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Predictive modelling for rabbit health monitoring system using machine learning techniques

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Abstract

The early detection and continuous monitoring of rabbit health are vital for improving animal welfare, reducing mortality, and enhancing farm productivity. This research presents a predictive modelling framework for rabbit health monitoring using machine learning techniques, specifically Logistic Regression, Random Forest, and K-Nearest Neighbors (KNN). The proposed system integrates a structured data pipeline encompassing data preprocessing, feature engineering, vector representation, model training, and evaluation. A dataset comprising physiological and behavioral features was collected and used to train and test the models. Evaluation metrics such as accuracy, precision, recall, F1 score, and ROC-AUC were employed to assess model performance. Among the three models, Random Forest achieved the highest performance with an accuracy of 99%, F1 score of 99.16%, and ROC-AUC of 99.96%, demonstrating exceptional capability in detecting unhealthy rabbits. KNN and Logistic Regression also performed reasonably well but showed limitations in sensitivity and overall predictive power. The findings suggest that Random Forest is the most reliable model for real-time health monitoring in rabbits, offering a promising tool for smart farming and veterinary applications.

Keywords: Predictive modelling; Livestock Disease Detection; Machine Learning; Supervise Learning; Rabbit health

1. Introduction

Over the past decade, advances in machine learning (ML) and data science have revolutionized numerous sectors, including healthcare and veterinary medicine. These technologies have enabled the development of sophisticated predictive models capable of analyzing large-scale data, offering real-time insights, and facilitating proactive interventions in the management of animal health. Among small companion animals, rabbits present unique challenges for veterinary care due to their delicate and often difficult-to-diagnose health conditions [1]. Despite their widespread popularity as pets and their economic importance in agriculture, particularly in meat and fur production, rabbits are prone to a range of diseases that are difficult to diagnose early without clinical intervention [2]. Thus, there is a critical need for advanced health monitoring systems that can predict and mitigate these health risks, ultimately enhancing animal welfare and reducing mortality rates.

Rabbits are particularly susceptible to a variety of health conditions, such as gastrointestinal stasis, respiratory infections, and dental issues, many of which can escalate quickly and result in severe complications if not addressed promptly [3]. Traditional diagnostic approaches often rely on physical examinations and symptom recognition, which can be insufficient, especially for diseases that present only subtle early warning signs. Consequently, there has been a growing interest in developing automated, data-driven systems that can track a rabbit's health in real-time, offering early alerts for potential health issues based on predictive models.

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Machine learning techniques, with their ability to analyze complex, multi-dimensional data, are well-suited for this task. By leveraging large datasets from diverse sources, including behavioral patterns, environmental conditions, biometric data (e.g., heart rate, temperature), and clinical histories, ML models can identify hidden patterns that may not be apparent to human observers. These predictive models can then forecast potential health issues before they become critical, allowing for timely intervention and improving the overall well-being of the rabbit [5].

In particular, a variety of ML algorithms have shown promise in animal health applications. For example, decision trees and random forests are widely used due to their ability to handle both categorical and continuous variables, making them ideal for clinical decision support systems [5]. Support vector machines (SVM), on the other hand, are well-suited for classification tasks and have been used to categorize animal health conditions based on physiological parameters [6]. Furthermore, more recent developments in deep learning, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated their potential for handling unstructured data, such as images and time-series data, thereby enabling the prediction of diseases with high accuracy [7].

As the availability of data from sensors and wearable devices for animal health monitoring increases, these systems have become more practical and accessible. For instance, smart collars, wearable activity trackers, and environmental sensors can continuously monitor vital statistics such as body temperature, movement, and heart rate, feeding real-time data into machine learning models [2]. By training predictive models on this continuously updated data, it becomes possible to detect early signs of distress or disease, such as sudden changes in behavior, activity levels, or physiological metrics, which may indicate the onset of health problems like dehydration or stress-induced conditions.

While the concept of predictive health monitoring has been successfully applied to livestock and pets such as dogs and cats, its implementation in rabbits remains underexplored. The unique biological characteristics of rabbits, coupled with the absence of standardized health monitoring protocols for the species, make the development of such systems more challenging [1]. However, with the right integration of technology and machine learning techniques, predictive models for rabbit health have the potential to offer significant improvements in early disease detection, personalized care, and overall animal welfare management.

