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Hybrid CNN-LSTM Model with an Attention Mechanism for Early Detection of Lameness in Cattle Based on Sensor Data

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Abstract

This paper presents a hybrid CNN-LSTM model with an attention mechanism for the early detection of lameness in cattle using data from a pedometer-type wearable sensor unit. The input feature set includes accelerometer, gyroscope, and magnetometer measurements, generated statistical activity indicators, and demographic and physiological variables. In the proposed architecture, CNN layers extract local temporal patterns, LSTM layers model longer-term dependencies, and the attention mechanism emphasizes diagnostically informative sequence fragments. In preliminary validation on the available experimental dataset, the model achieved an accuracy of 98.6%. Further evaluation using an independent test set and data collected under real farm conditions is required to confirm the robustness and practical applicability of the approach.

Keywords: Cattle lameness; Sensor data; Accelerometer; Gyroscope; CNN-LSTM; Attention mechanism; Deep learning

1. Introduction

Lameness is one of the most significant health and welfare problems in cattle farming. It is associated with reduced milk yield, loss of body weight, impaired reproductive performance, and a lower quality of life for affected animals [1]. As a result, farms may incur substantial economic losses. Early detection of lameness and timely therapeutic and preventive measures can reduce these losses, support herd productivity, and decrease veterinary costs.

Modern digital technologies, including sensor-based monitoring systems and artificial intelligence algorithms, offer a promising approach to the early detection of lameness [2]. In particular, accelerometers, gyroscopes, and magnetometers can record animal movement parameters and support the automatic identification of patterns associated with gait abnormalities.

In recent years, animal health monitoring using sensor devices has become an important area of digital livestock farming. On dairy farms, these technologies make it possible to monitor the general condition of animals more precisely and to detect possible health disorders at an earlier stage [3, 4]. Machine learning methods are commonly applied to data collected from sensors. In studies of animal motor activity, methods such as support vector machines [5-8], random forests [9, 10], and decision trees [11-13] have been used.

However, traditional machine learning methods usually require preliminary manual extraction of features from sensor signals. Such features may be obtained using frequency analysis of accelerometer data [14] and statistical feature extraction methods [15]. Although these approaches can be effective, they are labor-intensive, depend strongly on expert-defined feature sets, and may not fully capture diagnostically relevant movement patterns [16].

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For this reason, increasing attention has been paid to deep learning approaches, which can automatically extract informative representations directly from raw or minimally processed data. Under appropriate training and validation conditions, such models can improve classification performance and reduce dependence on manual feature engineering [17].

One of the key tasks in sensor-based lameness detection is distinguishing movement patterns corresponding to normal and impaired gait. If manually selected features do not reflect the essential characteristics of a motor disorder, the algorithm's ability to detect abnormal changes may be limited. Therefore, the present study considers a deep learning-based approach in which the model learns hidden relationships and temporal patterns in the input data, thereby forming a more informative representation of animal movement [18-20].

2. Materials and Methods

Monitoring cattle activity can support the early detection of changes in animal health. For such analysis, it is necessary to collect reliable data on movement parameters with sufficient temporal resolution. In this study, sensor devices were used to register motor activity in near real time.

During monitoring, the sensors record physical parameters of the animal's movement. The collected data are then transmitted to a central server, where they are stored and processed for analysis, monitoring, and prediction tasks.

Reliable and continuous data collection requires the selection of wearable sensor devices with sufficient measurement accuracy and operational stability. In this study, a pedometer-type wearable sensor unit was used as the primary data collection device. The device combines several motion sensors, enabling a comprehensive assessment of cattle motor activity.

