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Optimizing Data Processing in Animal Sensing Systems using Deep Learning Algorithms for Efficient Habitat Monitoring

Dr.K.A. Yashaswini[1*], Saniya Khurana[2], Dr. Sagar Gulati[3], Girish K. Deokar[4], Ashmeet Kaur[5], and Shweta Singh[6]

[1*]Department of Information Technology, Manipal Institute of Technology Bengaluru, Manipal Academy of Higher Education, Manipal, India. yashaswini.ka@manipal.edu, https://orcid.org/0000-0001-6794-3458

[2]Centre of Research Impact and Outcome, Chitkara University, Rajpura, Punjab, India. saniya.khurana.orp@chitkara.edu.in, https://orcid.org/0009-0005-3659-5362

[3]Department of Computer Science and Information Technology, JAIN (Deemed-to-be University), Bangalore, Karnataka, India. sagar.gulati@jainuniversity.ac.in, https://orcid.org/0000-0001-5498-7347

[4]Department of Life Sciences, PIAS, Parul University, Vadodara, Gujarat, India. girish.deokar27383@paruluniversity.ac.in, https://orcid.org/0009-0003-3074-705X

[5]Chitkara Centre for Research and Development, Chitkara University, Himachal Pradesh, India. ashmeet.kaur.orp@chitkara.edu.in, https://orcid.org/0009-0003-8780-9792

[6]Maharishi School of Engineering & Technology, Maharishi University of Information Technology, Uttar Pradesh, India. shwetasingh580@gmail.com, https://orcid.org/0000-0001-5458-9269

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Abstract

Black Vue camera traps. Camera traps and GPS collars are some of the types of animal sensing technologies used for wildlife and habitat monitoring. However, the data collected by these systems can be voluminous, and how to mine that data for useful information has confounded researchers. Witnessing the ability of deep learning models (a subset of artificial intelligence (AI) models capable of learning from high-dimensional input) to analyze and derive biological insights from this massive dataset efficiently is stunning. They design a DL-based approach to compress data during the demanding process of scanning data in animal sensing frameworks, aiming to improve habitat surveillance. In the first phase, we will develop a data pipeline using deep learning to identify and classify animals in camera trap images. For this purpose, they propose deep convolutional neural networks, which have already achieved remarkable results in many classification tasks. That automation means researchers have more time and energy to analyze a greater amount of data. Here, we have part 1 next. Next, we will add a frontend and plug it into a system for handling data from multiple sensors, such as a camera trap, GPS collar, and weather sensor. The algorithm employs both deep and machine learning methods to analyze the information and infer knowledge about the animals' movement patterns and habitat selections.

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*Corresponding author: Department of Information Technology, Manipal Academy of Higher Education, Manipal, India.

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1 Introduction

Addressing performance computing for data processing is required in animating systems and making them efficient. The systems are designed for tracking, studying, or managing the behavior of game animals in the wild. These data are applied to varying degrees of research, monitoring, conservation, and management (Christin et al., 2019). The primary motivation for optimizing the data process is that it allows you to spend less time and resources on data aggregation and analysis. We will train our model on datasets of animal locations. Still, we hope that our network will be specifically tailored to localize animals well in situ, where sensing can occur, rather than close to the nest, due to the limited range and cost of recovery (Ditria et al., 2020). This is also because, in part, the data reflects who we are and how well or poorly we are doing. Animal sensing systems in island animals experience idle service time due to high levels of noise and errors in sensor data, such as those used in wildlife sensors, which are influenced by environmental factors like weather and animal activity (AL-Nabi et al., 2024). This is where refining data processing methods contributes to eliminating such errors and improving overall data quality. Some techniques and technologies have been proposed for improving the operation of data processing device(s) in animal sensing systems (Jasim, 2024). An instance of this is data compression, where you transform the format of the data space while limiting the amount of data without losing essential information. For those interested in compression, as it is a highly efficient method for reducing data size, especially in wireless communication systems, consider consulting the Python Documentation at any layer. A second path is data fusion (Nguyen et al., 2017), where a combination of several sensor data is merged and analyzed to yield a complete understanding of the animals' behavior (Lahoz-Monfort & Magrath, 2021). This results in more meaningful analysis and conclusions, significantly enhancing the quality and reliability of the data. Furthermore, the data processing of animal sensing systems is also facilitated by advanced algorithms and machine learning techniques. Such instruments can handle massive volumes of data in near real-time, recognize patterns and anomalies, and forecast animal behavior. To conclude, the efficient and accurate collection, processing, and utilization of animal sensing data require that data gathering provides input to the important variables closest to the recording question or, more specifically, data processing improvement (Dujon et al., 2021). This facilitates an increased understanding and conservation of these animal populations and their environments among researchers, conservationists, and managers. Optimizing data processing within animal monitoring systems presents numerous challenges in achieving effective and accurate data. The problems essentially belong to two main categories: hardware and software (Lamba et al., 2019). It is also a significant challenge for hardware to have limited power and computational resources in the sensing devices. This is the reason why the data processing algorithms implemented in these systems have been fine-tuned to operate under such constraints without compromising the accuracy of the reported results (Alqaralleh et al., 2020). The second hardware limitation is the limited storage these devices contain. In addition, information on such devices is continually increasing, as it is common to have higher-resolution sensors and longer recording times (Jeantet et al., 2021). There is, therefore, a need for efficient data compression and storage techniques to minimize storage and retain only the necessary information for analysis. One important problem is the processing of data produced by the animal perception foraging systems (Lopez-Vazquez et al., 2020). These heterogeneous data sources are typically a combination of structured and unstructured data, complicating the process of extracting knowledge from these data sources. This requires an efficient data processing and analysis methodology to act quickly and accurately on these report datasets. The main contribution of the research has the following:

