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RESEARCH ARTICLE

A Recognition Method for Aggressive Chicken Behavior Based on Machine Learning

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ABSTRACT Aggressive behavior is an important indicator of chicken welfare assessment. At present, the aggressive behavior of chickens typically requires human observation for welfare assessment, and the assessment results are influenced by the subjective judgment of humans. This paper proposes an aggressive chicken behavior identification method based on a hybrid strategy improved Sparrow Search Algorithm combined with Support Vector Machine (ISSA-SVM). Nine-axis inertial sensors were used to collect the behavioral data of chickens. A total of 231-dimensional feature data in the time and frequency domains of the behavioral data were extracted through a 1 s sliding window. To reduce feature redundancy, the initial population is initialized using circle chaotic mapping instead of random initialization of the original sparrow algorithm to increase the uniformity of the initial population distribution in the feature space; adaptive weights are introduced to increase the search range of the early iteration, and the global optimal solution of the previous generation is introduced to improve the global search capability of the algorithm; the optimal solution is perturbed using the dimension-by-dimension mutation strategy of adaptive t-distribution to increase the diversity of the feature distribution. ISSA-SVM reduced the feature dimensionality from 231 to 17, indicating a reduction of 92.6%. The recognition overall accuracy of ISSA-SVM for aggressive chicken behavior was 94.27%, which improved by 1.33% compared to SVM. The results of the experiment show that of all the aggressive chicken behaviors during the 5-day experiment, fighting behavior occurred most frequently from 11:00 to 13:00 and from 17:00 to 18:00. This study provides a method for the automatic identification of aggressive chicken behavior and can serve as an informational tool for poultry welfare assessment.

INDEX TERMS Aggressive behavior, chicken, ISSA-SVM, feature selection, inertial sensors.

I. INTRODUCTION

Animal behavior directly reflects the physiological health of animals and is an important assessment indicator for assessing animal welfare [1], [2]. Animal welfarist Fraser emphasized the need for animals to behave naturally [3]. Using behavior to assess chicken welfare avoids destructive damage caused by studies such as biological sampling and reduces chicken suffering [4]. The evaluation of social behavior in the welfare assessment of chickens included aggressive behavior, plumage damage, and crown pecking wounds [5]. Traditional manual observation of aggressive behavior in chickens has high labor costs and is easily affected by subjective human judgment, making accurate observation difficult to achieve. In contrast, modern technology can record the movement details [6]. The aggressive behavior of chickens is complex [7], [8], [9], [10], [11]. Automatic monitoring of aggression chicken behavior and

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objective analysis are conducive to the assessment of chicken welfare [12], [13].

Inertial sensors are widely used in the field of behavior recognition of livestock and poultry [14], [15], [16], [17], [18]. The feasibility of using wearable sensors to identify chicken behavior has been demonstrated by wearing the sensors on the back and neck of chickens [19], [20]. Machine learning is an effective method for analyzing the animal behavior information [21], [22]. Many machine learning algorithms have been used to analyze the behavior data from wearable sensors [23]. For example, Banerjee et al. [24] used neural networks to detect the daily behaviors of laying hens, Yang et al. [25] used SVM and KNN to classify the behaviors of broiler chickens such as feeding, drinking, and walking, and Li et al. [26], [27] used machine learning algorithms such as K-means and XG-Boost to implement multi-behavioral recognition and analysis of caged breeding roosters. Machine learning and accelerometers have also been used to analyze the activity level of chickens, such as the Random Forest has been used to identify the low, medium and high intensity activity of laying hens at different weeks of age [28], and the Bagged Tree has been used to classify the static, semi-dynamic and highly dynamic behavior of laying hens [29]. In monitoring chicken health and welfare, Mei et al. [30] used sensors to monitor broilers and used machine learning algorithms such as KNN and Decision Tree to identify aflatoxin-poisoned broilers based on behavioral differences, and He et al. [31] wore sensors on the broilers' legs to detect the lameness using the Logistic Regression. These studies suggest that the use of inertial sensors to monitor chicken behavior can help to automate the quantification of specific behaviors.

In summary, it is feasible to use wearable sensors and machine learning to analyze chicken behavior. However, while using wearable sensors to obtain chicken behavior information, there is no consistent way to deal with the feature redundancy problem of the data. Especially for complex chicken aggressive behavior, redundant features will directly affect the recognition results. Therefore, the objective of this study is to analyze aggressive chicken behavior using nine-axis inertial sensors combined with machine learning methods, and to construct an aggressive chicken behavior recognition model based on a hybrid strategy improved sparrow search algorithm combined with support vector machine (ISSA-SVM) to identify three aggressive chicken behaviors: threatening, fighting, and evading. This research provides an informative means for poultry production management and welfare assessment.

II. MATERIALS AND METHODS

A. DATA ACQUISITION

The experiment was conducted at the experimental base of Hebei Agricultural University in Baoding, Hebei Province. This research on live animals met the guidelines approved by the Institutional Animal Care and Use Committee (IACUC). The test chickens were five 40-week-old *Taihang* chickens. The chickens were numbered 1-5 and marked with five different colors of special spray paint for animal marking. During the data collection period, five chickens were housed in a cage with a size of 1 m × 0.6 m × 0.7 m. Behavioral data were collected for a total of 5 days, from November 11 to 15, 2022, during the time period 09:00–18:00. The daily feeding times were 9:00 a.m., 12:00 noon, and 6:00 p.m. Nipple drinkers were used to provide fresh water, and chickens were not limited in feeding and drinking during the experiment.

In this study, the Wit-motion Bluetooth 5.0 nine-axis inertial sensors model BWT901BLECL5.0 (51 mm× 36 mm×15 mm, 20 g, Wit Intelligent Technology Co., China) were used to monitor the behaviors of chickens. Each sensor has a unique number, which corresponds to the number of test chickens. The sampling frequency is 20 Hz. Each sensor was mounted on the chicken's neck by a self-adhesive Velcro strap. The sensor is worn with a 1cm space between the chicken's neck and the strap to enable freely movement and ensure that the strap does not rotate. The sensor was located directly in front of the chicken's neck after mounted, and its X, Y, and Z axes pointed to the front and rear, up and down, and left and right directions of the chicken (Fig.1). The sensors were worn for three days before the beginning of the experiment to allow the chickens to adapt to them.

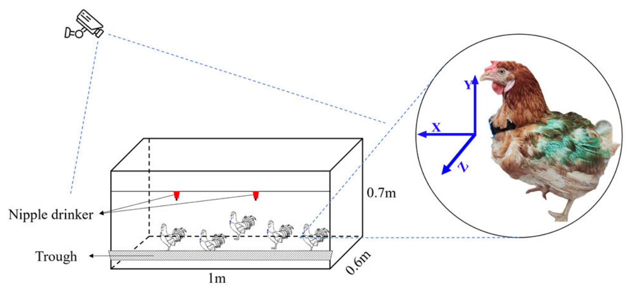


FIGURE 1. **The experimental device and the chicken wearing the sensor.**

Three types of data can be acquired simultaneously: triaxial acceleration (A_x, A_y, A_z), triaxial angular velocity (G_x, G_y, G_z), and triaxial Angle (M_x, M_y, M_z). The collected behavior data were transmitted wirelessly to the multilink adapter through Bluetooth, and then sent to the host computer through the serial port and exported as an excel file with timestamps. A Hikvision network HD camera was installed above the side of the cage to monitor the chicken's activities throughout the day. The recorded video data were time-synchronized with the sensors and used to manually mark the chickens' behavior classification labels.

