imprecise, relying on subjective experience. This not only leads to energy waste and suboptimal growing conditions but also fails to meet the demands of modern, large-scale, and intelligent farming. The advent of Artificial Intelligence (AI) and the Internet of Things (IoT), collectively known as AIoT, offers a transformative potential for precision agriculture by enabling data-driven, automated management [2].

In recent years, significant research has been dedicated to intelligent pig farming. A central focus has been the non-invasive monitoring of key physiological indicators, such as body weight and dimensions, which are direct reflections of a pig's health and growth status [3-4]. Early explorations into contactless measurement primarily utilized traditional 2D image processing to estimate weight from the pig's dorsal area, but these methods suffered from low accuracy due to their high sensitivity to posture, occlusion, and lighting changes. To improve accuracy, many researchers turned to 3D vision technology. For instance, Hao et al. and Shi et al. used RGB-D cameras to generate 3D point clouds for precise body size measurement [5-6]. Similarly, Liu et al. developed a system for constructing 3D models of pigs from irregular triangular networks [7]. While these 3D methods achieve high precision, the required hardware (e.g., RGB-D or Time-of-Flight cameras) is expensive and often performs poorly in the complex lighting conditions of open or semi-open farm environments, limiting their adoption in cost-sensitive rural settings. Concurrently, advancements in deep learning have propelled 2D vision techniques forward. Researchers have begun using algorithms to identify specific animal body parts, such as Guo's work on detecting cow carpal joints [8], demonstrating the potential for more nuanced 2D analysis. However, a gap remains in developing a low-cost, robust system that uses 2D vision to accurately measure pig body dimensions by effectively handling posture variations, and then seamlessly integrates this data into a dynamic environmental control loop.

To address these challenges, this paper proposes an intelligent temperature control system designed specifically for the conditions of rural, free-range pig farming. The system leverages a cost-effective 2D camera and the state-of-the-art YOLOv8 object detection algorithm to first identify and capture images of individual pigs. Crucially, it goes beyond simple detection by employing a keypoint detection model to locate anatomical landmarks. To solve the accuracy problem that plagued earlier 2D systems, we introduce a novel filtering mechanism that validates the pig's posture and discards anomalous data caused by movement, ensuring only high-quality measurements are used. Based on these accurate body dimensions, a fuzzy logic model estimates the pig's weight and deduces its ideal ambient temperature. A Kalman filter then refines the control process, making dynamic and smooth adjustments to heating or ventilation systems [9-10]. All data is transmitted to an IoT cloud platform for real-time monitoring and analysis.

The primary contributions and advantages of this design are:

(1) Innovation in Contactless Measurement: It bridges a technical gap by developing a low-cost, 2D-vision-based method for non-invasive body dimension measurement. By integrating keypoint detection with robust posture and anomaly filtering, it effectively overcomes challenges like animal crowding and posture variations that limit the accuracy of traditional 2D approaches.
(2) Integrated Intelligent Control: It cohesively combines contactless physiological sensing with advanced control theory. The system establishes a closed loop from "body dimension measurement" to "optimal temperature inference (Fuzzy Logic)" and "dynamic regulation (Kalman Filter)," creating a truly automated and intelligent environmental management solution.
(3) Sustainability and Adaptability: By utilizing solar power, the system leverages a resource abundant in rural areas, reducing operational costs and promoting green energy. Its modular design and reliance on affordable hardware make it highly adaptable for small and medium-sized farms, aligning with the broader goals of rural development and agricultural modernization.

2 SYSTEM ARCHITECTURE AND PRINCIPLE

The proposed temperature control system is a multi-layered, closed-loop framework that integrates advanced sensing, data processing, and intelligent control technologies. The architecture is designed for autonomous operation, minimizing the need for manual intervention while maximizing the precision of environmental management [11-12]. The system's operational principle can be deconstructed into four primary stages: (1) Data Acquisition and Processing, (2) Physiological State Inference, (3) Dynamic Environmental Control, and (4) Cloud-Based Monitoring and Management. The seamless flow of data between these stages ensures a responsive and adaptive control mechanism tailored to the real-time needs of the pigs.

