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A smart IoT-based monitoring system in poultry farms using chicken behavioural analysis

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ABSTRACT

Poultry farming is crucial to feeding the world's growing population. Birds' abnormal behaviour can harm the birds, and disease detection relies on poultry behaviour. Integrating Internet of Things (IoT) technology into poultry farming can revolutionize the way to monitor and manage poultry health. Feeding, preening, and dustbathing are poultry's daily routines. In response to the problem of detecting correct poultry behaviour and health status, this paper proposes a smart poultry monitoring system that leverages IoT sensors to detect and monitor chicken behaviour in poultry farms and provides valuable information to industry stakeholders for management decisions and individual poultry health status. The phases of the proposed system are data preprocessing, feature extraction, feature selection, and detection of poultry behaviour via different classification algorithms. An optimized synthetic minority over-sampling technique (SMOTE) via an artificial hummingbird algorithm (AHA) is applied to solve the data imbalance problem. The experimental results show that an optimized SMOTE obtains better accuracy with 97 % than other algorithms. Further, to attain accuracy in predicting poultry behaviours, Random Forest (RF) achieves superiority compared to other machine learning algorithms with an accuracy of 98 %.

1. Introduction

Nowadays, some diseases are particularly important because of the significant economic liabilities that aggravate poultry production. But there is also a fair amount of risk involved in the chicken farming industry [1], as shown by the sheer number of chicken farming companies that have failed because of various difficulties [2]. Precision animal and poultry farming relies on the monitoring of animal data and a reliable decision-making aid. Numerous things, including financial difficulties, illnesses, poor livestock management, and other things, can cause this phenomenon. In the chicken farming industry, problems are often caused by mistakes and a lack of care in how chickens are managed and cared for.

Chickens are an important part of achieving the worldwide need for low-fat, high-protein foods. For centuries, the poultry industry has been trying to meet the growing demand for chicken and eggs. Consumers' worries about the chicken they buy are on the rise, along with the industry's response to rising demand. When it comes to the health and safety of the consumer and the quality of poultry products, animal welfare is of paramount importance. The health of poultry products is always enhanced by good animal welfare

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because it decreases the prevalence of disease in poultry chickens. Chickens are notorious for spreading disease among themselves and across entire farms, which has led to significant economic losses in the poultry sector [3]. Reducing losses and slowing the spread of disease in poultry flocks through early detection of sick birds by labelling or classifying individuals based on their behaviour.

Poultry farming has attracted an increasing number of researchers in recent years [4]. Using the Internet of Things (IoT) and analysis of images, as well as other technologies that assist farmers in poultry health administration and surveillance to track and maintain manufacturing information in real-time, other researchers create online platforms and employ smart sensors [5]. The process of extracting information entails analysing the statistical properties of the raw data before defining an extensive hierarchy of the features extracted for upcoming analyses of novel/unknown instances. But things like the shape and size of the data, the loudness and unstructured data, attribute values loss, imbalanced data, and redundant data tend to make it harder for data mining processes to find patterns that make sense. By leveraging interconnected devices and sensors, IoT enables real-time monitoring of animal behaviors, offering insights into movement, interactions, and health status [6] employed IoT sensors to track pet cat behaviors, revolutionizing our understanding of their habits and ecological dynamics.

Despite the numerous methods available, data can be classified in various ways and there are problems that affect its accuracy and efficiency. One of the most important problems that affect classification is the imbalance of data, which consequently affects the extraction of accurate features. Imbalanced datasets are characterized by a significant disparity in the number of samples among different classes [7]. The performance of machine learning (ML) classifiers suffers as a result of this difficult problem of uneven class distribution. As a result, a vast literature has focused on enhance the performance of machine learning classifiers to handle imbalanced datasets [8]. Other factors besides class imbalance should be considered when classifying imbalanced data, such as sample size and class overlap.

There are multiple approaches for oversampling imbalanced datasets that increase the minority class into the majority class, such as the Synthetic Minority Oversampling Technique (SMOTE) [9]. SMOTE uses interpolation to create additional minority class examples in regions close to the existing ones. In spite of its potential to increase minority class accuracy, this method often introduces noisy instances and overfitting issues because it ignores the distribution of neighbouring samples.

Sampling techniques are required for processing imbalanced datasets. There are three main methods for balancing the distribution of negative and positive classes; they are positive instances, negative instances, and combination sampling between positive and negative instances. Data mining techniques [10] can be applied to the series data that is extracted from these IoT sensors to gain insight into the behaviour of animals.

There is frequently a significant amount of imbalance when a decision-making process is applied to isolate a special circumstance. The issue of imbalance has received more focus in recent years. Many practical contexts feature imbalanced data sets, including identifying dishonest phone users, spotting oil spills in satellite radar images, teaching word pronunciation, categorizing texts, spotting fake phone calls, and carrying out information retrieval and filtering tasks. The classification of imbalanced data has attracted a lot of attention. Already in the review [11], over 500 papers were gathered and explored in terms of applied methods and actual outcomes on data sets. Most publications, highly specialized workshops, and conferences have increased dramatically since then. There is ongoing research into better ways to categorise imbalanced data. There are a few ways to handle imbalanced datasets, including under-sampling the data in the majority class, over-sampling the minority class, or a hybrid of the two.

The main contributions of this paper are summarized as follows:

- Design a smart poultry monitoring system that detects and monitors the behaviours of the chickens in poultry farms.
- Handling an imbalanced dataset using an optimized SMOTE via the artificial humming optimization algorithm
- Prediction of the poultry's behaviours via different machine learning techniques.
- Detection of poultry disease status via the classification of sick and healthy chickens on a poultry farm according to poultry behaviours.
- Selection of the best features from extracted new features using feature selection-based optimization.
- Provides a performance validation comparison between various algorithms.

The paper is organized as follows. Section 2 discusses other studies that are related to this paper. The preliminaries, like the essential concepts for SMOTE and the standard optimization algorithm for the artificial hummingbird, are provided in Section 3. Section 4 describes the details of the proposed poultry system. The measures of performance evaluation are discussed in Section 5. The experiment results are discussed in Section 6. Section 7 discusses the paper's conclusion as well as future work.

2. Literature review

Traditional classification algorithms suppose a balanced training dataset, but they struggle to identify minority classes. Traditional classification algorithms perform poorly on class-imbalanced datasets. On the other hand, since the uncommon classes typically represent intriguing concepts, it is typically most crucial to identify the minority classes. Furthermore, gathering these minority class examples can be costly or difficult. The uneven distribution in the datasets is what gives rise to the issue of class imbalance. As a result, it makes sense to think about rebalancing through the data space sampling to lessen the impact of class imbalance. One benefit of such a solution is that it can be used regardless of the classifier, so it can also be used as a pre-sampling technique. Under-sampling and over-sampling are the two fundamental concepts that are at the core of resampling methods, which are used to achieve a more equitable class distribution. The terms "random under-sampling" (RUS) and "random over-sampling" (ROS) refer to the elimination of representative samples from the majority classes and the systematic duplication of examples from the minority classes, respectively. The most prominent over-sampling method is SMOTE [12], which has garnered a lot of interest in recent years.

A hybrid method was proposed for pre-processing imbalanced datasets by [13] for generating new samples using SMOTE and rough set theory. They noticed excellent average results from the experimental findings. Similarly, [14] introduced the Majority Weighted Minority Oversampling Technique (MWMOTE) to address issues with unbalanced learning. The method first identifies samples from the minority class that are challenging to learn and gives them weights based on their Euclidean distance from the closest majority samples. The SMOTE algorithm was utilized by [15] to resample the data, which they paired with a collection of extreme learning machines, a feature selection ensemble, and a decision tree (DT) to develop an original mechanism for forecasting the future to predict the two-class imbalance.

A new semi-supervised adversarial generative adversarial network with spectral normalisation was proposed by [16]. (SN-SSCGAN). The idea behind it is to use minority fault samples that have been partially labelled to rebalance the dataset, it is necessary to produce additional samples with a comparable spread. To obtain a time-frequency matrix and to address these issues, a pre-process such as smooth the vibration signal using the wavelet transform is implemented, second, adversarial training is used to achieve Nash equilibrium on the partially labelled time-frequency fault data before generating data with a similar distribution.

Random under-sampling (RUS) and the AdaBoost algorithm are two sampling techniques that have been used extensively in research that builds on ensemble learning [17]. Because of the unpredictability of the random sampling technique, instances may occasionally not be representative, making it difficult to see how the model can be improved. [18] proposed the SMOTE Boost algorithm for building a balanced and high-quality dataset.

In [19], authors use Internet of Things (IoT) sensors to gather information about waste features like waste bin size, waste size, and smell in the bin to alert truck drivers, waste management, and authorities. In addition to solving the problem of missing data and choose best optimal path for waste truck from disposal center to suitable waste bins in many different places in the city have embedded devices.

Table 1
The relevant literature summaries.

Ref	Dataset focus	Techniques	Contributions	Limitations
[12]	Imbalanced dataset	SMOTE	• Solving imbalanced dataset	Determining the *k* value of k-neighbors by randomly inside the SMOTE algorithm
[13]	Imbalanced dataset	hybrid method	• The construction of new samples for datasets	Evaluation includes only synthetic instances falling within the minority class's lower approximation will be used.
[14]	Imbalanced dataset	MWMOTE	• produces synthetic samples using weighted, enlightening minority class samples.	The quantity of synthetic samples generated was negligible.
[15]	Imbalanced dataset	SMOTE- ELM -DT	• Re-size the imbalanced dataset.	Dimensionality reduction can be performed after the dataset has been preprocessed.
[16]	Imbalanced dataset	SN-SSCGAN	• Creating new samples with the same distribution using minority fault samples, and enhancing the fault diagnosis model's capacity for generalization	Only use flow distribution data that can be found in the bearing deterioration process.
[17]	Imbalanced dataset	RUSBoost	• Examines RUSBoost and SMOTEBoost's Effectiveness.	Increasing training time and Complexity.
[18]	Imbalanced dataset	SMOTEBoost	• Enhancing the minority classes' prediction.	Need to increase the number of comparisons until it shows efficiency and needs automatic determination of the amount of SMOTE
[19]	Frequencies of chicken Peak	The audio recording procedures	• Monitoring the growth of chickens	Because the humming sound vibrations are interconnected, the poultry industry cannot profit from it.
[20]	Analysis of vocal sound	Fisher Discriminate Analysis (FDA)	• Diagnosis of Disease	It is challenging to implement in large poultry farms because vocal analysis is challenging due to the vocal vibration overlapping
[21]	Vibrations of Sound	Support vector machines (SVM)	• Detection of flu in poultry	Determine the presence of flu in chickens at large poultry farms
[22]	Images of faces from chickens monitoring	Campylobacter control	• Diseases Detection and Monitoring Abnormal Feeding	Small-scale study of abnormal feeding behaviour in chickens.
[23]	Chickens Images	A lighting preference test system uses the weight method	• Feeder Crowd Surveillance	Keeping the lighting conditions ideal for viewing camera images.
[24]	Data extracted from sensors attached to the poultry body	Smart nest box based on RFID	• Controlling the production of eggs.	Only allows for tracking the chickens inside and outside the nest.
[25]	Data extracted from sensors attached to the poultry body	Automated position monitoring	• Tacking of poultry's whereabouts	Only describes the tracking method.
[26]	Data extracted from sensors attached to the poultry body	Decision tree (DT)	• Prediction of Lameness for poultry through walking speed, acceleration, genetic strain, and sex.	Need to compare with multiple other algorithms to prove that it is the best method

An intelligent method was proposed by [20] who implemented it to detect and classify chickens based on their vocalization and using fisher discriminate analysis (FDA) using signals detection to sort healthy chickens from sick ones. [21] Detect method for avian influenza according to the sound (noise) analysis of poultry via SVM. By examining the poultry chickens' feces, it is possible to keep track of their behaviour and make an early infection diagnosis [22]. A managed lighting environment and an IR camera have been used to determine the number of chickens in poultry [23].

[24] proposed an IoT platform that allows for the real-time analysis of each hen's egg production, enabling the substitute of chicken whose egg production falls below a predetermined level to achieve the overall target egg yield rate. The health, cleanliness, and growth of the poultry chickens were determined by tracking their [25]. One of the factors contributing to poor poultry welfare is lameness [26], and when lameness is detected early, farmers and veterinarians can take preventative measures.

Table 1 summarizes the related work including the data sets type, used techniques, the main contribution, and limitations. The majority of the existing literature focuses on predicting diseases in poultry, and other research deals with imbalanced databases. But it did not consider the imbalance of data when detecting behaviours and diseases in poultry. Most of the previous research largely lacked an effective strategy for boosting the real-world effectiveness of a model trained with an imbalanced dataset when detecting diseases in poultry.

3. Preliminaries

3.1. SMOTE for balanced data

Synthetic Minority Over-sampling Technique (SMOTE) [27] is regarded as an improved version of the randomized oversampling technique that increases the classifier's validation dataset generalization capability and lowers the likelihood of overfitting. By adding a synthetic minority class to the original dataset between the minority class and its nearest neighbours using random linear interpolation, it focuses on enhancing the dataset's imbalance.

