Cattle behavior recognition system using machine learning and Internet of Things

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Abstract: Cattle behavior recognition system is an innovative way to assess the well-being of cattle by analyzing their behavior data. Non-intrusive monitoring systems using accelerometers have become popular due to their affordability and ease of use, especially when coupled with machine learning algorithms. However, accurately identifying different behaviors can be challenging, as similar acceleration data may be associated with different actions. To address this issue, we present an efficient approach that combines leg-mounted and collar-mounted accelerometers to recognize six distinct cow behaviors: Walking, Standing-Resting, Grazing, Lying-Resting, Lying-Ruminating, and Standing-Ruminating. To determine the best accuracy, different machine learning algorithms were employed and their performance is analyzed. With its non-intrusive design and high-performance capabilities, this technology has the potential to revolutionize the livestock industry by allowing farmers to monitor their herds more effectively and make informed decisions to improve their welfare.

Keywords: Cattle;monitoring; acceleration; sensor; classification; behavior; leg-mounted; collar-mounted

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1 Introduction

Lameness is a prevalent issue on modern dairy farms, which has a negative impact on animal welfare and farm economics through various direct and indirect ways. This condition increases the likelihood of involuntary culling, reduces fertility and productivity, and results in direct expenses for the farmer. Furthermore, economic models suggest that up to 32% of the costs associated with lameness arise from subclinical cases that often go unnoticed and untreated. Scoring movement and administering treatment for lameness can be time-consuming, making it difficult to manage alongside other tasks. In general, lame cattle tend to spend more time lying down and less time feeding than healthy ones. As a result, changes in behavior can be a useful tool for early detection of lameness on farms. Early treatment of mild to moderate lameness can reduce the number of severely lame cattle in the herd, leading to a reduction in associated expenses. Some of the common infections associated with lameness in cattle include foot rot, hairy heel warts, laminitis, joint infections, and toe ulcers.

Cattle-attached sensors or accelerometers can track ruminating and feeding when attached to the neck while measuring laying behavior and activity when attached to the leg. When a cow is lame, they frequently lie down for longer periods and do so less frequently during the day. Additional activity

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indications of lameness that can be monitored with accelerometers include shorter eating intervals, shorter eating sessions, altered day-to-night activity ratios, and slower reaction times when being fed. Healthy dairy cattle had a lower feed intake, fewer feeding sessions, and spent less time lying down. Moreover, lame dairy animals with higher locomotor scores had fewer, larger meals and consumed their feed over a shorter time overall. Changes in feed intake and feeding time, as well as feeder visits, have been proposed as indicators to identify health problems in dairy cattle. When compared to non-lame cattle, temperately lame cattle had shorter eating times and fewer chews (jaw motions), while sensible lameness had no noticeable effects on rumination duration, number, or chews.

In the past, dairy farmers had to rely on a labor-intensive and sometimes unreliable approach to monitor the health of their cattle. This involved constant observation, which not only required a significant amount of effort but could also lead to inaccurate and inconsistent results. Such a technique could ultimately compromise the health and well-being of the cows. To address this issue, an innovative automatic health monitoring system has been proposed. This system can swiftly and accurately track a range of health parameters, allowing for timely and appropriate treatment if necessary. By eliminating the need for constant human observation, the system reduces the workload for farmers and provides more reliable data on the health status of their cows. This revolutionary approach to dairy farm cattle health monitoring has the potential to revolutionize the industry by improving the efficiency and effectiveness of animal care. With its automated and accurate tracking capabilities, it ensures that cows receive the care they need, when they need it, ultimately leading to healthier and happier animals.

The contribution of this paper includes:

The presented approach uses both leg-mounted and collar-mounted accelerometers to recognize six distinct cow behaviors: Walking, Standing-Resting, Grazing, Lying-Resting, Lying-Ruminating, and Standing-Ruminating.

Different machine learning algorithms were employed to determine the best accuracy, and their performance is analyzed.