B. BEHAVIOR DESCRIPTION

Based on the observation of chicken behavior and with reference to the description of aggressive chicken behavior by Estevez et al. [32], the description of chicken behavior in this paper is shown in Table 1. The collected behavioral data were checked and marked against the video, and the threatening, fighting, and evading behaviors of chickens were labeled according to Table 1. In addition, considering the diversity of chicken behaviors in practice, the three daily behaviors of chickens—feeding, drinking, and walking—were labeled as "others" in our study. The definition of "others" behavior is referenced from Yang et al. [27].

C. DATASET CONSTRUCTION

Based on the triaxial acceleration (A_x, A_y, A_z), triaxial angular velocity (G_x, G_y, G_z) and triaxial Angle (M_x, M_y, M_z) of chicken behavior data, the composite acceleration (A_c) and composite angular velocity (G_c) were added, which together constitute the chicken behavior sample dataset. Where the formulas for composite acceleration (A_c) and composite angular velocity (G_c) are as follows:

$$A_c = \sqrt{A_x^2 + A_y^2 + A_z^2} \quad (1)$$

$$G_c = \sqrt{G_x^2 + G_y^2 + G_z^2} \quad (2)$$

Sensor data for aggressive behaviors (threatening, fighting, evading) and other daily behaviors (feeding, drinking, walking) were manually labeled by a trained person by observing chicken behaviors in recorded videos. A total of 30,802 samples were labeled. Among them, there were 15,986 aggressive behavior samples, including 5,720 threatening samples, 6,250 fighting samples, and 4,016 evading samples; and 14,816 others behavior samples, including 5,068 feeding samples, 5,172 drinking samples, and 4,576 walking samples. In the process of data labeling, the erroneous data collected in that state were rejected if the sensors were observed to be dislodged from the video.

TABLE 1. Description of chicken behavior.

Behavior		Description
Aggressive behavior	Threatening	One chicken stood in front of another individual with its neck feathers up and a rigid stance.
	Fighting	One chicken flies, jumps or runs toward another chicken and quickly pecks the body or feathers, or two chickens peck each other's body or feathers violently.
	Evading	A chicken ducking away from another chicken when threatened or attacked by it.
Others		A chicken pecking at a trough and swallowing is considered foraging; a chicken pecking at a nipple drinker was considered drinking; and a chicken moving forward four or more steps was considered walking.

1) MEDIAN FILTERING

Taking the triaxial acceleration as an example, the waveforms of each behavior are shown in Fig.2. We took 4 seconds of acceleration data for each behavior to ensure that it contained 1-2 complete movements of the chicken. Threatening behavior (Fig.2(a)) fluctuated more gently, fighting behavior (Fig.2(c)) and evading behavior (Fig.2(e)) fluctuated more, but evading behavior shows a greater change in acceleration on the x-axis compared to fighting behavior.

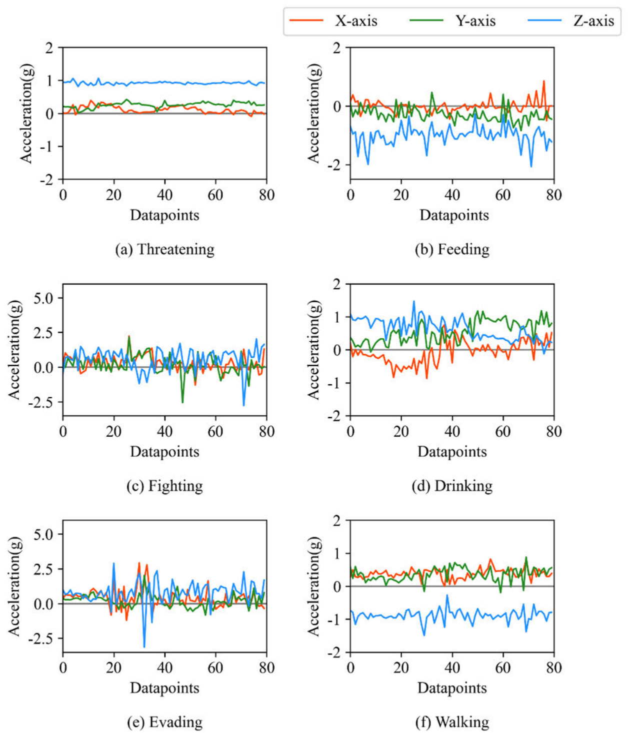


FIGURE 2. Examples of triaxial acceleration curves for threatening (a), fighting (c), evading (e), feeding (b), drinking (d), and walking (f).

The raw data must be filtered to remove noise from the original signal. In this study, the data are processed using a median filter with a window size of three to avoid signal distortion caused by using a window that is too large. The mathematical model is as follows:

$$x_i = Med(x_{i-1}, x_i, x_{i+1}) \quad (3)$$

where x_i ($i = 1, 2, \ldots, n$) is the sensor data sample and Med is the median taking function.

The filtered waveform is shown in Fig.3. The filtered data is relatively smooth and reduces the interference of high-frequency noise.

2) FEATURE EXTRACTION

In this paper, feature extraction was performed with Python 3.8. The time and frequency domain features were extracted from the filtered data using a sliding window of length 1 s with 50% overlap. In this paper, 21 features in the time and frequency domains were extracted from the triaxial acceleration, triaxial angular velocity, triaxial angle, and composite acceleration and composite angular velocity data to obtain 231 (21 × 11) dimensional feature data. Among them, the time domain features included the average, variance, standard deviation, mode, maximum, minimum,

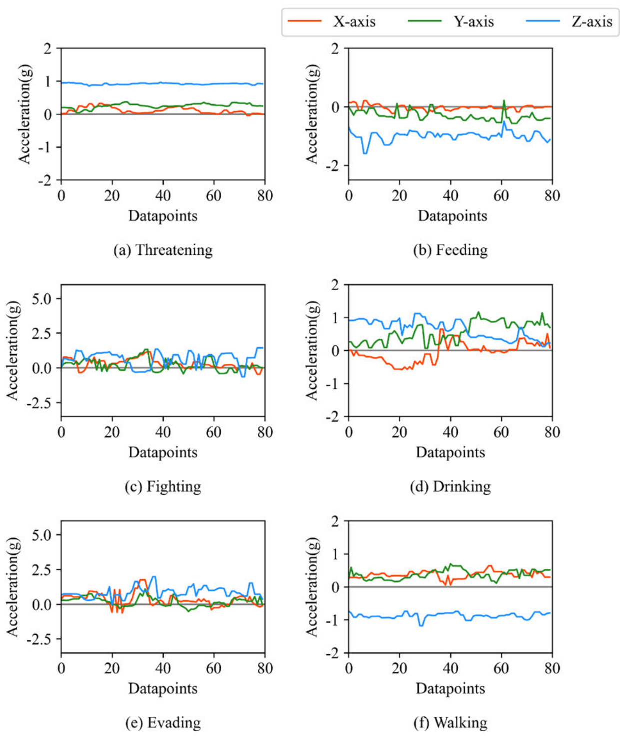


FIGURE 3. Examples of filtered triaxial acceleration profiles for threatening (a), fighting (c), evading (e), feeding (b), drinking (d) and walking (f).

range, number of crossing zero points, IQR, and energy (sum of absolute values of data). The frequency domain features included the DC component, the mean, variance, standard deviation, skewness, and kurtosis of the shape, and the mean, variance, standard deviation, skewness, and kurtosis of the amplitude. The total number of feature set samples was 3081, including 344 threatening behavior feature samples, 625 fighting behavior feature samples, 402 evading behavior feature samples, and 1482 others behavior feature samples. The feature set data were normalized according to (4) to reduce the effect of data size differences.

$$x' = \frac{x - \mu}{\sigma} \tag{4}$$

where x' is the standardized data value, x is the original data value, μ is the mean of the data, and σ is the standard deviation of the data.