The imbalanced data issue is ameliorated by SMOTE. The specific concept is put into practice as follows: Identity data set X's k closest neighbours in the minor class, choose n samples at random, and record them as X_i. Finally, interpolation defines the new sample X_{new} as defined in Eq. (1):

$$X_{new} = X_{origin} + rand * \left(X_i - X_{origin} \right), \; i = 1, \; 2, \; \ldots, \; n \tag{1}$$

Where rand represents a random number uniformly distributed within the range of (0, 1). But there are some issues with the SMOTE algorithm Fig. 1. The choice of the value for k is unrelated to the selection of the nearest neighbors. Additionally, replicating the distribution of the original data is challenging due to potential repeatability issues and the presence of noisy, indistinct boundaries between the classes of positive and negative in the artificially generated samples from the minor class samples located at the periphery.

3.2. Artificial hummingbird optimization algorithm (AHA)

A brand-new bio-inspired algorithm is introduced the Artificial Hummingbird Algorithm (AHA) has been proposed by [28] to address global optimization problems. The world's smallest bird and most beautiful creature. To the extent that brain size correlates with overall intelligence, hummingbirds would rank at the top of the animals. Hummingbirds have a top speed 45 km/h. While some of the smallest seeds can reach speeds of over 80 beats per second, the largest seeds can emerge in the air at a rate of about 12 beats per second. Hummingbirds must forage to maintain their metabolism, and nectar tends to make up a majority of their nutrition. AHA

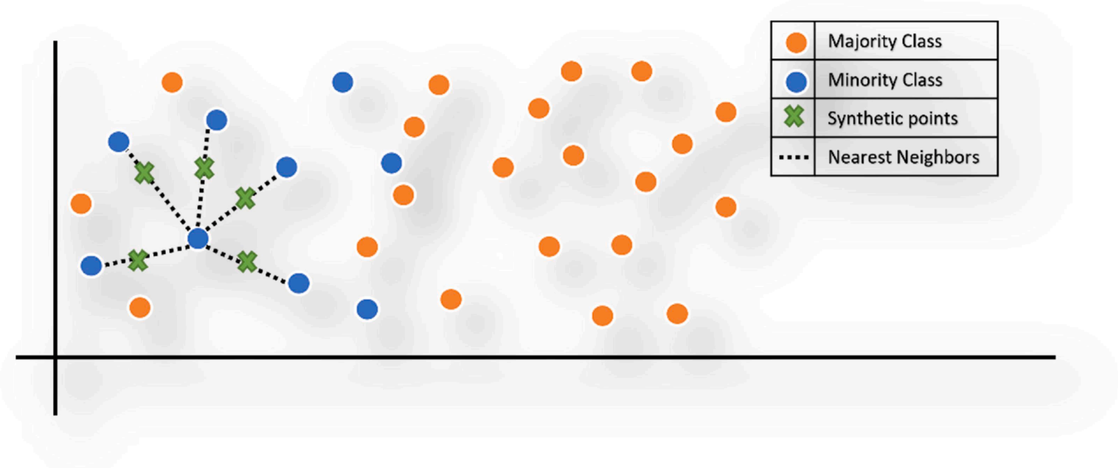


Fig. 1. Chart for generating synthetic data.

consists of three components as follows:

- Sources of Food: the decision of hummingbird on which flower to visit next for food depends on several factors, including the quality and content of flower nectar, and the refill rate of the flower nectar, and the hummingbird's previous frequency of visits to the flower.
- Hummingbirds: Each species of hummingbird has its unique food source, and the hummingbird and its source of the food are always in the same relative location. When a hummingbird finds a reliable source of nectar, it will tell the other members of its population where to find it and how often it will be refilled.
- Visit Table: For each food source, data on the visit level is kept, which indicates how long it has been since the same hummingbird last visited that particular source.

Initialization phase:

Hummingbirds in a population of n are distributed at random among *n* food sources using Eq. (2).

$$x_i = Low + r * (Up - Low), \ i = 1, \ \ldots, \ n \tag{2}$$

The upper and lower boundaries are denoted as Low and Up respectively, while x_i 's representation of the location of the ith food source. The visit table is illustrated by Eq. (3).

$$VT_{(i,j)} = \begin{cases} 0, & \text{if } i \neq j \\ Null, & \mathrm{i} = \mathrm{j} \end{cases} \tag{3}$$

Foraging with a guide:

Every hummingbird possesses an inherent inclination to visit the food source containing the highest volume of nectar. Consequently, a desirable food source should exhibit a high rate of nectar refilling and a longer duration between visits by a particular hummingbird.

To facilitate guided foraging behaviour, a hummingbird is permitted to identify food sources based on their visit levels and subsequently choose the one with the highest nectar-refilling rate as its target source. Once identified, the hummingbird can then direct its flight towards the desired food source. Three types of flight maneuvers, namely omnidirectional, diagonal, and axial flights, are employed for foraging purposes, as outlined from Eqs. (4) to (6).

$$\text{Each flight definition}: D^{(i)} = \begin{cases} 1, & \text{if } i = randi([1, d]) \\ 0, & \text{else} \end{cases} \tag{4}$$

$$D^{(i)} = \begin{cases} 1, & \text{if } i = P(j), j \in [1, k], \mathrm{P} \ = \ \mathrm{randperm}(\mathrm{k}), k \in 2\lceil.[r1 * (d-2) + 1\rceil \\ 0, & \text{else} \end{cases} \tag{5}$$

$$D^{(i)} = 1 \quad i = 1, \ldots, d \tag{6}$$

The function $randi([1, d])$ generates a random number ranging from 1 to d, while randperm(k) produces a random permutation of numbers ranging from 1 to *k*. Additionally, r_1 represents a random number that falls within the range of 0–1.

A. Foraging on the frontier: After a hummingbird finish consuming all the nectar from its target food source, it prefers to forage for food in new locations rather than revisit old ones. Consequently, Hummingbirds are able to move freely between different parts of their territory using Eqs. (7) & (8).

$$\nu_i(t+1) = x_i(t) + bDx_i(t) \tag{7}$$

$$b \ \sim \ N(0,1) \tag{8}$$

The factor of territorial, denoted as *b*, has a normal distribution, which describes it by N(0,1). Where 0 is mentioned as the mean and 1 is the standard deviation.

B. Foraging migration: If the food supply in a hummingbird's regular feeding spot dwindles, it may move to a nearby flower bed, the hummingbird typically undertakes a migration to a farther food source for feeding purposes. Hummingbird migration behaviour can be modelled using Eq. (9) by first determining the source with the lowest nectar-refilling rate and then simulating the bird's transition to a new source that is generated randomly.

$$\mathrm{x}_{\mathrm{wor}}(t+1) = low + r(Up - low) \tag{9}$$

x_{wor} represents the food source within the population that possesses the poorest nectar-refilling rate.

4. The proposed smart poultry monitoring system (SPMS)

The utilization of wearable sensing devices enables the precise observation of individual chickens, as they are tracked and monitored for a specific period of time. Rapid trends in sensing technology have reduced the cost of such devices, making sensor-driven data analysis a more viable option. More recent research has also helped to enhance data collection techniques for livestock and poultry farming by making use of wearable sensing devices [29].

This paper proposes a smart poultry monitoring system to classify poultry behaviours that affect the status of poultry (sick or healthy). Fig. 2 depicts the overall architecture of the proposed system.

4.1. Dataset description phase

The process of obtaining the desired input data from various resources is known as the dataset collection phase. Data size and data characteristics were all considered during the data collection process. By placing wearable accelerometers over individual chickens, the research [30,31] created a dataset of poultry. The data stores three-axis chicken data, which depicts the behaviours of poultry chickens like dustbathing, preening, and pecking. Both healthy and sick chickens were included in the dataset of these activities. The external parasites covering the chickens' skin were purposefully embossed by the researchers, stressing the animals.

The data generated from the sensor, which is attached to the chicken's back to collect data, can be used to record a wide range of natural behaviours. The Activity AX3 sensor is a tri-axial accelerometer, measuring static and dynamic acceleration on three orthogonal axes (X, Y, and Z) and weighing only 11 g. The X, Y, and Z axes were all oriented dorsoventrally, laterally, and anteriorly-posteriorly, respectively. The sensor is set up with a 100 Hz sampling frequency and +/− 8 g sensitivity, allowing for two weeks of continuous data collection on a single charge. The following actions are hypothesised to be related to poultry health based on a survey of the available literature [32]. The 24 unique poultry chickens distributed among four different flocks make up the 20-week dataset. The dataset includes the daily averages for each chicken's pecking, preening, and dustbathing in six different flocks. The available poultry behaviour dataset attributes are shown in Table 2 which describes raw data X, Y, and Z axes of the accelerometer which describes the chicken behaviours cases.

Table 3 describes the three labelled behaviour classes. Fig. 3 demonstrates pre-processing of raw data are created from the input labelled data (pecking, preening, and dustbathing). The labelled dataset was used to feed the model and then used to validate it.

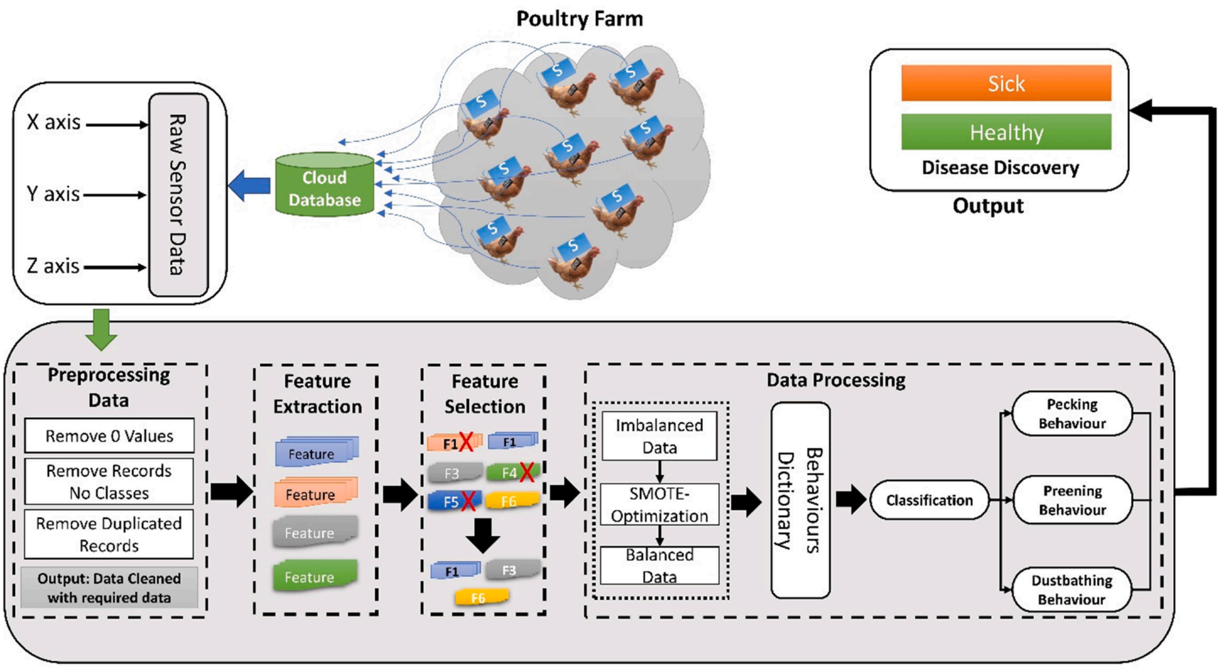


Fig. 2. The general architecture of the proposed system.

Table 2
Description of tri-axial accelerometer raw data.

Raw data	Description
X-axis	Is a horizontal axis that runs from left to right.
Y-axis	Is a vertical axis that runs from the bottom.
Z-axis	Is a third axis that runs perpendicular to the X-axis and Y-axis.
Class	Describes the behaviour (Peaking/Feeding, preening, and dustbathing) of poultry according to three axes.

Table 3
Description of the three behaviour classes monitored.

Class id	Behaviour	Description
2	**Pecking**	The frequency for bringing the beak to the ground
3	**Preening**	The frequency of preening of the feathers by the beak.
4	**Dustbathing**	The frequency of bird which is in a sitting or lying position with feathers raised in a vertical wing-shake.
0	**No Behaviour**	——

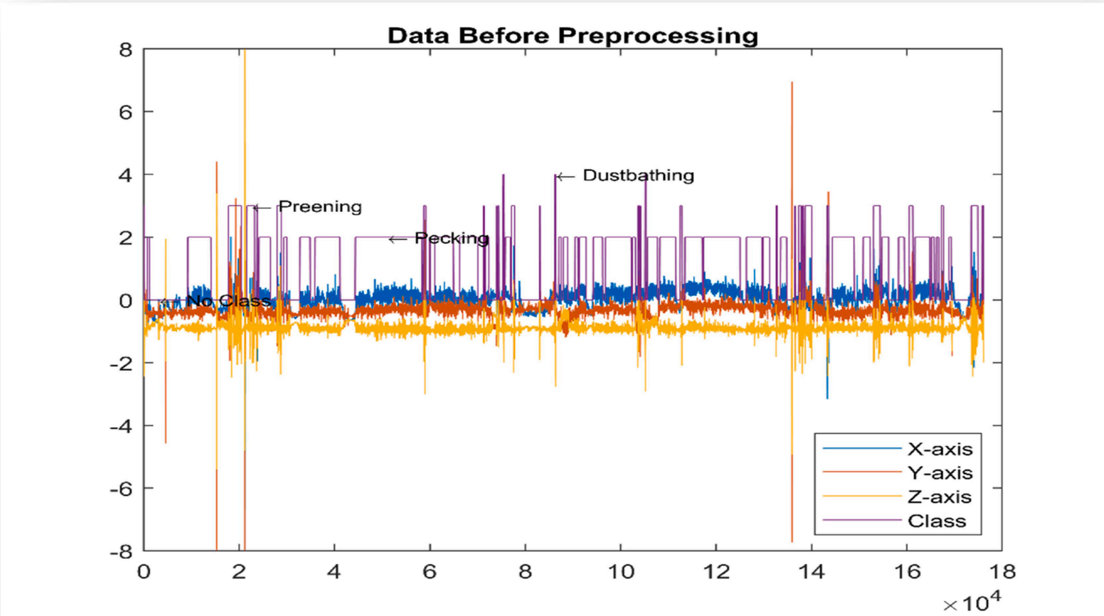


Fig. 3. Visualization of tri-axial accelerometer data before preprocessing.