The objective of this paper is to explore the potential of predictive modelling using machine learning techniques for rabbit health monitoring systems. We focus on the application of various ML algorithms to model and predict common health issues in rabbits, highlighting the benefits, challenges, and future directions for such systems. Specifically, we examine the role of feature engineering, model selection, and the integration of sensor data in creating robust predictive tools that can be utilized by veterinarians, researchers, and pet owners alike. We aim to establish the foundation for a comprehensive, scalable rabbit health monitoring framework that can reduce the reliance on traditional, reactive care models and shift toward more proactive, data-driven healthcare for rabbits.

2. Related Works

Due to the advance technologies and recent techniques of ML, various studies have been conducted to examine the real-time health monitoring data of various animals, mainly on early disease detection and initial therapy plan. Nevertheless, less works has been conducted in the area of rabbit health monitoring system. Hence, this study aims to explore the ML techniques that are appropriate in predicting rabbit health condition. This section reviews works that have been conducted in the field of machine learning applications for animal health, focusing specifically on predictive techniques, sensor-based monitoring, and early diagnosis, with an emphasis on gaps and opportunities for rabbit health.

2.1. Machine Learning in Veterinary Health Monitoring

Machine learning has shown substantial promise in improving diagnostic accuracy, predicting health risks, and providing insights for veterinary care [5]. One prominent approach in veterinary predictive modelling is the use of supervised learning algorithms, such as decision trees and support vector machines (SVM), to predict health outcomes based on various features like physiological parameters, activity levels, and environmental factors [5]. For example, models trained on data from cattle and poultry farms have successfully predicted outbreaks of diseases like avian influenza and bovine tuberculosis, enabling early intervention [4]. These studies highlight the potential for similar approaches to be applied to rabbits, leveraging their unique physiological data to forecast health conditions.

Additionally, deep learning algorithms, particularly convolutional neural networks (CNNs), have been applied to analyze images for disease detection in veterinary practice. For example, CNNs have been employed in skin lesion classification and detection of pneumonia in livestock [7]. While such approaches have been widely explored in larger

animals, applying deep learning techniques for more subtle and complex health issues in rabbits, such as gastrointestinal stasis or dental problems, remains an underexplored area.

2.2. Sensor-Based Monitoring and Real-Time Health Data

Wearable technology has revolutionized the field of animal health monitoring. Devices such as GPS collars, heart rate monitors, and accelerometers have become increasingly common in veterinary applications. These sensors provide continuous, real-time data, which is crucial for detecting early signs of health problems. In rabbits, wearable devices like activity trackers can be used to monitor key health indicators such as physical activity, feeding behavior, and body temperature. By analyzing these data streams using ML algorithms, researchers can identify behavioral changes that correlate with health issues such as gastrointestinal stasis, dehydration, and stress [1].

Several studies have demonstrated the effectiveness of sensor-based monitoring systems in other small mammals and livestock. For example, a study by [4] used wearable sensors to monitor the activity levels and body temperature of pigs, developing predictive models that could identify the onset of illness based on sudden changes in behavior. Similarly, wearable technology for rabbits could offer an analogous framework, providing veterinarians and pet owners with real-time alerts about health changes and enabling prompt intervention.

2.3. Challenges and Opportunities for Rabbit Health Prediction

One of the main challenges in developing predictive models for rabbit health lies in the complexity of their physiological systems and the relatively small amount of data available for training robust models. Rabbit health data are often sparse, and large-scale datasets that combine sensor data with clinical records are lacking. Unlike larger livestock or even cats and dogs, rabbits are not as commonly studied in veterinary informatics, which complicates the task of creating generalizable health models [3]. Furthermore, differences in breed, age, diet, and environmental factors can introduce significant variability in health outcomes, which makes predictive modelling more challenging.

Despite these challenges, the increasing availability of advanced sensors, mobile health devices, and cloud computing platforms presents an opportunity to overcome data limitations and build scalable health monitoring systems. Integrating sensor data with electronic health records and environmental information could facilitate the development of accurate, dynamic predictive models for rabbit health.

3. Methodology

This section provides detail description on research framework used in predicting rabbit health monitoring system using ML techniques. There are several phases involved in this framework which include a) data collection, b) data pre-processing, c) feature engineering, d) vector representation, e) ML modelling and evaluation and f) visualization. The research framework is depicted in Figure 1 and detail information is given in below section.

3.1. Data Collection

Data collection is an essential step in this research. A robust and representative dataset is crucial for an effective ML development. This primary dataset is obtained from veterinary clinic located at Changlun, Sintok, Kedah. For the development of a predictive model tailored to rabbit health, the dataset collection process is meticulously designed to capture diverse physiological, environmental, and behavioral parameters relevant to the health status of rabbits.

