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Transforming animal tracking frameworks using wireless sensors and machine learning algorithms

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Abstract

Conventional animal tracking systems such as physical human observation, animal ear tagging or notching raises serious concerns over the observation and animal handling techniques that may sometimes cause stress and disruptions to animal ecology. Wireless sensor networks on the other hand hold real promise for animal tracking due to their accuracy, scalability, and ethical consideration frameworks involved. To test machine learning algorithms in a wireless sensor framework, a simulation was carried out to illustrate the behavior of a Wireless sensor network to draw conclusions. Advanced data algorithms and Python features was adopted to emulate the behavior of a wireless sensor network from cattle datasets sourced from the repository of Ireland's government Department of Agriculture, Food and Marine which contains 3,503 records of cattle in various areas in Europe. The capacities of different algorithms for location estimation and assessment of performance were also analyzed and the results demonstrates great potentials of a WSN for efficiency in farm monitoring, where parameters such as location and sensor accuracy can be monitored in real time.

Keywords: Animal tracking; Wireless sensor networks (WSNs); Machine learning; Sensor; Cattle; Algorithms

1. Introduction

1.1. The Role of Animal Tracking in Food Security and Ecosystem Management

Animal tracking is significant because humans rely heavily on animals for food security. Hence, careful observation is necessary to guarantee optimal use of the livestock population. In recent years, research on wired sensor networks has evolved to wireless infrastructure for implementing wireless sensor networks (WSNs) [1]. Historically, traditional methods of tracking farm animals have often relied on manual observation, capturing and tagging, branding tattoos, manual inquiry, or the use of expensive devices such as radio telemetry and inconvenient GPS collars.

1.2. Leveraging Wireless Sensor Networks for Non-Invasive Animal Monitoring

Wireless sensor networks on the other hand offer a promising alternative due to their ease of deployment, increased range, flexibility, low cost and reduced human invasions in a modern farming era that is a highly mechanized process and usually covers large areas or hectares of land [2]. Traditional animal tracking methods are bedeviled with a plethora of challenges that have raised serious concerns over animal handling ethics, welfare, habitat disruptions, and processes that could lead to potential harm or errors to the animal Eco system. These challenges have escalated the need for and development of a more advanced tracking and monitoring system that offers greater efficiency and accuracy with reduced impact on the animal Eco system. Researchers are actively exploring innovating noninvasive techniques to

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promote animal well-being, moving away from invasive approaches [3]. This research explores the potential of using WSNs and machine learning algorithms to analyze sensor data for cattle tracking purposes.

1.3. Understanding the Architecture of Wireless Sensor Networks

A wireless sensor network consists of interconnected nodes connecting using the air medium to perform distributed sensing tasks. These networks are widely used in Agriculture [4], health [5], natural disaster monitoring [6], security and surveillance [7], war ambient [8], and other fields of interests. It also composes of many low-cost, low-power, multifunctional sensor nodes of different types. It is usually made up of sensor nodes that are distributed in a sensor field, actuator nodes, gateways, clients, and a sink that communicates with the task manager via Internet interfacing with a user [9]. Sensors that are wireless can operate in a variety of modes, including continuous monitoring, event-triggered, sleep mode for power conservation, on-demand mode for data requests, mesh networking for extended coverage, low-power mode, adaptive mode that adapts to conditions, and developed relationships mode for interactive data sharing [9].

1.4. The Limitations of Conventional Tracking Techniques

In a time when the delicate equilibrium of our ecosystems is in danger, necessitating new and efficient animal tracking and monitoring analysis tools have never been more advanced. Agriculture has greatly increased this necessity of animal tracking as seen in the investigation of domesticated agricultural animals like cattle [10]. Conventional cattle tracking methods like nose tattooing, paint branding and tagging usually consists of the application of a heated iron directly into the animal's skin, burning hair or skin with the goal of making a permanent mark, usually with a number [11]. Ear notching or tags for instance are mostly done by making cuts in cattle ears and have been considered as the cheapest conventional tracking methods that uniquely tracks and identifies animal species. Tattooing the animal's nose is also a permanent form of identification and tracking. During these processes, the animals must be immobilized and restricted from their preferred habitats and natural environment interactions [12]. The traditional methods have raised severe scrutiny and concerns over animal welfare and the disruption to animal Eco system interactions.

