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Original Paper

Intelligent Monitoring of Individual Nest-building Behavior in Group-raised Geese

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Abstract

Breeding geese often exhibit frequent nest-building behaviors under group rearing conditions, which significantly reduces egg-laying efficiency. However, it remains challenging to accurately identify the occurrence and duration of individual nest-building in such environments. To address this, this study integrates wearable activity monitoring sensors with RFID identification technology to develop a nest-building behavior characterization system based on activity rhythms and posture features. Building on this foundation, we propose an Integrated Feature Engineering-Driven Stacking Recognition Model (IFESM-GND) that enhances nest-building behavior recognition accuracy by leveraging interpretable feature engineering. Experimental results demonstrate a 93.5% detection accuracy, representing a 15%-21% improvement over traditional methods. The application value of nest-building behavior monitoring in early egg-laying anomaly detection and breeding management decision-making is validated. This precise monitoring method for individual nest-building behaviors in breeding geese provides crucial technical support for optimizing reproductive performance, improving egg-laying efficiency, and achieving precision management. The research holds significant theoretical and practical implications for advancing the intelligent and modernization of China's goose industry.

Keywords

Group-raised goose monitoring, nest-guarding behavior, feature engineering, integrated learning, intelligent farming

1. Introduction

China is the world's largest goose farming country (Hou Shuisheng et al., 2024). As the core of the goose breeding system, breeding geese' egg production efficiency directly determines their renewal rate and commercial generation potential (Djermanovic et al., 2024). However, under ground flock rearing models, breeding geese commonly exhibit frequent nest-building behaviors that last for extended periods. Nest-building not only immediately interrupts egg production but also reduces subsequent egg-laying activity, making it a key limiting factor for breeding efficiency (Yao Ying et al., 2018). Therefore, precise identification and long-term monitoring of individual nest-building behaviors are crucial for improving breeding performance and strengthening precision management in goose farming.

However, in group-rearing environments, frequent interactions between individuals and significant overlap in activity patterns, combined with the pronounced circadian rhythms of breeding geese and the striking similarity in resting and nest-building behaviors, make it challenging for researchers to reliably determine whether individuals are nesting and the timing of such behavior (He Mengqi, 2013). Current methods like video monitoring are prone to obstructions, light variations, and individual clustering, while RFID nest box identification relies on fixed egg-laying locations, making it difficult to detect nesting behavior in non-nesting areas (Okinda et al., 2020). Therefore, there is an urgent need for an intelligent monitoring method that can continuously and individually identify nesting behavior under group-rearing conditions.

To address these challenges, this study proposes an integrated "identity recognition + behavioral perception + model interpretation" approach for intelligent monitoring of goose nest-building behavior. The method aims to accurately capture the occurrence timing, duration, and intensity variations of nest-building activities. This breakthrough resolves the technical bottleneck of individual behavior differentiation in traditional group-raising systems, providing a scalable technical pathway for breeding high-yield goose varieties, regulating reproductive rhythms, and implementing intelligent management. The innovation holds significant theoretical and practical value for advancing China's goose industry toward digitalization and intelligent transformation.

2. Materials and Methods

2.1 Data Preprocessing

To achieve real-time monitoring of breeding geese activity, this study uses a wing-tag activity sensor based on a triaxial accelerometer, designed specifically for monitoring individual geese. The use of a wearable sensor enables continuous tracking of goose movement data with individual-level precision.

The raw data from the triaxial accelerometer are continuously collected at a sampling frequency of 16

Hz, with a measurement range of ±2 g. These data are transmitted to a server via a gateway using a 4G network, and are ultimately retrieved and analyzed through a web-based application. The collected data are shown in the Figure 1.