The pedometer-type device is designed for continuous tracking of movement parameters throughout the day. It contains an accelerometer and additional motion sensors that record changes in motor activity and store them in digital form. For continuous monitoring, the device is attached to the leg of the animal and transmits the collected data to a server. This makes it a central element of the data collection and motor activity analysis system. The use of such wearable sensor devices offers the following advantages:

- High temporal resolution: the device provides continuous information on animal physical activity and can register relatively small changes in movement behavior.
- Continuous monitoring: placement of the device on an animal's leg enables round-the-clock data collection and supports prompt detection of deviations.
- Process automation: the use of wearable sensors reduces reliance on manual observation and decreases the likelihood of subjective assessment errors.
- Suitability for long-term observation: long-term data collection is important for identifying persistent or chronic disorders and improving the effectiveness of veterinary interventions.

The pedometer used in this study includes three types of sensors: an accelerometer, a gyroscope, and a magnetometer. Each performs specific functions in recording movement parameters.

The accelerometer records linear acceleration along the x, y, and z axes. It can be used to estimate step-related activity, activity duration, acceleration, and deceleration. In the context of this study, accelerometer data make it possible to assess the animal's overall activity, movement intensity, and periods of immobility.

The gyroscope records angular velocity around the x, y, and z axes. This sensor helps characterize changes in body orientation, turns, tilts, and gait symmetry, which may be associated with early signs of lameness.

The magnetometer determines the device's orientation relative to the Earth's magnetic field. It complements accelerometer and gyroscope data by supporting estimation of movement direction and spatial orientation during long-term observation.

The combined use of accelerometer, gyroscope, and magnetometer data provides a more complete description of the animal's movement and body orientation. While the accelerometer reflects movement intensity, the gyroscope characterizes changes in angular position, and the magnetometer supports estimation of movement direction in space.

A diagram showing the installation of the sensor device on the leg of a cow and the orientation of the sensor axes is presented in Fig. 1.

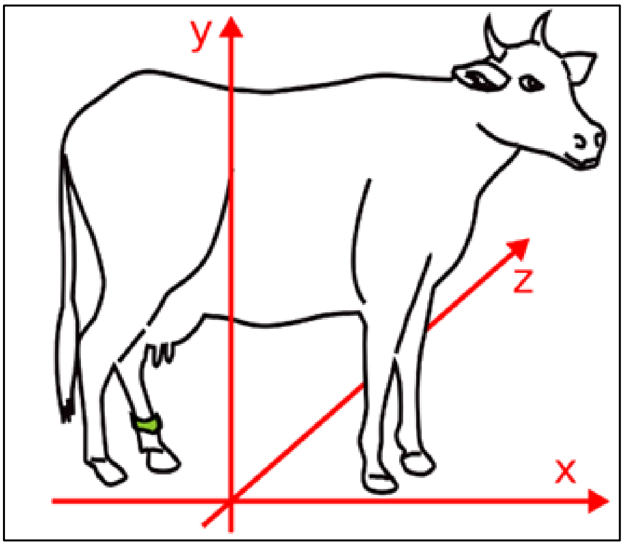

Figure 1 Sensor orientation

In this study, parameters obtained from sensor devices, together with generated statistical features and animal-specific characteristics, were used as input data for the neural network model. The input feature set was divided into three groups.

2.1. Parameters obtained from sensors installed in the wearable device:

- A_x - acceleration along the x-axis;
- A_y - acceleration along the y-axis;
- A_z - acceleration along the z-axis;
- G_x - gravitational component along the x-axis;
- G_y - gravitational component along the y-axis;
- G_z - gravitational component along the z-axis;
- R_x - angular velocity along the x-axis;
- R_y - angular velocity along the y-axis;
- R_z - angular velocity along the z-axis;
- *Roll* - angular position relative to the longitudinal axis;
- *Pitch* - angular position relative to the transverse axis;
- *Yaw* - angular position relative to the vertical axis.

2.2. Statistical movement parameters generated from processed sensor data:

- S_{step} - number of steps per hour;
- v_a - average movement speed per hour;
- T_a - duration of the activity period per hour;
- T_r - duration of the rest period per hour;
- P - number of body position changes, including transitions from standing to lying and vice versa.

3. Demographic and physiological data:

- A - age of the animal;
- W - body weight of the animal;
- B - breed of the animal.