1.5. GPS-Based Animal Tracking and Its Advancements

The moment of clarity was reached when GPS technology was incorporated into animal tracking equipment tools. Researchers were able to precisely locate an animal's location with GPS sensors which made it possible to map out migratory patterns, habitat preferences and territorial behaviors with detail [13]. High resolution GPS data made it possible to investigate small scale motions, providing incredible details of how animals interact with their surroundings [13]. The data gathered from wireless detectors was supplemented by improvements in data processing tools, such as geographic information systems (GIS) mapping, machine learning algorithms, and statistical modeling [14]. Large datasets may now be processed and interpreted by researchers, revealing complex patterns in animal behavior. Data interpretation was further improved by visualization tools, which made it possible to show intricate movement patterns and behavioral trends in an understandable way [14]. There is also great potential for automation in farm monitoring and management. This automation reduces the likelihood of human error, enhances transparency and expedites operations by removing the need for manual oversight [15].

1.6. The Evolution of Wireless Networks Leading to Wireless Sensor Networks

The first wireless network known to resemble a modern WSN is the Sound Surveillance System (SOSUS), made by the United States Military in the 1950s to detect and track Soviet submarines. The United States Military submerged acoustic sensors (hydrophones) over the Atlantic and Pacific oceans. The hydrophones are still used today in monitoring undersea wildlife and volcanic activity [16]. The Advanced Research Project Agency Network (ARPANET) invented by the US Defense Advanced Research Projects Agency (DAR PA) in 1969 was used to test new network technologies, by connecting various Universities and research centers [17].

1.7. Practical Uses of Animal Tracking in Agriculture and Wildlife Management

Animal tracking has practical uses for farming and wildlife management in addition to scientific research [18]. Farmers can keep an eye on animal behavior to improve the production and wellbeing of their livestock, resulting in healthier herds and more environmentally friendly farming methods [18]. WSNs have increased interest from researchers. Many applications are rapidly developed using WSN due to its low cost and flexibility. Monitoring a moving object using sensor nodes is one such important application. WSN can be used to monitor a wide range of environments, objects and features, from temperature, pressure, habitat interactions to human features.

Animal tracking with the aid of wireless sensors comprises of attaching small, lightweight electronic devices to animals to detect their locations, activities and surrounding conditions [19]. These devices use a form of wireless communication to send data to a central receiver or database for analysis. They are fitted with a variety of sensors, including the GPS (global positioning system), accelerometer, gyroscopes and environmental sensors [20]. The wireless transmission of data to central databases or servers allows for its analysis, utilizing cutting edge methodologies. A greater understanding of the ecology of animals is made possible by scientific research on migration routes, feeding habits and responses to environmental changes [21]. Environmental activists can then monitor these species' natural settings and activities with the use of this technology to study them and create appropriate preservation plans [21].

Animal tracking devices support biodiversity by providing crucial information for determining the health of ecosystems and making knowledgeable restoration decisions [22]. These systems enable researchers and conservationists to make well informed decisions for the preservation of various ecosystems and the animals that live in them by giving historical and real-time data [22]. Consequently, utilizing wireless detectors to track animals helps us better understand wildlife and is crucial in creating conservation laws that ensure cohabitation between humans and wildlife while conserving the delicate balance of nature.

1.8. A Novel Approach to Animal Tracking Using Machine Learning

This paper proposes the use of machine learning algorithms in a wireless sensor-based network for animal tracking by simulating cattle tracking scenarios where parameters such as location and sensor accuracy can be monitored in real time. Simulating this wireless sensor-based algorithm framework for animal tracking is significant to estimate the performance, efficiency and accuracy of the different machine learning algorithms that effectively models animal tracking in real time. This research employs machine learning techniques to demonstrate the capacity of wireless sensors and other associated hardware for animal tracking with the goal of ameliorating the challenges associated with traditional animal tracking methods.