The dataset was compiled from multiple sources to ensure comprehensiveness and reliability:

- **Veterinary Records:** Clinical records were obtained from veterinary hospitals and rabbit care centers, including diagnoses, treatments, and outcomes.
- **On-farm Monitoring Systems:** Data was collected using IoT-enabled sensors placed in rabbit enclosures to continuously monitor temperature, humidity, activity levels, heart rate, and respiratory rate.

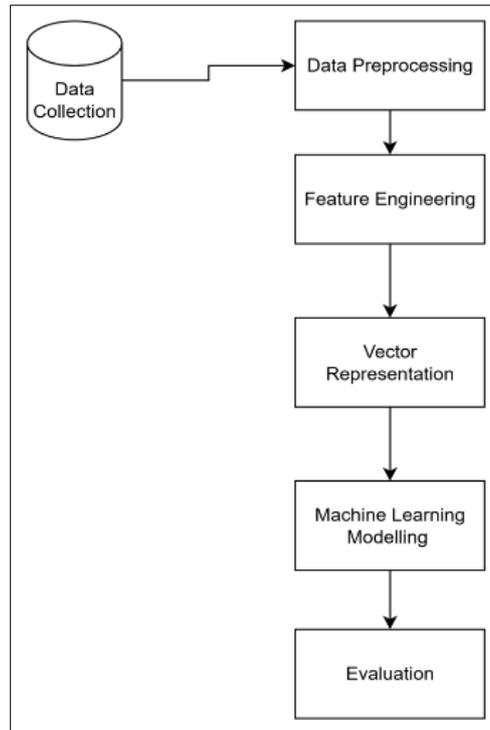


Figure 1 Research framework for Rabbit Health Monitoring System

- **Manual Observations:** Trained personnel recorded periodic observational data such as appetite, fur condition, mobility, eye clarity, and faecal consistency (dropping condition), which are often related as early indicators of illness.

The data collected for this research provides a good baseline of 500 records to build a predictive model that help in monitoring rabbit health. This kind of data helps us understand how a healthy rabbit behaves and makes it easier to spot signs when something is wrong with the rabbits. For example, if a rabbit's activity level or hydration suddenly drops, it might indicate that the rabbits are getting sick. The environmental data also helps to explore other factors such hot or humid weather may affect rabbits' health. Overall, this dataset provides useful information to train a machine learning model to detect early illness that might occurs in rabbits. This will make it easier for farmers to take care of their rabbits before problems get worse.

3.2. Data Preprocessing

Data preprocessing involves several key steps aimed at enhancing the quality of the data. First, cleaning is an essential process where incomplete or erroneous data is removed, and any missing values are handled either by imputing (filling in) the missing data or eliminating the affected entries altogether. Next, normalization and standardization are applied to ensure consistency in the dataset. For instance, textual data may be scaled to a range of 0 to 1, ensuring that all variables are on a similar scale and preventing any one feature from disproportionately influencing the subsequent analysis.

3.3. Feature Engineering

Feature engineering is the process of using domain knowledge to select, modify, or create new features from raw data that will help improve the performance of machine learning models. Essentially, it's about transforming raw data into a more useful format that can better capture the underlying patterns or relationships in the data, making it easier for algorithms to learn from it. In this study, Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) are used in determining important features that predict rabbit's health condition. PCA is used to reduce number of feature while keeping the data variability and RFE is employed to select the most predictive features and removing the unnecessary features. Hence, several features have been selected based on its important as depicted in Figure 2.

```
In [7]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 17 columns):
#   Column                Non-Null Count  Dtype
---  ---                -
0   Rabbit_ID             500 non-null    object
1   Body_Temperature_C    500 non-null    float64
2   Heart_Rate_bpm        500 non-null    int64
3   Activity_Level        500 non-null    int64
4   Feeding_Status        500 non-null    object
5   Weight_kg             500 non-null    float64
6   Respiration_Rate_bpm  500 non-null    int64
7   Env_Temperature_C     500 non-null    float64
8   Env_Humidity_%        500 non-null    float64
9   Health_Status         500 non-null    object
10  Ear_Temperature_C     500 non-null    float64
11  Hydration_Level_%     500 non-null    float64
12  Nasal_Discharge       93 non-null     object
13  Eye_Condition         500 non-null    object
14  Fur_Condition         500 non-null    object
15  Droppings_Condition   500 non-null    object
16  Alertness_Level       500 non-null    int64
dtypes: float64(6), int64(4), object(7)
```