2 Related Works

Tran et al. (2021) have developed an innovative and highly effective approach to cow behavior recognition using accelerometers attached to both the collar and legs. By analyzing data from a 16-second window (sampling every second) and extracting features such as root mean square, standard deviation, and mean, the method can accurately recognize four key behaviors: walking, feeding, lying, and standing. The random forest (RF) algorithm, employed, proves to be exceptionally adept at identifying potentially dangerous behaviors with high accuracy rates for each behavior: eating (0.914), lying (0.998), standing (0.88), walking, and standing (0.998). Additionally, the algorithm demonstrates impressive sensitivity (0.996) and positive predictive value (0.956) for eating behavior. Achour et al. (2019) have introduced an innovative unsupervised approach for monitoring dairy cows' behavior using an Inertial Measurement Unit (IMU) attached to their backs. This non-invasive sensor-based monitoring system has the potential to significantly improve dairy cow welfare and health by detecting changes in behavior before clinical signs appear. The study aims to construct an unsupervised classification model using data from IMUs attached to dairy cows in free-stall facilities. By merging data from different segmentation windows and sampling frequencies, the model is able to categorize real-time observations of cows' actions, including standing, sitting, lying down, getting up, walking, and remaining stationary. In their research paper, Tian et al. (2021) introduced a novel approach for real-time recognition of dairy cow behavior based on acceleration and geomagnetic information. They identified that various behaviors such as eating, ruminating, jogging, resting, tossing their heads, drinking, and strolling can provide crucial insights into the health of dairy cows. To collect data on these behaviors, the researchers developed a multi-sensor system that utilized a collar-style device equipped with acceleration and geomagnetic sensors. The collected data was then used to train a dairy cow behavioral recognition fusion model that employed both the RF and K-nearest neighbors (KNN) models.

Totani et al. (2019) developed a real-time, low-power CPU-based system to analyze animal feeding behavior and detect the learning of new behaviors. The system uses image recognition techniques to separate the animal from the background, allowing for fast recognition and improving the accuracy of an autonomous learning system. Kumar et al. (2021) proposed a low-cost framework using machine learning algorithms and accelerometer-based activity monitoring to identify individual cattle's health status. The system utilizes images from cow muzzle point photographs to improve the algorithm's recognition of animals and classify behavioral actions for health monitoring. Shen et al. (2020) suggested a dairy cow rumination detection system based on noseband pressure change. Chewing pressure equipment accurately records dairy cow's chewing pressure and counts cuds to monitor rumination, unlike audio and acceleration sensor equipment that can be influenced by background noise or weather conditions. Feng et al. (2021) propose an Internet of Things (IoT) based animal social behavior sensing framework for the detection and control of mastitis in dairy cows. They track cows' travel patterns and contacts through Global Positioning System devices to develop directed and weighted cattle social behavior graphs. Cabezas et al. (2022) present a system for categorizing the behavior of agricultural cattle using low-cost 3-D accelerometers and GPS sensors. They extract 108 features from the acceleration meter signals and use video recordings to train a RF machine learning classifier. GPS location is taken every 5 minutes to conserve battery life. Vázquez Diosdado et al. (2015) propose a decision-tree system to classify biologically significant behavior in dairy cows and to identify transition events between reclining and standing using tri-axial accelerometer data from a neck-mounted sensor. They gather data from six dairy farms. Arablouei et al. (2021) focus on real-time classification of cattle behavior using accelerometer data from collar tags attached to ten cattle. They develop a preprocessing, feature extraction, and classification pipeline specifically designed for executing inference on embedded sensor-node systems. They examine the accelerometer data's statistical and spectral characteristics to create statistical models for the classification of cow behavior.