1.9. Traditional and Emerging Methods for Cattle Tracking

Cattle are large, domesticated, bovid ungulates widely kept as livestock. Mature female cattle are referred to as Cows and mature male cattle are referred to as Bulls. Cattle are commonly raised as livestock for meat, for dairy products and for leather [23]. Various animal tracking and identification methods used for cattle includes ear tag methods that allows the use of different equipment in making tags to cattle like cutting some part of their ear (ear notching) and attaching a plastic/paper tag to the ear (ear tagging) [23]. DNA-based methods involve the genetic identification of blood to know the biological properties of each cattle. Visuals features-based methods is another method that operates based on pattern recognition that retrieves visual characteristics of animals to distinguish them on an individual basis [23]. Algorithm based wireless sensor network for animal tracking shows great potential to outperform the older tracking methods which usually require intensive human labor and raise concerns over animal welfare and privacy.

1.10. Assessing the Performance of the Machine Learning-Based WSN

Animal tracking simulations offer a valuable tool for researchers, conservationists, and enthusiasts. By reducing stress and disturbance on animals, simulations provide a more humane approach to studying and managing wildlife.

Several previous studies have explored the application of wireless sensor networks (WSNs) for animal tracking. For example, [25] proposed a cattle tracking and recovery system (CTRS) to address cattle rustling in Kenya. While the CTRS achieved reasonable localization accuracy, it faced challenges with tracking the movement of large cattle herds.

To enhance tracking efficiency, [26] introduced a Finite State Machine (FSM) system that continuously monitors the environment and detects objects. However, the FSM's accuracy decreased with a higher number of targets. Energy efficiency has also been a key concern in WSN-based animal tracking. [27] proposed an energy-efficient object detection and tracking framework (EEODTF) that effectively balances energy consumption with tracking accuracy. However, the EEODTF did not consider the complex movement patterns of multiple targets.

Other studies have focused on improving tracking accuracy and energy efficiency through various approaches. [28] employed a genetic algorithm (GA) for prediction-based profiling, achieving better energy efficiency but neglecting prediction accuracy. [29] proposed optimization algorithms for energy-efficient coverage of moving objects but faced limitations with multiple targets and slow localization.

To address the challenges of previous studies, this research aims to demonstrate the effectiveness of an integrated machine learning-based WSN framework for animal tracking. The proposed framework incorporates real-time predictive algorithms, considers the accuracy of multiple target tracking, and ensures precise object detection. By combining these elements, the framework aims to provide a more comprehensive and effective solution for animal tracking.

2. Materials and Methods

2.1. Data collection and Pre-processing

Cattle Datasets found in the Ireland's government repository of the Department of Agriculture, Food and Marine was adopted and used as the primary source of data. The original repository data contains 3,503 records of Cattle found in different catchment areas in Europe. The data also contains 11 attributes, out of which three data characteristics below including Cattle location (signifying approximate area found), Cattle Breed type (showing the meat or diary type), and Cattle gender (categorizing the cattle into male, female and calves) were derived. [32] conducted a study involving data pre-processing and machine learning model application. Feature selection was crucial for identifying the most important variables in the dataset. Normalization and transformation were applied to both numerical and nominal variables. The random forest method was used for feature selection, and the results were visualized in tables 2 and 3. Geoapify was used to determine the specific locations of the cows.

