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A comparative study on time series data-based artificial intelligence approaches for classifying cattle feeding behavior

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ABSTRACT

Cattle feeding behavior analysis is crucial for optimizing livestock management practices and ensuring animal well-being. This study presents a comparative analysis of three models: two machine learning algorithms including random forest and support vector machine (SVM), in addition to a deep learning convolutional neural networks (CNN) model, for classifying cattle feeding behaviors (eating, ruminating, and other) using time series data generated from a 3-axis accelerometer. The results of this study highlight the performance of these methods in accurately categorizing cattle feeding behaviors and demonstrate the importance of precise and efficient livestock monitoring and contributing to the improvement of animal well-being and enhancing the overall effectiveness of livestock operations.

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1. INTRODUCTION

Cattle feeding behavior plays an important role in determining the overall health and productivity of the livestock [1]. Understanding the various behaviors, such as eating and ruminating can provide valuable insights into the nutritional status and well-being of the animals [2]. With the advancements in sensor technology, 3-axis accelerometers have become a popular choice for monitoring and classifying animal behaviors such as feeding behavior [3]. In the context of cattle behavior research, the field has witnessed remarkable advancements driven by the continual development of cutting-edge sensors. Researchers are increasingly benefitting from the emergence of new sensor technologies that offer enhanced data collection capabilities. These sensors encompass a wide array of modalities, from sophisticated accelerometers to wearable devices and specialized environmental sensors. For instance, some innovative solutions incorporate global positioning system (GPS) trackers to enable location-based monitoring, allowing researchers to gain insights into cattle grazing patterns and herd dynamics [4].

Additionally, the integration of video and image capture devices with computer vision algorithms has opened up new ways for behavior analysis. Furthermore, there is a growing trend in the use of internet of things (IoT) sensors and wireless networks for real-time data transmission, ensuring that data acquisition and analysis become more immediate and streamlined [5]. As these sensor technologies continue to evolve, they promise to further empower researchers to comprehensively study and understand cattle behavior, ultimately contributing to improved livestock management practices and better overall productivity [6]. Time-series data, in the context of cattle feeding behavior analysis, possesses unique properties that demand specialized classification techniques [7]. First and foremost, time-series data is inherently sequential, meaning that the order of observations matters. In this case, the accelerometer data reflects the temporal evolution of cattle movements, exhibiting distinctive patterns during various feeding activities [8]. These patterns can be subtle and complex, requiring models capable of capturing temporal dependencies.

Furthermore, feeding behaviors may vary over time due to factors like diurnal rhythms or environmental conditions [9]. Accurate classification necessitates the recognition of these recurring patterns. Also, time-series data can be subject to noise and irregularities, making robust classification techniques essential for handling data imperfections [10]. The chosen classification methods must effectively account for the dynamic and evolving nature of cattle behavior [11], making them well-suited for the analysis of time-series data in this research context. In this research, we compare three classification methods. It includes random forest and support vector machine (SVM) machine learning algorithms, and a convolutional neural networks (CNN) deep learning model. The goal is to assess their suitability for accurate classification of cattle feeding behaviors using time series data generated by the 3-axis accelerometers.

The primary aim of this study is to develop an efficient and accurate classification model for classifying cattle feeding behaviors, specifically focusing on eating and ruminating. By comparing the performance of these three distinct algorithms, we seek to assess the suitability of each approach for this critical livestock monitoring task. Ultimately, the research aspires to support better-informed livestock management practices, reinforcing both animal welfare and agricultural productivity.

2. METHOD

2.1. The dataset

The dataset used in this research is referred to as precision beef-animal behaviour classification [12]. It encompasses sensor data that records three different behaviors of cattle: eating, rumination, and other. The dataset contains information from 18 individual animals that were part of three farm trials conducted at Easter Howgate Farm in Edinburgh, United Kingdom. Each animal within the dataset is assigned a distinctive identifier within the range of 01 to 18. These animals are equipped with two separate devices. An afimilk silent herdsman collar and a rumiwatch halter.