In this paper, the training set and test set were divided according to 6:4. The dataset categories were imbalanced due to the fact that more daily behaviors and fewer aggressive behaviors were observed in chickens. Therefore, SMOTE (Synthetic Minority Oversampling Technique) sampling [33] was used to balance the number of the training set samples by increasing the number of samples in minority classes to balance training set data. To ensure model accuracy, model performance was still evaluated using the imbalanced original test set [34].

TABLE 2. Number of samples of threatening (t), fighting (f), evading (e), and others (o) behaviors in the training set and test set.

	Behavior				
	T	F	E	O	Total
Training set					
before SMOTE	344	376	241	889	1848
after SMOTE	620	620	620	889	2749
Test set	228	249	161	593	1231

Table 2 shows the size of the training and test sets before and after SMOTE sampling. To prevent model overfitting, we expanded the sample size of threatening, fighting and evading behavior to about 70% of others behavior. A total of 2749 samples were included in the training set after SMOTE sampling, with 620 samples for each of the threatening, fighting, and evading, and 889 samples for the others behavior.

D. CLASSIFICATION MODEL SELECTION

In order to select the classifier with the best recognition performance, four popular classification algorithms, Support Vector Machine (SVM), Logistic Regression (LR), K Nearest Neighbors (KNN), and Decision Tree (DT), were analyzed in this study. All models were trained in python 3.8 on Windows 11 system. SVM performs multi-classification of input data by mapping the data to a high dimensional space through kernel function. In this paper, we used the one-vs-rest method to achieve the classification of four behaviors by constructing four binary SVM classifiers. LR is a probability-based classification algorithm that performs multi-classification by training multiple binary classifiers. The probability that a sample is or is not each classifier is calculated and the one with the highest probability is selected as the final class. KNN classifies the input sample based on the distance between the input sample and the K nearest training samples to it. In this paper, the value of K was taken as 5. DT is a classical tree classifier that generates subtrees recursively until all leaf nodes belong to the same category.

The recognition results of the four algorithms for threatening, fighting, evading and other behaviors of chickens are shown in Fig.4. The overall recognition accuracies of SVM, LR, KNN, and DT are 92.94%, 89.6%, 88.45%, and 87.31%, respectively. SVM has the highest overall recognition accuracy. Therefore, the SVM classifier is used in this study to achieve better recognition results.

E. CONSTRUCTION OF ISSA-SVM MODEL

The recognition process of the aggressive behavior of chickens in this paper is illustrated in Fig.5. The redundant feature data are reduced using the ISSA-SVM feature selection method proposed in this paper. The optimal feature subset is selected and input to the classifier for training to obtain the final ISSA-SVM aggressive chicken behavior recognition model.

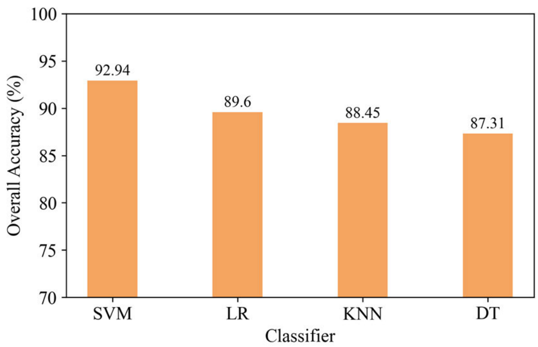


FIGURE 4. Comparison of overall recognition accuracy of four classification algorithms.

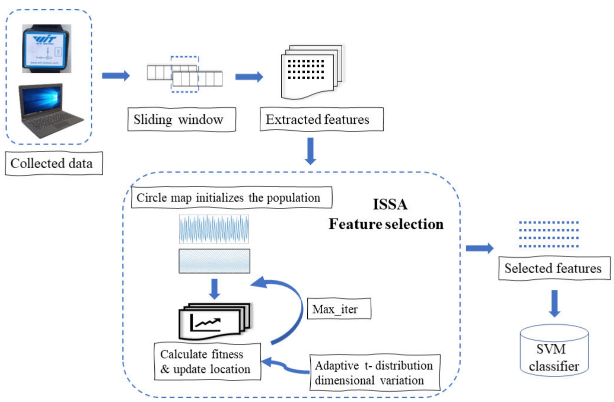


FIGURE 5. ISSA-SVM behavior recognition process.

1) ISSA ALGORITHM

We need to perform feature selection on the extracted 231-dimensional feature data to select the most representative and optimal combination of features to reduce redundant features and improve the performance of the model [35]. The Sparrow Search Algorithm (SSA) has been well recognized by many researchers because of its fast convergence and stability [36], [37]. However, it also has the disadvantages of uneven initial population distribution, insufficient late search capability, and it easily falls into a local optimum [38]. To address these problems, this paper proposes a hybrid policy-improved SSA (ISSA), and the algorithm flow is shown in Fig.6. The parameters of ISSA in this paper are shown in Table 3. The basic parameters of the sparrow algorithm were set with reference to the literature [36]. In addition, considering the high feature dimensions in this paper, the population size of the algorithm was set to 50 and the number of iterations was set to 100.

TABLE 3. Parameter settings of issa.

Parameters	Value
Max iterations (M)	100
Sparrow populations (n)	50
Producers (PD)	0.7 n
Scroungers (SD)	0.2 n
Safety threshold (ST)	0.6

a: CIRCLE CHAOTIC MAPPING INITIALIZES THE POPULATION

Using chaotic mapping instead of random initialization of populations can result in a more uniform distribution of the initial populations [39], [40], [41]. Circle chaotic mapping has characteristics such as ergodicity and uniformity, and its formula is (5):

$$x_{i+1} = \mathrm{mod}(x_i + 0.2 - (\frac{0.5}{2\pi}) \sin(2\pi \times x_i), 1) \tag{5}$$

where x is the position of individuals in the population, i is the dimension of the search space, and mod is the residual function. As shown in Fig.7, the use of circle mapping instead of random initialization of populations enables a more uniform distribution of populations in the search space.

For the 231-dimensional feature data obtained above, we set the sparrow population size to 50, and each sparrow then represents a different set of feature subsets. Each feature in the 231 dimensions has a certain probability of being selected. Thus, the distribution of the initial population is a 50×231 matrix. Fig.8 shows the number of times each of the 231-dimensional features were selected, and the variance and range were calculated to reflect the uniformity of the distribution of the selected features. As shown in Table 4, the variance and polar deviation of the initialized population of the circle mapping are smaller than those of the random initialized population, which indicates that circle mapping makes the distribution of feature data more uniform.

TABLE 4. Variance and range of the feature frequency distribution with different initialization methods.

Initialization mode	Var(variance)	Range(Xmax-Xmin)
Random initialization	13.316	19
Circle map initialization	9.319	8

b: ISSA UPDATE STRATEGY

After initialization, the fitness values of the individuals in the initial population are calculated and ranked. Some of the sparrows with high fitness values are selected as producers, and the producer update formula in the SSA algorithm is shown in (6):

$$x_{i,j}^{t+1} = \begin{cases} x_{i,j}^{t} \cdot exp\left(\dfrac{-i}{\alpha \cdot iter_{max}}\right) & R_2 < ST \\ x_{i,j}^{t} + Q \cdot L & R_2 \geq ST \end{cases} \tag{6}$$

where t is the current number of iterations, $x_{i,j}$ is the position of the ith sparrow in the jth ($j = 1, 2, \ldots$, d, d is the dimension of the search space) dimension, $\alpha \in (0, 1)$, $iter_{max}$ is the maximum number of iterations, Q is a random number from a normal distribution, L is a $1 \times d$ all-1 matrix, R_2 is the alarm

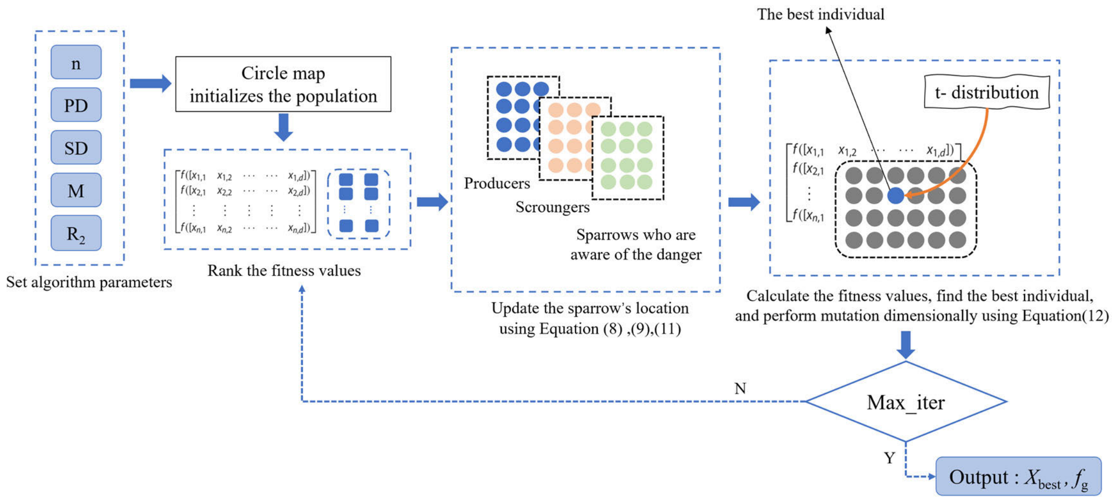
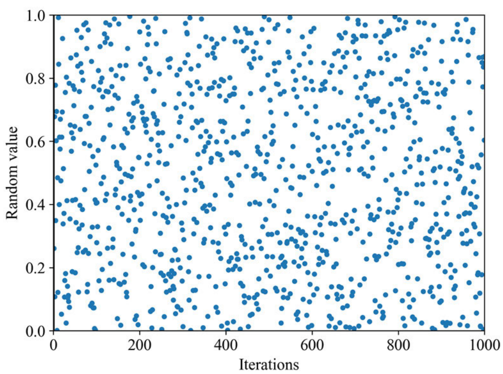
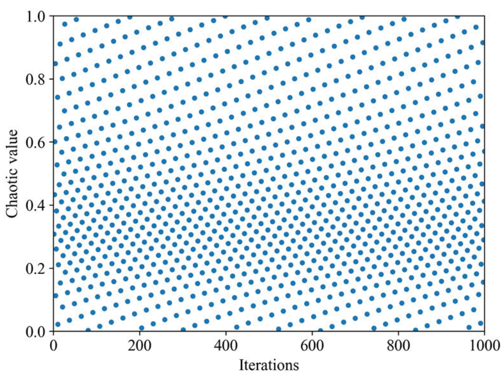


FIGURE 6. Flowchart of ISSA algorithm. Where *n* is the number of sparrow populations, *PD* is the number of producers, *SD* is the number of scroungers, *M* is the maximum number of iterations, and *ST* is the safety threshold.



(a) Random initialized populations.



(b)circle mapped initialized populations.

FIGURE 7. Distribution of (a) random initialized populations and (b)circle mapped initialized populations for 1000 iterations.

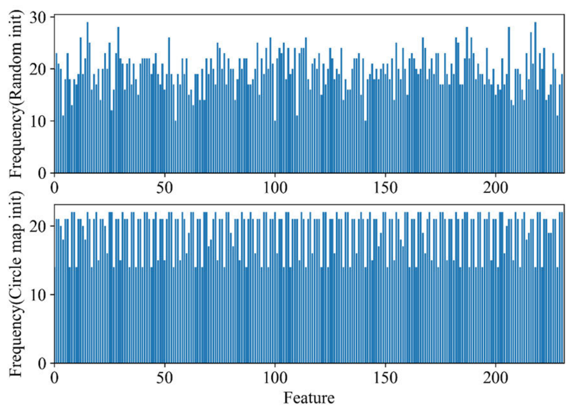


FIGURE 8. Frequency distribution of features under different initialization methods. Where the horizontal coordinate represents 213 features. The vertical represents the number of times the feature occurred.

value, and ST is the safety threshold. As shown in Fig.9(a), the rapid convergence of individuals in the early iterations leads to an insufficient search range and weak global search capability.

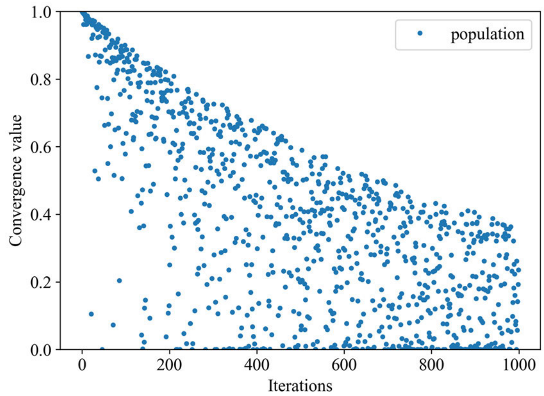
In this paper, we introduce a dynamic weight factor ω ((7)) in the producer's location update to increase the search range in the early iteration (Fig.9(b)). The previous generation of global optimal solutions is also introduced to improve the global search capability of the algorithm [42]. The improved location update strategy of the producer is shown in (8).

$$\omega = \frac{e^{2\left(1-\frac{t}{iter_{max}}\right)} - e^{-2\left(1-\frac{t}{iter_{max}}\right)}}{e^{2\left(1-\frac{t}{iter_{max}}\right)} + e^{-2\left(1-\frac{t}{iter_{max}}\right)}} \tag{7}$$

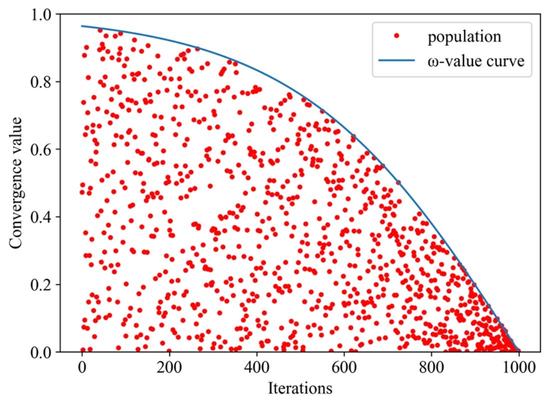
$$x_{i,j}^{t+1} = \begin{cases} x_{i,j}^{t} + \omega\left(f_{i,j}^{t} - x_{i,j}^{t}\right) \cdot rand & R_2 < ST \\ x_{i,j}^{t} + Q & R_2 \geq ST \end{cases} \tag{8}$$

where $f_{i,j}^{t}$ is the global optimal solution of the jth dimension in the previous generation.

As shown in Fig.10, the improved producer has a larger distribution and search range over the feature space, and each dimensional feature is selected more frequently.



(a) SSA-Producers' location update strategy.



(b) ISSA-Producers' location update strategy and ω-value curve.

FIGURE 9. Producers' location update strategy and ω-value curve before and after improvement.

The remaining sparrows, as scroungers, have a location update strategy as in (9):

$$x_{i,j}^{t+1} = \begin{cases} \exp\left(\dfrac{x_{worst}^t - x_{i,j}^t}{i^2}\right) & i > \dfrac{n}{2} \\ x_p^{t+1} + |x_{i,j}^t + x_p^{t+1}| \cdot A^+ \cdot L & i \leq \dfrac{n}{2} \end{cases} \tag{9}$$

where x_{worst}^t is the current global worst position, x_p^{t+1} is the position of the best adapted individual after updating, n is the number of sparrows, and A is a $1 \times d$ matrix of 1 or -1.

Some individuals in the population were randomly selected as sparrows who are aware of danger, and the position was updated according to (10):

$$x_{i,j}^{t+1} = \begin{cases} x_{best}^t + \beta \cdot |x_{i,j}^t - x_{best}^t| & f_i > f_g \\ x_{best}^t + K \cdot \left(\dfrac{\left|x_{i,j}^t - x_{worst}^t\right|}{(f_i - f_w) + \varepsilon}\right) & f_i = f_g \end{cases} \tag{10}$$

where x_{best}^t is the best position of the current global and β is a normal distribution with a mean of 0 and a variance of 1, which is used to control the step size. f_g and f_w are the current global best and worst fitness values, respectively, and ε is the minimum constant. It can be observed that if the current sparrow is not in the optimal position, it will escape to the vicinity of the current optimal position. If the sparrow is in an optimal position, it will escape to a position near itself, but that position is determined by the ratio of the difference between its own position and the worst position to the difference between the food at its own position and at the worst position. This update approach tends to lead the algorithm into a local optimum.

In this paper, we improve the position updating strategy of sparrows who are aware of danger. If the sparrow is not in the optimal position, it will escape to the position between the current position and the optimal position; otherwise, it will escape to the position between the optimal position and the worst position to prevent the algorithm from falling into a local optimum. The improved position update strategy of sparrows who are aware of danger is shown in (11):

$$x_{i,j}^{t+1} = \begin{cases} x_{best}^t + \beta\left(x_{i,j}^t - x_{best}^t\right) & f_i \neq f_g \\ x_{best}^t + \beta\left(x_{worst}^t - x_{best}^t\right) & f_i = f_g \end{cases} \tag{11}$$

c: ADAPTIVE T-DISTRIBUTION DIMENSION-BY-DIMENSION MUTATION

Regarding the problem that it is difficult to break out of a local optimum in population search, the method of mutation interference on individuals is usually used to increase the population diversity so that it can break out of the local optimum. The problem of interdimensional interference in high dimensions can be effectively avoided by using the dimension-by-dimension mutation method [43], [44], [45]. Due to the uncertainty of the mutation interference results, only the optimal individual is mutated dimension by dimension, which is conducive to reducing the computational effort and improving the search efficiency [46].

In this paper, the adaptive t-distribution operator is used for dimension-by-dimension mutation of optimal individuals. The t-distribution mutation operator $t\,(iter)$ with degree of freedom parameter t is introduced on the basis of the original position information. The mathematical expression is given in (12):

$$x_{new}^j = x_{best}^j + x_{best}^j \cdot t\,(iter) \tag{12}$$

where x_{new}^j is the position of the optimal individual after the dimension-by-dimension mutation, and *iter* is the number of the current iteration. Since the two boundaries of the t-distribution are the Cauchy distribution $(t\,(n = 1) \rightarrow C\,(0, 1))$ and the Gaussian distribution $(t\,(n \rightarrow \infty) \rightarrow N\,(0, 1))$ [47], respectively, the degree of freedom parameter t increases with continuous iterations, and the t-distribution gradually tends to the Gaussian distribution from the Cauchy distribution, which is conducive to improving the global search capability of the algorithm and breaking out of the local optimum. As shown in Fig.11, the optimal individual in the iterative process is selected, and its distribution on the feature space before and after the mutation is visualized. It can be seen that the diversity of the feature distribution increases after the mutation.

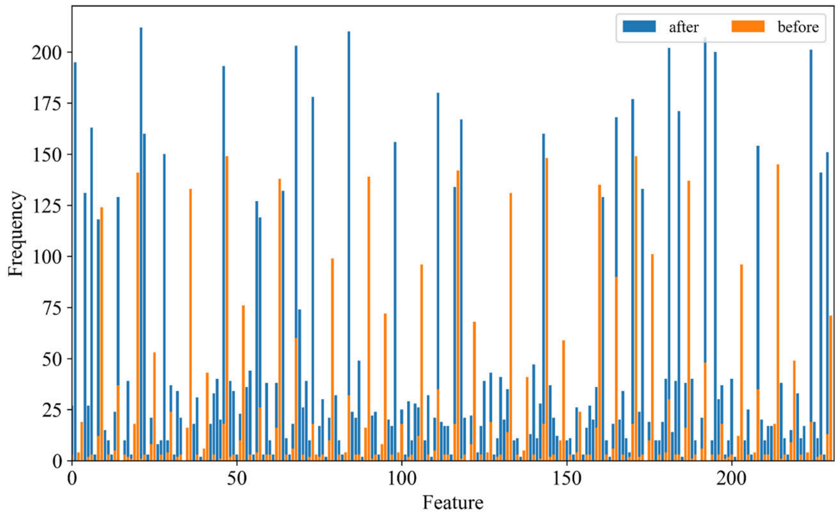
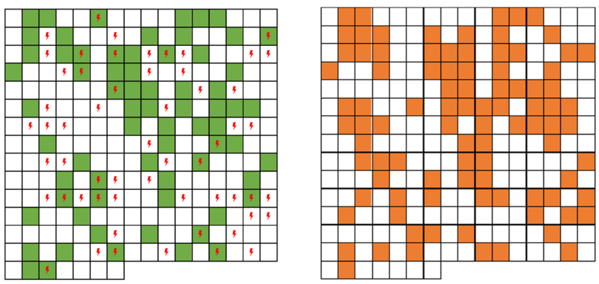


FIGURE 10. Frequency of the 231-dimensional feature distribution in the first 30 iterations. Where the horizontal coordinate represents 213 features. The vertical represents the number of times the feature occurred in the first 30 iterations.



(a) Features distribution before mutation interference.
(b) Features distribution after t-distribution mutation interference.

FIGURE 11. The distribution of optimal individuals in the feature space before and after mutation in the iterative process.

F. MODEL EVALUATION

For the evaluation of feature subsets in the feature selection process, the fitness function in this paper is shown in (13). In this paper, the SVM classification error rate was set as a penalty term and given a certain weight in the fitness function, which can improve the recognition accuracy while reducing the feature dimension.

$$fun = \alpha \cdot error + (1-\alpha) \cdot \frac{num\_sclectfeat}{num\_feat} \tag{13}$$

where α is the weight, which equals 0.9 in this paper; error is the classification error rate of SVM for the selected feature subset; *num_sclectfeat* is the number of selected features; and *num_feat* is the number of all features.

The model performance was evaluated by confusion matrix. The accuracy, precision, recall and F1-score of the model were calculated according to (14)-(17):

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{14}$$

$$Precision = \frac{TP}{TP+FP} \tag{15}$$

$$Recall = \frac{TP}{TP+FN} \tag{16}$$

$$F1-score = 2 \times \frac{Recall \times Precision}{Recall + Precision} \tag{17}$$

where TF is the number of positive samples predicted to be positive, TN is the number of positive samples predicted to be negative, FP is the number of negative samples predicted to be negative, and FN is the number of negative samples predicted to be negative.

III. RESULTS

A. COMPARATIVE ANALYSIS OF FIVE FEATURE SELECTION METHODS

The use of swarm intelligence algorithms is often required to maximize the performance of the classifier while minimizing the feature subset in classification. In this study, the feature selection ability and model recognition accuracy of five swarm intelligence algorithms, ISSA, SSA, PSO (Particle Swarm Algorithm), GA (Genetic Algorithm), and FPA

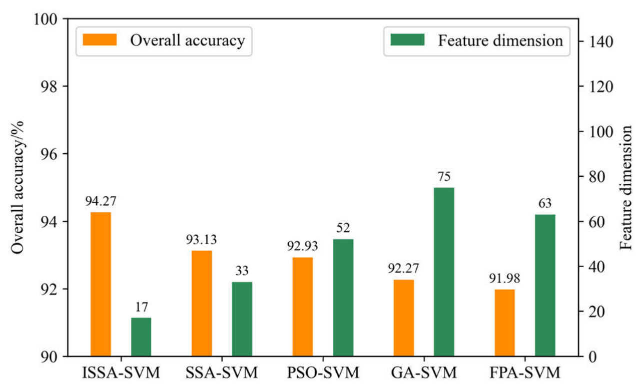


FIGURE 12. Performance comparison of five feature selection methods.

(Flower Pollination Algorithm), were compared based on SVM classifier. The populations were set to 50 and the number of iterations was set to 100 for each of the five algorithms. The results are shown in Fig.12. The feature subsets selected by PSO, GA and FPA are all above 50 dimensions, and the recognition accuracies are all below 93%. This may be due to the insufficient global search capability of the algorithms resulting in them falling into local optimization. SSA reduces the feature dimension to 33 with an accuracy of 93.13%, but its ability to search in feature space could be improved. The ISSA proposed in this paper has the highest accuracy while having the least number of features. The ISSA reduces the original features from 231 to 17 dimensions, which reduces 92.6% of redundant features, while the recognition accuracy is 94.27%.

B. ANALYSIS OF FEATURE SELECTION RESULTS BASED ON ISSA-SVM

The optimal combination of features selected by ISSA-SVM is shown in Table 5.

TABLE 5. Optimal subset of features selected using ISSA-SVM.

Feature dimension	Optimal feature combination		
	Time Domain		Frequency Domain
17	*time_ave_A_y*[a]	*time_min_G_z*	*fft_dc_G_a*
	time_ave_G_a	*time_range_A_x*	*fft_shape_skew_G_x*
	time_ave_M_z	*time_range_G_x*	*fft_mean_M_z*
	time_std_A_x	*time_energy_A_x*	
	time_std_M_x	*time_energy_A_y*	
	time_mode_M_y	*time_energy_M_x*	
	time_max_G_z	*time_energy_M_z*	

[a] *a_b_c*: a indicates whether *a* feature belongs to the time domain (*time*) or frequency domain (*fft*), *b* indicates the feature type, and *c* indicates the sensor data component.

The most frequent feature in the selected subset of features is the energy from the time domain, which is due to the fact that energy provides a comprehensive assessment of the overall performance of behavior data within a time window. The selected features are ranked by importance, as shown in Fig.13. The top three features in terms of importance were selected as *time_energy_M_x*, *fft_dc_G_a*, and *time_energy_M_z*. The frequency distributions of the above three features for threatening, fighting, evading and others behaviors are shown in Fig.14. For feature *time_energy_M_x*, the data points corresponding to evad-

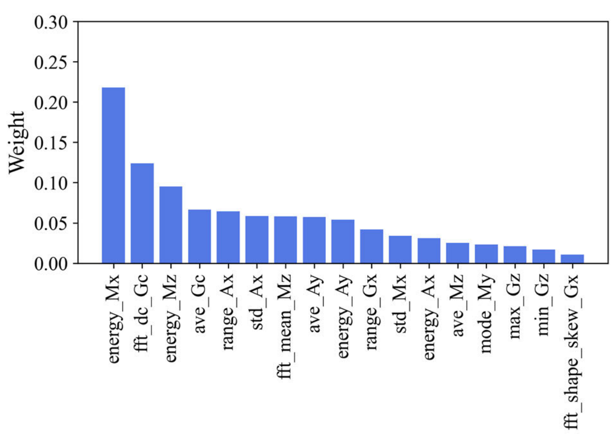
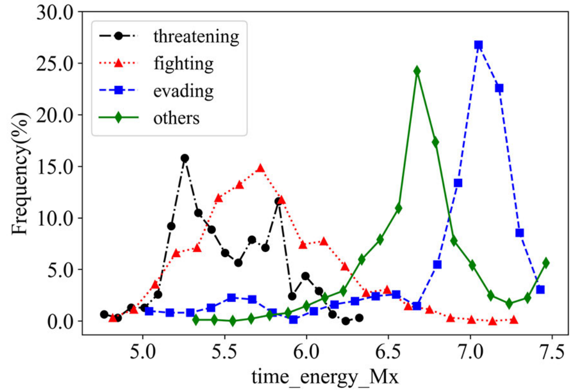
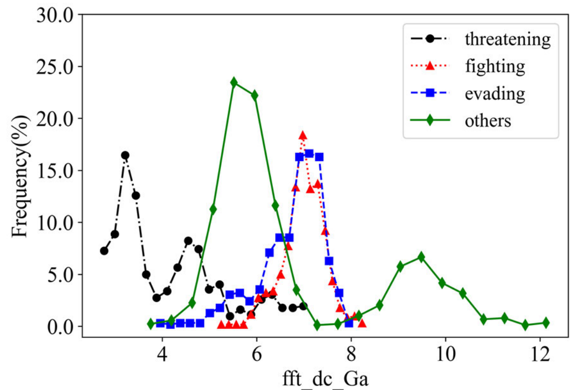


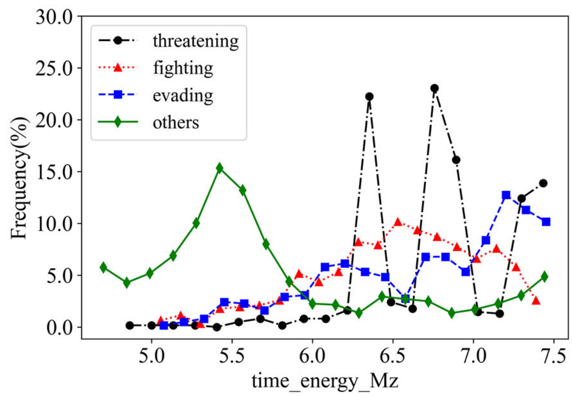
FIGURE 13. Importance ranking of the selected features on the recognition results of ISSA-SVM.



(a) Data distribution of *time_energy_Mx*.



(b) Data distribution of *fft_dc_Ga*.



(c) Data distribution of *time_energy_Mz*.

FIGURE 14. Data distribution of the top three features. All feature data were log-transformed for easy observation. The energy data are represented as Log(100+x), and the frequency domain DC component data are represented as Log(10+x).

ing behavior can be well distinguished, whereas there are overlapping parts of the frequency distribution of threatening and fighting behaviors (Fig.14(a)). The frequency distribution of feature $fft\_dc\_G_a$ shows that the data points for fighting and evading behaviors overlap considerably, but the data points for threatening behavior are separable (Fig.14(b)). The combination of feature $time\_energy\_M_x$ and the feature $fft\_dc\_G_a$ can distinguish the fighting behavior from the other three. The frequency distribution of feature $time\_energy\_M_z$ shows that others behavior can be well distinguished, but there are still some overlaps with the other three behaviors (Fig.14(c)). In summary, from the frequency distributions, the selected features have strong separability for different behaviors. However, a single feature cannot classify the four behaviors, and it needs to be combined with other features to achieve accurate behavior recognition.

C. ISSA-SVM MODEL PERFORMANCE

The performance of the ISSA-SVM and SVM models is shown in Table 6. ANOVA test is used to record the differences between ISSA-SVM and SVM, and the p-value is 0.025 ($p < 0.05$), which indicates that ISSA-SVM is significantly different from SVM. The recognition accuracy of the SVM model without feature selection is 92.94%. The ISSA-SVM model reduces the feature dimensions by 92.6% while the overall recognition accuracy is 94.27%, which is an improvement of 1.33% compared to SVM. As shown in Fig.15, the recognition precision of threatening, fighting, and others behaviors is improved by 1.28%, 1.85%, and 1.42%, respectively, whereas the recognition precision of evading behavior is improved by only 0.64%. The recall of evading behavior is increased by 5.59%, which indicates an increase in the number of times evading behavior is correctly identified. The F1-score of threatening, fighting, and evading behaviors is increased by 1.08%, 1.34%, and 3.31%, respectively, whereas there is no significant increase in the F1-scores of others behavior. The results demonstrate that ISSA-SVM reduces a large number of indistinguishable features in the original feature set, and the selected features can distinguish easily confused aggressive behaviors more efficiently.

TABLE 6. Performance and results comparison of ISSA-SVM and SVM models.

Model	Behavior	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)	Feature dimension	p-value
ISSA-SVM	Threatening	94.35	95.18	94.48	94.27	17	0.025
	Fighting	90.87	91.97	92.15			
	Evading	89.61	85.71	87.62			
	Others	98.06	98.54	98.30			
SVM	Threatening	93.07	94.30	93.68	92.94	231	
	Fighting	89.02	91.16	90.08			
	Evading	88.97	80.12	84.31			
	Others	96.64	98.29	97.46			

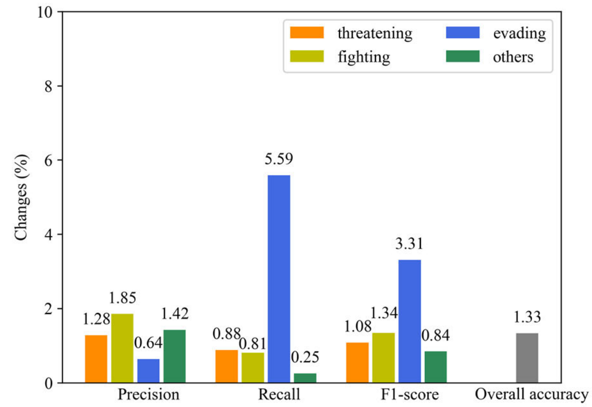


FIGURE 15. Changes in classification performance using ISSA-SVM compared to SVM.

D. CONFUSION MATRIX

The confusion matrix of ISSA-SVM recognition results is shown in Fig.16. From the confusion matrix, the sensitivity of ISSA-SVM for chicken aggressive behavior recognition is calculated to be 93.14%. Aggressive behaviors of chickens can be well distinguished from the other daily behaviors. However, the identification of aggressive behaviors is prone to confusion.

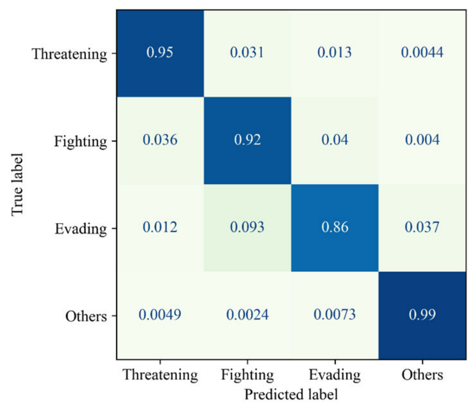


FIGURE 16. The confusion matrix of ISSA-SVM recognition results.

3.1% of fighting behavior and 1.3% of evading behavior were mistaken for threatening behavior. 3.6% of threatening behavior and 4% of evading behavior were mistaken for fighting behavior. And 1.2% of threatening behavior and 9.3% of fighting behavior were mistaken for evading behavior. The confusion is due to the fact that when chickens threaten each other by reaching their heads forward or upward, a significant movement of the neck will cause large fluctuations in the sensor signal, which may be mistaken for fighting behavior. When a chicken is attacked by another and

TABLE 7. The proportions of threatening, fighting, and evading behaviors to the total aggressive behaviors in each hour.