4.2. Data preprocessing phase

The data from an accelerometer comprises readings from three float numeric axes (x, y, z). All the identified exercises are confined within the range of [−8, 8] for each axis. Subsequently, these readings were employed to identify three behaviours: pecking/feeding, preening, and dustbathing. The size of dataset is 176,154 records before data cleaning. The dataset size after cleaning and deleting all the duplicate data is 99,998 records.

To prepare the data for the classification process, it will go through several processes. Data cleaning (removing zeros values) and data duplication are the processes involved. According to the techniques employed during the classification model, the raw data is formatted into the necessary system. In essence, the decision class is included at the end of the entire column, and the data is presented using an r * c matrix, where r and c represent several rows and columns, respectively. The best advantage of pre-processing is that it helps to minimize data redundancy and improve overall dataset organization. To improve classification results, perform a feature selection task to extract a subset of pertinent features from the dataset. This task also helps eliminate the possibility of incorrect training by removing redundant features and noise. Fig. 4 demonstrates tri-axial accelerometer data after removing null values, zero

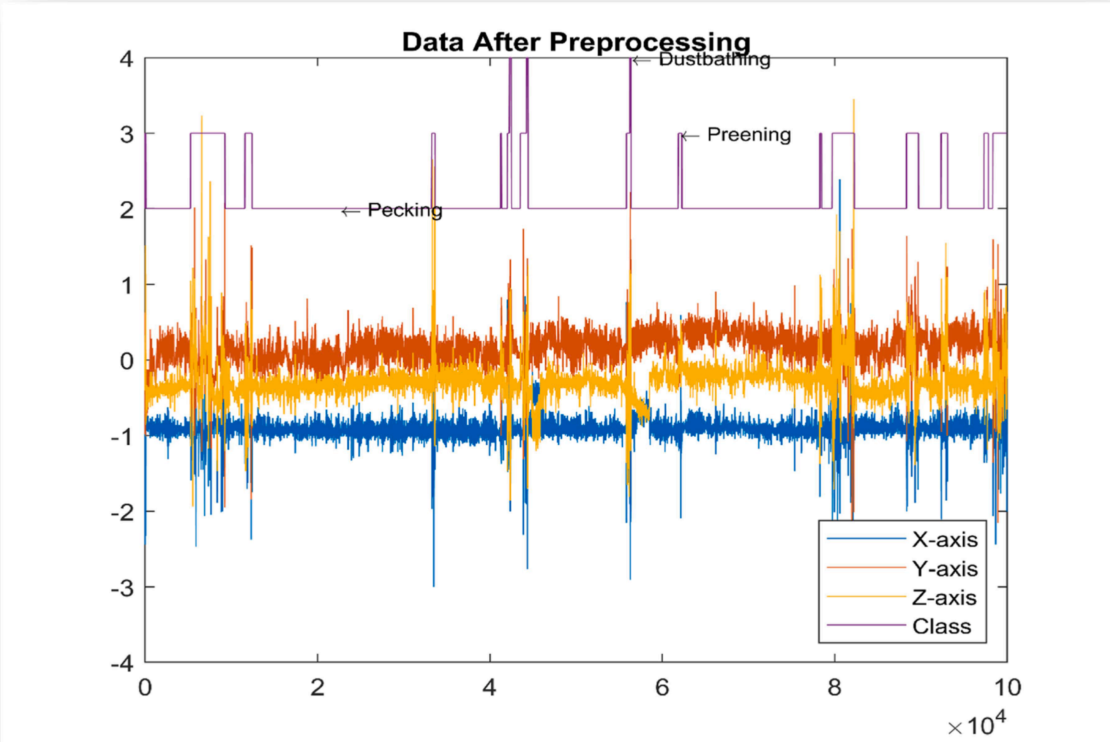


Fig. 4. Visualization of tri-axial accelerometer data after pre-processing.

Table 4
Formulations for motion characteristics of broilers utilizing triaxial acceleration data.

Feature	Formulas
Acceleration of X axis	x_t
Acceleration of Y axis	y_t
Acceleration of Z axis	z_t
Average X-axis (Ax)	$A_x = \frac{1}{K}\sum_{t=1}^{K} x(t)$
Average Y-axis (Ay)	$A_y = \frac{1}{K}\sum_{t=1}^{K} y(t)$
Average Z-axis (Az)	$A_z = \frac{1}{T}\sum_{t=1}^{K} z(t)$
Movement Variation (MV)	$MV = \frac{1}{N}\left(\sum_{i=1}^{N-1} \lvert x_{i+1} + x_i \rvert + \sum_{i=1}^{N-1} \lvert y_{i+1} + y_i \rvert + \sum_{i=1}^{N-1} \lvert z_{i+1} + z_i \rvert\right)$
Signal Magnitude Area (SMA)	$SMA = \frac{1}{T}\left(\sum_{t=1}^{T} \lvert a_x(t)\rvert + \sum_{t=1}^{T} \lvert a_y(t)\rvert + \sum_{t=1}^{T} \lvert a_z(t)\rvert\right)$
Average Intensity (AI)	$AI = \frac{1}{T}\left(\sum_{t=1}^{T} MI(t)\right)$
	Where $MI(t) = \sqrt{a_x(t)^2 + a_x(t)^2 + a_x(t)^2}$
Entropy	$EN = \frac{1}{n}\left(\sum (1 + Ts_i)\ln(1 + Ts_i)\right)$
	Where $Ts = Ax + Ay + Az$
Energy	$E = \frac{1}{n}\left(\sum (TSS_i^2)\right)$
	Where $TSS = Ax^2 + Ay^2 + Az^2$
Maximum X (MaxX)	The highest acceleration along the X-axis.
Maximum Y (MaxY)	The highest acceleration along the Y-axis
Maximum Z (MaxZ)	The highest acceleration along the Z-axis
Minimum X (MinX)	The lowest acceleration along the X-axis.
Minimum Y (MinY)	The lowest acceleration along the Y-axis
Minimum Z (MinZ)	The lowest acceleration along the Z-axis

classes, and duplicate records.

4.3. Feature extraction phase

A systematic evaluation was conducted to determine the usefulness and significant features for distinguishing between various activities by employing different classification models and ranking their importance. Classification models were used to identify the relative importance of the seventeen features. The process of feature extraction was carried out via MATLAB (2019a). There are 17 instant characteristics through 3D accelerations (X, Y, Z), Single Magnitude Area (SMA), Average Intensity (AI), Movement Variation (MV), Energy, and Entropy were calculated via formulas listed in Table 4, where i is the record index, were chosen according to the length of time each behaviour lasted. For instance, feeding/pecking typically take very little time, about one peck per second, when compared to the time it takes a broiler to preening, which is roughly 3 s for 4 steps. This resulted in a total number of features, all of which were incorporated into the model training process.

4.4. Feature selection phase

Various classification models were employed systematically to evaluate the utility of features and identify the most significant ones for distinguishing between different activities. In the field of data science, it is essential to determine the most relevant features within a dataset for training learning algorithms [33]. Some features may not contribute to improving the performance of the learning algorithm and can even degrade its accuracy. Consequently, feature selection (FS) algorithms are utilized to identify a subset of features that can enhance the machine learning model's performance. FS algorithms also help prevent overfitting and expedite the training process of the learning algorithm. Furthermore, knowledge about the selected features can provide valuable insights into the datasets.

4.4.1. Fitness function

The hummingbird swarm consists of individual birds, each representing a solution for feature selection. These birds are encoded using real numbers, as demonstrated in Eq. (10). Each solution, denoted as X, is comprised of n real numbers, n denotes the overall features of the dataset being analysed. The x_i dimension of X corresponds to the decision of selecting or not selecting a particular feature. To form a subset of features, a decoding process must be performed on the bird's position. This allows for the conversion of the bird's position into a subset of selected features.

$$X = [x_1,\ x_2,\ \dots,\ x_n] \tag{10}$$

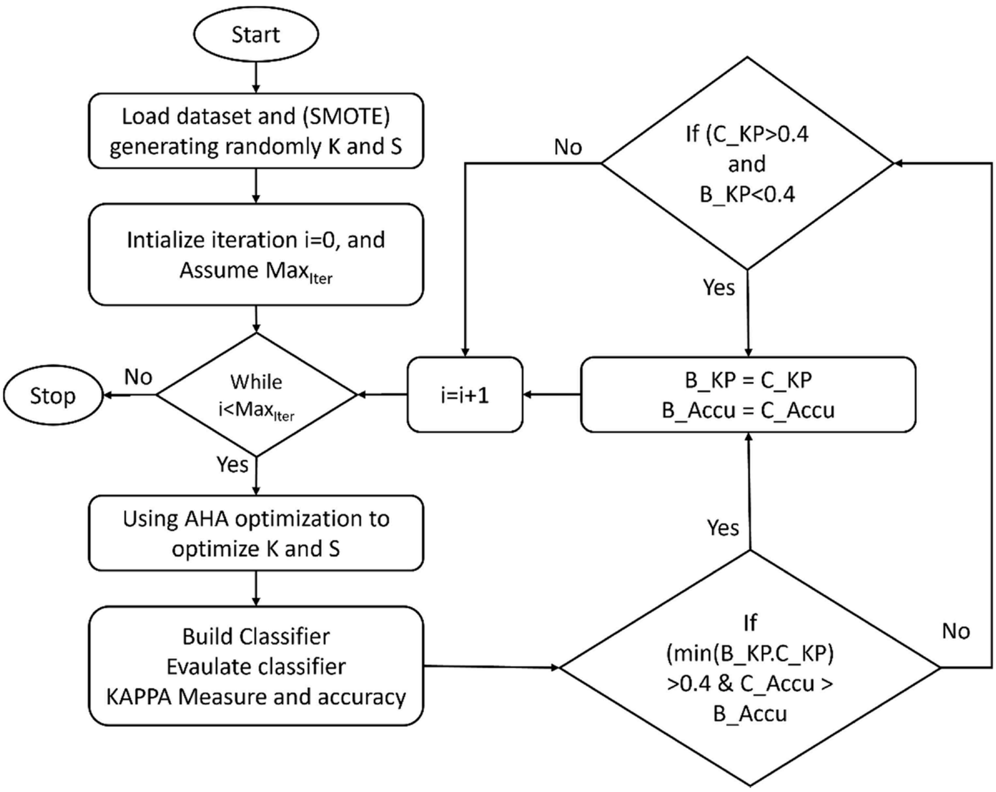


Fig. 5. Flowchart of the proposed balancing dataset with optimized SMOTE.

$$S_d = \begin{cases} 0, & x_d > 0.5 \\ 1, & else \end{cases} \tag{11}$$

The subset of features obtained after decoding the d-dimensionality of each solution is represented by S_d in Eq. (11). The value of x_d in the d-dimension determines whether S_d is selected as 0 or 1. If x_d corresponds to a selected feature, then S_d is set to 1. Conversely, if x_d corresponds to a non-selected feature, then S_d is set to 0.

Feature selection aims to identify an optimal combination of features that optimize the accuracy of classification while reducing the number of selected features. While it involves finding a suitable combination of features, the primary objective is to optimize the classification accuracy. The fitness function is designed to maximize the accuracy of classification for the test sets while maintaining the minimum number of selected features. Eq. (12) demonstrates the simultaneous consideration of these two aspects in the fitness function.

$$Obj(i) = \propto * ACC(i) + (1 - \propto) * \left(\frac{ObjSum(i)}{Total\ Features} \right) \tag{12}$$

Where, constant value $\propto$, between 0 and 1, is utilized to control the relative significance of classification accuracy versus the number of selected features. As $\propto$ increases, classification accuracy is given greater weight. The accuracy of the classifier for bird i is represented by ACC(i), while the number of features selected by bird i is denoted as ObjSum(i). The total number of features in the dataset is represented by *Total Features*.

4.5. An optimized SMOTE for solving the data imbalance problem

This stage is considered one of the most important stages that solves the data imbalance problem that significantly and tangibly affects the results related to poultry management. Incorporate (Artificial Humming Algorithm) AHA's optimization process with DT and RF to prevent local convergence. Additionally, the proposed hybrid metaheuristic will serve as the foundation for an algorithm that optimizes hyperparameters to determine the optimum values of *N* and *k* for balancing class distribution of training data over parameter range.