2.1.1. Afimilk silent herdsman collar

The afimilk silent herdsman device included in the collar records raw acceleration traces using a 3-axis accelerometer that operates at a frequency of 10 Hz. The data collected from the collar is stored in comma-separated values (CSV) format files, which are named as accel-XX.csv, where XX represents the unique animal identifier. Each of these files consists of four columns as shown in Table 1.

The orientation of the device's axes is structured as shown in Figure 1. The x-axis is aligned parallel to the animal's body (parallel to the ground). The y-axis is vertical to the animal's body (perpendicular to the ground). The z-axis is oriented perpendicular to the animal's body (parallel to the ground).

Table 1. Afimilk silent herdsman collar information details

Column	Function
Timestamp	This column provides the date and time when the data was recorded, and it is presented in ISO 8601 format, without the 'T' character, in the format of YYYY-MM-DD HH: mm: ss.SSS.
x	This column represents the acceleration in the x-direction.
y	This column denotes the acceleration in the y-direction.
z	This column records the acceleration in the z-direction.

2.1.2. Rumiwatch halter

The rumiwatch halter is specifically designed to measure the pressure exerted by jaw movements and provides behavior classifications at a rate of 10 Hz. Data collected from the halter is stored in CSV format files, which are named as halter-XX.csv, corresponding to the unique identifier (XX) of each animal. Each of these files contains two columns as shown in Table 2.

It's worth noting that this device makes separate predictions for eating and drinking behaviors. However, for the purposes of this study, drinking events have been combined into the eating category. After undergoing pre-processing, the halter shown in Figure 2 provides three distinct behavior classifications, which are mapped as follows: 0 for other behavior, 1 for ruminating and 2 for eating (including drinking).

We combined both the accelerometer and the Rumiwatch Halter's data to obtain the correspendant label for each acceleorometer record. The final dataset consists of five columns. Timestamp, x, y, z, and label. The raw accelerometer data is preprocessed to extract relevant features. It includes time-domain features, frequency-domain features, and statistical measures of the acceleration patterns. These features serve as input for the machine learning models.

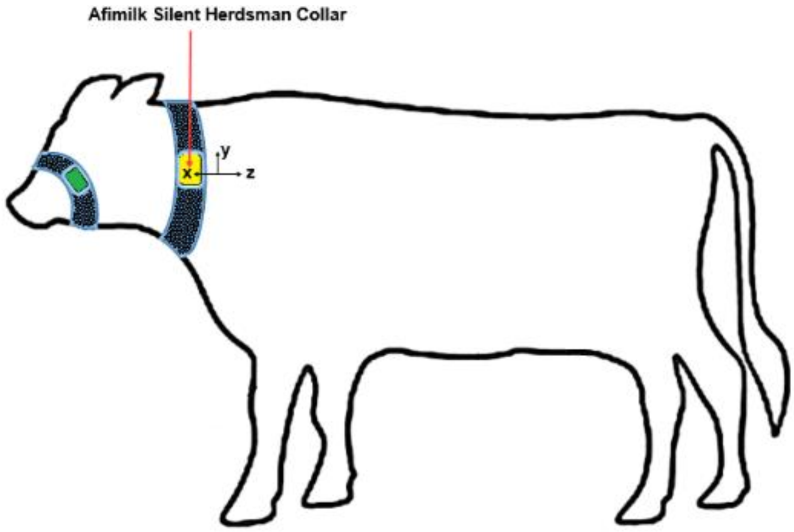

Figure 1. Afimilk silent herdsman collar

Table 2. Rumiwatch halter information details

Column	Function
Timestamp	This column indicates the date and time when the data was recorded, and it is presented in ISO 8601 format, without the ‘T’ character, following the format of YYYY-MM-DD HH: mm: ss.SSS.
Classification	This column represents the behavior classification as predicted by the Rumiwatch Halter.

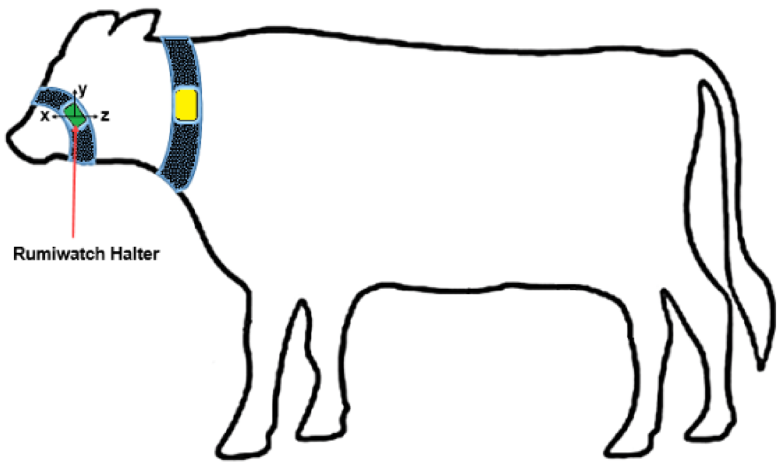

Figure 2. Rumiwatch halter

2.2. Classification models

In this subsection, we provide an overview of the three methods used for the classification task. In addition to details on the configuration of each model. The choice of these algorithms specifically is due to their popular use in time series data’s classification.

2.2.1. Random forest

The random forest is a learning technique that enhances accuracy by combining numerous decision trees. It proves especially effective in classification tasks and is capable of handling both numerical and categorical data [13]. In the context of this study, a random forest classifier was trained using the accelerometer features that were extracted.

2.2.2. Support vector machine

The SVM is a supervised learning algorithm extensively used for classification tasks. SVM's objective is to identify the hyperplane that effectively distinguishes various classes within the feature space [14]. In our experiment, we used an SVM classifier to categorize cattle feeding behaviors based on accelerometer data.

2.2.3. Convolutional neural network

CNNs are deep learning models well-suited for tasks involving spatial or sequential data. In this research, we designed a CNN architecture for processing time series accelerometer data. The network includes convolutional layers to automatically extract relevant patterns from the data [15]. Table 3 shows the overall architecture of the CNN model. It summarizes the layers and their configurations in the CNN model, along with the output shape at each stage. The model is designed for data classification with an input shape of (3, 1, 1) and three classes in the output layer.

Table 3. CNN model architecture

Layer	Configuration	Output shape
Input layer	Input shape: (3, 1, 1)	(3, 1, 1)
Convolutional 1	Filters: 32 Kernel size: (9, 9) Activation: ReLU Padding: 'same'	(3, 1, 32)
Max-pooling 1	Pool size: (1, 1) Strides: 2	(3, 1, 32)
Convolutional 2	Filters: 96 Kernel size: (3, 3) Activation: ReLU Padding: 'same'	(3, 1, 96)
Max-pooling 2	Pool size: (1, 1) Strides: 2	(3, 1, 96)
Convolutional 3	Filters: 96 Kernel size: (3, 3) Activation: ReLU Padding: 'same'	(3, 1, 96)
Max-pooling 3	Pool size: (1, 1) Strides: 2	(3, 1, 96)
Flatten layer		(288,)
Dense layer 1	Units: 128 Activation: ReLU	(128,)
Output layer	Units: 3 (for 3 classes) Activation: Softmax	(3,)

2.3. Classification metrics

Classification metrics are essential tools for assessing the performance of classification models. It helps to understand how well a model is distinguishing between different classes and whether it is making errors in prediction. To evaluate the performance of the three models, we relied on the following metrics.

2.3.1. Accuracy

Accuracy (ACC), a key metric in classification tasks, measures the proportion of correctly categorized instances out of the entire dataset [16]. It provides a fundamental assessment of a model's overall performance in correctly identifying data points. A higher accuracy score indicates a more reliable classification model.

$$ACC = (TP + TN)/(TP + TN + FP + FN) \quad (1)$$

where:
- True positives (TP): this represents the count of instances that were correctly predicted as positive.
- True negatives (TN): this denotes the number of instances that were correctly predicted as negative.
- False positives (FP): signifies the number of instances that were actually negative but were incorrectly predicted as positive.

– False negatives (FN): indicates the count of instances that were actually positive but were incorrectly predicted as negative.

2.3.2. Precision positive predictive value (PPV)

Precision, a crucial metric, delves into the accuracy of positive predictions by measuring the proportion of true positive predictions among all the predictions labeled as positive [17]. This metric is invaluable in assessing the reliability and correctness of a model's affirmative forecasts. With precision, we gain a deeper understanding of the model's ability to avoid false positives and make precise positive predictions.

$$PPV = TP/(TP + FP) \quad (2)$$

2.3.3. Recall

Recall is a metric that quantifies the proportion of correct positive predictions (true positives) relative to the total number of actual positive instances. It is a crucial evaluation measure for assessing the effectiveness of a predictive model, particularly in scenarios where the identification of all positive cases is of high importance, such as in medical diagnoses or fraud detection [18]. High recall values indicate that the model is successfully capturing a significant portion of the positive cases within the dataset.

$$Recall = TP/(TP + FN) \quad (3)$$

2.3.4. F1-score

The F1-score, also known as the F1-measure or F1-statistic, plays an important role in evaluating the performance of classification models. It is a composite metric that harmoniously combines two essential classification metrics, precision and recall, providing a balanced measure of a model's accuracy and ability to correctly identify positive instances. This makes the F1-score particularly valuable when dealing with imbalanced datasets or situations where both high precision and high recall are important [19].

$$F1 - score = 2 * (Precision * Recall)/(Precision + Recall) \quad (4)$$

3. RESULTS AND DISCUSSION

3.1. Results

To classify the accelerometer data, the dataset was randomly split into training (70%), testing (20%), and validation (10%) sets. Additionally, the models were trained for 30 epochs. Table 4 shows the performance of the three models through the evaluation metrics. The graph in Figure 3 shows the evolution of the F1-score and the loss during training for the three models.

Table 4. Models performance

Metric	Random forest	SVM	CNNs
Accuracy	0.72	0.83	0.95
Precision	0.71	0.82	0.96
Recall	0.72	0.83	0.95
F1-score	0.72	0.83	0.95

The experimental results indicate that all three machine learning algorithms perform well in classifying cattle feeding behaviors based on 3-axis accelerometer data. However, CNN achieved the highest accuracy and F1-score, indicating its superiority in this specific task. CNNs are known for their ability to automatically learn and extract complex patterns from sequential data, which makes them well-suited for time series analysis. SVM also provided competitive results. It demonstrates its effectiveness for this classification task. Random forest showed slightly lower performance but still delivered satisfactory results.

The findings of this experiment suggest that CNN models are a promising method for cattle feeding behavior classification using time-series data generated by accelerometers. CNN models can be used to develop automatic feeding behavior monitoring systems. This can can help farmers to improve animal health, welfare, and productivity.