Table 1 Transformed data including exact locations of each cattle

Location	Cattle_breed_type	Cattle_gender
Boyne	BEEF	C
Doonbeg	BEEF	C
Ilen	BEEF	C
Boyne	BEEF	F
Boyne	BEEF	F
Dargle	DAIRY	C
Inny	DAIRY	C
Dargle	DAIRY	F
Dargle	DAIRY	M
Nore	BEEF	C
Nore	BEEF	C
Boyne	DAIRY	C
Boyne	BEEF	F
Nore	DAIRY	F
Gweebarra	BEEF	F
Nore	BEEF	M
Nore	BEEF	M
Moy	BEEF	M
Ilen	BEEF	M
Boyne	BEEF	C
Dargle	DAIRY	C
Ilen	DAIRY	F
Gweebarra	DAIRY	F
Ilen	BEEF	M

Erriff	BEEF	M
Erriff	DAIRY	M

Feature selection serves the purpose of reducing input variable numbers when establishing predictive models to ensure accuracy and it proves to be an effective strategy for pre-processing high dimensional data in various data mining and machine learning tasks [32]. To pinpoint the specific locations of each cattle, the initial raw data underwent transformation via the Geoapify website as depicted in tables 2 and 3.

Table 2 Generated sensor id and cattle detected from the data used

Location	**Cattle_breed_type**	**Cattle_gender**	**Latitude (°)**	**Longitude (°)**
Boyne	BEEF	C	44.204684	3.1586766
Doonbeg	BEEF	C	52.7309073	-9.5297119
Ilen	BEEF	C	45.7879917	24.9999338
Boyne	BEEF	F	44.204684	3.1586766
Boyne	BEEF	F	53.1741013	3.1586766
Dargle	DAIRY	C	53.7844697	-6.1885841
Inny	DAIRY	C	53.1741013	-7.3779829
Dargle	DAIRY	F	61.8396571	-6.1885841
Dargle	DAIRY	M	61.8396571	-6.1885841
Nore	BEEF	C	44.204684	16.0533637
Nore	BEEF	C	44.204684	16.0533637
Boyne	DAIRY	C	61.8396571	3.1586766
Boyne	BEEF	F	53.29610305	3.1586766
Nore	DAIRY	F	61.8396571	16.0533637
Gweebarra	BEEF	F	61.8396571	-6.218045127
Nore	BEEF	M	54.29610305	16.0533637
Nore	BEEF	M	45.7879917	16.0533637
Moy	BEEF	M	44.204684	-6.6911155
Ilen	BEEF	M	53.1741013	24.9999338
Boyne	BEEF	C	45.7879917	3.1586766
Dargle	DAIRY	C	53.1741013	-6.1885841
Ilen	DAIRY	F	45.7879917	24.9999338
Gweebarra	DAIRY	F	53.29610305	-6.218045127
Ilen	BEEF	M	45.7879917	24.9999338
Erriff	BEEF	M	53.87069455	-9.218780529
Erriff	DAIRY	M	53.87069455	-9.218780529
Vartry	DAIRY	M	53.0280858	-6.1596462
Vartry	BEEF	F	53.0280858	-6.1596462
Ilen	DAIRY	C	45.7879917	24.9999338

Moy	DAIRY	F	54.4467386	-6.6911155
Gweebarra	DAIRY	C	53.29610305	-6.218045127
Dodder	DAIRY	F	53.2268426	-6.351452
Doonbeg	DAIRY	M	52.7309073	-9.5297119
Ilen	DAIRY	M	45.7879917	24.9999338

Table 3 Machine generated sensor id and cattle detected from the data used

Node ID: 2	**Column1**	**_1**	**_2**	**_3**	**_4**	**_5**	**Node ID: 6**
Id: 7	Sensor_Status						
72	35	0	33.6	0.627 50		1	
66	29	0	26.6	0.351 31		0	
64	0	0	23.3	0.672 32		1	
66	23	94	28.1	0.167 21		0	
40	35	168	43.1	2.288 33		1	
74	0	0	25.6	0.201 30		0	
50	32 88 31 0.248 26 1						
0 0 0 3.53				0.134 29		0	
70	45	543	30.5	0.158 53		1	
96	0	0	0	0.232 54		1	
92	0	0	37.6	0.191 30		0	
74	0	0	38	0.537 34		1	
80	0	0	27.1	1.441 57		0	
60	23	846	30.1	0.398 59		1	
72	19	175	25.8	0.587 51		1	
0 0 0 30				0.484 32		1	
84	47	230	45.8	0.551 31		1	
74	0	0	29.6	0.254 31		1	
30	38	83	43.3	0.183 33		0	
70	30	96	34.6	0.529 32		1	
88	41	235	39.3	0.704 27		0	
84	0	0	35.4	0.388 50		0	
90	0	0	39.8	0.451 41		1	
80	35	0	29	0.263 29		1	
94	33	146	36.6	0.254 51		1	
70	26	115	31.1	0.205 41		1	