The values of the two most important parameters are optimized with the swarm algorithm in Fig. 5, which depicts the optimization of the SMOTE algorithm. Every iteration the search agents (such as hummingbird in AHA) move, the new approach is expected to locate the optimal combination of K and S through a classifier decision tree to produce the best Kappa and accuracy performance. Then, using iterative processing to determine the optimal *K* and *S*, compare the performance measures with the conditions to enhance the

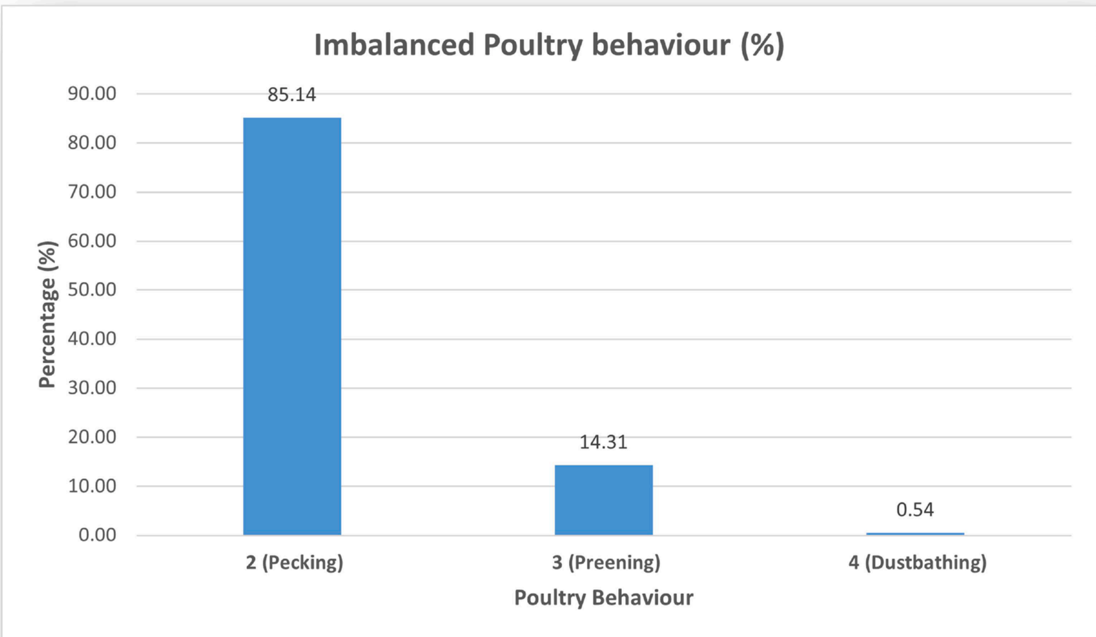


Fig. 6. Imbalanced analysis dataset for poultry behaviours.

Kappa, the accuracy values, and the imbalanced ratio (min/maj).

Each step interval for the S and K parameters in the computation is different. The proportion of the majority class to the minority class has the highest value for S. S must have a minimum value of 1 %. If there are two possible labels for the target class in the dataset, The majority class has 1000 instances, while the minority class has only 10. This implies that the minority class sample must grow by at least 20 times and up to 100,000 times, $K_{\min} = 2$, and $K_{\max} = 10$.

As a result of the testing dataset's consistency, Kappa [34] is regarded as a substitute measure of computing performance of classification. The classifier model's reliability is represented by kappa. The accuracy is more credible because the Kappa value is higher. The range of Kappa values (also known as simply Kappa) is from −1 to 1. While this is going on, three Kappa thresholds are used to determine the credibility of classification accuracy: The first measure in Kappa is considered to have strong consistency and high accuracy when Kappa is greater than or equal to 0.75. Second, if Kappa is greater than or equal to 0.4 and less than or equal to 0.75, the accuracy's confidence level is generally considered to be high. The third threshold is that accuracy is astounding if Kappa is less than 0.4.

When the observation in one class is higher than the observation in the other two classes, there is a class imbalance. This dataset is to detect poultry behaviours. As you can see in Fig. 6, pecking behaviour is around 85.14 % when compared with preening and dustbathing at 14.31 % and 0.54 %, respectively. Therefore, we want the preening and dustbathing data to be balanced with the chicken pecking data so that the data can be analysed, and behaviour predicted efficiently.

4.6. Dictionary for poultry behaviours

To attempt the automatic construction of a dictionary behaviours or query-templates, our training/testing data as shown in Fig. 7. A dictionary's list of query-templates (behaviours) is presented in Column_1, Column_2, …, Column_n; each query has a class (Column_1. class), a threshold value is shown in Column_2, and Column_3 depicts an axis (X or Y or Z) property, in addition to the query data points. We need a threshold that defines our acceptable rate of false positives and false negatives for each class.

In theory, a single behaviour could have multiple possible instantiations, just as the number seven has two different but equivalent written forms (the traditional "7" and the middle line "7̶"). A polymorphic dictionary describes this type of dictionary. From what we've seen in the chickens, we've deduced that each behaviour has only one correct execution. However, expanding this code to work with any polymorphic dictionary is so simple that it's been left out for the sake of brevity.

A dictionary of chicken behaviours can be constructed that searches annotated regions for motifs of highly conserved sequences

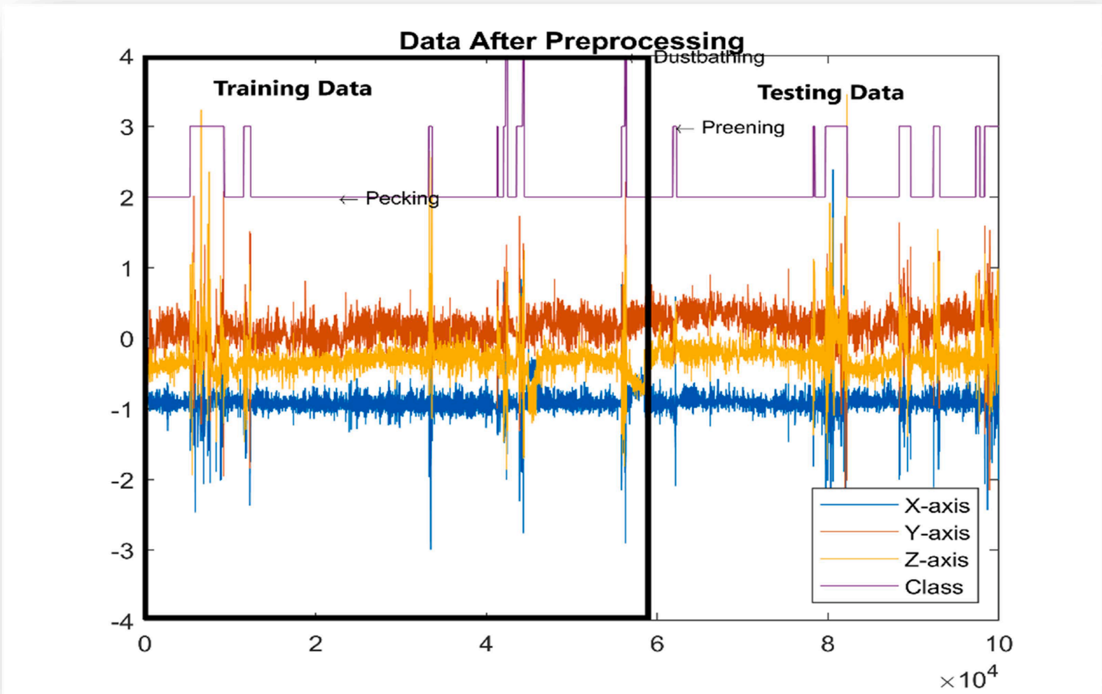


Fig. 7. Tri-axial accelerometer for chicken time series.

[35]. Think about the corresponding difficulty in the discrete string space to get a feel for this. We count, categories, and time-stamp certain behaviours as they occur in the time series data stream. The data stream is filtered using a sliding window. If the sequence meets the matching criteria for a query-template (behaviour) in the dictionary, it is associated with that behaviour and given a timestamp. The effectiveness of feeding/pecking, preening, and dustbathing behaviours are all assessed and reported. Out-of-sample evaluation is the only objective of the test dataset after the training dataset has been used to construct the dictionary of behaviours.

Perhaps the most recognizable behaviour in chickens is the act of pecking/feeding. Dictionary has discovered the query-template in Fig. 8 to analyse pecking/feeding behaviour in a training dataset, where matching subsequences along the (left) X-axis and (right) Z-axis need to be identified, which incorporates subsequences that match those in the training dataset. Subsequence matches outside of regions annotated as feeding/pecking behaviour are considered false positives (FP), but those within these regions are considered true positives (TP). The query-template and corresponding subsequences from the training dataset for preening behaviour are shown in Fig. 9.

Figs. 10 and 11 demonstrate how challenging it can be to detect dustbathing behaviour, as it was infrequent in both the training and test datasets. Only two occurrences of the green colour of dustbathing were present in the training dataset, and only one was found in the test dataset. These figures display the query template and matching subsequences regarding behaviour involving dustbathing in the test dataset, with the X-axis and Z-axis shown on the left and right, respectively.

4.7. Classification of poultry behaviours phase

Behaviour, which is evident through actions and posture, is widely recognized as one of the most indicators that are crucial, most widely used, and most easily understood indicators of animal welfare and health, even more so than stress and output. Therefore, enhancing animal welfare and detecting sick chickens early necessitates real-time, automatic, and nondestructive monitoring of poultry behaviour.

The following behaviours are hypothesized to be related to poultry health. When feeding or pecking, the bird lowers its beak to the ground and picks up a tidbit of food. Feather care routines that involve the beak include preening and dustbathing. Ectoparasite-infected birds, in particular, are thought to engage in increased preening/dustbathing. The various algorithms are used to categories pecking, preening, and dustbathing.

Our analysis of the behaviour of broiler chickens was informed by the results of the preliminary behavioural posture pre-processing. Feeding/pecking, preening, and dustbathing are the three behaviours we assign to the test data. The chickens' daily routine typically consists of them strolling around and chowing down. When prompted, such as by noise in the environment, they will take off running and only stop when they are fatigued. Additionally, there is a phenomenon where sick chickens lie down, and this behaviour warrants related study [36]. Preening is a common behaviour as well, accounting for about 11 % of a bird's daily time. Chickens' actions are assumed to be unrelated to one another; for instance, we don't think chickens would run around the yard while munching on some food. In Section 6.1 we can see how the algorithm for classifying chicken behaviour recognition in this paper. The classification models of poultry behaviour were implemented via MATLAB (2019a) using Machine Learning Toolbox. Classification algorithms examined in this study are KNN, Decision Tree, Random Forest, Logistic Regression, Gaussian Naïve Bayes, and AdaBoost.

4.8. Diagnosis of poultry disease phase

Seven prediction models were investigated for their ability to predict the poultry' health.

Table 3 provides a brief overview of the dataset that was used for this study. The dataset was chosen because it represents a comprehensive set of broiler behaviours, all of which are necessary for proper analysis: feeding/pecking, preening, and dustbathing.

Real-world datasets were used to train the machine learning classification models. This paper proposes two techniques, AHA-DT and AHA-RF, and conducts experiments with supervised learning algorithms including k-Nearest Neighbor, Decision Tree, Random

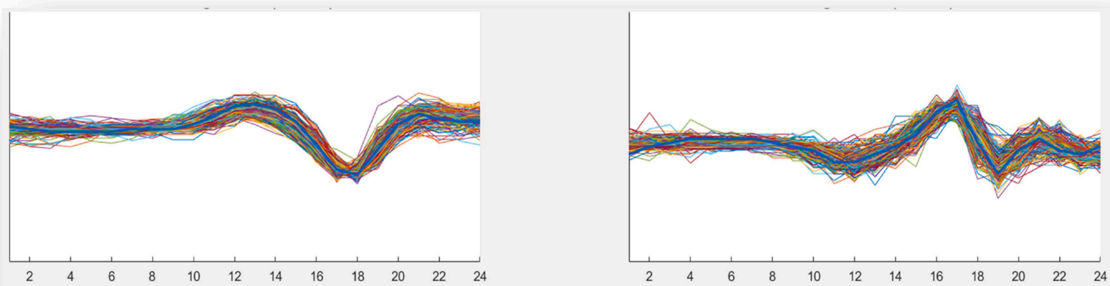


Fig. 8. A query template for pecking/feeding behaviour.

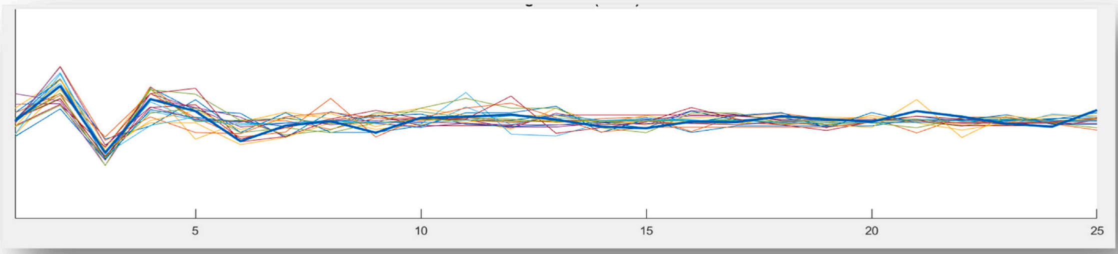


Fig. 9. A query template for preening behaviour.