Figure 2 Features used in this study

4. Vector representation

Vector representation refers to the process of converting objects such as words into numerical vectors, typically in the form of arrays of numbers. These vectors capture the characteristics of the original data in a way that makes it easier for ML algorithms to process and understand. In this study, we have used one-hot-encoding technique to convert categorical variables into binary vectors. For instance, in this research the following features have been converted to numerical values prior subsequent analysis

Features	Before vectorization value	After vectorization value
Feeding status	{Normal, Reduced}	{1,2}
Health Status	{Healthy, Sick}	{1,0}
Nasal Discharge	{Normal, Mild, Severe}	{0,1,2}
Eye Condition	{Clear, Redness}	{0,1}
Dropping Condition	{Normal, Soft}	{0,1}

Figure 3 One-hot encoding technique

4.1. Machine Learning Modelling

In this study, ML plays an important role in building predictive models to assess rabbit health based on physiological and behavioral data. Logistic Regression, Random Forest, and K-Nearest Neighbors (KNN) have been used in this study as they offer a balance between interpretability, accuracy, and computational efficiency. Moreover, these models were chosen due to their proven effectiveness in biomedical and animal health domains [8].

4.1.1. Logistic Regression

Logistic Regression (LR) is a statistical model widely used for binary classification tasks. It estimates the probability that a given input belongs to a particular class using the logistic function. In the context of rabbit health, LR can predict whether a rabbit is “healthy” or “unhealthy” based on features such as temperature, heart rate, activity level, and feeding behavior. The model outputs a probability between 0 and 1, allowing for a threshold-based decision.

Despite its simplicity, LR is effective for problems where the relationship between the dependent variable and the independent features is approximately linear. Moreover, its coefficients can provide insights into the significance of various predictors, enhancing the interpretability of the model [7,9].

4.1.2. Random Forest

Random Forest (RF) is an ensemble learning technique that constructs a multitude of decision trees during training and outputs the mode of the classes for classification tasks. RF is robust to overfitting and can handle both numerical and categorical variables, making it suitable for complex health datasets involving rabbit behavior and vital signs.

One of the key advantages of RF is its ability to handle missing values and noisy data, which is often encountered in animal health monitoring environments. Additionally, it provides measures of feature importance, allowing researchers to identify the most influential health indicators [10].

4.1.3. K-Nearest Neighbors (KNN)

K-Nearest Neighbors is a non-parametric, instance-based learning algorithm that classifies an instance based on the majority class among its k closest neighbors in the feature space. For rabbit health prediction, KNN can detect abnormalities by comparing the current physiological parameters of a rabbit with historical data of similar conditions.

KNN is particularly useful in scenarios where the decision boundary is highly nonlinear. However, it is sensitive to the choice of k and the distance metric used. Proper normalization and dimensionality reduction (e.g., PCA) may be applied to enhance its performance in high-dimensional health datasets [8].

4.2. Evaluation

To assess the effectiveness of the predictive models developed for rabbit health monitoring, a set of standard classification evaluation metrics were employed. These include the confusion matrix, precision, recall, F1-score, and Receiver Operating Characteristic (ROC) curve with Area Under the Curve (AUC). These metrics provide both threshold-based and probabilistic insights into the performance of each model.

4.2.1. Confusion Matrix

The confusion matrix summarizes the model's classification results by presenting the counts of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). In this study, a TP represents correctly predicted unhealthy rabbits, while a TN corresponds to correctly predicted healthy rabbits. FP and FN represent misclassifications. This matrix is crucial for understanding the types of errors made by each classifier, particularly in medical or veterinary contexts where false negatives (undetected illness) may have critical consequences.

4.2.2. Precision

Precision is defined as the ratio of true positives to the sum of true and false positives:

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

High precision indicates that when the model predicts a rabbit as unhealthy, it is often correct. This is especially important in minimizing false alarms, which could lead to unnecessary interventions.

4.2.3. Recall (Sensitivity)

Recall, also known as sensitivity, is the ratio of true positives to the sum of true positives and false negatives

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

A high recall value ensures that the model detects most cases of actual illness, making it essential for health-critical applications, where failing to identify an unhealthy rabbit could be harmful.

4.2.4. F1-Score

The F1-score is the harmonic mean of precision and recall:

$$F1\ Score = 2 * \frac{precision * recall}{precision + recall}$$

This metric balances the trade-off between precision and recall. It is particularly useful in datasets with class imbalance, which is common in health-related prediction problems.