McDonagh et al. (2021) proposed a method to predict dairy cow behavior using picture recognition tools. They used video surveillance to observe cows before calving and noted their habits. A non-local neural network was trained to identify seven actions with over 80% accuracy. Pavlovic et al. (2022) used neck-mounted accelerometer-equipped collars to track and categorize cattle behaviors, including early sickness detection and automatic monitoring of the beginning of oestrus cycles. They created algorithms that categorized cattle states and used classification models to train the features, which were based on Mutual Information and Backward Feature Elimination. Balasso et al. (2021) mounted a triaxial accelerometer on the left flank of dairy cows to identify posture and behavior using machine learning techniques. They extracted 32 features and used a prediction model to classify posture and behavior. Stangaferro et al. (2016) used rumination and activity monitoring to identify cows with mastitis. They attached an electronic rumination and activity monitoring tag to Holstein cows and used an alert system (health index score) that combines rumination time and physical activity to identify cows with mastitis. Hamilton et al. (2019) used motion-sensitive bolus sensors to identify the rumination in cattle using support vector machines. They built accelerometers into pH boluses to detect the beginning of oestrus by detecting changes in behavior patterns. Pavlovic et al. (2021) used neck-mounted accelerometer-equipped collars and convolutional neural networks to classify cattle behaviors. They monitored behaviors such as the amount of time spent resting and eating and used algorithms to categorize cattle states. Benaissa et al. (2019) explore the use of on-cow accelerometers to classify behaviors in dairy barns. Peng et al. (2019) use a recurrent neural network and IMUs to classify multiple cattle behavior patterns. Robert et al. (2009) evaluate three-dimensional accelerometers for monitoring and classifying behavior patterns in cattle. González et al. (2015) classify data from collars containing motion sensors in grazing cattle. Finally, Pavlovic et al. (2021) use neck-mounted accelerometer-equipped collars and convolutional neural networks to classify cattle behaviors.

3 System models and methods

Figure 1 depicts the development process, which involved data acquisition, data pre-processing, feature extraction, and performance evaluation. The process began with the collection of data using a neck mounted sensor module capable of capturing 'Ruminating' and 'Eating' behaviors through overall animal movement and neck muscle contractions. A leg mounted sensor module was also utilized to capture 'Walking', 'Standing', and 'Lying' behaviors through measurements of overall leg movement of the animals. Following data acquisition, the collected data underwent pre-processing to remove any noise or errors. Feature extraction was then performed to identify relevant features from the pre-processed data. Finally, performance evaluation was carried out to determine the accuracy and effectiveness of the developed system. The development process is summarized in the block diagram shown in Figure 1.

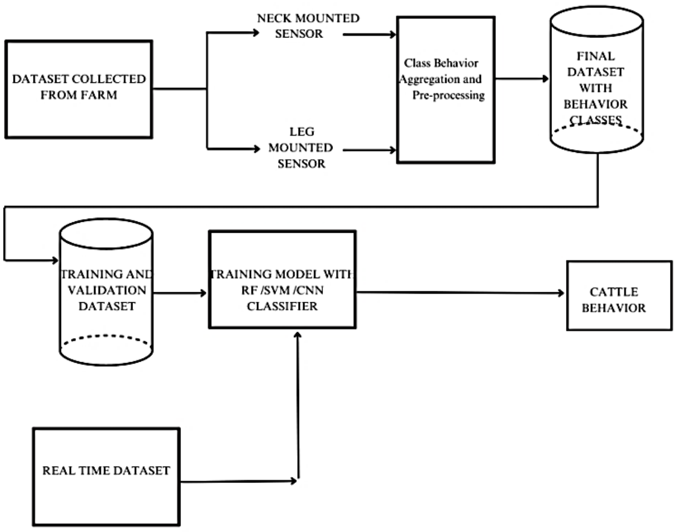

Figure 1 Block diagram of proposed methodology for cattle behaviour recognition

The proposed system for predicting cattle behavior involves mounting hardware on the leg and collar of the cattle. This allows for the prediction of behaviors such as walking, lying, standing, grazing, and ruminating in real time. Data is collected from the cattle using an MPU6050 sensor and stored in the cloud. The real-time sensor data includes 3-axis accelerometer and 3-axis gyroscope values, which are transmitted to the Thingspeak cloud. Figure 2 illustrates the hardware setup of the proposed system, where the accelerometer sensors are connected to a nodemcu and attached to the leg and collar of the cattle.

The ESP8266 NodeMCU and 3.7V battery are also used in the collar-mounted module, which is fastened around the neck of the cattle. Both modules use the MPU6050 sensor to collect data on the cattle's movements, including walking, lying, standing, grazing, and ruminating. The real-time data from the sensor, which includes 3-axis accelerometer and 3-axis gyroscope values, is transmitted to the ThingSpeak cloud for storage and analysis. The proposed system is designed to predict cattle behavior in real-time, and the hardware setup is shown in Figure 3.