- Refining data processed in animal sensory systems within the context of machine learning should enable algorithm development that can achieve rapid processing of large amounts of data in a very reliable and accurate manner. This will enhance the accuracy and predictive capacity of animal detection systems, as well as expand our knowledge of the behavior and biology of biological processes (Sikarwar et al., 2025).
- Optimization of data processing involves using methods to store and access huge amounts of data efficiently. One approach might be to incorporate techniques such as data compression and reduce the amount of disk space required to store the raw data. This is particularly useful for long-term studies that collect data continuously over extended periods of time.
- Study of animal sensing systems for comparison with other system systems to understand animal behavior. This may provide a more comprehensive view of animal activity, offering insights into larger-scale patterns, trends, and shifts. This also has implications for conservation efforts and services to the agricultural industry, whereby support can be given to ensure the welfare and management of their farmed animals.
- The remaining part of the research has the following chapters. Chapter 2 describes the recent works related to the research. Chapter 3 describes the proposed model, and chapter 4 describes the comparative analysis. Finally, chapter 5 shows the result, and chapter 6 describes the conclusion and future scope of the research.

2 Related Words

Villon et al., 2020 have proposed a new method that employs several deep-learning algorithms in a cascaded architecture for species recognition. This aspect is beneficial in decreasing error rates when classification can be performed more accurately and reliably. The system also includes a feedback loop that allows it to learn from its mistakes, making it increasingly better at identifying species. (Petso et al., 2022) have discussed the importance of identifying and identifying wildlife species and individuals for population management, conservation, and research. There are various methods to identify sharks, including physical features, tracking techniques, genetic testing, behavioral analysis, and citizen science programs. Identifying species distribution, migration patterns, and behavior is crucial in both theoretical and practical aspects of conservation and management. (Jung et al., 2021) have proposed a deep learning-based cattle vocal classification model that utilizes advanced algorithms to identify and classify cattle vocalizations in real time. Maborca Howling Dog Whistle: It's an ideal way to identify potential health or behavioral issues at an early stage. The associated livestock monitoring system utilizes noise reduction methods to process and interpret vocal data, enabling farmers to make informed decisions regarding livestock management. (Widya et al., 2023). The application objectives of this study are to delineate the potential distributions of raccoon habitats using spatial statistics and deep learning (Nayak et al., 2025). By analyzing environmental and climatic data and utilizing machine learning algorithms, the current research aims to precisely predict the favorable habitats of this species, thereby facilitating conservation and management. (Neethirajan et al., 2020). Sensors are employed to record measurements related to several parameters, including temperature, humidity, and animal activity in animal farming, to guide management operations. This data is then processed using big data methods to understand the health and well-being of the animals. Finally, the use of machine learning is discussed to ensure efficient farm control and good animal welfare. (Høye et al., 2021) have described deep learning and computer vision as exciting new technologies that could significantly impact the field of entomology. These technologies can achieve this by utilizing complex algorithms and big data, which enable them to detect and categorize insects accurately, monitor their activities, and help optimize pest control practices. It will democratize the approach entomologists take toward studying and understanding these insects and can lead to new, more effective pest control measures. (Dikow et al., 2022). