IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 5, October 2025, pp. 3835~3846
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i5.pp3835-3846

Early goat disease detection using temperature models: k-nearest neighbor, decision tree, naive Bayes, and random forest

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Article Info

Article history:

Received Jul 3, 2024
Revised Jun 20, 2025
Accepted Jul 10, 2025

Keywords:

Body temperature
Decision tree
Disease detection
K-nearest neighbor
Naive Bayes
Random forest

ABSTRACT

This study aims to aid livestock activities by enabling early detection of diseases in goats through body temperature measurement. Early detection is crucial to prevent disease spread and improve livestock welfare. Using the knowledge discovery in databases (KDD) methodology, the study involves collecting, processing, and analyzing goat body temperature data. Four algorithms—k-nearest neighbor (KNN), decision tree, naive Bayes, and random forest—were used to develop disease detection models. The decision tree algorithm was found to be the most accurate, achieving 100% accuracy. This demonstrates its effectiveness in detecting diseases based on body temperature. Implementing this model is expected to significantly benefit farmers by helping maintain the health and productivity of their livestock.

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1. INTRODUCTION

In today's world, human activities are closely tied to rapidly advancing technology, but not all activities have completely moved away from traditional methods [1]. One activity that still often uses traditional techniques is livestock farming. However, by utilizing modern technology, livestock farming can be made much easier. One example of applying technology in livestock farming is monitoring the health of animals by detecting diseases through their body temperature and behavior.

Goats are an important source of livestock that significantly contributes to meeting human needs for meat, milk, and other derived products. However, goat health is often a major concern in farming activities. Diseases in goats can lead to various negative impacts, such as decreased meat and milk production, as well as increased costs for treatment and care [2]. Early detection of diseases in goats is crucial for the prevention and control of these diseases. One important indicator that can be used to detect diseases in goats is body temperature. An abnormal body temperature can be an early sign of illness in livestock. In this context, the use of information technology is very helpful in providing early detection as an effort to prevent and control diseases in goats. One technology that can help achieve this is machine learning [3].

Machine learning can help address challenges arising from big data by uncovering hidden patterns and essential knowledge from vast stored information [4]. With machine learning, a system can be developed to control and manage livestock health, including monitoring body temperature. Additionally, maintaining health records and predicting goat health for early disease diagnosis based on symptoms are crucial. This allows farmers to provide first aid before conditions worsen. This problem can be tackled with a model that predicts and accurately detects diseases based on body temperature.

Recent developments in machine learning have markedly improved disease detection in various sectors, including agriculture, livestock, and human health. Probabilistic models like naive Bayes have proven crucial in addressing diagnostic uncertainty, achieving excellent classification accuracy in medical applications, particularly in diabetes diagnosis [5]. Comparative assessments of classification models indicate that random forest surpasses other algorithms in liver disease diagnosis, obtaining an accuracy of 97.3% along with elevated precision, recall, and F1-score metrics [6]. Simultaneously, image-based deep learning architectures such as ResNet-50 and distance-based classifiers like k-nearest neighbor (KNN) have demonstrated superior performance in visual and spatial data classification tasks, the diagnosis of chronic liver disease [7], and the recognition of plant diseases [8]. In addition to disease classification, these models have been utilized for stress monitoring through sleep pattern analysis [9] and for agricultural disease surveillance employing ensemble learning [10]. Hybrid models combining ResNet50V2 and DenseNet201 have been employed for the detection of potato leaf diseases, efficiently evaluating disease severity by k-means clustering [11]. These works collectively highlight the increasing growth for ensemble and probabilistic models in medical and agricultural diagnostics, emphasizing their versatility and robustness in early-stage illness identification.

These studies collectively emphasize the potential of machine learning algorithms—particularly KNN, decision tree, naive Bayes, and random forest—in advancing early disease detection across various domains. By leveraging these algorithms, researchers have developed models capable of analyzing complex biological data, from livestock body temperatures to human health indicators, with high accuracy and reliability. The application of these models in detecting diseases early on not only aids in improving health outcomes but also offers significant practical benefits for sectors such as agriculture and healthcare. As seen in the case of goat disease detection using body temperature, integrating these machine learning models provides a robust foundation for predictive diagnostics, paving the way for more proactive, data-driven approaches to managing livestock and human health. Despite these promising advancements, major challenges remain, including the need for high-quality data, model interpretability, and the development of infrastructure capable of supporting these machine learning systems in real-world settings. Addressing these challenges will be crucial to ensuring that early disease detection models can consistently deliver accurate and actionable insights across different environments.