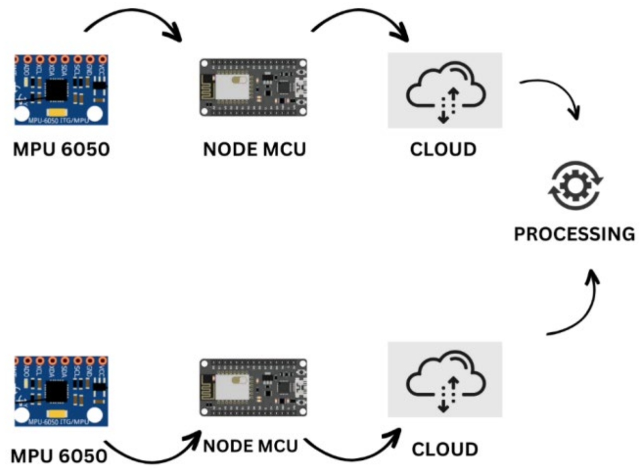

Figure 2 Hardware setup of the proposed system

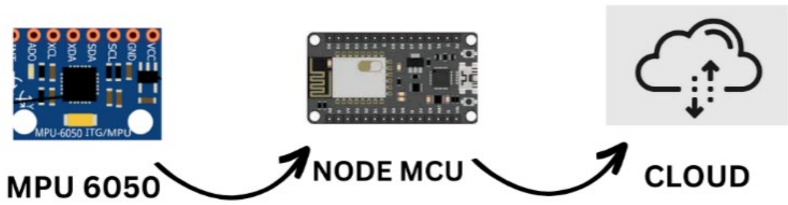

Figure 3 Leg and collar mounted module

The MPU6050 sensor module is a powerful 6-axis motion tracking device that combines a 3-axis gyroscope, a 3-axis accelerometer, and a digital motion processor in a compact package. It also includes an on-chip temperature sensor as an additional feature. The module interfaces with microcontrollers through an I2C bus interface, and it is capable of measuring velocity, orientation, acceleration, displacement, and other motion-related features with high accuracy. Its versatility and small form factor make it a popular choice for a wide range of motion tracking applications, including those in the field of animal behavior analysis, such as the study of cattle behavior.

Machine learning methods for classification: Accelerometer data can be classified using machine learning techniques such as supervised learning, unsupervised learning, and deep learning.

Decision tree classifier: Decision trees are a popular algorithm for machine learning that can be applied to both classification and regression tasks. They are simple to interpret and visualise, making them an effective instrument for comprehending how an algorithm makes predictions. Based on the values of the input features, decision trees partition the feature space into smaller regions in a recursive manner. A decision is made at each node of the tree based on the value of one of the input features. The objective is to construct a tree that maximises the separation between classes or minimises the mean squared error in regression problems. Overfitting can occur in decision trees when the model is overly complex and captures noise in the data rather than the underlying pattern. It is possible to reduce overfitting and enhance the performance of decision trees by employing pruning, ensemble methods, and regularisation.Many fields, including finance, medicine, and marketing, have effectively implemented decision trees.

Linear SVM : Support vector machine (SVM) is a supervised learning algorithm that is commonly used for classification problems in Machine Learning. The objective of SVM is to find the best decision boundary or hyperplane that can separate ndimensional space into classes so that new data points can be accurately classified. SVM accomplishes this by mapping the input data into a higher-dimensional space, where it is more likely to be linearly separable according to Cover's theorem. The decision boundary or hyperplane is selected in such a way that it maximizes the margin between the two classes, i.e., the distance between the hyperplane and the closest data points from each class. The SVM algorithm also allows for the use of a kernel function, which can transform the input data into a more suitable form for classification.

Ensemble boosted trees: Ensemble methods are commonly used to improve the performance of decision trees. Bagging and boosting are two popular ensemble approaches that have been applied to decision trees. Bagging is a technique that reduces the variance of a decision tree by dividing the training data into several subsets, each used to train a decision tree. The ensemble of multiple models generated by bagging is more reliable than using a single decision tree, as it utilizes the average of predictions from multiple trees. Boosting, on the other hand, involves training decision trees sequentially, with later trees correcting the errors made by previous ones.