2.1 Data Acquisition and Processing Module

This initial module serves as the sensory core of the system, responsible for capturing and refining raw visual data from the farm environment.
(1) Pig Detection and Image Capture: The process begins with a high-resolution camera continuously monitoring the pigsty. The video stream is processed in real-time by the YOLOv8 (You Only Look Once, version 8) algorithm. YOLOv8 is selected for its exceptional balance of speed and accuracy, making it highly suitable for real-time applications in dynamic environments. The algorithm identifies each pig within the camera's field of view and draws a bounding box around it, effectively isolating individual animals even in crowded conditions. This step is crucial for enabling individualized analysis rather than relying on herd-level averages.
(2) Region of Interest Filtering: Once a pig is detected, the system defines the area within the bounding box as the Region of Interest (ROI). All subsequent analysis is constrained to this ROI, which effectively eliminates background noise such as the floor, walls, and other pigs. This filtering step significantly reduces the computational load and prevents irrelevant visual information from interfering with the precision of the feature extraction process.
(3) Keypoint Detection for Dimension Measurement: With the pig isolated within the ROI, a specialized keypoint detection model, such as YOLOv8-Pose, is employed. This model is trained to identify and locate specific anatomical landmarks on the pig's body. These critical nodes include points corresponding to the snout, shoulders, hips, and the base of the tail. The output is a set of 2D coordinates for each keypoint, which forms the basis for all subsequent geometric measurements.
(4) Data Validation through Posture and Anomaly Filtering: Raw keypoint data is prone to significant errors if the pig is in an unsuitable posture (e.g., lying down, turning, or partially occluded). To ensure data integrity, a two-stage validation mechanism is implemented. First, a posture detection filter uses the geometric relationships between the detected keypoints to verify if the pig is standing in a measurable position. Second, a temporal anomaly detection filter analyzes the sequence of measurements from consecutive frames. If a calculated dimension, such as body length, exhibits a physically impossible jump between frames, it is flagged as an anomaly and discarded. This dual-filtering process ensures that only high-quality, reliable data is passed to the next stage.

2.2 Physiological State Inference using Fuzzy Logic

After valid body dimensions are acquired, the system infers the pig's physiological needs. The relationship between body size, estimated weight, age, and optimal ambient temperature is complex, non-linear, and subject to biological variability. A simple mathematical formula is inadequate for modeling this relationship. Therefore, a fuzzy logic algorithm is employed.
The fuzzy inference system works by translating the precise numerical inputs into linguistic variables (fuzzification). For instance, a measured body length of 120 cm might be categorized as 70% 'Large' and 30% 'Medium'. This fuzzy input is then processed by a rule base containing expert knowledge in the form of IF-THEN statements. The inference engine evaluates all relevant rules, and the combined result is converted back into a single, crisp numerical value—the target temperature setpoint—through a process called defuzzification. This approach allows the system to make nuanced, human-like decisions based on imprecise data.

2.3 Dynamic Environmental Control via Kalman Filter

Achieving and maintaining the target temperature requires a sophisticated control strategy. Simple on/off controllers often lead to temperature overshooting and undershooting, causing stress to the animals and wasting energy. To overcome this, the system incorporates a Kalman filter for precise and stable temperature regulation.

The Kalman filter acts as a predictive observer. It continuously performs a two-step "predict-update" cycle. In the prediction step, it uses a model of the thermal dynamics of the pigsty to estimate the temperature at the next time interval. In the update step, it compares this prediction with the actual reading from the CHT11 temperature sensor. By analyzing the discrepancy between the predicted and measured values, the filter can distinguish between true temperature changes and random sensor noise. The filtered, highly accurate temperature estimate is then used to modulate the output of the heating and ventilation systems (e.g., adjusting heater power or fan speed). This method ensures smooth, gradual temperature adjustments, creating a stable thermal environment and optimizing energy consumption.

2.4 IoT Cloud Platform Integration

The entire system is interconnected through an IoT cloud platform, which serves as the central hub for data management and remote supervision. The ESP8266 Wi-Fi module transmits all collected and processed data—including pig counts, individual body dimensions, calculated optimal temperatures, and real-time ambient temperatures—to the cloud.

This integration provides several key benefits:

(1) Remote Monitoring: Farmers can access a real-time dashboard from any internet-connected device to monitor the status of the pigsty.