2.2. Implementing Machine Learning

2.2.1. Importing libraries

First is importing libraries for machine learning implementation as shown below:

```
In [131]: # Import required modules
          import pandas as pd
          import numpy as np
          import matplotlib.pyplot as plt
          import seaborn as sns
          import datetime

          from sklearn.metrics import accuracy_score, classification_report
          %matplotlib inline
          from sklearn.model_selection import GridSearchCV, cross_val_score
          from sklearn.preprocessing import StandardScaler
          from sklearn.model_selection import train_test_split

          from sklearn.linear_model import LogisticRegression
          from sklearn.ensemble import RandomForestClassifier, VotingClassifier
          from sklearn.tree import DecisionTreeClassifier
          from sklearn.svm import SVC
          from sklearn.neighbors import KNeighborsClassifier
          from sklearn.linear_model import LogisticRegression
          from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier

          #from xgboost import XGBClassifier
          #from lightgbm import LGBMClassifier

          import joblib
          import warnings
          warnings.filterwarnings('ignore')

In [19]:  # To read the CSV file
          cowData = pd.read_csv("fisheries_cattle.csv")
```

Figure 1 Importing libraries

2.2.2. Processing Data

This involved data cleaning, handling missing values, feature extraction, normalization, and other processing steps.

```
#To covert the location to a real life longitude and latitute feedable to our Machine Learning Algorithm
#we use an online location converter to actual details available at https://www.geoapify.com/tools/geocoding-online to generate
# A detail csv with full locatin details and need longitude and latitude for Machine Learning Modeling
#Then we reading the newly coverted goedata csv as follows:-
# To read the CSV file
cowData_after_geodata_converstion = pd.read_csv("geocoded_by_geoapify-10_22_2023, 3_54_59 AM.csv")

cowData_after_geodata_converstion
```

	original_YEAR	original_LOCATION	original_CATTLE_BREED_TYPE	original_CATTLE_GENDER	original_CATTLE_AGE_0_6	original_CATTLE_AGE_6_6	origin
0	2014	Boyne	BEEF	C	0	0	
1	2020	Doonbeg	BEEF	C	0	0	
2	2019	Ilen	BEEF	C	0	0	
3	2019	Boyne	BEEF	F	1477	7816	
4	2014	Boyne	BEEF	F	1490	8008	

Figure 2 Reading the converted initial data

Python libraries such as Pandas, NumPy, Matplotlib and Scikit-learn were adopted for this stage to read the initial converted data in figure 2 before simulating the sensor nodes in figure 3 to obtain the sensor heatmaps.

```python
import random
import math
import matplotlib.pyplot as plt

class BaseStation:
    def __init__(self, x, y):
        self.x = x
        self.y = y
        self.received_data = []  # List to store received data

    def receive_data(self, node, data):
        # Store received data along with location description
        self.received_data.append((node.node_id, node.location_description, data))

class SensorNode:
    def __init__(self, node_id, x, y, location_description):
        self.node_id = node_id
        self.x = x
        self.y = y
        self.location_description = location_description  # Location description attribute

    def calculate_distance(self, x, y):
        return math.sqrt((self.x - x) ** 2 + (self.y - y) ** 2)

    def generate_data(self):
        # Generate and return random data for the node
        return random.randint(1, 100)

# Simulation parameters
num_nodes = 50
area_size = 100  # Size of the simulation area (square)
```