4.2.5. Receiver Operating Characteristic (ROC) and AUC

The ROC curve plots the true positive rate (recall) against the false positive rate at various classification thresholds. The AUC measures the entire two-dimensional area underneath the ROC curve and represents the probability that a randomly chosen positive instance ranks higher than a randomly chosen negative one.

A model with an AUC close to 1.0 indicates excellent discriminatory ability, while an AUC of 0.5 suggests random guessing. ROC analysis provides a visual representation of a classifier's performance across thresholds and is widely used in medical diagnosis and animal health monitoring.

4.3. Experimental Results and Discussion

A health prediction system using machine learning is developed to help farmers solve these issues. By analyzing related data such as body temperature, activity level, feeding status, and many more, the system can help monitor their health. This can help farmers take early action needed that can improve the rabbits' health. Prior model development, distribution of our dataset is tested to ensure the data is relevance enough for subsequent analysis. Figure 4 shows the distribution of some of features in our dataset.

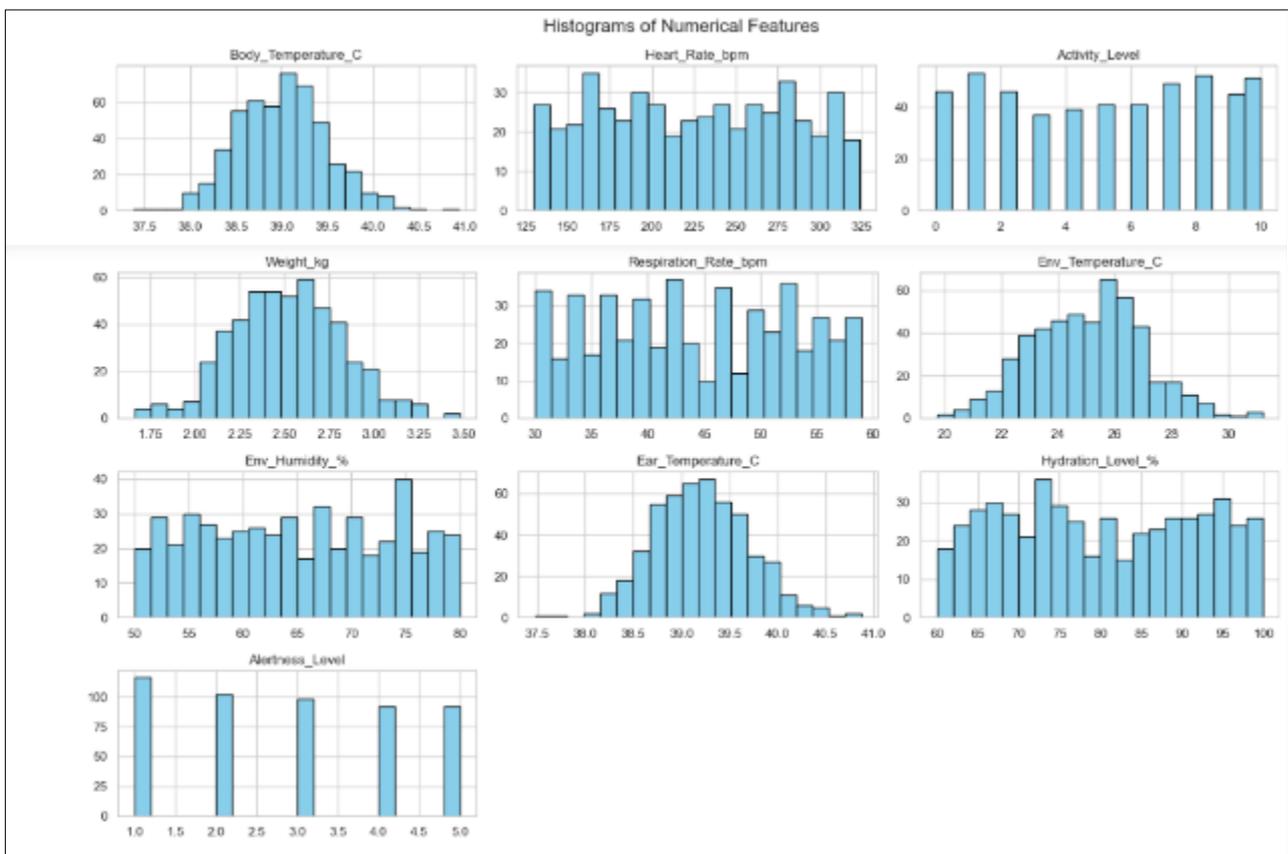


Figure 4 Distribution of some of features in our dataset

To build the system, we will be using logistic regression, a simple yet fast model that can predict the outcome of whether a rabbit is ill or healthy. It also helps us in understanding which features have the most impact in making the prediction. Additionally, we also use random forest, which can improve the accuracy when combined with a decision tree. The algorithm performs well with large data and handles noisy data well. K-Nearest Neighbors was used too, as it is suitable in comparing rabbits with similar health features. This dataset contains 500 rows and 16 columns, including body

temperature, heart rate, hydration level, activity level, and environmental factors. The target variable will be the Unhealthy Status. Figure 5 shows the import code for rabbit dataset.

```

from sklearn.model_selection import train_test_split

# Features and target variable
X = df.drop("Health_Status", axis=1)
y = df["Health_Status"]

# Encode target (category)
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
y_encoded = le.fit_transform(y) # Healthy = 0, Ill = 1

# Perform stratified split
X_train, X_test, y_train, y_test = train_test_split(
    X, y_encoded, test_size=0.2, stratify=y_encoded, random_state=42
)

```

Figure 5 Import code for rabbit dataset

Table 1 Parameter setting for the three models

Models	Parameter Settings
Logistic Regression	Regularization = L2, C = 1.0
Random Forest	n_estimators = 100, max_depth = 10
KNN	k = 5, distance metric = Euclidean