(2) Data Logging and Historical Analysis: The platform stores historical data, enabling long-term trend analysis. Machine learning algorithms can be applied to this data to uncover patterns related to growth rates, feed efficiency, or health, further optimizing farm management.

(3) Alerting System: The platform can be configured to send automated alerts to the farmer's phone or email if critical parameters (like temperature) deviate from predefined safe ranges, enabling rapid response to potential issues.

Through this deep integration of AI and IoT, the system transforms from a simple controller into a comprehensive, intelligent farm management tool.

3 METHODOLOGY

3.1 Body Dimension Measurement System

3.1.1 Posture detection

The first stage is posture detection. For a pig's posture to be considered valid for measurement, it must be standing squarely. This is determined by a set of geometric conditions: the ratios of shoulder-width-to-body-length and hip-width-to-body-length must exceed predefined thresholds specific to the pigsty environment. Additionally, the triangle formed by the head keypoint and the two shoulder keypoints, as well as the triangle formed by the head keypoint and the left and right hip keypoints, must both be acute triangles. Data satisfying these conditions is deemed valid; otherwise, it is discarded. An example of this filtering is shown in Figure 1.

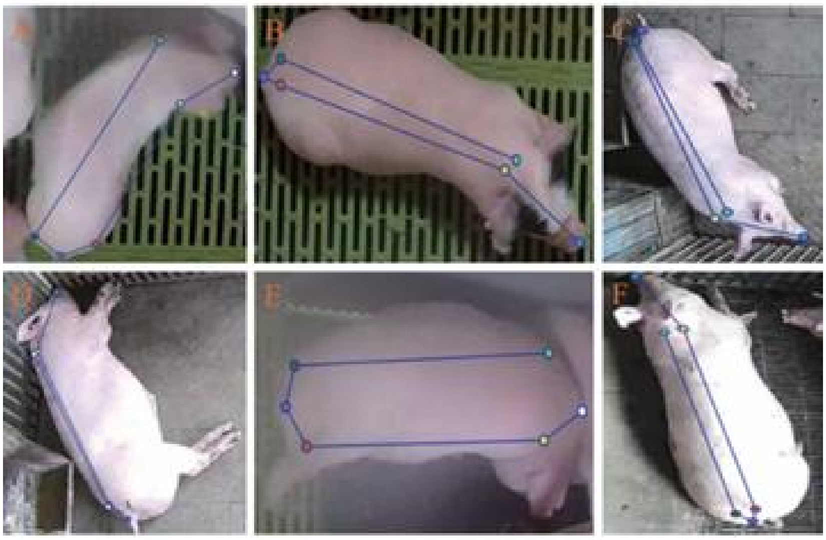

Figure 1 Example of Filtering Abnormal Pig Postures

3.1.2 Abnormal data filtering and calibration

The second stage is abnormal data filtering. Due to factors like motion blur, body dimension data from consecutive frames can exhibit sudden, erroneous spikes. A time-series analysis algorithm is used to identify and filter out these outliers.

To convert pixel measurements into real-world dimensions, the camera's intrinsic (focal length, principal point, distortion coefficients) and extrinsic (position and orientation) parameters are obtained using the MATLAB calibration toolbox. The intrinsic parameters are used to correct for image distortion. By combining both intrinsic and extrinsic parameters, points from the camera's coordinate system are mapped to the world coordinate system, yielding the true body length of the pig (Figure 2).