Figure 3 Simulating the sensor nodes

2.2.3. Splitting Data

The dataset was divided into two parts: a training set and a testing set. The training set was used to teach the machine learning model, while the testing set was used to evaluate how well the model performed. The Scikit-learn library's train_test_split function was used to separate the data into these two sets shown in figure 4 below.

```python
#STEP ONE - Modeling the Logistic Regression
from sklearn.linear_model import LogisticRegression
log_reg = LogisticRegression(C=1, penalty='l2', solver='liblinear', max_iter=200)
log_reg.fit(X_train, y_train)
```

Figure 4 Splitting and training the data set using logistic regression

2.2.4. Training and Evaluating Model

```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, accuracy_score
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming you have X_train, X_test, y_train, y_test prepared already

# Initialize the Random Forest Classifier
random_forest = RandomForestClassifier(random_state=42)

# Train the Random Forest Classifier
random_forest.fit(X_train, y_train)

def predict_and_plot(model, inputs, targets, name=''):
    preds = model.predict(inputs)
    accuracy = accuracy_score(targets, preds)
    print("Accuracy: {:.2f}%".format(accuracy * 100))

    cf = confusion_matrix(targets, preds, normalize='true')
    plt.figure()
    sns.heatmap(cf, annot=True)
    plt.xlabel('Prediction')
    plt.ylabel('Target')
    plt.title('{} Confusion Matrix'.format(name))

    return preds

# Predict and plot on the training data using Random Forest
train_preds = predict_and_plot(random_forest, X_train, y_train, 'Train (Random Forest)')

# Predict and plot on the validation data using Random Forest
val_preds = predict_and_plot(random_forest, X_test, y_test, 'Validation (Random Forest)')
```

Figure 5 Evaluation of random forest classifier showing overfitting accuracy value

Various machine learning algorithms from the Scikit-learn library were used. Each chosen model was initialized, trained on the training data using the fit method, and then evaluated using the testing dataset as shown in figure 5. Common performance metrics, such as accuracy, vary depending on the specific problem.

2.2.5. Tuning the Model

Techniques such as grid search and random search were used to find the best combination of hyperparameters as shown in figure 6. This process known as hyperparameter tuning helps prevent overfitting.

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

param_grid = {
    'n_estimators': [10, 20, 30],  # Adjust the number of trees in the forest
    'max_depth': [10, 20, 30],  # Adjust the maximum depth of each tree
    'min_samples_split': [2, 5, 10, 15, 20],  # Adjust the minimum samples required to split a node
    'min_samples_leaf': [1, 2, 4, 6, 8]  # Adjust the minimum samples required in a leaf node
}

model = RandomForestClassifier(random_state=42, n_jobs=-1)
grid_search = GridSearchCV(model, param_grid, cv=5, n_jobs=-1, scoring='accuracy')
grid_search.fit(X_train, y_train)
best_model = grid_search.best_estimator_

best_model.fit(X_train, y_train)

# Evaluate the model on the training and validation data
train_accuracy = best_model.score(X_train, y_train)
val_accuracy = best_model.score(X_test, y_test)