2. THE PROPOSED ALGORITHMS

2.1. Previous research

The prediction of diabetes was enhanced through a hybrid Bayesian-optimized TabNet model where explainability was prioritized, while higher predictive strength was obtained through an ensemble of classifiers [5], [12]. The complementary focus on transparency and accuracy was emphasized in these works. A naive Bayes method was applied to diabetes classification, demonstrating that simpler algorithms can still yield meaningful outcomes [13]. This finding was supported by a broader comparison of supervised algorithms for disease prediction where it was shown that no single model consistently outperformed the others [14]. The importance of context-specific algorithm selection was thus highlighted. Machine learning evaluation was extended into the agricultural domain by comparing regression, naive Bayes and random forest for cattle survival prediction [15]. Similar comparative approaches were also adopted for disease prediction and plant health detection, confirming that cross-domain testing can provide transferable insights regarding model suitability [14], [16]. A systematic review was conducted on stress monitoring using wearable devices, showing the increasing significance of physiological data in health-related modeling [17]. This perspective was positioned in line with the broader applications of machine learning for health prediction [5], [12], [14]. The detailed of previous researches can be seen at Table 1.

2.2. Machine learning

Machine learning is a branch of artificial intelligence that allows computers to learn from data without being explicitly programmed [18]. This learning process involves identifying patterns in data to make predictions or decisions [19]. The main goal of machine learning algorithms is to extract knowledge in a way that can be useful for logical investigation [4]. There are several approaches in machine learning, including supervised learning, unsupervised learning, and reinforcement learning [20].

Supervised learning involves using labeled data to train a model to make predictions or decisions on new, unseen data [21]. Unsupervised learning, on the other hand, involves using unlabeled data to find previously unseen structures or patterns in the data [22]. Reinforcement learning involves an agent (usually simulated as a computer) interacting with an environment to learn to make optimal decisions [23]. Machine learning has been applied in various fields, including facial recognition, fraud detection, natural language processing, and computer games. With its ability to learn from data, machine learning has become one of the most valuable tools for tackling complex problems and driving innovation in technology.

Table 1. Previous researches

Reference	Results
[5]	The study on a Bayesian optimized TabNet model for diabetes classification achieved 92.2% accuracy on the Pima dataset and 99.4% on an early-stage diabetes dataset. It outperformed traditional classifiers and remained interpretable by identifying important features such as insulin and polyuria.
[15]	Research comparing logistic regression, naïve Bayes, and random forest on dairy health data showed that random forest produced the best results. This finding emphasized the strength of ensemble methods when dealing with complex datasets.
[14]	A review of supervised algorithms for disease prediction reported that random forest achieved the highest accuracy in 53% of cases, while support vector machines performed best in 41%. This confirmed that random forest remains one of the most consistent classifiers for medical datasets.
[13]	Research comparing six algorithms for diabetes detection found that KNN achieved the highest accuracy at 96.09%, with sensitivity of 98.54% and specificity of 93.63%. The study highlighted how a simple but well-tuned model can outperform more complex approaches.
[17]	This study developed models for stress detection based on physiological signals such as heart rate and skin conductance. Random forest achieved higher accuracy than decision tree, with performance exceeding 85%, showing its effectiveness for classifying stress conditions during different sleep and activity states.
[16]	Researchers compared several machines to learn algorithms to detect diseases in rice leaves. support vector machine and random forest consistently produced higher accuracy, around 90%, while KNN and naive Bayes performed less effectively, highlighting the advantages of more complex classifiers.
[12]	The study proposed an ensemble framework combining multiple classifiers for diabetes prediction. Results demonstrated improved accuracy, reaching approximately 92%, outperforming individual models and confirming the potential of ensemble methods to enhance reliability in medical prediction tasks.

2.3. Data mining

Data mining is the process of discovering useful patterns or valuable information from large and complex datasets [24]. The main goal of data mining is to uncover previously unseen insights that can be used for better decision-making in various fields such as business, science, and healthcare. This process involves using statistical, mathematical, and artificial intelligence techniques to analyze data and identify significant patterns.