This set of input features provides a comprehensive characterization of the animal's motor activity. Temporal changes in acceleration, gravitational components, and angular position describe movement dynamics; statistical features summarize activity levels, rest periods, step count, and body position changes; and demographic and physiological data help account for individual animal characteristics.

Thus, the generated parameter set provides a meaningful basis for developing a neural network model. Based on these data, the model can learn patterns associated with normal and abnormal movement dynamics and use them for the classification of lameness-related indicators.

4. Development and Evaluation of a Hybrid Neural Network Model

Preliminary experiments considered the separate application of LSTM and CNN models because sensor-based movement data are represented as time sequences. LSTM models are suitable for identifying temporal dependencies; however, they may be less effective at capturing local changes and short-term motion patterns in sensor signals. CNN models, in contrast, are well suited for extracting local features, but their ability to model long-term dependencies is limited compared with recurrent architectures. Therefore, this study proposes a hybrid architecture that combines the strengths of both approaches.

The main idea of the hybrid model is that CNN layers first extract local temporal and spatial features from the sensor data, after which LSTM layers analyze longer-term dependencies. This structure makes it possible to consider both local changes in movement and more general gait patterns. However, standard LSTM layers do not explicitly indicate which time intervals are most diagnostically informative, although different fragments of a sequence may have unequal importance for lameness detection.

To address this limitation, the model incorporates an attention mechanism. This mechanism allows the neural network to assign greater weight to informative time points and reduce the influence of less relevant fluctuations in the data. As a result, the model can focus on movement fragments that are more strongly associated with lameness-related patterns. The general structure of the proposed hybrid CNN-LSTM model with an attention mechanism is shown in Fig. 2.

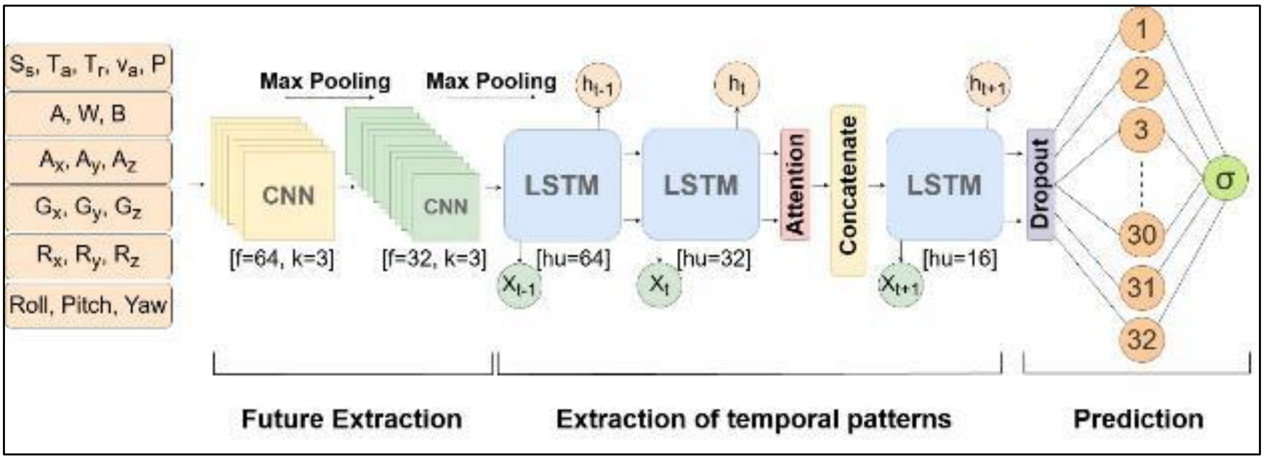

Figure 2 Proposed neural network architecture

In the proposed architecture, the CNN layers perform two main functions. First, they extract local features, such as rapid changes in acceleration or angular velocity. Second, together with pooling operations, they reduce the temporal dimension of the data before passing it to the LSTM layers, thereby improving the efficiency of subsequent time-series processing.