KNN: The KNN algorithm can be mathematically expressed as follows: Given a training dataset D consisting of tuples of the form (x_i, y_i), $i = 1, 2, ..., n$, where x_i is the feature vector of the i^{th} instance and y_i is its corresponding class label. Given a new data point x, the kNN algorithm finds the KNN of x from the training dataset D. Let $Nk(x)$ denote the set of KNN of x, then the class label of x is determined by a majority vote among the class labels of the instances in $Nk(x)$: $y = mode(y_1, y2, ..., y_k)$.

where y is the predicted class label of x, and y_i is the class label of the i-th instance in $Nk(x)$. The mode function returns the most common class label among the KNN.

Table 1 Number of samples in the dataset for cattle behaviour recognition

Activity	Number of samples
Walking	1229
Standing-Resting	1559
Grazing	5732
Lying-Resting	1702
Lying-Ruminating	2034
Standing-Ruminating	832

Random Forest: RF is a powerful ensemble learning algorithm that combines multiple decision trees to achieve higher predictive accuracy than using a single decision tree. This algorithm can be used for both classification and regression tasks. The key idea behind the RF is to create multiple decision trees and then combine their outputs using a majority voting mechanism. Each decision tree in the RF is trained on a randomly sampled subset of the training data. This sampling is performed with replacement, a process known as bootstrapping. To build a RF model, we follow the following steps:

Randomly sample subsets of the training data with replacement.

Build a decision tree on each subset using a random subset of the features.

Repeat Steps 1 and 2 a fixed number of times to create an ensemble of decision trees.

Predict the class label (or regression value) of a new data point by taking the majority vote (or averaging) of the predictions made by all the decision trees in the ensemble. The output of the RF algorithm is therefore the combined prediction of all the decision trees in the ensemble. This helps to reduce overfitting and improve the generalization performance of the model.

4 Results and discussions

This dataset shows in Table 1 (Santos, 2022) contains 11 attributes which is including the label also. The attributes are Acc-x, Acc-y, Acc-z, Mag-x, Mag-y, Mag-z, Gir-x,Gir-y, Gir-z, Displacement and the labels. These dataset contains 13,089 samples.

Table 2 shows the confusion matrix of the tree classifier. The classes are Grazing, Lying-Resting, Lying-Ruminating, Standing-Resting, Standing-ruminating and Walking.

Table 2 Confusion matrix of cattle behaviour recognition using decision tree

	Grazing	**Lying-Resting**	**Lying-Ruminating**	**Standing-Resting**	**Standing-Ruminating**	**Walking**
Grazing	5400	35	25	131	49	92
Lying-Resting	140	856	482	179	44	1
Lying Ruminating	17	138	1650	180	49	
Standing-Resting	132	19	301	1001	101	5
Standing-Ruminating	36	8	142	373	267	6
Walking	89	1	4	8	8	1119

Table 3 Confusion matrix of cattle behaviour recognition using SVM classifier

	Grazing	**Lying-Resting**	**Lying-Ruminating**	**Standing-Resting**	**Standing-Ruminating**	**Walking**
Grazing	5324	104	38	137	3	126
Lying-Resting	308	489	683	220	1	1
Lying Ruminating	17	232	1401	381		3
Standing-Resting	102	102	251	1097	1	6
Standing-Ruminating	80	26	131	587	2	6
Walking	35	1	3	8		1182

Table 4 Confusion matrix of cattle behaviour recognition using optimizable SVM classifier

	Grazing	Lying-Resting	Lying-Ruminating	Standing-Resting	Standing-Ruminating	Walking
Grazing	5402	56	9	124	23	118
Lying-Resting	39	1328	240	66	28	1
Lying-Ruminating	17	186	1740	55	35	1
Standing-Resting	100	67	64	1145	175	8
Standing-Ruminating	23	25	37	182	560	5
Walking	145		1	8	1	1074

From the confusion matrix provided, we can see that the model performed well in correctly classifying Grazing, Lying-Resting, and Walking behaviors. However, it struggled with correctly classifying Lying-Ruminating and Standing-Ruminating behaviors, often misclassifying them as Lying-Resting or Standing-Resting. For example, the cell in the second row and third column (482) indicates that the model predicted Lying-Ruminating behavior for 482 observations that were actually Lying-Resting behavior. Similarly, the cell in the fifth row and third column (142) indicates that the model predicted Standing-Ruminating behavior for 142 observations that were actually Lying-Resting behavior.The Decision Tree Classifier achieved an accuracy of 78.6%. In terms of precision, it had a score of 0.7027, indicating that when it predicted a positive result, it was correct 70.27% of the time. The recall score was 0.6646, meaning that out of all actual positive results, the classifier correctly identified 66.46% of them. The F1 score, which balances precision and recall, was 0.6302.

The Table 3 describes the confusion matrix of SVM classifier by the True Class and the Predicted Class. The SVM Classifier achieved an accuracy of 72.5%. In terms of precision, it had a score of 0.5674, indicating that when it predicted a positive result, it was correct 56.74% of the time. The recall score was 0.6039, meaning that out of all actual positive results, the classifier correctly identified 60.39% of them. The F1 score, which balances precision and recall, was 0.5442. Based on this confusion matrix, it can be observed that the model performs relatively well for Grazing, Lying-Resting, and Standing-Resting, as most instances are correctly classified. However, the model struggles with classifying Lying-Ruminating and Standing-Ruminating, as these behaviors are often confused with other behaviors. For example, Lying-Ruminating is often confused with Lying-Resting, as seen in the misclassification of 232 instances. Similarly, Standing-Ruminating is often confused with Standing-Resting or Walking, as seen in the misclassification of 587 and 2 instances, respectively.

The optimized SVM classifier achieves an accuracy of 85.9% with Bayesian optimization for the optimal parameters of the SVM model. Additionally, Table 4 provides the confusion matrix of the optimized SVM classifier, which indicates the number of correct and incorrect predictions for each class.

Table 5 presents the Confusion Matrix of the RF Classifier, which achieves an accuracy of 89.5%. The diagonal values indicate correct predictions, while the off-diagonal values indicate misclassifications. For example, the model correctly classified 5402 instances of Grazing, but misclassified 39 instances of Lying-Resting as Grazing.

Table 5 Confusion matrix of cattle behaviour recognition using random forest classifier

	Grazing	Lying-Resting	Lying-Ruminating	Standing-Resting	Standing-Ruminating	Walking
Grazing	5548	9	7	60	10	98
Lying-Resting	53	1388	178	72	10	1
Lying-Ruminating	13	104	1843	51	22	1
Standing-Resting	121	27	64	1231	111	5
Standing-Ruminating	33	2	34	203	554	6
Walking	66	1	1	6	1	1154

The RF Classifier achieved a high accuracy of 89.5%. In terms of precision, it had a score of 0.7369, indicating that when it predicted a positive result, it was correct 73.69% of the time. The recall score was 0.7366, meaning that out of all actual positive results, the classifier correctly identified 73.66% of them. The F1 score, which balances precision and recall, was 0.7322. The given confusion matrices show the performance of a behavioral classification system for dairy cows with six behavioral categories: Grazing, Lying-Resting, Lying-Ruminating, Standing-Resting, Standing-Ruminating, and Walking. The performance of the system improves over time as shown by the increasing number of correct predictions in the diagonal elements and decreasing number of misclassifications in the off-diagonal elements.

In the study comparing the performance of six different machine learning algorithms on dataset, it was found that RF achieved the highest accuracy of 89.5%, followed by KNN at 88.1% and Optimizable SVM at 85.9%. Tree, Linear SVM, and Boosted Tree algorithms achieved lower accuracy scores of 78.6%, 72.5%, and 75.3%, respectively. These results suggest that the RF algorithm is a strong performer on this dataset, and may be the best choice for accurately predicting outcomes in similar datasets. However, it's important to note that the choice of algorithm may vary depending on the specific dataset and the research question being addressed.

5 Conclusion

In conclusion, the proposed system for cow behavior classification using leg-mounted and collar-mounted accelerometers represents a significant contribution to the field. The synchronized acceleration data from these sensors enabled improved accuracy in behavior classification, with the RF and KNN algorithms performing the best. The system outperformed traditional methods and will be an important component of an IoT-based system for monitoring and classifying cow behaviors with high accuracy. Future work will focus on implementing the IoT-based system, which is expected to have significant implications for enhancing animal welfare and improving livestock management efficiency in the agricultural industry.

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Conflict of Interest

The authors declare that they have no conflict of interest.

Data Availability Statement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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