Data mining involves various techniques that help in uncovering meaningful insights from large sets of data. One commonly applied method is clustering, which groups similar data points together based on shared traits. Another is classification, used to forecast which category a particular piece of data belongs to, by learning from existing labeled data. There's also the association method, which identifies patterns of relationships between different elements within a dataset.

These techniques contribute significantly to smarter decision-making, as they reveal trends and patterns that might otherwise go unnoticed. By enabling the analysis of massive and often complicated datasets, data mining has become an essential tool for both organizations and individuals striving to make informed choices in a fast-paced and data-driven world.

2.4. Knowledge discovery in database

The knowledge discovery in database (KDD) is a process of extracting useful knowledge from databases [25]. KDD focuses on discovering knowledge from data, including data storage and access, efficient execution of algorithms on large datasets, and the proper interpretation and visualization of the results. The KDD process is a widely recognized approach used in data mining to uncover meaningful insights and hidden structures within large datasets. By applying a range of algorithms, KDD helps identify patterns that may not be immediately obvious. This process is carried out through several essential stages: selecting relevant data, preparing and cleaning the data, transforming it into a suitable format, performing the mining itself, and finally interpreting and evaluating the results.

At its core, the purpose of KDD is to tap into the rich potential of data stored in databases. Through careful analysis, the process reveals patterns that are then further examined and visually presented to make the findings clearer and more accessible to users. A visual representation of the KDD process is provided in Figure 1, start with pre-KDD: research is conducted to understand the domain of the project to be developed and to determine the necessary steps to obtain relevant knowledge. The final outcome is the establishment of project objectives from the end-user's perspective. Selection: the target dataset is compiled based on the data collected in the previous stage. The obtained data will be integrated into a single dataset focused on specific variables or data samples. Pre-processing: this stage is the data cleaning stage, which involves removing noise, gathering necessary information for modeling, handling missing data, and considering time sequence information and known changes. Transformation: this stage is the data preparation stage for the data mining process. In this stage, features representing the data will be identified. Methods commonly used in this stage include dimensionality reduction, such as feature selection and extraction. Data mining: this process involves several steps, starting with selecting a data mining method that aligns with the KDD objectives, choosing algorithms and methods to discover important patterns in the data, and iteratively implementing data mining algorithms to find interesting patterns in the dataset to achieve optimal results. Evaluation: interpreting or evaluating the patterns found in the previous steps to ensure that the results align with the KDD objectives set at the beginning. Repeating previous steps may also be done to produce some changes. Post-KDD: taking steps based on the final results obtained. The generated knowledge can be used directly, implemented into systems, and documented or reported.

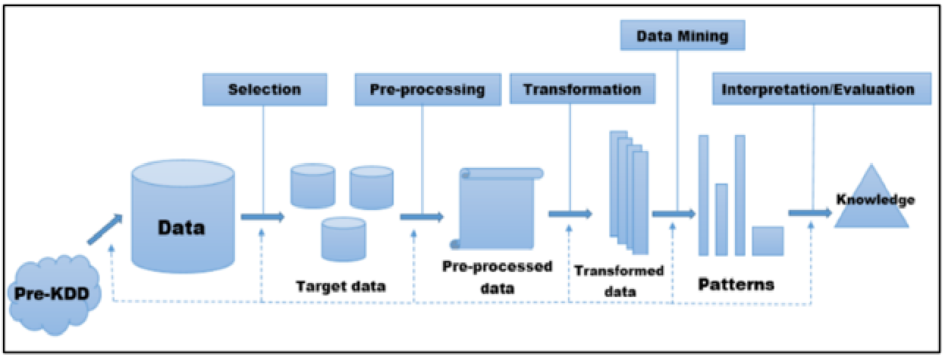

Figure 1. KDD process

2.5. K-nearest neighbor

The KNN algorithm is a widely used technique in the field of classification [26]. In this approach, the parameter k determines how many of the closest neighboring data points are considered when assigning a class to a new data instance. Known for its simplicity, KNN is commonly applied to both classification and regression tasks in machine learning. The core idea behind the algorithm is that data points with similar characteristics are typically located near each other in the feature space [27]. KNN works by identifying the 'k' nearest neighbors of a data sample that needs to be classified or have its value predicted. These neighbors are selected based on the closest distance in the feature space, usually using distance metrics such as Euclidean, Manhattan, or Minkowski. In the research on disease detection in goat livestock based on body temperature, KNN can be used to classify the health condition of goats based on the measured body temperature. By comparing the measured body temperature with the body temperature data from the training dataset, KNN can help identify whether the goat is healthy or experiencing a specific disease.

2.6. Decision tree

Decision tree is a data processing method used to predict future outcomes by creating classification or regression models in a tree structure format [28]. This process involves continuously splitting the data into smaller subsets while gradually building a decision tree structure. This structure consists of decision nodes, such as weather/outlook, which lead to branches indicating choices like hot, cloudy, and rainy, as well as leaf nodes that mark the outcomes.

Additionally, decision trees are very useful for data exploration and for revealing the relationships between various potential input variables and a target variable [29]. They are often considered an effective initial step in data modelling that can be followed or enhanced by other techniques to obtain the final model. One of the main advantages of using decision trees is their ability to ignore irrelevant data, reducing the need to process samples that do not meet certain criteria. This makes the method highly efficient in handling data and making predictions. The decision tree algorithm works by splitting the dataset into subsets based on specific features, following rules that maximize the separation of classes or target values. This process continues recursively until each subset contains only one class or no features are left to split.

In the context of research on disease detection in goat livestock based on body temperature, a decision tree can be used to build a model that predicts the health condition of the goats. By using body temperature data and other features, decision tree can help identify patterns and rules that indicate whether the goat is healthy or affected by a disease.

2.7. Naive Bayes

Naive Bayes is a classification algorithm that relies on Bayes' theorem, assuming that all input features contribute independently to the outcome [30]. This means that, according to this model, the presence or absence of one feature doesn't affect the presence of another when predicting a class. Bayes' theorem allows us to compute the posterior probability of a class C given a feature set X, by using the prior probability of the class $P(C)$, the likelihood $P(X|C)$, and the overall evidence $P(X)$. The mathematical expression of Bayes' theorem is shown in (1).

$$P(C|X) = \frac{P(X|C).P(C)}{P(X)} \quad (1)$$

In the context of research on disease detection in goat livestock based on body temperature, the naive Bayes algorithm can be used to classify the health condition of the goats. By using body temperature data and other features, naive Bayes can help predict whether the goat is healthy or experiencing a specific disease based on probabilities.

2.8. Random forest

Random forest is a machine learning algorithm that falls under the category of ensemble learning, where random forest combines predictions from multiple models to make more accurate predictions than individual models [31]. This algorithm uses many decision trees to make the final decision. The main concept of random forest is that a collection of many simple models, each trained with slightly different subsets of data, can produce more accurate and robust predictions than a single decision tree trained with the entire dataset.

Random forest is an ensemble learning method that begins with a strategy known as bootstrap aggregating, or simply bagging. This involves generating multiple random subsets from the original dataset by sampling with replacement—meaning some data points may be duplicated in a subset while others might be left out. Each of these subsets is then used to train a separate decision tree. Because each tree learns from slightly different data, they tend to produce varied results. To improve accuracy and reduce the risk of overfitting—a common problem with single decision trees—the model combines the outputs from all individual trees. For regression tasks, the final prediction is calculated by averaging the predictions of all trees. For classification tasks, the result is determined by majority vote—whichever class is predicted most often wins. By aggregating multiple decision trees, random forest enhances prediction accuracy and stability. Its strength lies in balancing out the weaknesses of individual models, making it a reliable tool for handling complex datasets and avoiding the overfitting issues commonly seen with single-tree models.

3. RESEARCH METHODS

In this research, the main object of study is the dataset on livestock symptoms and diseases. The selection of livestock symptoms and diseases was taken from the Kaggle at the time the research was conducted in February 23, 2024. This dataset was created synthetically for research purposes and can be used for various visualizations and analyses. This selection was based on the completeness of the information in the dataset, which includes research objects related to the relationship between diseases in livestock goats and body temperature.

Figure 2 represents the livestock symptoms and diseases dataset used as the main object of research in this study. This research focuses on creating a model for detecting goat livestock diseases based on body temperature using the KDD method. The stages of this method include pre-KDD, selection, pre-processing, transformation, data mining, evaluation, and post-KDD. These stages are applied in the process of developing the disease detection model for goat livestock based on body temperature.