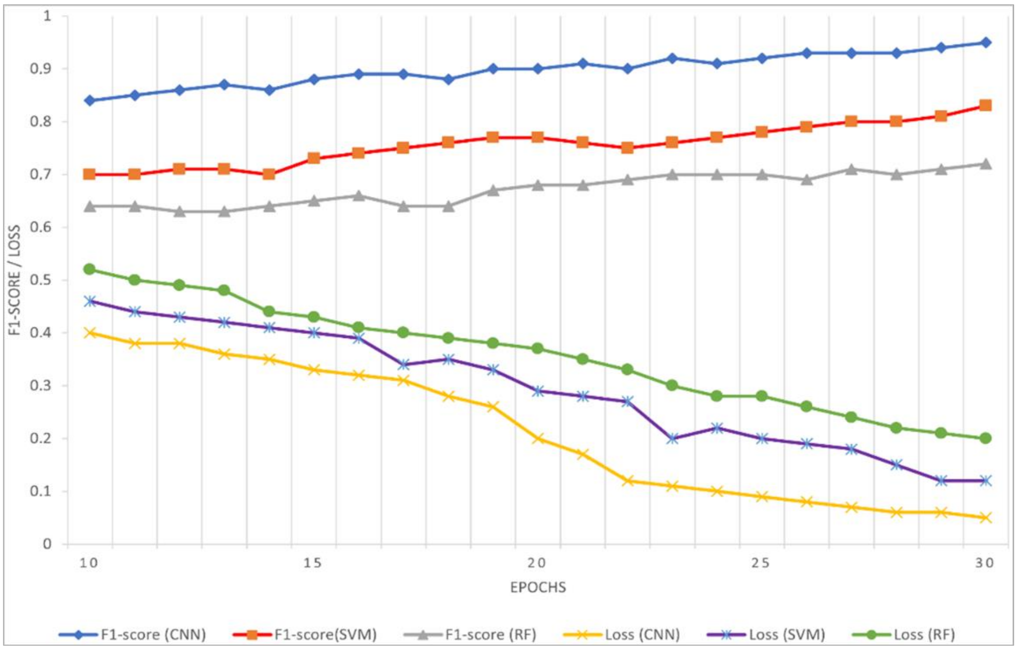

Figure 3. F1-score and loss evolution during training

3.2. Discussion

The superior performance of the CNN model in classifying cattle feeding behaviors using time series data from 3-axis accelerometers can be attributed to several factors. Firstly, CNNs are adept at learning hierarchical features from raw sensor data. Additionally, the model's ability to automatically extract spatial and temporal dependencies within the data allows it to outperform random forest and SVM, as indicated in the following subsections.

3.2.1. Feature learning

CNNs are designed to automatically learn hierarchical features from raw data. In the case of accelerometer data, they can capture complex patterns and temporal dependencies in the data, which may be difficult for traditional machine learning models like random forest and SVM to extract. This ability to learn meaningful features directly from the raw data is particularly beneficial for time series data [20].

3.2.2. Spatial hierarchies

CNNs are well-suited for detecting spatial hierarchies in data. In the context of accelerometer data, different feeding behaviors may have distinct spatial patterns or arrangements of acceleration values, which CNNs are proficient at recognizing. This allows CNNs to capture both short-term and long-term patterns in the data [21].

3.2.3. Translation-invariant

CNNs are capable of learning translation-invariant features. This means that they can recognize patterns regardless of their exact position in the input data. In the case of cattle feeding behaviors, animals might perform the same behavior in slightly different ways, but CNNs can still classify them correctly because they focus on the underlying patterns [22].

3.2.4. Adaptive learning

CNNs use adaptive learning algorithms like backpropagation. This allows them to continually refine their internal representations and adapt to the nuances of the data. Over time, CNNs become increasingly specialized in recognizing the specific patterns in the accelerometer data [23].

3.2.5. Deep architectures

CNNs can be designed with deep architectures, which enables them to model highly complex relationships in the data. Deep networks can capture both simple and complex features. This makes them well-suited for tasks like behavior classification [24].

3.2.6. Parameter tuning

CNNs are fine-tuned with large numbers of parameters, which allows them to achieve high performance. While random forest and SVM have their hyperparameters to optimize, CNNs offer more flexibility in terms of architecture. This can lead to better performance when tuned correctly [25].