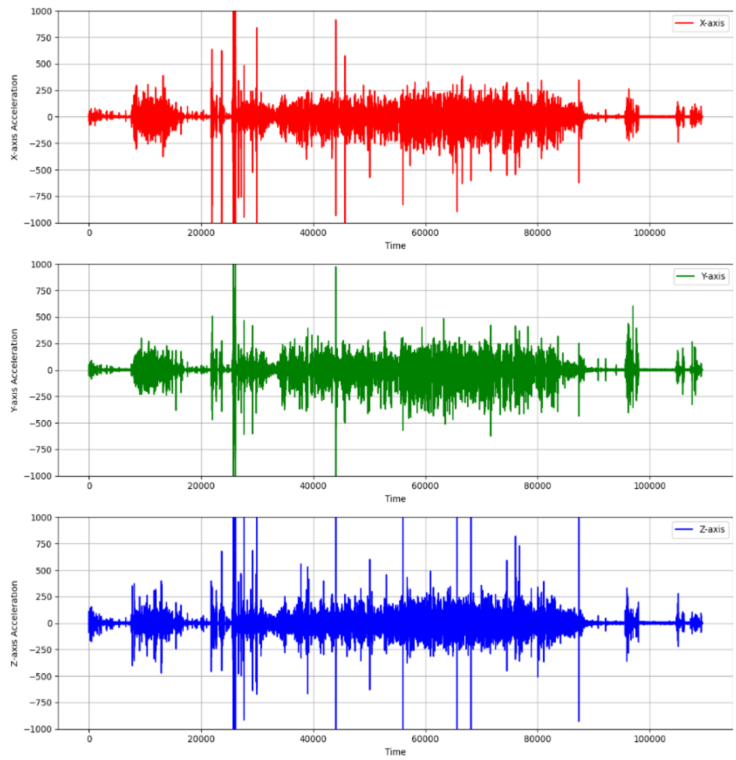

Figure 1. Feature Engineering Flow Chart

To ensure the availability and computational stability of acceleration data, the data preprocessing includes the following steps:

(1) Noise reduction and smoothing: Low-pass filtering is used to remove high-frequency noise such as wing beating, and sliding average is used to smooth the signal, retaining low-frequency features related to nest-holding behavior.

(2) Missing value filling: Linear interpolation is used to maintain the continuity of time series signals.

(3) Feature normalization: Z-score standardization is applied to acceleration values across all axes to unify dimensions and improve model convergence.

(4) Time window division: The continuous signal is divided into fixed length behavioral fragments by using overlapping sliding window, which provides a sample basis for the construction of subsequent time series features.

2.2 Nesting Behavior Characterization Using Explainable Feature Engineering

The goose nest-building behavior, characterized by low activity, prolonged duration, and weak periodicity, is a key limiting factor affecting egg production in flock rearing environments. To accurately characterize nest-building behavior from acceleration data, this study establishes an interpretable feature engineering framework comprising three stages: multi-dimensional feature extraction, significance screening, and cross-axis fusion, as shown in Figure 2.