Based on comparisons with other methods, the KDD approach has several advantages over cross-industry standard process for data mining (CRISP-DM) because KDD is broader and more comprehensive. KDD includes a more extensive domain understanding phase, allowing researchers to thoroughly understand the context of goat livestock diseases. This can help in determining the most relevant body temperature factors for disease detection.

KDD also involves broader data processing steps, including the integration of data from various sources and necessary data transformations. In this context, KDD can help combine body temperature with other animal health data for a more comprehensive understanding. KDD encompasses a more in-depth pattern discovery phase, which can aid in identifying body temperature patterns associated with specific diseases in goat livestock. This can enable the development of more accurate disease detection models.

Additionally, KDD includes a broader pattern evaluation phase, which can help measure the quality of the developed disease detection model. This comprehensive evaluation is crucial to ensure the model's accuracy and reliability. Thus, using the KDD approach in this research can provide a more comprehensive understanding of the relationship between body temperature and diseases in goat livestock, as well as help in developing a more effective disease detection model.

	Animal	Age	Temperature	Symptom 1	Symptom 2	Symptom 3	Disease
0	cow	3	103.1	depression	painless lumps	loss of appetite	pneumonia
1	buffalo	13	104.5	painless lumps	loss of appetite	depression	lumpy virus
2	sheep	1	100.5	depression	painless lumps	loss of appetite	lumpy virus
3	cow	14	100.3	loss of appetite	swelling in limb	crackling sound	blackleg
4	sheep	2	103.6	painless lumps	loss of appetite	depression	pneumonia
...	...	...	...	...	...	...	...
43773	goat	9	102.2	swelling in muscle	lameness	crackling sound	blackleg
43774	buffalo	3	101.8	loss of appetite	sores on mouth	difficulty walking	foot and mouth
43775	buffalo	15	104.1	swelling in extremities	chills	shortness of breath	anthrax
43776	cow	9	104.9	crackling sound	lameness	swelling in muscle	blackleg
43777	buffalo	4	103.5	difficulty walking	sores on gums	loss of appetite	foot and mouth

43778 rows × 7 columns

Figure 2. Livestock symptoms and diseases dataset

4. RESULT AND DISCUSSION

4.1. Decision tree modeling result

After training the dataset, the accuracy results of the created model are obtained. This accuracy is used to determine whether the model's performance is good by looking at the accuracy of both the training and testing data. The accuracy achieved on the livestock symptoms and diseases dataset using the decision tree algorithm is 100% for the training data and 100% for the testing data based on model evaluation. The overall results can be seen in Figure 3. Next, to ensure the accuracy obtained is correct and appropriate, the following step is to examine the results of the confusion matrix on the validation data and testing data. Figure 4 shows the confusion matrix from the validation data of the livestock symptoms and diseases dataset.

In the Figure 4, the results of the confusion matrix from the validation data can be seen. There are 1,166 data points classified as anthrax, 504 data points classified as blackleg, and 456 data points classified as healthy. The accuracy obtained from the confusion matrix for the validation data is 100%. For a comprehensive view of the evaluation results for the validation data, please refer to Figure 5.

```
Accuracy of Decision Tree Classifier on training set: 1.00
Accuracy of Decision Tree Classifier on test set: 1.00
```

Figure 3. Decision tree accuracy result

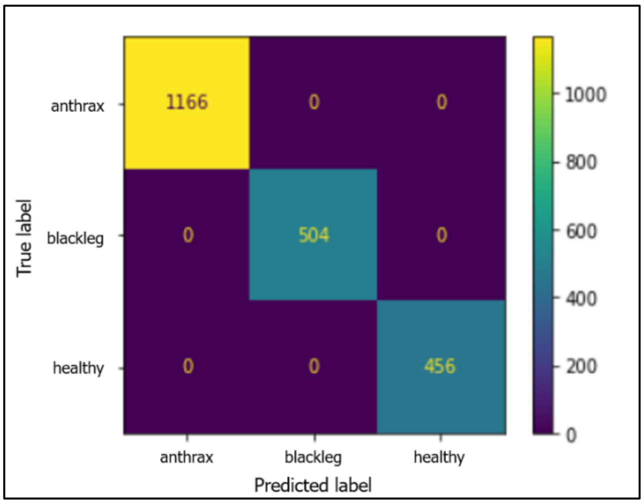

Figure 4. Decision tree confussion matrix

```
Classification Report Model :

              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      1166
         1.0       1.00      1.00      1.00       504
         2.0       1.00      1.00      1.00       456

    accuracy                           1.00      2126
   macro avg       1.00      1.00      1.00      2126
weighted avg       1.00      1.00      1.00      2126
```