After processing by the convolutional layers, the data are passed to LSTM blocks, where patterns that occur over longer time intervals are analyzed. The attention mechanism is then used to focus the model on key sequence fragments that are most relevant for lameness prediction. The convolutional layers use same padding; therefore, the sequence length is preserved before max-pooling operations. The model structure and trainable parameters of its layers are presented in Table 1.

Table 1 Structure of the proposed model and number of trainable parameters

No.	Layer type	Output shape	Number of trainable parameters
1	InputLayer	(72, 20)	0
2	Conv1D (64, k=3)	(72, 64)	3,904
3	BatchNormalization	(72, 64)	128
4	MaxPooling1D (p=2)	(36, 64)	0
5	Conv1D (32, k=3)	(36, 32)	6,176
6	BatchNormalization	(36, 32)	64
7	MaxPooling1D (p=2)	(18, 32)	0
8	LSTM (64)	(18, 64)	24,832
9	LayerNormalization	(18, 64)	128
10	LSTM (32)	(18, 32)	12,416
11	LayerNormalization	(18, 32)	64
12	Attention	(18, 32)	0
13	Concatenate	(18, 64)	0
14	LSTM (16)	(16)	5,184
15	Dropout (0.3)	(16)	0
16	Dense (32, ReLU)	(32)	544
17	Dense (1, sigmoid)	(1)	33

The training behavior of the proposed hybrid CNN-LSTM model with an attention mechanism was evaluated using accuracy and loss values calculated for the training and validation subsets. The accuracy dynamics are presented in Fig. 3, whereas the corresponding loss dynamics are shown in Fig. 4.

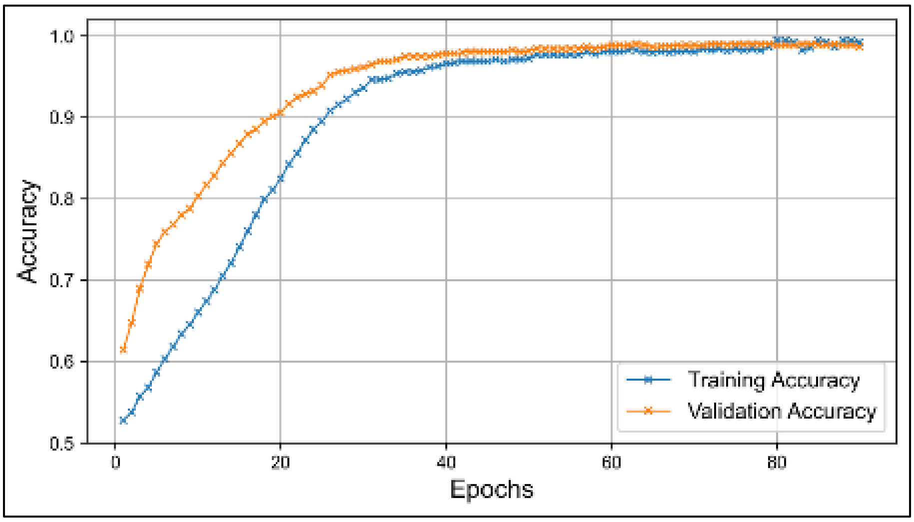

Figure 3 Training and validation accuracy curves of the proposed hybrid CNN-LSTM model with an attention mechanism