Behavior	9:00-10:00	10:01-11:00	11:01-12:00	12:01-13:00	13:01-14:00	14:01-15:00	15:01-16:00	16:01-17:00	17:01-18:00	Total
Threatening	(21)[a] 7.4%[b]	(26) 9.1%	(62) 21.5%	(23) 7.9%	(85) 29.6%	(16) 5.4%	(20) 7%	(13) 4.4%	(22) 7.7%	(286) 35.7%
Fighting	(7) 2.2%	(23) 7.2%	(59) 18.7%	(54) 17.3%	(38) 12%	(23) 7.3%	(43) 13.6%	(22) 7%	(46) 14.7%	(313) 39.2%
Evading	(25) 12.2%	(27) 13.5%	(17) 8.2%	(10) 5%	(56) 27.9%	(32) 15.7%	(9) 4.5%	(12) 5.7%	(15) 7.2%	(201) 25.1%
Total	(53)[c] 6.6%[d]	(76) 9.4%	(137) 17.1%	(87) 10.8%	(178) 22.3%	(70) 8.8%	(72) 8.9%	(46) 5.8%	(83) 10.3%	(799) 100%

[a] Number of occurrences of threatening behavior occurred in that hour.
[b] Ratio of the number of threatening behavior occurrences in that hour to the total number of threatening behavior occurrences.
[c] Number of occurrences of threatening, fighting, and evading behaviors occurred in that hour.
[d] Ratio of the number of threatening, fighting, and evading behaviors occurrences in that hour to the total number of behaviors.

doesn't initiate a counterattack, it will choose to lower its head and run (or walk) away quickly to evade the attack. These movements are fast and variable, and have a strong resemblance to fighting behavior, which leads to misclassification. In addition, the aggressive behaviors of chickens are affected by various factors, such as individual differences and the environment, and sometimes occurs consecutively within a short period of time, resulting in more difficult identification.

E. ANALYSIS OF AGGRESSIVE CHICKEN BEHAVIOR

Our experiment collected behavior data for 5 days from November 11 to 15. A total of 799 aggressive behaviors of chickens were monitored during the 5-day period, including 285 threatening behaviors, 313 fighting behaviors, and 201 avoidance behaviors. The proportions of threatening, fighting, and evading behaviors to the total threatening, fighting, and evading behaviors during each of the nine hours of data collection are shown in Table 7. From the results, the percentage of fighting behaviors were 39.2% of all 799 aggressive behaviors. Among 313 fighting behaviors, 18.7% happened from 11:00 to 12:00, 17.3% from 12:00 to 13:00, and 14.6% from 17:00 to 18:00. These periods are around feeding time, when more fighting behavior occurs may indicate that feeding problems are an important factor for chicken fighting behavior. Too much fighting behavior may cause physical injuries or even death of chickens. Therefore, the results can provide data support for the development of chicken welfare assessment methods and provide a reference for managers to scientifically manage poultry houses.

IV. DISCUSSION

Although aggressive behavior is a relatively small part of a chicken's daily behavior, it's of great value in chicken welfare assessment [48]. Although previous studies have developed methods for chicken welfare assessment [49], some indicators still rely on subjective human judgment, and no clear quantitative criteria are given [5]. Using sensors to collect samples of chicken behavior can provide data to support the development of efficient welfare assessment methods. The results of the experiments in this paper showed that the highest occurrence of fighting behavior in chickens occurred around midday feeding time, this result validates the previous findings of Anderson et al. [50] that 67% of the occurrence of aggressive behavior in chickens was related to feeding problems.

However, there are still some limitations in this study. The sensor used in this study weighed 20 g, although it had less mass than the 36 g sensor used in the previous study by Stadig et al. [51], the chicken still needed some time to get used to wearing the sensor. Battery life of the sensor used in this study was around 20 hours, which needed to be replaced with a new sensor daily. Therefore, it is necessary to develop wearable sensors that are more portable and have better endurance in future research. In addition, the screening and labeling process of the sensor behavioral data was done manually in the early stages, and this method has not been well addressed in the actual commercial environment. Therefore, there is a need to develop more technological tools to be employed in practical farm applications.

For data processing of wearable sensors, deep learning as a branch of machine learning is able to avoid manually calculating features [52]. However, the aggressive behavior of chickens is small-targeted and multi-scale. The feature data extracted by deep learning is poorly interpretable, which is not conducive to practical production deployment. And it is difficult to optimize the model at a later stage with poor generalization performance. Traditional machine learning models are simple and efficient, and its generalization ability is stronger. The method proposed in this paper avoids the problem of fewer features computed in the traditional behavior recognition process while having high recognition accuracy. Feature selection can better express the intrinsic characteristics and patterns of the data. In addition, traditional machine learning models are more interpretable [53], which facilitates subsequent model optimization. Therefore, it is more favorable for the application of chicken welfare assessment.

Compared with existing feature reduction methods such as PCA [54] and RPCA [55], we use swarm intelligence algorithm for feature selection to reduce the feature dimension, and the proposed ISSA-SVM takes into account feature dimension and recognition accuracy. Swarm intelligence algorithms are data-driven based. The adaptation function can be designed based on specific performance metrics such as accuracy, and by evaluating the feature subset performance to select the best subset. Swarm intelligence algorithms have global search capability which can find the optimal solution in the entire search space. In comparison, methods such as PCA and RPCA may not be guaranteed to find the global optimal solution.

V. CONCLUSION

In this study, we used nine-axis inertial sensors and machine learning methods to build the ISSA-SVM chicken aggressive behavior recognition model, which can accurately identify the three aggressive behaviors of chickens: threatening, fighting, and evading. The main conclusions are as follows:

(1) Chicken behavior data were collected using nine-axis inertial sensors and processed by median filtering for noise reduction. A total of 231-dimensional feature data in the time and frequency domains were extracted by 1 s sliding window to establish a chicken aggressive behavior feature dataset.

(2) In this paper, we propose a feature selection method for the hybrid strategy-improved sparrow search algorithm (ISSA), which increases the uniformity of the feature distribution in the search space and the search capability at the later stages of iterations. The ISSA-SVM aggressive chicken behavior recognition model constructed in this paper reduces the number of feature dimensions by 92.6%, improves the accuracy by 1.33% to 94.27%, and improves the recall and F1-score of the indistinguishable evading behavior by 5.59% and 3.31%, respectively.

(3) For the feature $time\_energy\_M_x$, threatening behavior shows strong separability; for the feature $fft\_dc\_G_a$, evading behavior shows strong separability; and for the combination of the feature $time\_energy\_M_x$ and the feature $fft\_dc\_G_a$, fighting behavior shows strong separability. According to the distribution of fighting behavior of chickens during the experiment, fighting behavior occurred mostly between 11:00-13:00 and 17:00-18:00.

The method proposed in this paper provides an informative tool for the study of aggressive chicken behavior and provides a reference for the chicken welfare assessment. In addition, this study lays the foundation for further refining studies on chicken aggressive behavior.

APPENDIX
ABBREVIATIONS

See Table 8.

TABLE 8. Abbreviation cross-reference in text.

Abbreviations	Description
SVM	Support Vector Machine
KNN	K-Nearest Neighbor
XGBoost	eXtreme Gradient Boosting
DT	Decision Tree
LR	Logistic Regression
SMOTE	Synthetic Minority Oversampling Technique
SSA	Sparrow Search Algorithm
ISSA	Improved Sparrow Search Algorithm
PSO	Particle Swarm Algorithm
GA	Genetic Algorithm
FPA	Flower Pollination Algorithm
ave	average
std	standard deviation
max/min	maximum/ minimum
dc	DC component in frequency domine
skew	skewness

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