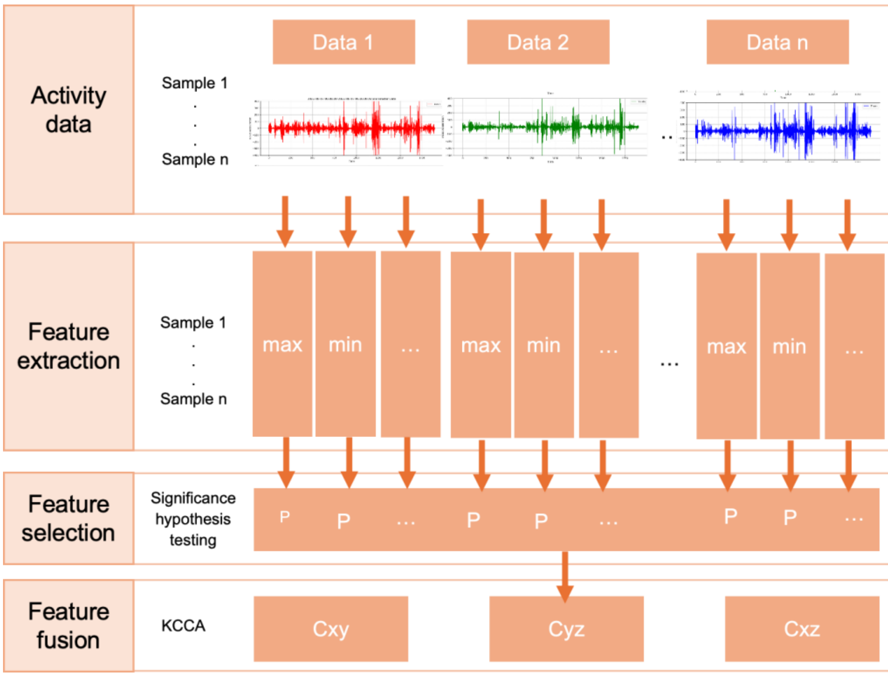

Figure 2. Feature Engineering Flow Chart

To comprehensively describe the macroscopic and microscopic dynamic characteristics of nest-building behavior, we utilized Tsfresh (Christ et al., 2018) to automatically extract features from accelerated sliding windows. These features include: time-domain characteristics for characterizing low-amplitude and posture stability during nest-building; frequency-domain characteristics to capture periodic micro-movements with energy concentration at low frequencies; statistical-dependent features reflecting high persistence and internal consistency; and autoregressive features to depict temporal inertial structures during nest-building. To eliminate redundant features and enhance discriminative power, we conducted Kolmogorov–Smirnov tests (Berger et al., 2014) to analyze the significance of feature distribution differences between nest-building and non-nest-building samples, retaining only core features with distinct discriminative capabilities.

Considering the nest-building posture as a three-dimensional coordinated movement, single-axis features cannot fully capture its complexity. This study employs Kernel Canonical Correlation Analysis (KCCA) to perform nonlinear fusion of X, Y, and Z-axis features (Zheng et al., 2006; Nadil et al., 2016; Bai et al., 2018). KCCA extracts the maximum correlation projections between multiple axes through kernel mapping, enhancing the precision and recognition of nest-building behavior representation while generating deep fusion features (Yan et al., 2014), as shown in Figure 3.

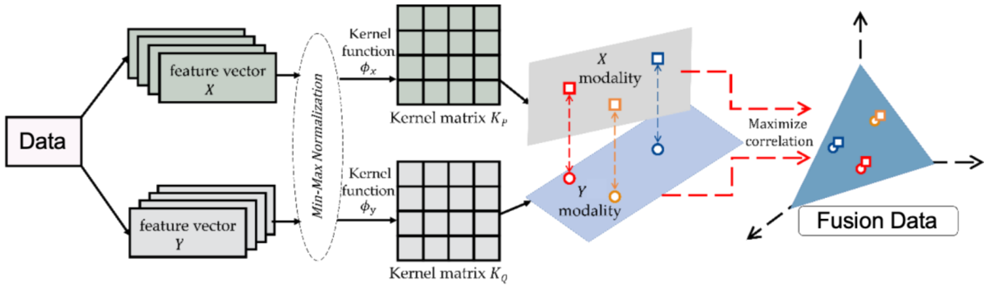

Figure 3. KCCA Cross-axis Feature Fusion Diagram

2.3 Construction of the IFESM-GND Nesting Detection Model

After completing the multidimensional feature representation of nest-building behavior, this study developed an interpretable feature-engineered stacked integration model (IFESM-GND) to achieve high-precision automatic recognition, the model architecture is shown in Figure 4. By leveraging the predictive advantages of multi-learner fusion (Pavlyshenko, 2018), the model enhances its ability to identify nest-building behavior characterized by "low activity, ambiguous boundaries, and weak inter-class differences". The model adopts a dual-layer architecture comprising a base learner layer and a meta-learning layer.

The foundational learning layers capture cluster characteristics from diverse learning mechanisms. This study selects four complementary classifiers as base learners: MLPs mine nonlinear combinations of features; SVMs construct high-dimensional hyperplanes emphasizing boundary discrimination; Random Forests handle feature randomness through multi-tree voting; and XGBoost utilizes gradient boosting to capture fine-grained feature variations. After feature engineering, samples are fed into these four base learners, with each model independently outputting a cluster probability as the first-layer prediction.

The meta-learner layer utilizes the prediction probabilities from the base learners as new meta-features, with XGBoost constructing a meta-classifier to integrate final decisions. By learning the complementarity and bias correction strategies among base learners, the meta-learner achieves more robust ensemble results. This study employs k-fold cross-validation for both training and evaluation to ensure the model's generalization across different populations and time periods.