The hyperparameters were tuned using GridSearchCV with 5-fold cross-validation. Parameter setting for the three models are given in Table 1. The code for models' evaluation is given in Figure 6.

```

models = {
    "Logistic Regression": logreg_grid,
    "Random Forest": rf_random,
    "KNN": knn_grid
}

for name, model in models.items():
    y_pred = model.predict(X_test)
    print(f"\n{name} Evaluation:")
    print(classification_report(y_test, y_pred))
    print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
    if hasattr(model, "predict_proba"):
        y_prob = model.predict_proba(X_test)[: , 1]
    else:
        y_prob = model.decision_function(X_test)
    print("ROC-AUC:", roc_auc_score(y_test, y_prob))

```

Figure 6 Code for models' evaluation

Logistic Regression provided reasonable performance and high interpretability, making it a good candidate for resource-constrained environments or for use by non-technical stakeholders such as veterinarians as shown in Figure 6. However, it underperformed on non-linear feature interactions.

The Random Forest classifier on the other hands has outperformed the other models across all metrics as depicted in Figure 8. Its ensemble-based structure enabled it to handle nonlinear relationships and complex feature interactions effectively. The feature importance scores also highlighted that body temperature, stool quality, and activity level were the most significant indicators of rabbit health.

Furthermore, KNN performed well but was slightly less accurate than Random Forest as given in Figure 9. Its performance depends heavily on the value of k and the scale of input features. Since it is an instance-based learner, prediction times were slower, especially with increasing data size.

```

Logistic Regression Evaluation:
      precision    recall  f1-score   support

   0       0.74      0.85      0.80      41
   1       0.89      0.80      0.84      59

 accuracy          0.82      100
 macro avg         0.82      0.83      0.82      100
 weighted avg      0.83      0.82      0.82      100

Confusion Matrix:
[[35  6]
 [12 47]]
ROC-AUC: 0.9222819346837536
    
```

Figure 7 Logistic Regression models' evaluation

```

Random Forest Evaluation:
      precision    recall  f1-score   support

   0       1.00      0.98      0.99      41
   1       0.98      1.00      0.99      59

 accuracy          0.99      100
 macro avg         0.99      0.99      0.99      100
 weighted avg      0.99      0.99      0.99      100

Confusion Matrix:
[[40  1]
 [ 0 59]]
ROC-AUC: 0.9995866060355518
    
```

Figure 8 Random Forest models' evaluation

```

KNN Evaluation:
      precision    recall  f1-score   support

   0       0.78      0.95      0.86      41
   1       0.96      0.81      0.88      59

 accuracy          0.87      100
 macro avg         0.87      0.88      0.87      100
 weighted avg      0.89      0.87      0.87      100

Confusion Matrix:
[[39  2]
 [11 48]]
ROC-AUC: 0.9578338156262919
    
```