Figure 5. Decision tree classification report model

4.2. KNN modeling result

After training the dataset, the accuracy of the created model was evaluated. This accuracy is used to determine whether the model's performance is satisfactory by comparing the accuracy of the training and testing data. The accuracy obtained for the livestock symptoms and diseases dataset using the KNN algorithm is 99% for the training data and 98% for the testing data, according to the model evaluation. The overall results can be seen in Figure 6. To ensure that the obtained accuracy is accurate and appropriate, the next step is to examine the results from the confusion matrix on the validation data and testing data. Figure 7 shows the confusion matrix for the validation data of livestock symptoms and diseases.

In the Figure 7, the results of the confusion matrix generated from the validation data can be seen. There are 1,166 data points classified as anthrax, 481 data points classified as blackleg, and 444 data points classified as healthy. The accuracy obtained from the confusion matrix for the validation data is 98%. For a complete evaluation of the validation data results, refer to Figure 8.

```
Accuracy of K-NN Classifier on training set: 0.99
Accuracy of K-NN Classifier on test set: 0.98
```

Figure 6. KNN accuracy result

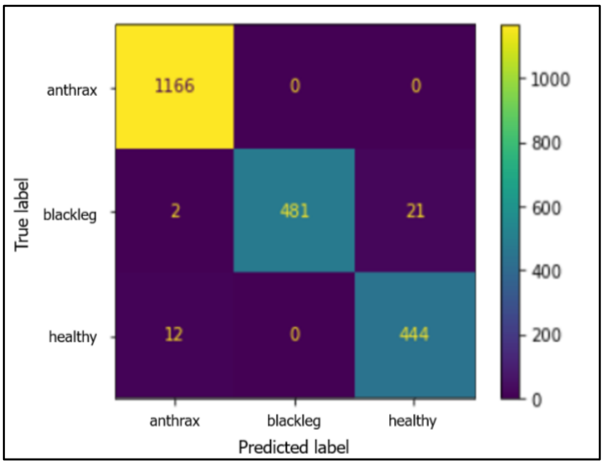

Figure 7. KNN confussion matrix

```
Classification Report Model :

              precision    recall  f1-score   support

         0.0       0.99      1.00      0.99      1166
         1.0       1.00      0.95      0.98       504
         2.0       0.95      0.97      0.96       456

    accuracy                           0.98      2126
   macro avg       0.98      0.98      0.98      2126
weighted avg       0.98      0.98      0.98      2126
```

Figure 8. KNN classification report model

4.3. Random forest modeling result

After conducting the training dataset, there are accuracy results for the model that has been created. This accuracy is used to find out whether the performance of the model created is good or not, based on the accuracy of training and testing. The accuracy obtained on the livestock symptoms and diseases dataset in the model using the decision tree algorithm was 86% for training data and 87% for testing data based on the evaluation model. The overall results can be seen in Figure 9. Then, to ensure whether the resulting accuracy is correct and appropriate, the next step is to look at the results of the confusion matrix in data validation and data testing. Figure 10 is a confusion matrix from validation data for livestock symptoms and diseases.

In the Figure 10 you can see the results of the confusion matrix resulting from data validation. There are 1,166 data classified as anthrax, then 504 data classified as blackleg, and 456 data classified as healthy. For the accuracy results obtained from the confusion matrix for data validation, the results were 100%. To see the overall evaluation results for data validation, see Figure 11.

```
Accuracy of Random Forest Classifier on training set: 0.86
Accuracy of Random Forest Classifier on test set: 0.87
```