3.2.7. Classification nature

The choice of model can also depend on the specific nature of the classification task. CNNs are well-known for their performance in sequence data, which could be highly relevant to accelerometer data. This makes them a more suitable choice [26]. It's essential to note that the choice of the most suitable algorithm often depends on the specific dataset, the problem, and available computational resources. In this case, the CNN appears to outperform random forest and SVM due to its ability to capture complex temporal and spatial patterns in the accelerometer data, making it a strong candidate for this specific classification task. However, further analysis and experimentation may be required to fine-tune the model and ensure its robustness in real-world applications.

3.3. The impact of using cattle feeding behavior analysis

Analyzing cattle feeding behavior using time series data generated from a 3-axis accelerometer can have a significant impact on productivity, optimizing livestock management practices and ensuring animal well-being. Such insights can lead to more efficient feeding schedules and improved resource allocation. Some of the key benefits and impacts of such analysis are indicated in the following subsections:

3.3.1. Improved feeding efficiency

By monitoring cattle feeding behavior, you can gain insights into when and how often they eat. This data can help optimize feeding schedules and reduce feed wastage, leading to cost savings. It also contributes to more efficient and sustainable farming practices.

3.3.2. Early detection of health issues

Changes in feeding behavior, such as reduced feed intake or unusual feeding patterns, can be indicative of health issues in cattle. An accelerometer can detect these changes. This allows for early intervention and potentially reducing the severity of diseases.

3.3.3. Enhanced nutrition management

Analyzing feeding behavior data can provide information about the quality and quantity of feed consumed by individual cattle. This data can be used to adjust dietary plans for better nutrition management. This ensures that each animal's nutritional needs are met.

3.3.4. Stress and well-being monitoring

Accelerometer data can reveal patterns of restlessness or stress during feeding times. This information can help identify environmental stressors or issues with feeding infrastructure. Addressing these issues can improve animal well-being.

3.3.5. Reduced labor costs

Automated monitoring of cattle feeding behavior can reduce the need for manual observations. This can lead to labor cost savings. Farmers can focus their efforts on other aspects of livestock management.

3.3.6. Environmental impact

Implementing optimized feeding practices in livestock farming not only minimizes feed wastage and prevents overconsumption but also leads to a significant reduction in the overall environmental impact of the industry. This approach enhances resource efficiency, reduces greenhouse gas emissions, and conserves valuable natural resources, making it a sustainable choice for the future of agriculture. By carefully managing feed intake, livestock farmers can contribute to a more eco-friendly and economically viable agricultural system.

3.3.7. Data-driven decision making

Farmers and barn managers can enhance their livestock management practices by collecting and analyzing feeding behavior data over time. This information empowers them to make well-informed decisions, optimizing their operations for maximum efficiency and animal well-being. Furthermore, it enables them to adapt swiftly to changing conditions in the agricultural industry, ensuring the sustainability and profitability of their farms.

3.3.8. Better animal welfare

Monitoring feeding behavior is an essential component of a holistic approach to guaranteeing animal well-being. It enables a proactive response to issues like hunger, stress, or diseases that can affect the welfare of cattle. By implementing this approach, we can significantly improve the health and happiness of the animals.

3.3.9. Research and breeding improvement

Long-term feeding behavior data can be valuable for research and selective breeding programs. It can help in identifying traits associated with efficient feed conversion and overall health. This contributes to breeding for healthier and more productive cattle.

4. CONCLUSION

In this study, we conducted a comparative analysis of three machine learning models, namely random forest, SVM, and CNN, for classifying cattle feeding behaviors using time series data from 3-axis accelerometers. Our findings suggest that all three algorithms can be effective for this task, with CNNs outperforming the others in terms of accuracy and F1-score. These results highlight the potential for precise and efficient livestock monitoring, contributing to better cattle management and animal welfare practices. Future research may explore the optimization of hyperparameters and consider the deployment of these algorithms in real-world livestock management scenarios to assess their practical utility.

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