Figure 9 KNN for models' evaluation

Confusion matrix is another technique to visualize how the models performed by plotting the true vs. predicted labels. They show the model's errors (false positives and false negatives) and successes (true positives and true negatives) as

given in Figure 10. In the case of Logistic Regression, the model correctly classified 35 healthy rabbits and 47 unhealthy rabbits, indicating a reasonable balance between identifying both classes. However, it misclassified 12 unhealthy rabbits as healthy, which is concerning in a health monitoring context whereby failing to detect illness can have serious consequences. The presence of 6 false positives also shows that a few healthy rabbits were incorrectly flagged as unhealthy, which might lead to unnecessary interventions. This result suggests that while Logistic Regression performs moderately well, it struggles to capture the complex, potentially nonlinear relationships in physiological data associated with rabbit health.

Random Forest, on the other hand, achieved the most accurate classification performance among all the models. It correctly identified all 59 unhealthy rabbits and 40 out of 41 healthy rabbits, with only a single false positive. This near-perfect classification outcome reflects Random Forest's strength in handling both linear and nonlinear patterns by aggregating multiple decision trees. Its ensemble nature contributes to its robustness and high generalization capability, making it especially suitable for health-related prediction tasks where accuracy and recall are crucial.

The K-Nearest Neighbors (KNN) model demonstrated good classification ability as well, identifying 48 unhealthy rabbits and 39 healthy rabbits correctly. However, it misclassified 11 unhealthy rabbits as healthy, which raises concerns similar to those observed in Logistic Regression. While its number of false positives was low (only two cases), the relatively higher count of false negatives indicates that KNN may not be the best choice when the primary goal is to maximize the detection of at-risk rabbits. This limitation could stem from the model's sensitivity to the choice of k and the structure of the feature space, especially in datasets with overlapping class distributions or unnormalized data.

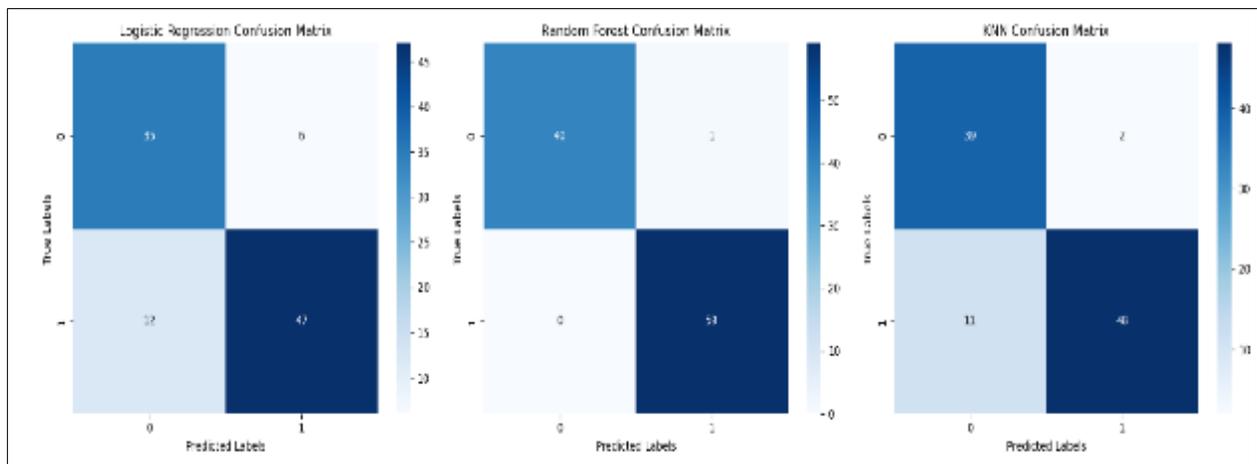


Figure 10 Confusion matrices for all models

Additionally, the ROC-AUC scores show in Figure 11 indicates that all models maintained strong discriminative power, with Random Forest outperformed other models. The Random Forest model exhibits an AUC of 1.00, which is the highest possible score and indicates perfect classification performance. Its ROC curve hugs the top-left corner tightly, demonstrating that at almost every threshold, the model maintains both a high true positive rate and a very low false positive rate. This aligns with the earlier confusion matrix results, where Random Forest achieved 100% sensitivity (no false negatives) and nearly perfect specificity. Such performance highlights Random Forest's suitability for health monitoring systems, where detecting all actual cases of illness is critical.