Figure 9. KNN accuracy results for random forest

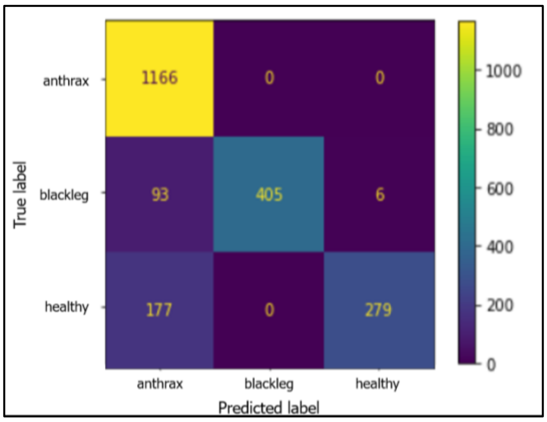

Figure 10. Confusion matrix random forest model

```
Classification Report Model :

              precision    recall  f1-score   support

         0.0       0.81      1.00      0.90      1166
         1.0       1.00      0.80      0.89       504
         2.0       0.98      0.61      0.75       456

    accuracy                           0.87      2126
   macro avg       0.93      0.81      0.85      2126
weighted avg       0.89      0.87      0.86      2126
```

Figure 11. Classification report random forest model

4.4. Naive Bayes modeling result

After conducting the training dataset, there are accuracy results for the model that has been created. This accuracy is used to find out whether the performance of the model created is good or not, based on the accuracy of training and testing. The accuracy obtained on the livestock symptoms and diseases dataset in the model using the decision tree algorithm was 63% for training data and 63% for testing data based on the evaluation model. The overall results can be seen in Figure 12. Then, to ensure whether the resulting accuracy is correct and appropriate, the next step is to look at the results of the confusion matrix in data validation and data testing. Figure 13 is a confusion matrix from validation data for livestock symptoms and diseases.

In the Figure 13, you can see the results of the confusion matrix resulting from data validation. There are 1,166 data classified as anthrax, then 504 data classified as blackleg, and 456 data classified as healthy. For the accuracy results obtained from the confusion matrix for data validation, the results were 100%. To see the overall evaluation results for data validation, see Figure 14.

```
Accuracy of Naive Bayes Classifier on training set: 0.63
Accuracy of Naive Bayes Classifier on test set: 0.63
```

Figure 12. Accuracy results for naive Bayes

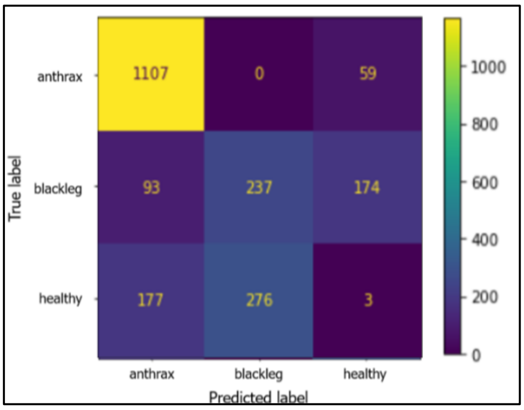

Figure 13. Confusion matrix naive Bayes model

Classification Report Model :

	precision	recall	f1-score	support
0.0	0.80	0.95	0.87	1166
1.0	0.46	0.47	0.47	504
2.0	0.01	0.01	0.01	456
accuracy			0.63	2126
macro avg	0.43	0.48	0.45	2126
weighted avg	0.55	0.63	0.59	2126

Figure 14. Classification report naive Bayes model

4.5. Discussions

Through the use of machine learning with decision tree, random forest, KNN, and naive Bayes algorithms, the modelling provides predictions of the relationship between diseases and body temperature in goats. This, of course, helps farmers make early prevention decisions when they observe that a goat's body temperature is at an abnormal level. The performance metrics produced by the machine learning algorithms used yield varying results: the decision tree algorithm has the highest accuracy compared to the other algorithms. This algorithm has the highest average accuracy value which is 100%. The KNN algorithm has a fairly high average accuracy value of 98%. The random forest algorithm also has a high average accuracy value of 87%, and the naive Bayes algorithm has the lowest average accuracy compared to the other three algorithms. This is due to the assumption that each variable is independent, which reduces accuracy as there is usually a correlation between variables. The disease detection modelling in goats based on body temperature shows that the random forest algorithm outperforms other models, even though decision tree and KNN have higher accuracy, at 100% and 98% respectively. The advantage of random forest lies in its ability to handle overfitting, which often occurs in decision tree and KNN models. Additionally, random forest provides more stable and reliable results because it uses a combination of multiple decision trees, making it better equipped to handle more complex data variations.