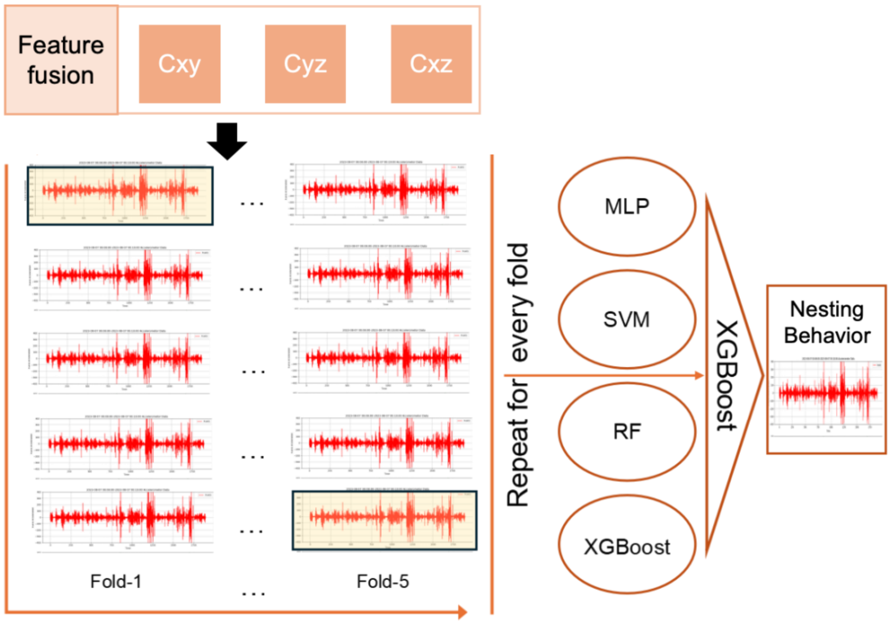

Figure 4. FESM-GND Architecture Diagram

3. Results and Discussion

3.1 Effect Verification of KCCA Cross-Axis Fusion Features

To evaluate the improvement of cross-axis fusion features on the performance of nest-holding behavior recognition, this paper designs two sets of comparative experiments:

(1) Using TSFRESH features: Extract time-domain, frequency-domain, and statistical features from triaxial acceleration, then directly input them into the FESM-GND model after significance testing.

(2) TSFRESH + KCCA fusion features: Building upon the filtered TSFRESH features, KCCA is employed to extract nonlinear coupling features across three axes, which are then combined with the original features for model training.

Table 1 demonstrates that the KCCA fusion features outperform TSFRESH features across all metrics. Accuracy improves from 86.5% to 93.5%, with precision and F1 score increasing by 6.9% and 5.62% respectively, while recall rate rises by 4.25%. These enhancements indicate KCCA effectively captures multi-axis coordination patterns inherent in nest-building behavior, enabling the model to distinguish between low-amplitude resting behaviors and microperiodic nest-building actions, thereby significantly improving the classifier's discriminative power and robustness.

Table 1. The Comparison Results between TSFRESH Features and Cross-axis Fusion

Model	Input	accuracy （%）	precision （%）	recall（%）	F1 （%）
FESM-GND	TSFRESH	86.5	85.2	87.3	86.2
	Fusion feature	93.50	92.10	91.55	91.82

3.2 Nesting Detection Results and Performance Analysis

As shown in Table 2, the model achieves an accuracy rate of 93.5%, precision of 92.1%, recall of 94.8%, and F1 score of 93.4%, significantly outperforming traditional methods. The confusion matrix reveals a 95.04% accuracy rate for nest-building recognition (1226/1290) and 91.90% accuracy for non-nesting behavior (1328/1445). These results demonstrate that the FESM-GND model, developed with optimal feature configuration, delivers exceptional performance in nest-building detection. The proposed framework combining "interpretable feature engineering, cross-axis fusion, and stacked models" effectively captures the occurrence, duration, and termination of nest-building behaviors.

Table 2. Confusion Matrix of Brooding Detection

	predicted number of brooding individuals	predicted number of non-brooding individuals
actual number of brooding individuals (1290)	1226	64
actual number of non-brooding individuals (1445)	117	1328

4. Conclusion

By integrating wearable activity monitoring sensors with RFID identity recognition technology, this study achieved intelligent monitoring of individual nest-building behavior in group-raised breeding geese, yielding the following key findings: The developed IFESM-GND interpretable feature-engineered stacked model demonstrated 93.5% detection accuracy, representing a 15%-21% improvement over traditional methods and significantly enhancing the efficiency of detecting nest-building behavior's impact on egg production. With strong interpretability, the model supports precision management strategies to help reduce egg production losses caused by nest-building behavior.

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