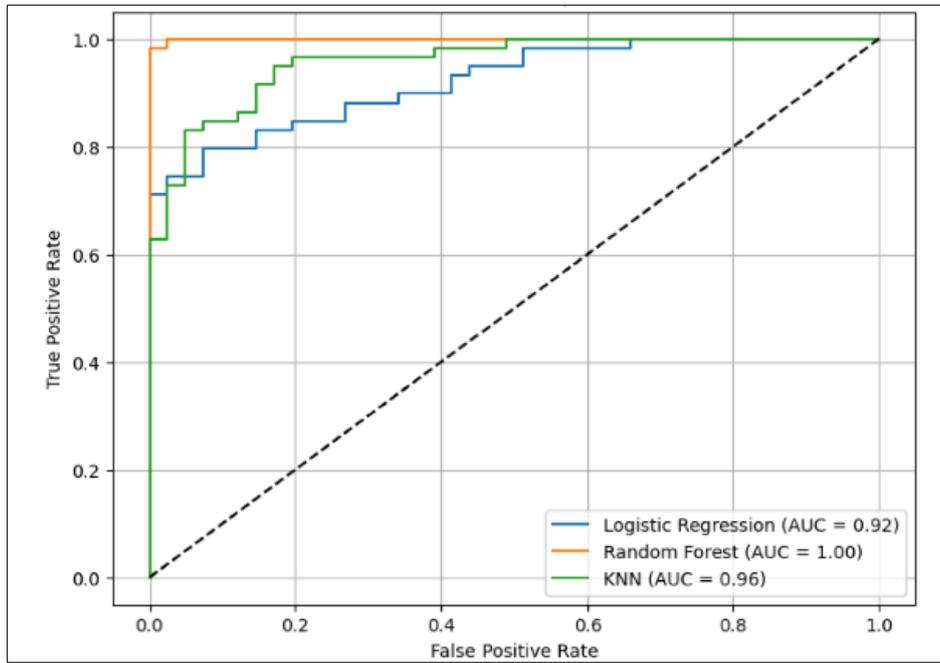


Figure 11 ROC Curve for models' evaluation

	Model	Accuracy	Precision	Recall	F1 Score	ROC AUC
1	Random Forest	0.99	0.983333	1.000000	0.991597	0.999587
2	KNN	0.87	0.960000	0.813559	0.880734	0.957834
0	Logistic Regression	0.82	0.886792	0.796610	0.839286	0.922282

Figure 12 Code for models' evaluation

To conclude, based on Figure 12, the evaluation results demonstrate that the Random Forest classifier is the most effective model for predictive modelling of rabbit health. It achieved the highest accuracy (0.99), perfect recall (1.000), and an F1 Score of 0.9916, indicating that it not only correctly identified nearly all health conditions but did so with minimal misclassification. Furthermore, the ROC AUC of 0.9996 confirms its superior ability to distinguish between healthy and unhealthy rabbits at various decision thresholds.

The K-Nearest Neighbors (KNN) model performed reasonably well, with an accuracy of 0.87, precision of 0.96, and a recall of 0.814, suggesting it is also a competent model, especially in scenarios prioritizing fewer false positives. However, its lower recall and F1 score compared to Random Forest indicate a slightly reduced sensitivity to identifying all unhealthy cases.

Logistic Regression, while still a valid option, exhibited the lowest performance across most metrics, with accuracy of 0.82, recall of 0.797, and an F1 score of 0.839. Although it provides interpretability and simplicity, it falls short in capturing complex patterns in the dataset, particularly those necessary for reliably identifying unhealthy rabbits.

5. Conclusion

The early detection and continuous monitoring of rabbit health are vital for improving animal welfare, reducing mortality, and enhancing farm productivity. This research presents a predictive modelling framework for rabbit health monitoring using machine learning techniques, such as Logistic Regression, Random Forest, and K-Nearest Neighbors (KNN). The proposed system integrates a structured data pipeline encompassing data preprocessing, feature engineering, vector representation, model training, and evaluation. A dataset comprising physiological and behavioral features was collected and used to train and test the models. Evaluation metrics such as accuracy, precision, recall, F1 score, and ROC-AUC were employed to assess model performance. Among the three models, Random Forest achieved the highest performance with an accuracy of 99%, F1 score of 99.16%, and ROC-AUC of 99.96%, demonstrating exceptional capability in detecting unhealthy rabbits. KNN and Logistic Regression also performed reasonably well but showed limitations in sensitivity and overall predictive power. The findings suggest that Random Forest is the most

reliable model for real-time health monitoring in rabbits, offering a promising tool for smart farming and veterinary diagnostic frameworks.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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