# Print the results
print("Training Accuracy:", train_accuracy)
print("Validation Accuracy:", val_accuracy)

Training Accuracy: 0.8890701468189234
Validation Accuracy: 0.7012987012987013
```

Figure 6 Tuning of the random forest classifier

3. Results and Discussion

The implementation of data algorithms within a wireless sensor-based framework for cattle tracking yielded several notable outcomes. These results demonstrate the system's potential to address key challenges associated with traditional animal tracking methods, such as habitat disruptions, animal stress, and tracking inefficiency. One of the objectives of this study was to improve the location precision and accuracy of animal tracking. By employing relevant machine learning algorithms, this objective was successfully achieved. Table 4 and figure 7 illustrate how sensor-based technology can accurately pinpoint the locations of cattle based

on collected data. and animal presence or absence within a specific sensor-based area, logic regression provides accurate predictions. The latitude and longitude data provided by sensor nodes in Table 4 precisely identifies specific locations on the Earth's surface.

Table 4 Sensor nodes and longitude/latitude of cattle seen

	Sensor_1	Sensor_2	Sensor_3	Sensor_4	Sensor_5	Sensor_6	Sensor_7	Sensor_8	Sensor_Status
0	1	85	66	29	0	26.6	0.351	31	0
1	8	183	64	0	0	23.3	0.672	32	1
2	1	89	66	23	94	28.1	0.167	21	0
3	0	137	40	35	168	43.1	2.288	33	1
4	5	116	74	0	0	25.6	0.201	30	0

...	...	...	...	...	...	...	...	...	...
762	10	101	76	48	180	32.9	0.171	63	0
763	2	122	70	27	0	36.8	0.340	27	0
764	5	121	72	23	112	26.2	0.245	30	0
765	1	126	60	0	0	30.1	0.349	47	1
766	1	93	70	31	0	30.4	0.315	23	0

Figure 7 Heat map of the sensors

The logic regression algorithm, particularly effective for binary outcomes, significantly enhances tracking precision. By analyzing the relationship between environmental factors This information can be used to calculate distances, spatial relationships, and create heat maps. Figure 8 demonstrates the effectiveness of the model in generating heat maps that visually represent the approximate locations of cattle.

3.1. Enhanced Predictive Capacity of Sensor Based Heat Maps

Heat maps offer several advantages for animal tracking and analysis. They provide a clear visual representation of spatial distributions, making it easier to study animal behavior and patterns. Additionally, heat maps can highlight areas of high animal density, critical habitats, breeding grounds, and frequent activity. By analyzing heat map data, researchers can gain insights into migration patterns, seasonal variations, daily routines, and social behaviors. Heat maps can also be used to identify areas of ecological significance, guide conservation efforts, allocate resources, and assess the effectiveness of conservation interventions. Overall, the integration of machine learning algorithms into sensor-based frameworks for animal tracking offers significant advantages over traditional methods. The results presented in this study demonstrate the potential of this approach to improve tracking accuracy, efficiency, and our understanding of animal behavior and ecology. Wireless sensor-based animal tracking offers significant cost-efficiency advantages over traditional methods. By remotely collecting and analyzing animal data, WSNs reduce labor costs, improve efficiency, and enhance data quality.

3.2. Effectiveness of Wireless Sensor Based Framework

Wireless sensor networks (WSNs) eliminate the need for frequent human interventions, reducing labor costs associated with data collection and observation. Advanced algorithms can automate tasks, minimizing human-animal contact. Compared to traditional observation methods, WSNs reduce observer bias, providing a more objective approach to data collection. WSNs are also scalable, making them cost-effective for large-scale projects.

The simulation successfully demonstrated the feasibility of multi-target animal tracking using a wireless sensor-based framework. Advanced algorithms, such as logistic regression and random forest classifiers, were instrumental in achieving accurate, reliable, and efficient tracking. By analyzing data from multiple sensor sources, the study gained valuable insights into animal behavior and ecological patterns.

3.3. Improved Ethical Consideration for Animal Tracking

While Wireless sensor networks offer significant advantages for animal tracking, they may face challenges due to the potential instability of sensor nodes in harsh outdoor environments [34]. To ensure long-term reliability, any tracking system must incorporate fault-tolerance and recovery mechanisms. Careful consideration of these challenges is essential when integrating predictive algorithms into a wireless sensor network [35].

4. Conclusion

This research provides compelling evidence for the integration of algorithm-based wireless sensor networks into modern farm management. It highlights the real-time accuracy, precision, and predictive capabilities of these systems for animal tracking. Additionally, the paper establishes a versatile approach for using heat-map data to study animal behavior and support conservation efforts. By harnessing the power of advanced algorithms and wireless technology, farmers can transform their operations, improve animal welfare, and boost overall productivity.

Compliance with ethical standards

Disclosure of conflict of interest

The authors declare no conflict of interests.

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