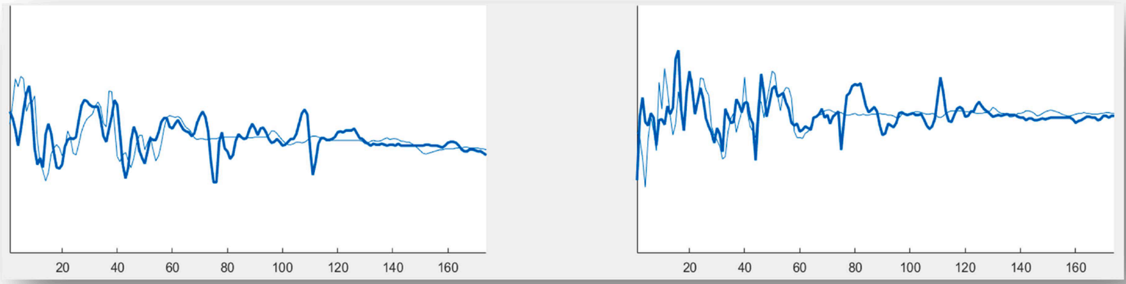
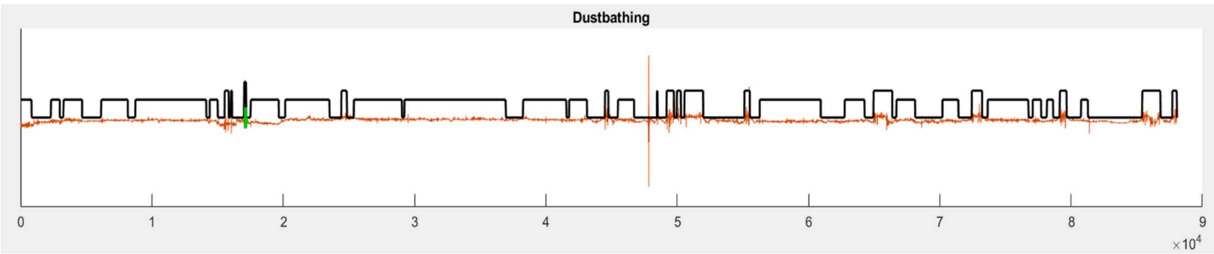
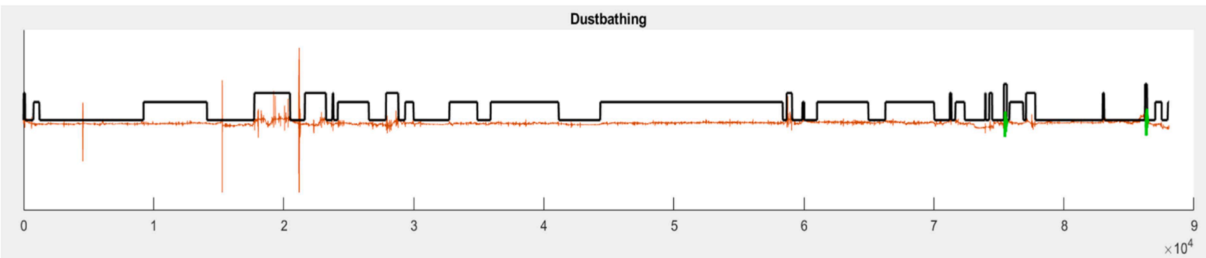


Fig. 10. A query template for dustbathing behaviour.



a. Testing data



b. Training data

Fig. 11. Matching sub-sequences for dustbathing behaviour.

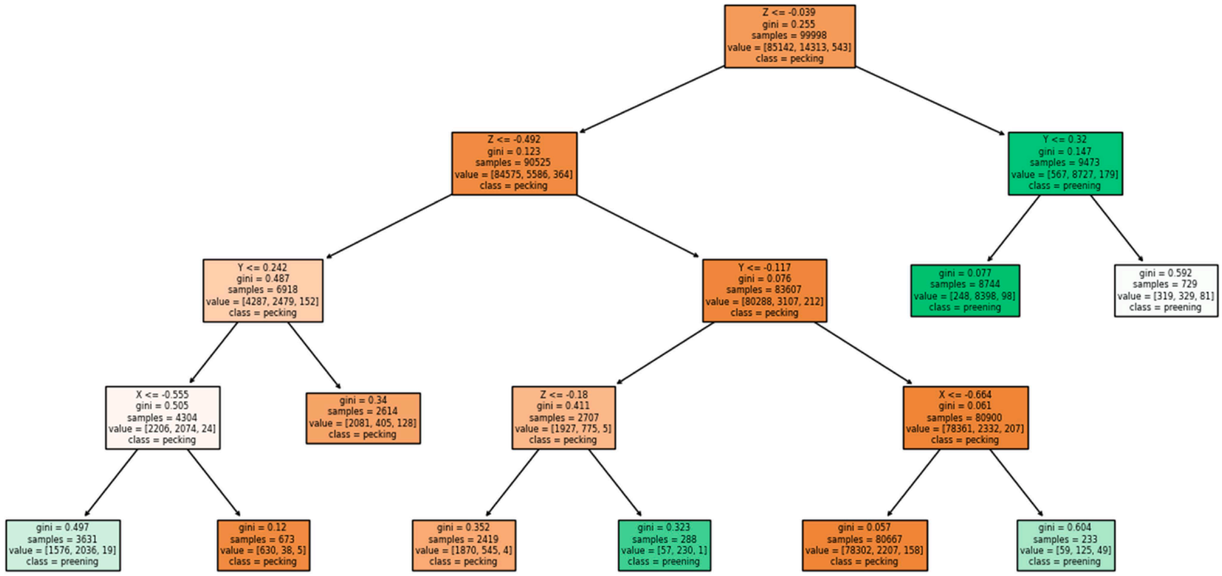


Fig. 12. Standard decision tree for poultry dataset classification.

Forest, Naive Bayes, and Support Vector Machine to improve the classification of the poultry according to extracted data from the poultry dataset. Fig. 12 demonstrates the standard Decision Tree classifier, which contains X, Y, and Z that represent three axis values which predict poultry behaviours pecking, preening, and dustbathing, respectively.

5. Performance evaluation measures

The performance measures in the proposed system include multiple measures: measures for evaluating the balance of data and other measures for evaluating the best classification of the proposed methods. All measures are based on the following confusion matrix; refer to Fig. 13. When evaluating learning algorithms on a dataset quantitatively, the confusion matrix is a useful component. Important comparison parameters are computed using an empirical method. It also includes the crucial metrics defined by Eqs. (13)–(23):

- True Positive (TP): indicates that the event was correctly predicted.
- True Negative (TN): indicates that the system has correctly predicted that no event will occur.
- False Positive (FP): represents a system's incorrect prediction of an event.
- False Negative (FN): represents a system's incorrect prediction of no event.

Accuracy: measures the proportion of samples that are correctly classified into all samples Eq. (13).

$$\textbf{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}$$

F-measure: It is defined as a metric for evaluating an algorithm's effectiveness and is computed by combining the recall and precision metrics. Calculating F-measure using Eq. (14):

$$F - \text{measure} = 2 * \frac{precision * recall}{precision + recall} \tag{14}$$

where the values of precision and recall are calculated using Eqs. (15) & (16), respectively.

	Positive	**Negative**
Positive	True Positive (TP)	False Positive (FP)
Negative	False Negative (FN)	True Negative (TN)

Fig. 13. Confusion matrix.

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

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

Area Under Curve (AUC): It is the plot that evaluates the classification model. The classification effect of the model is better with a higher AUC value. Classifiers with a value closer to 1 have faster convergence, while those with a value closer to 0 have sub-optimal performance Eq. (17).

$$\textbf{Area Under Curve (AUC)} = \sum_{i \in P} rank_i \frac{-(1 + TP)TP/2}{(TP * TN)} \tag{17}$$

G-value calculates using recall and precision average which Classification models perform better at classifying imbalanced data when the G-value is high Eq. (18).

$$G - \text{value} = \sqrt{\textbf{Precision} \;\; X \;\textbf{Recall}} \tag{18}$$

$\mathbf{OOB^{error}}$: is the average percentage of incorrect predictions made by each decision tree. where ntree is the number of decision trees. The more accurate a model's classification is, the lower the acceptable OOB^{error} Eq. (19).

$$\mathbf{OOB^{error}} = \frac{\sum_{k=1}^{ntree} OBB_k^{error}}{ntree} \tag{19}$$

Kappa value: can also be called Cohen's Kappa Eq. (20) which be determined by using a confusion matrix that lists the percentages of each class's TP, FP, and TN which clarifies p_0 indicates the overall accuracy and p_c is a metric for evaluating the degree to which predicted and actual class values.

$$\text{Kappa} = \frac{\mathbf{P0} - \mathbf{Pc}}{1 - \mathbf{Pc}} = 1 - \frac{1 - \mathbf{P0}}{1 - \mathbf{Pc}} \tag{20}$$

where **P0** and **Pc** are given as respectively Eqs. (21) & (22)

$$\text{P0} = \frac{TP + TN}{N} \tag{21}$$

$$\text{Pc} = \frac{(TP + FP) * (TP + FN) * (FN + TN) * (FP + TN)}{(P + N)^2} \tag{22}$$

Imbalanced Ratio (IR): is used to calculate the percentage of imbalanced data value where the total number of points for the minority class denoted by O_1 while the total number of points for the majority class is denoted by O_2. Whenever the percentage of imbalanced data is small, it indicates the efficiency and balance of the data Eq. (23).

$$\text{Imbalanced Ratio (IR)} = 1 - \frac{O_1}{O_2} \tag{23}$$

The most important key metrics to track the changes and results for solving imbalanced datasets are accuracy, Kappa, and the imbalance ratio (Min/Maj).

6. Experiments results and discussion

The findings of the experiments are discussed in this section along with the phases that were tested and the proposed system. The same computer contains the following specific settings: Hardware specification consists of Core (TM) i7-4500, 2.40 GHz, 16 G, and 1 TB that express Processor, Frequency, RAM, and Hard Disk respectively. Software specification contains Windows 11, and MATLAB R2019a that express operating system and programming language, respectively to extract and analyse the results.

6.1. Experiments of feature selection

Assuming a population size of 100, the fitness function employs an α value of 0.8. The dataset undergoes 20 independent

Table 5
Hyperparameter settings.

Algorithm	Parameters
AHA	r ∈ [0, 1]
WOA	a = 2–0, a2 = −1 to −2
PSO	w = 0.729, c1 = c2 = 1.49445
GA	Crossover = 0.7, Mutation = 0.25

experiments, with a maximum of 500 iterations set as the limit. To test the classification accuracy of the selection scheme for each bird, the KNN classifier (with $K = 7$) is utilized. The hyperparameter configurations for each algorithm are provided in Table 5. The information of dataset is composed of 20 poultry features, more than 99,998 instances, and two classes which are described if the poultry is sick or healthy.

The experimental results of the AHA algorithm for feature selection and three other comparison algorithms on a dataset are presented in Table 5. AHA is the algorithm with the highest mean classification accuracy and the AHA algorithm outperformed the other algorithms on test datasets, and its mean accuracy is better than that of CSO, PSO, and GA algorithms in feature selection. The worst mean accuracy in feature selection was observed for the GA algorithm. However, the dataset with better mean accuracy on full features saw an improvement of less than 10 %. The experimental outcomes prove the AHA algorithm is more effective.

Table 6 displays the average features and standard deviation in dimensions for the four algorithms following feature selection for the dataset. An intuitive observation shows that the AHA and CSO algorithms have a significant dimensionality reduction effect compared to the GA and PSO algorithms, and the dimensional standard deviation is low, indicating relatively high stability of the algorithms. The experimental results provide direct evidence that the AHA algorithm is highly effective, resulting in better classification accuracy on datasets and a significant reduction in the number of unnecessary features.

6.2. Experiments of handling imbalanced dataset

The study's experiments involve the utilization of both real-world and artificial datasets. An optimized SMOTE results in the creation of the synthetic dataset which is used to supplement the movement data of the poultry chickens and are a significant contribution to the proposed study for classifying poultry behaviours. The original dataset's sparsity is provided by the proposed generated synthetic dataset SMOTE-AHA-DT and SMOTE-AHA-RF to suggest a predictive behaviour of poultry farms for instantaneous chicken disease diagnosis, the experiment developed machine learning classification models.

The results of the proposed optimized SMOTE based on AHA using the Decision Tree (DT) and Random Forest (RF) classification models on the poultry dataset are shown in Table 7. The three-performance metrics of accuracy and Kappa with high accuracy and the best Kappa value. these best results indicate that, after undergoing training with the imbalanced data, the two proposed method with classification algorithms' power is completely useless. Regardless of the classification algorithm employed, the results remain subpar after processing the original dataset using SMOTE-PSO, SMOTE-GOA, and SMOTE-WOA with DT and RF classification for some but perhaps not optimal balance. Using the effectiveness of the proposed an optimized SMOTE as SMOTE-AHA-DT, and SMOTE-AHA-RF methods proposed in this paper demonstrated that, as shown in Table 8 The Kappa for SMOTE-AHA-DT is high and nearly equal to one with high accuracy of 98 % more than proposed SMOTE-AHA-RF. The proposed methods managed to maintain a manageable range of control over classification results. The change in the dataset's degree of imbalance ratio can be seen through the index of imbalance ratio, demonstrating that our methods work even when the dataset is not completely balanced.