The findings of this study indicate that decision tree and KNN achieved the highest accuracy in detecting goat diseases based on body temperature, with 100% and 98% respectively, while random forest offered more reliable and stable performance due to its resistance to overfitting. Similar strengths of ensemble methods were also emphasized where hybrid Bayesian-optimized models and multi-classifier ensembles were reported to enhance prediction and reliability in diabetes detection [5], [12]. The present results are therefore aligned with prior works that highlighted the importance of ensemble learning in achieving robustness across varying health data. The relatively lower accuracy of naive Bayes in this study reflects the limitations observed in previous research, where its independence assumption often reduced predictive capability [13]. Broader comparisons of supervised learning methods have also shown that no single model consistently dominates across all health-related tasks, suggesting that algorithm performance is highly context dependent [14]. This supports the interpretation that while decision tree and KNN yielded high values in this dataset, random forest may remain more dependable when applied to broader and more variable data conditions. In addition, the focus on animal health prediction connects with comparative studies in agriculture, such as survival prediction in dairy cattle and plant disease identification, where machine learning methods including random forest and deep learning were also shown to be effective [15], [16]. These parallels suggest that the application of machine learning to livestock health is consistent with trends across agricultural and medical domains. Furthermore, the increasing reliance on physiological indicators such as body temperature echoes systematic reviews in stress monitoring from wearable devices, which highlighted the value of continuous physiological data for health prediction [17].

The study also confirms the advantage of random forest in mitigating overfitting, a challenge often faced by decision tree and KNN models. Overfitting can reduce a model's effectiveness, particularly in datasets with significant variance or noise. Although random forest does not reach the absolute accuracy of decision tree and KNN here, its reliability in varied data contexts is valuable, making it especially suited to applications where data consistency may fluctuate. The model's resilience to overfitting makes it an essential tool for disease detection where stable, reliable results are paramount. In summary, this study corroborates findings from earlier research that decision tree, random forest, KNN, and naive Bayes each have specific strengths and limitations in disease detection. It particularly underscores random forest's stability and resilience in handling diverse datasets, making it an attractive option for complex, real-world applications, even when other models may offer slightly higher accuracy in controlled conditions. The high performance of decision tree and KNN models in detecting diseases based on body temperature suggests that these algorithms can serve as accurate, accessible diagnostic tools for livestock management, supporting farmers in early disease prevention and ultimately contributing to healthier and more productive herds.

However, this study has its limitations. One significant limitation is the reliance on a single type of feature body temperature for disease detection. While body temperature is a critical health indicator, other variables, such as behavioral changes or feed intake, could enhance the model's predictive power. Moreover, the dataset used in this study may not encompass the full range of conditions under which goats can fall ill, potentially limiting the generalizability of the findings. Another challenge is the computational complexity and resource requirements of the random forest algorithm, which may not be feasible for all farmers, particularly those with limited access to technology.

The implications of this research are significant for livestock management and animal welfare. By employing a robust model like random forest, farmers can make more informed and timely decisions regarding the health of their goats, ultimately leading to better herd management and reduced economic losses associated with disease outbreaks. Furthermore, this study highlights the potential of machine learning in agriculture, paving the way for innovative approaches to livestock health monitoring that could be adapted for other animal species as well. As technology continues to evolve, incorporating advanced predictive modeling into everyday farming practices could transform animal husbandry, enhancing productivity and sustainability in the sector.

5. CONCLUSIONS

The disease detection modeling in goats based on body temperature shows that the random forest algorithm outperforms other models, even though decision tree and KNN have higher accuracy, at 100% and 98% respectively. The advantage of random forest lies in its ability to handle overfitting, which often occurs in decision tree and KNN models. Additionally, random forest provides more stable and reliable results because it uses a combination of multiple decision trees, making it better equipped to handle more complex data variations. For future research, it is recommended to explore the integration of additional health indicators to improve the model's predictive accuracy. Future studies could also investigate the application of other machine learning algorithms or hybrid approaches that combine multiple algorithms to leverage their strengths while compensating for their weaknesses. Additionally, expanding the dataset to include a broader range of health conditions and environmental factors would provide a more comprehensive understanding of goat health and enhance model robustness.

ACKNOWLEDGMENTS

We would like to express deepest gratitude to Universitas Multimedia Nusantara.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Fareza Ananda Putra		✓	✓	✓	✓	✓	✓	✓	✓		✓			✓
Wella	✓	✓			✓				✓	✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to animal use has been complied with all the relevant national regulations and institutional policies for the care and use of animals.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [W] on request.

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