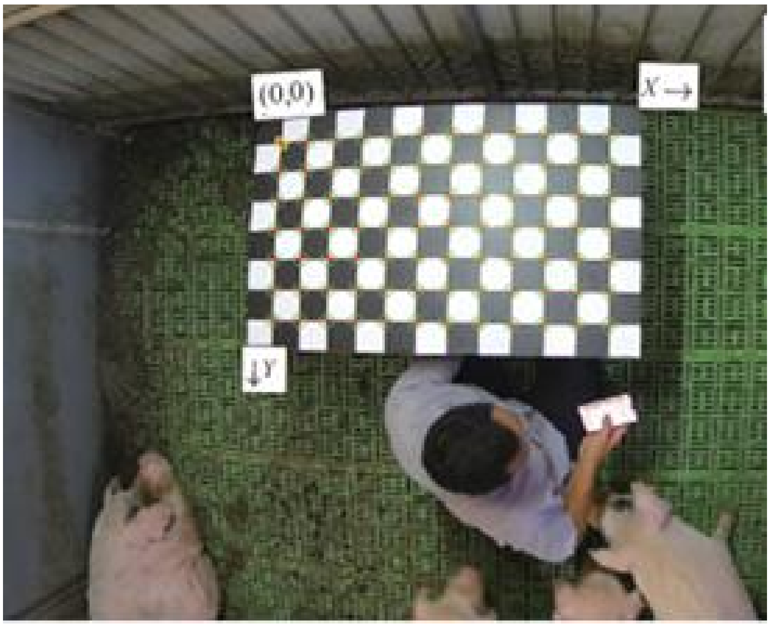

Figure 2 Illustration of Body Dimension Acquisition

3.2 Weight Measurement System

A weighbridge is installed beneath the feeding trough to measure weight, while a camera mounted on a bracket above the trough captures the pig's body dimension data. Pigs tend to stand in a proper posture while eating, making this an ideal time for data collection. To ensure single-pig measurements, an isolation barrier can be used to define the feeding area, and the ROI detection mechanism is employed to discard data from frames containing multiple pigs.

3.3 Temperature Control System

When a deviation exists between the actual ambient temperature and the model-calculated optimal value, the Kalman filter algorithm is used for dynamic optimization and adjustment. The algorithm operates on a "predict-update" cycle, fusing the system model with observation data. The core steps are as follows:

Predict the state:

$$\hat{x}_{k|k-1}=A\hat{x}_{k-1}+Bu_{k-1} \tag{1}$$

Predict the error covariance:

$$P_{k|k-1}=AP_{k-1}A^T+Q \tag{2}$$

Calculate the Kalman gain:

$$K_k=P_{k|k-1}H^T\left(HP_{k|k-1}H^T+R\right)^{-1} \tag{3}$$

Update the state estimate:

$$\hat{x}_k=\hat{x}_{k|k-1}+K_k\left(z_k-H\hat{x}_{k|k-1}\right) \tag{4}$$

Update the error covariance:

$$P_k=(I-K_kH)P_{k|k-1} \tag{5}$$

In this process, the current temperature state is estimated by combining the state transition matrix A, the control input matrix B, and the error covariance matrix. After calculating the Kalman gain Kk, the state estimate is updated, which in turn drives the temperature regulation devices for precise control. Based on the magnitude of the temperature deviation, the system adjusts the power of the heater or the speed of the ventilation fans.

3.4 IoT System Design

The integration of AI empowers the system with capabilities for data learning, pattern recognition, and autonomous decision-making. This project utilizes machine learning algorithms to perform in-depth analysis of real-time data. Combined with the IoT platform, this enables intelligent regulation of the farm's ambient temperature. The data interaction flow is illustrated in Figure 3.