Afterward, the proposed Swarm-SMOTE optimization algorithm was compared with other swarm optimization algorithms SMOTE-PSO, SMOTE-WOA, and SMOTE-GOA with two classification models decision tree (DT) and random forest (RF) and used G-mean and F-measure for dataset to confirm the classification performance of the model. In Table 8 and Fig. 14, the experimental findings are displayed and show that the proposed optimization algorithm achieves superior results in the F-measure compared to other algorithms in the poultry dataset and that it also outperforms competing algorithms in terms of G-mean. The dataset is correctly classified for all of them. The experimental findings demonstrate that the algorithm presented in this paper is superior for the classification of the minority class and provides a practical solution to the issue of data classification that is imbalanced.

Especially the poultry dataset is included. Classification results for the poultry dataset after being expanded using the proposed optimization SMOTE show an improvement of 7.073 % in accuracy and a decrease of 4.74 % in OOB^{error} value compared to the original data.

Fig. 15 depicts data points for each class in the poultry dataset consisting of pecking/feeding, preening, and dustbathing classes, and pecking/feeding is considered the majority class compared to preening and dustbathing. Fig. 15(a) represents a visualization of input data points for preening and pecking before generating synthetic data points, and Fig. 15(b) also has the same visualization of input data points for dustbathing and pecking before producing synthetic data points. Fig. 15(c) and (d) demonstrate visualization of input data points for preening and dustbathing after generating synthetic data points via an optimized SMOTE.

Table 9 and Fig. 16 demonstrate the runtime for the poultry data set using all optimization synthetic oversampling techniques in seconds. The most time-consuming oversampling techniques, according to an analysis of the data in the table, were SMOTE-AHA and SMOTE-WOA with DT and RF. However, among all the oversampling techniques compared, SMOTE-PSO and SMOTE-GOA with DT and RF were the lowest. SMOTE-WOA-DT and SMOTE-WOA-RF are the methods that are most similar to our suggested method in terms of runtime, but they got twice as long to complete.

Table 6
The mean, standard deviation (Std), and mean accuracy (MACC) after performing feature selection with various algorithms.

Dataset	AHA Mean	Std	MACC	CSO Mean	Std	MACC	PSO Mean	Std	MACC	GA Mean	Std	MACC
Poultry Dataset	5.85	0.65	**0.982**	5.85	0.65	0.921	6.00	1.34	0.893	6.20	1.78	0.843

Table 7
The results of an optimized SMOTE.

Algorithms	Accuracy (%)	Kappa	Imbalance ratio (Min/Maj) %
SMOTE	0.7814	0.20	0.4
SMOTE-PSO-RF	0.7189	0.18	0.21
SMOTE-WOA-RF	0.8355	0.65	0.28
SMOTE-GOA-RF	0.8447	0.05	0.33
Proposed optimized SMOTE-RF	**0.9626**	**0.71**	**0.07**
SMOTE-PSO-DT	0.8447	0.07	0.31
SMOTE-WOA-DT	0.6175	0.14	0.22
SMOTE-GOA-DT	0.7603	0.52	0.19
Proposed optimized SMOTE-DT	**0.9784**	**0.82**	**0.02**

Table 8
The different performances AUC, OOB^{error}, G-mean and F-measure for different algorithms.

Measures	AUC	OOB^{error}	F-value	G-value
Raw Data	0.7273	0.24285	0.8024	0.8453
SMOTE	0.7814	0.17918	0.7351	0.9304
SMOTE-PSO-RF	0.7189	0.19238	0.6594	0.9333
SMOTE-WOA-RF	0.8355	0.17764	0.5458	0.9367
SMOTE-GOA-RF	0.8447	0.16444	0.6730	0.8814
Proposed optimized SMOTE-RF	**0.9626**	**0.19018**	**0.9510**	**0.9809**
SMOTE-PSO-DT	0.8447	0.25385	0.7614	0.9672
SMOTE-WOA-DT	0.6175	0.19347	0.5137	0.9676
SMOTE-GOA-DT	0.7603	0.23012	0.8241	0.9124
Proposed optimized SMOTE-DT	**0.9784**	**0.17544**	**0.9743**	**1**

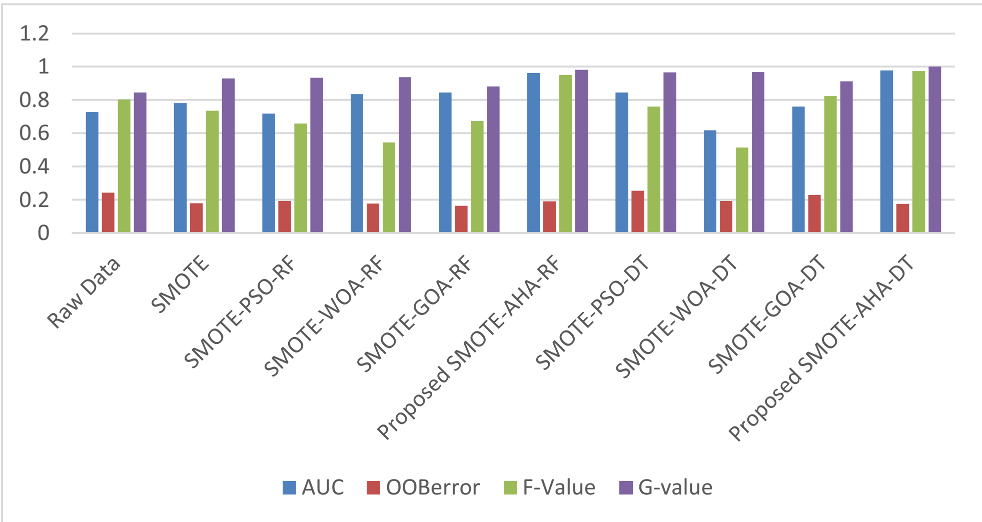


Fig. 14. Performances and rankings of proposed an optimized SMOTE with others under various k values. G-means, F-measures, AUC, and OOB^{error}.

6.3. Experiments of poultry behaviours prediction

For each predicted chicken behaviour, we determined whether it was a true positive (TP), true negative (TN), false positive (FP), or false negative (FN) based on how closely it matched the actual behaviour. Percent AUC, accuracy, F-measure, precision, and recall were used to assess these models' predictive efficiency.

For three behaviour datasets, RF, KNN, and Adaboost models showed high accuracies in classifying poultry pecking (99 %, 98 %, and 96 %, respectively), preening (98 %, 98 %, and 95 %, respectively), and dustbathing (99 %, 98 %, and 97 %, respectively) and RF method is considered the best model in terms of accuracy.

According to the research results, RF is the most effective classification model, with 90 % precision and recall when matching instances of the pecking behaviour. The second model, DT, matches instances of the pecking behaviour with a precision of 89 % and a recall of 90 %.

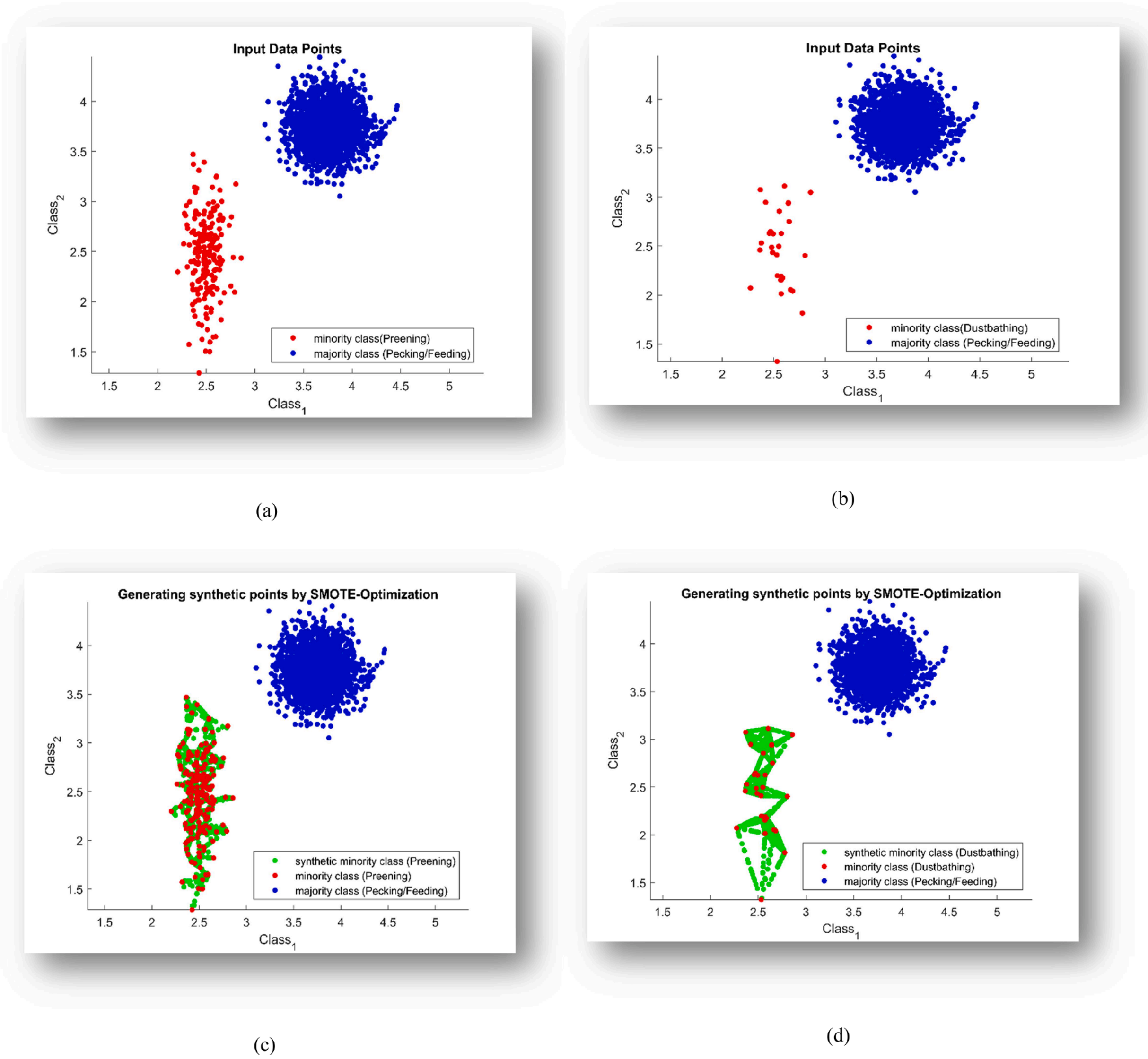


Fig. 15. Visualization of data points (feeding/pecking, preening, and dustbathing) before and after generating synthetic data points via an optimized SMOTE.

Table 9
Runtimes of all optimizations synthetic oversampling techniques under several iterations.

Algorithms \ Iterations	100	200	300	400	500	Overall
SMOTE	0.2131	0.3421	0.3616	0.3421	0.3612	1.6201
SMOTE-PSO-RF	0.2001	0.3349	0.2042	0.2301	0.2321	1.2014
SMOTE-WOA-RF	0.1914	0.1611	0.2421	0.2514	0.1442	0.9902
SMOTE-GOA-RF	0.2154	0.1963	0.1443	0.3465	0.4251	1.3276
Proposed SMOTE-AHA-RF	0.2834	0.1204	0.1028	0.2156	0.2301	**0.9523**
SMOTE-PSO-DT	0.3824	0.3677	0.2554	0.2214	0.2952	1.5221
SMOTE-WOA-DT	0.2231	0.2258	0.2364	0.1581	0.1287	0.9721
SMOTE-GOA-DT	0.2109	0.3607	0.1025	0.1645	0.2174	1.056
Proposed SMOTE-AHA-DT	0.1926	0.1862	0.2118	0.1265	0.1176	**0.8347**

Table 10 presents the results of the classification of pecking, preening, and dustbathing behaviours in the test dataset. According to the results of performance evaluation for each classification of poultry behaviours. ROC-AUC curve depicts in Fig. 17 according to the results of AUC for each classification models.