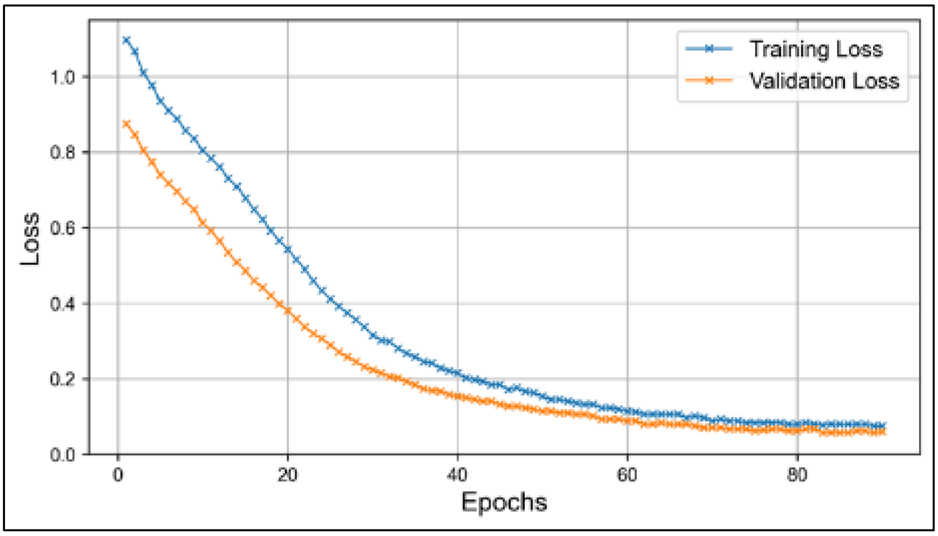

Figure 4 Training and validation loss curves of the proposed hybrid CNN-LSTM model with an attention mechanism

To reduce the risk of overfitting, the training procedure was configured for a maximum of 100 epochs, and an early stopping strategy was applied. The training process was terminated at the 87th epoch because subsequent epochs did not result in a substantial improvement in validation performance. This indicates that the model reached its most effective state before the predefined maximum number of epochs.

As shown in Fig. 3, both the training and validation accuracy values increased steadily during the learning process. The relatively small difference between these curves suggests that the model did not merely memorize the training data but learned representations that remained effective on the validation subset. Minor fluctuations in the validation curve are expected in supervised learning experiments and do not indicate pronounced instability of the proposed model.

Fig. 4 demonstrates a consistent decrease in loss values for both the training and validation subsets. The absence of a continuously widening gap between the two curves indicates that the training process remained stable and that no clear signs of severe overfitting were observed within the reported training interval.

On the validation subset, the proposed hybrid CNN-LSTM model with an attention mechanism achieved an accuracy of 98.6%. This result should be interpreted as performance obtained under the conditions of the experimental dataset. Therefore, further validation on independent datasets and in real farm environments is required to confirm the robustness and practical applicability of the model. From an architectural perspective, the CNN layers contribute to the extraction of local temporal and spatial features, the LSTM layers model long-term dependencies in sensor sequences, and the attention mechanism emphasizes diagnostically informative time intervals relevant to lameness detection.

The obtained results suggest that the proposed approach can analyze cattle movement parameters with high accuracy on the available experimental dataset and may serve as a basis for developing intelligent systems for early lameness detection. At the same time, the achieved accuracy should be interpreted cautiously because the stability of the model must be verified under real farm conditions, where data can be affected by the external environment, individual animal characteristics, sensor placement, and the operational quality of sensor devices.

5. Conclusion

This paper presented an approach to the early detection of lameness in cattle based on sensor data and deep learning methods. The input feature set was formed using parameters obtained from an accelerometer, a gyroscope, and a magnetometer, together with statistical, demographic, and physiological indicators. This combination of data provides a comprehensive description of animals' motor activity and supports the identification of deviations associated with gait abnormalities.

The proposed hybrid CNN-LSTM architecture with an attention mechanism combines the advantages of convolutional and recurrent neural networks. The CNN layers extract local features from sensor signals, the LSTM layers analyze long-term temporal dependencies, and the attention mechanism enables the model to focus on the most informative parts of a sequence. The training results showed that the model can achieve high classification accuracy on validation data and maintain stable generalization performance within the available experimental conditions.

The scientific and practical significance of the proposed approach lies in its potential to automate animal health monitoring and reduce the time required to identify early signs of disease. Further research should focus on expanding the experimental sample, using an independent test set, evaluating additional metrics such as precision, recall, F1-score, and ROC-AUC, testing the model under real farm conditions, and assessing its robustness across different breeds, age groups, and housing conditions.

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