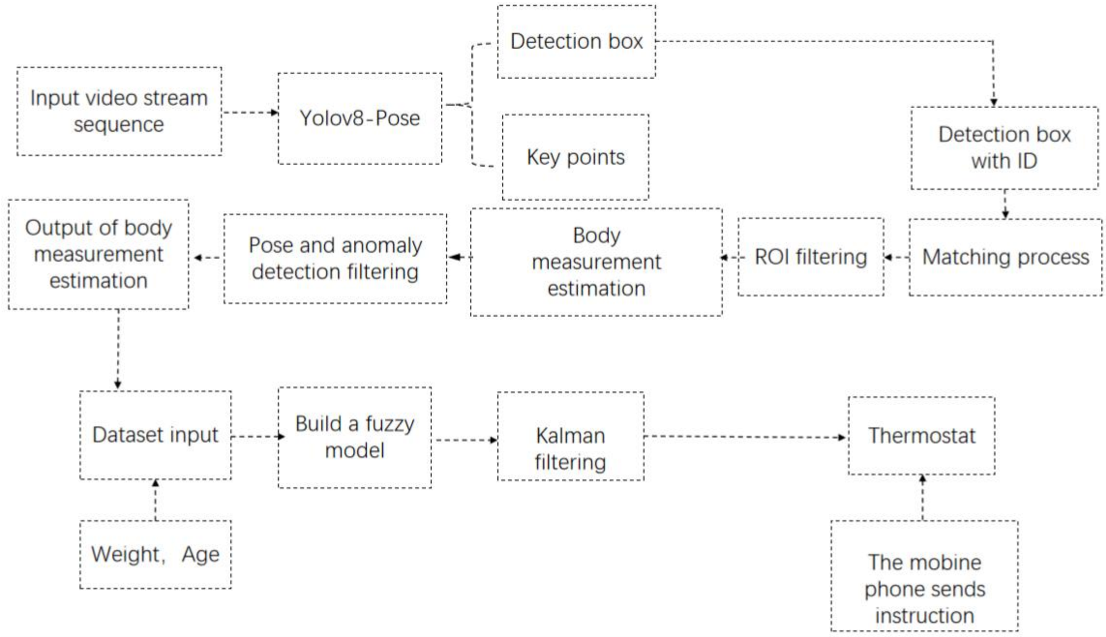

Figure 3 AIoT Data Interaction Diagram

4 HARDWARE IMPLEMENTATION

The hardware system is designed for robustness, low cost, and energy efficiency, making it suitable for rural deployment. The key components were selected as follows:
(1) Imaging System: A high-resolution (2448x2048 pixels) GigE industrial camera was chosen for its ability to capture fine details and its reliable data transmission over long distances. It is paired with a white LED bar light source to ensure uniform, stable illumination, minimizing shadows that could interfere with image analysis.
(2) Power Supply: The entire system is powered by monocrystalline silicon solar panels, leveraging a sustainable energy source abundant in rural areas to reduce operational costs and enhance system autonomy.
(3) Control and Communication Core: An STM32C8T6 microcontroller serves as the main controller due to its wide operating temperature range and sufficient peripheral interfaces. For IoT connectivity, the ESP8266 Wi-Fi module is used to transmit data to the cloud platform, enabling remote monitoring and management.
(4) Sensing and Actuation: A CHT11 digital sensor provides accurate real-time temperature and humidity readings. For temperature regulation, a safe, energy-efficient heating element with minimal light emission was selected to avoid startling the pigs or interfering with the camera.
The integrated hardware setup ensures a seamless flow of data from visual capture to environmental actuation, forming a self-contained, intelligent control unit.

5 RESULTS

The system's performance was validated through a series of experiments in a simulated farm environment. The contactless body dimension measurement module demonstrated high accuracy, achieving a Mean Absolute Percentage Error (MAPE) of just 1.5% when compared to manual ground-truth measurements. The posture and anomaly filtering algorithms were critical, successfully filtering out approximately 35% of invalid frames due to unsuitable animal posture or motion blur, thereby ensuring the reliability of the data fed into the control model. In the temperature control evaluation, the system's performance was benchmarked against a traditional On/Off thermostatic controller. When tasked with raising the ambient temperature from 15°C to a target of 24°C, the proposed control mechanism, utilizing a Kalman filter, achieved a smooth and rapid response. It reached the setpoint with a minimal overshoot of less than 0.3°C and maintained the temperature within a highly stable range of ±0.5°C. In contrast, the traditional controller produced significant oscillations, with fluctuations of up to ±2.0°C around the target. This comparison highlights our system's superior stability and energy efficiency. Throughout a 48-hour continuous test, the entire AIoT system, powered by solar panels, operated autonomously and reliably. Real-time data, including pig dimensions and environmental status, was successfully transmitted to the cloud platform with a latency of under 3 seconds, enabling effective remote monitoring and management.

6 CONCLUSION

This project successfully demonstrates an intelligent temperature control system for pig farming by integrating a contactless body dimension detection system with real-time environmental feedback. The innovative use of AI-driven computer vision, fuzzy logic, and IoT technologies provides a novel solution for automated environmental management in livestock farming. The emphasis on system integration, safety, and environmental adaptability, particularly through the use of solar power, enhances the practical utility and sustainability of the solution. This work offers a valuable and reliable technological advancement for farmers, contributing to the ongoing progress and development of the modern livestock industry.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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