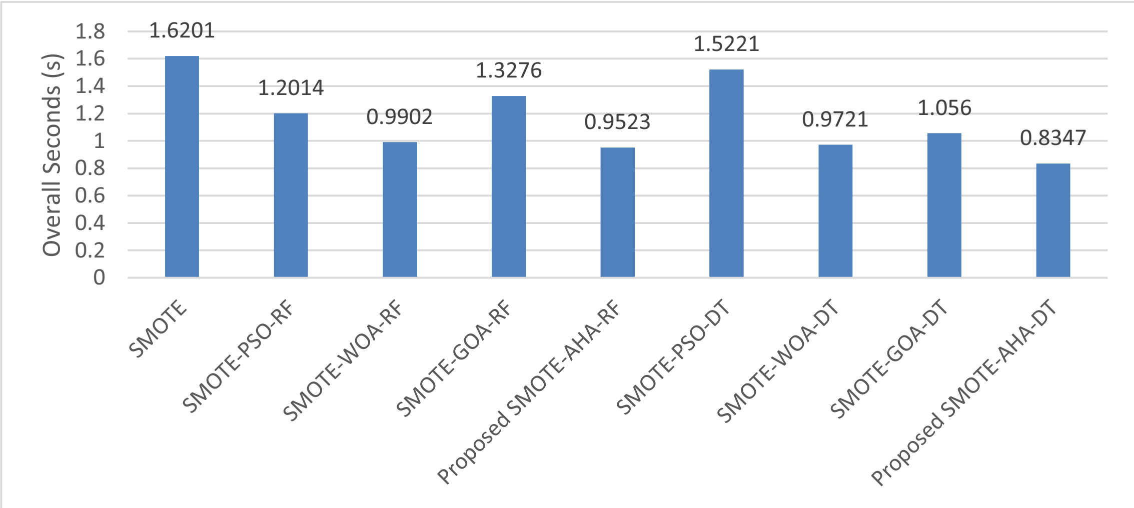


Fig. 16. Ranking of runtimes of all optimizations synthetic oversampling techniques.

Table 10
Different classification for chicken behaviours prediction.

Classification	Behaviour	AUC	Accuracy	F-measure	Precision	Recall
KNN	Pecking	0.983	0.887	0.885	0.886	0.887
	Preening	0.980	0.899	0.897	0.898	0.899
	Dustbathing	0.991	0.876	0.874	0.875	0.876
Decision Tree	Pecking	0.933	0.900	0.898	0.899	0.900
	Preening	0.948	0.912	0.910	0.911	0.912
	Dustbathing	0.976	0.889	0.887	0.888	0.889
Random Forest	Pecking	0.989	0.901	0.899	0.900	0.901
	Preening	0.983	0.913	0.911	0.912	0.913
	Dustbathing	0.994	0.890	0.888	0.889	0.890
Logistic Regression	Pecking	0.828	0.855	0.853	0.854	0.855
	Preening	0.890	0.867	0.865	0.866	0.867
	Dustbathing	0.495	0.844	0.842	0.843	0.844
Gaussain Naïve Bayes	Pecking	0.768	0.807	0.806	0.807	0.807
	Preening	0.876	0.819	0.818	0.819	0.819
	Dustbathing	0.861	0.796	0.795	0.796	0.796
AdaBoost	Pecking	0.959	0.894	0.893	0.893	0.894
	Preening	0.940	0.906	0.905	0.905	0.906
	Dustbathing	0.916	0.883	0.882	0.882	0.883

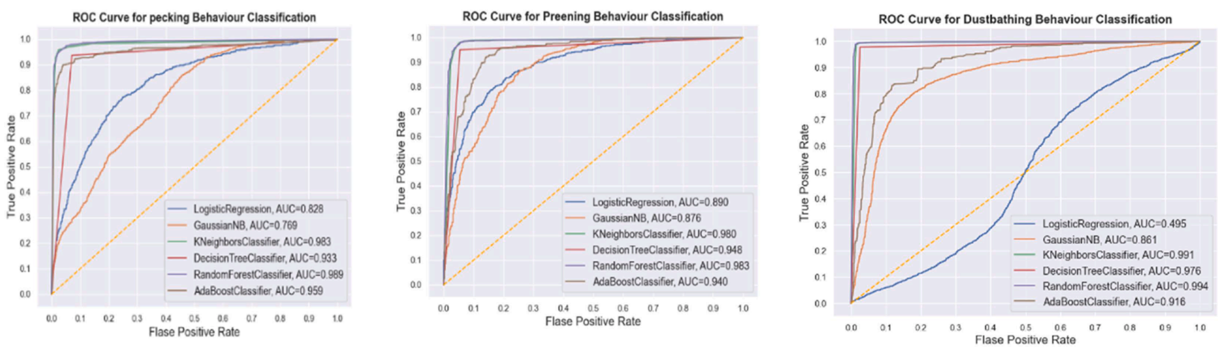


Fig. 17. ROC–AUC curve for each behaviour classification techniques.

The frequent aggregation of preening and dustbathing activities. Along the axis Ay, there is a noticeable concentration of preening and dustbathing occurrences. Because the sensor is in constant motion as the poultry moves, pecking events are spread out over a wider area. Because of how the sensor was built and how it moved when attached to Ay's back, the recorded motion was extremely useful for

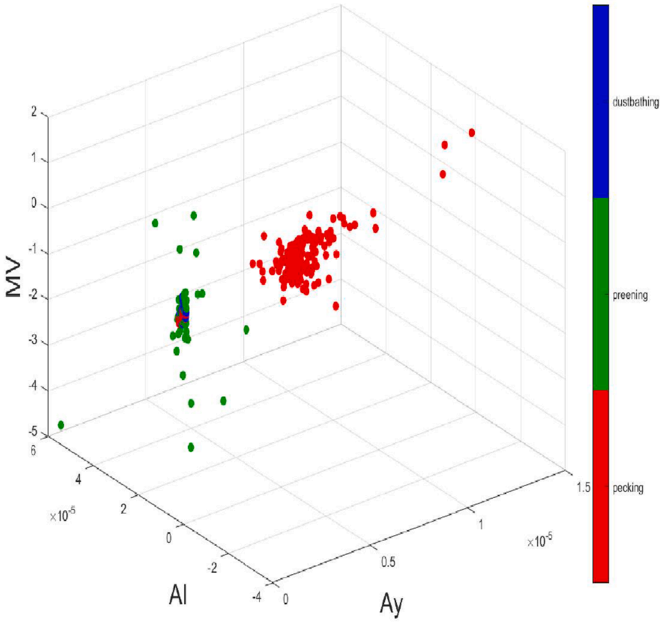


Fig. 18. Extracting behavioural features from the chicken's back accelerometer in a three-dimensional scatterplot, visualised via AI, Ay, and MV metrics.

differentiating between activity intensities and was especially useful for identifying dustbathing behaviour. Ay was able to detect and record the movement of the sensor caused by the preening behaviour of turning the head to the side. Fig. 18 data depicts that pecking behaviour can be distinguished from preening and dustbathing through the use of MV.

There was a clear separation of preening and preening events, as behavioural events for both activities occurred simultaneously Fig. 19. As a result, it becomes more difficult to tell these behaviours apart from others. Even though pecking events occur all over the place, the high prediction accuracy of this behaviour can be attributed to its isolation from other activities, as is especially evident

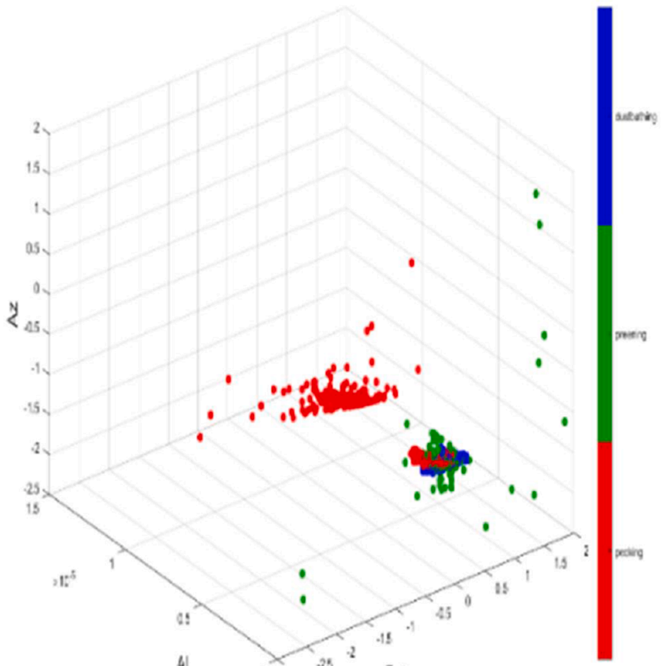


Fig. 19. Extracting behavioural features from the chicken's back accelerometer in a three-dimensional scatterplot, visualised via Az, AI and entropy metrics.

along the AI axis. Consequently, the AI metric can tell the difference between pecking, preening, and dust-bathing behaviours. By fusing signals from all directions, AI is able to determine the magnitude of a pecking motion, with the greater acceleration associated with pecking (particularly in the Z-axis plane) being recorded and used to distinguish it from the other three behaviours. The low sensitivity of dustbathing behaviours reflects the lack of a consistent categorization for these occurrences.

It became obvious that pecking and dustbathing behaviours did not fall into two distinct categories in Fig. 20. When comparing the intensity of movement during locomotion and resting postures, the MV metric proved invaluable. Due to the minimal distinction between preening and dustbathing, these two activities were inaccurately classified in Fig. 20. Because the X-axis clearly changes orientation when dustbathing, Ax has become an important metric for distinguishing between dustbathing and upright behaviour since its advent.

Fig. 21 shows the matching subsequence's for running the pecking, preening, and dustbathing behaviour in the test dataset which indicates in Fig. 21(a), (b), and (c), respectively. True positives are represented by green dots, while false positives by red ones.

6.4. Experiments for the diagnosis of poultry disease

As diseases cause significant economic losses in poultry production, they are of paramount importance. The costs associated with the disease can be reduced if it is detected and diagnosed quickly. We propose an algorithm for identifying sick chickens that can be used to reduce the spread of disease.

We examine the poultry dataset [30] about chickens over the course of a full day. We know that on the first day, all of the chickens were healthy and that on the second day, some chickens were sick (infested with ectoparasites). For this reason, it is essential that the proposed classification results provide a sufficient degree of confidence in their ability to differentiate between healthy and sick chickens.

Fig. 22 shows a chart depicting the frequency distribution of pecking behaviours across all of the chickens When observed, the subjects exhibited either a healthy state (indicated by the colour green) or a sick state (indicated by the colour red). The depicted figure demonstrates a certain degree of overlap between the peck counts of healthy and sick chickens.

The number of preening behaviours performed by each chicken, both when healthy (green) and when sick, is then analysed statistically (red). Based on the preening count alone, the proposed classifier accurately distinguishes between sick and healthy chickens, as evident from Fig. 23. The histogram of preening counts for healthy chickens exhibits a left-skewed distribution, whereas for sick chickens, it is concentrated more towards the middle and right. This observation underscores the reliable discriminatory ability of the algorithm in identifying the health status of chickens.

In Fig. 24, we compare the frequency of dustbathing between chickens in good health (green) and those in sick health (red).

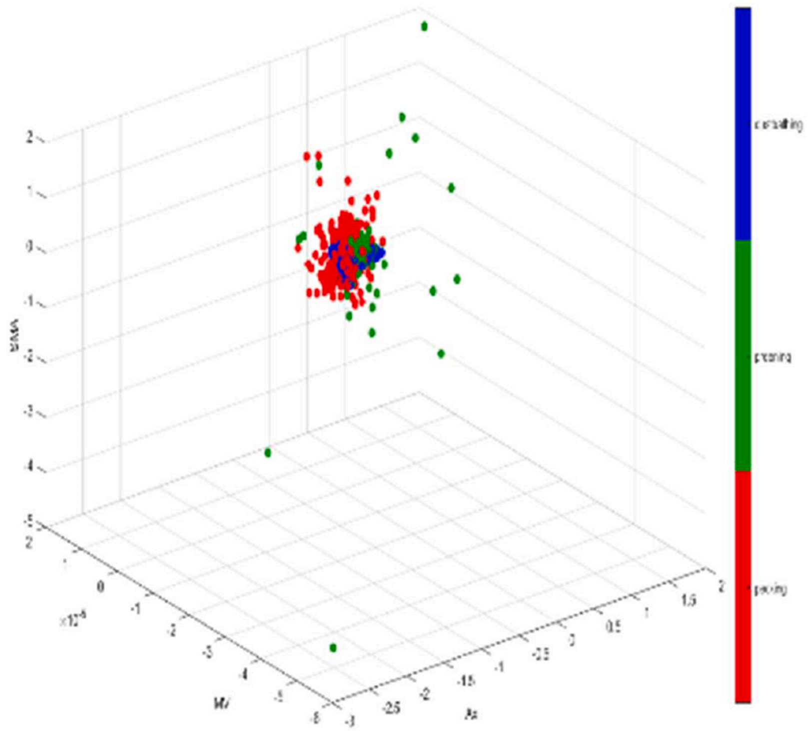


Fig. 20. Extracting behavioural features from the chicken's back accelerometer in a three-dimensional scatterplot, visualised via the Ax, SMA, and MV metrics.

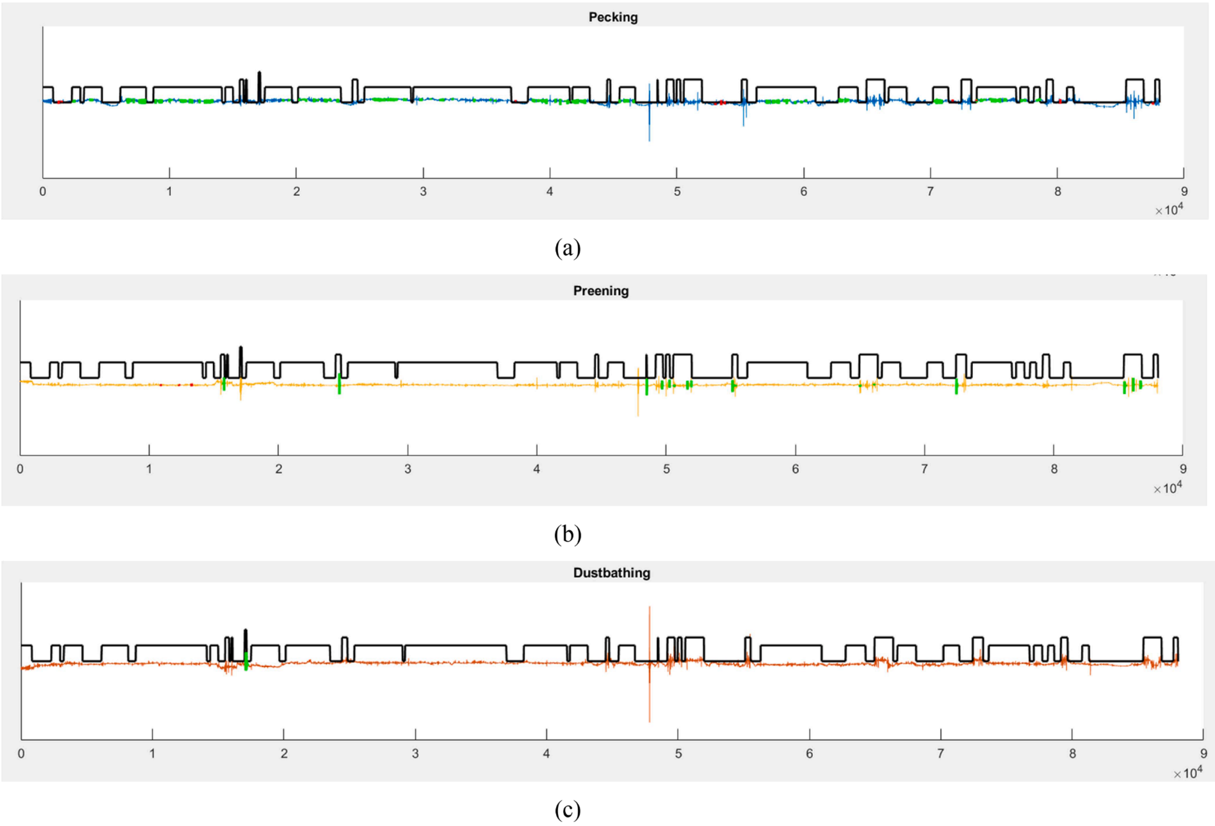


Fig. 21. Subsequence matching on the test set for feeding/pecking, preening, and dustbathing behaviours.

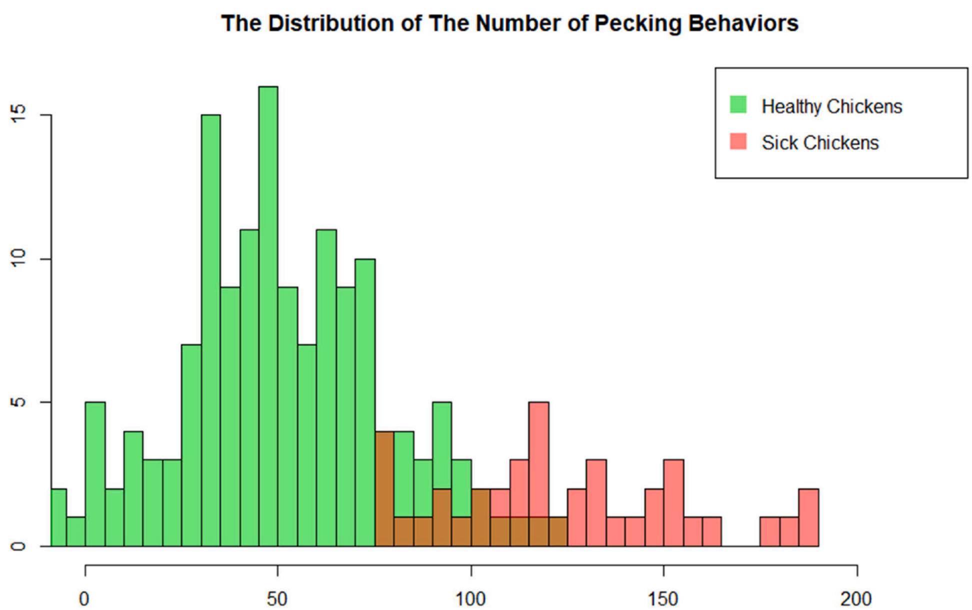


Fig. 22. Histogram for the number of pecking behaviours distribution.

Dustbathing is clearly more common on the left side of the histogram, which corresponds to healthy chickens. The dustbathing count for sick chickens which can be seen in the middle of the histogram. Overall, it appears that the pecking behaviour gives a sufficient degree of assurance in identifying healthy and sick chickens. Symptoms such as preening and dustbathing can be used as reliable

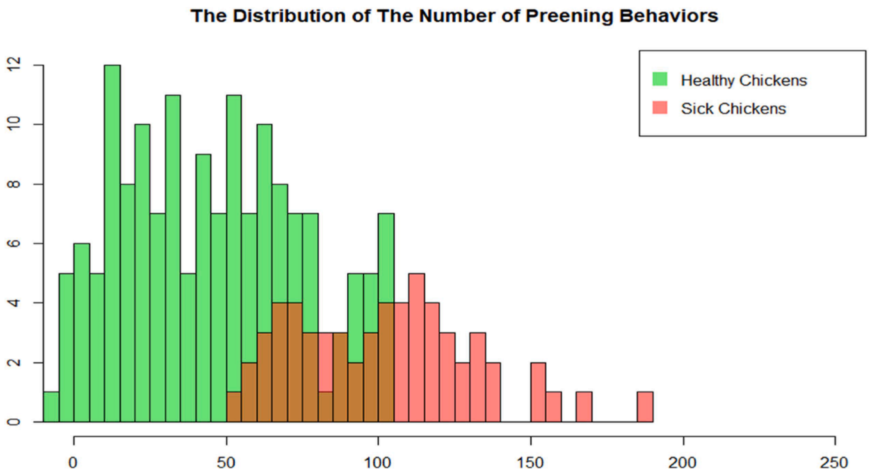


Fig. 23. Histogram for the number of peening behaviours distribution.

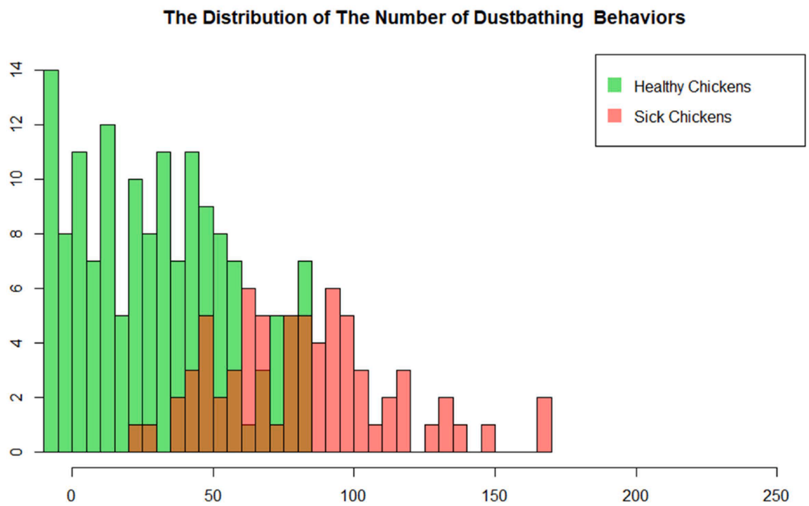


Fig. 24. Histogram for the number of dustbathing behaviours distribution.

indicators of whether or not a chicken is sick.

The evaluation of each supervised machine learning classification model's performance involves using metrics like Precision, Recall, F1-Score, and Accuracy. The effectiveness of the chosen classification models is summarized in Table 11 along with their percentages.

According to Table 11, which depicts different measures for each poultry behaviours prediction, the proposed classifier AHA-DT for pecking behaviour successfully distinguishes between sick as well as healthy poultry chicken in 98 % of the proposed study. On the real and made-up datasets for other classification models, when $K = 7$, the K-Nearest Neighbor (KNN) can accurately predict whether a chicken is healthy or sick by 79 %. Random Forest (RF) machine learning classifiers demonstrated well performance and yielded results with an accuracy of about 83 %, and Decision Tree also achieved a good accuracy of about 82 %. With an accuracy rate of 72 %, the SVM classification model performed the worst of all the techniques. With an accuracy rate of 80 %, logistic regression (LG) also achieves intermediate accuracy. With an accuracy of 80 %, Gaussian Naive Bayes classification outperformed KNN little. The accuracy of the AHA-DT is 98.63 %, and the accuracy of the AHA-RF is 94.14 %. The AHA-DT method stands out with the most significant impact on accuracy. This approach exhibits notable benefits in terms of its strong generalization capability and robustness when addressing poultry prediction scenarios. According to results of accuracy for each classification model according to pecking/feeding, preening, and dustbathing behaviours, respectively. The proposed AHA-DT overcomes all other classification models until another proposed AHA-RF reveals the true power of evolutionary algorithms. Finally, the results compare with SVM, KNN, LG, GNB, DT, and RF classification algorithms.

Table 11
Percentage measurements for different classification prediction of disease.

Behaviours	Classification models	Accuracy	Precision	Recall	F-score
Pecking/Feeding Prediction	K-Nearest Neighbor (KNN)	0.798	0.798	0.799	0.795
	Random Forest (RF)	0.839	0.832	0.842	0.839
	Decision Tree (DT)	0.827	0.824	0.825	0.824
	Support Vector Machine (SVM)	0.719	0.745	0.735	0.718
	Logistic Regression (LG)	0.805	0.807	0.808	0.803
	Gaussian Naive Bayes (GNB)	0.826	0.831	0.827	0.823
	Proposed AHA-DT	**0.986**	**0.989**	**0.994**	**0.983**
	Proposed AHA-RF	**0.941**	**0.893**	**0.871**	**0.876**
Preening Prediction	K-Nearest Neighbor (KNN)	0.773	0.773	0.774	0.77
	Random Forest (RF)	0.814	0.807	0.817	0.814
	Decision Tree (DT)	0.802	0.799	0.8	0.799
	Support Vector Machine (SVM)	0.694	0.72	0.71	0.693
	Logistic Regression (LG)	0.780	0.782	0.783	0.778
	Gaussian Naive Bayes (GNB)	0.801	0.806	0.802	0.798
	Proposed AHA-DT	**0.961**	**0.964**	**0.969**	**0.958**
	Proposed AHA-RF	**0.916**	**0.868**	**0.846**	**0.851**
Dustbathing Prediction	K-Nearest Neighbor (KNN)	0.744	0.744	0.745	0.741
	Random Forest (RF)	0.785	0.778	0.788	0.785
	Decision Tree (DT)	0.773	0.77	0.771	0.77
	Support Vector Machine (SVM)	0.665	0.691	0.681	0.664
	Logistic Regression (LG)	0.751	0.753	0.754	0.749
	Gaussian Naive Bayes (GNB)	0.772	0.777	0.773	0.769
	Proposed AHA-DT	**0.932**	**0.935**	**0.941**	**0.929**
	Proposed AHA-RF	**0.887**	**0.839**	**0.817**	**0.822**

7. Conclusion and future work

The poultry industry needs an automatic system to improve the productivity of healthy birds, keep track of their health, and predict disease outbreaks before the disease occurs. This paper proposes the smart poultry monitoring system, empowered by IoT sensors, which effectively gauges the health status of chickens, whether sick or healthy, according to their behaviour. The objectives of the proposed system are: (1) selecting the best features from extracted features; (2) proposing an oversampling-based optimization to balance the data through the utilization of SMOTE through an optimization technique called the Artificial Hummingbird Algorithm (AHA); (3) predicting poultry behaviours that assist stakeholders in making decisions for the health of poultry; and (4) detection of poultry disease by behaviour analysis. The conclusion that has been extracted from the results of the classification of poultry behaviour is that RF achieved the best results and diagnosis of poultry disease by optimizing decision tree classification via AHA-DT, which is superior and outperforms other techniques with the highest level of classification accuracy of 97.6 %.

In future work, we will extend SMOTE into multi-objective problem to deal with multi-classification imbalanced datasets due to the fact that in real-world applications, the issue of imbalanced datasets affects both binary and multi-classifications.

Ethics approval

The authors herewith do confirm that this manuscript has not been published elsewhere and is not also under consideration by the other journals.

Consent to participate

All the authors have seen and approved the content of the submitted manuscript.

Consent to publish

All the authors consent to publish the final manuscript.

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CRediT authorship contribution statement

Mohammed Mostafa Ahmed: Conceptualization, Data curation, Formal analysis, Investigation, Software, Visualization, Writing – original draft, Writing – review & editing. **Ehab Ezat Hassanien:** Supervision, Investigation, Resources, Writing – review & editing. **Aboul Ella Hassanien:** Conceptualization, Data curation, Formal analysis, Investigation, Supervision, Validation, Resources, Writing

– review & editing.

Declaration of Competing Interest

The authors declare no competing interests.

Data availability

Data will be made available on request.

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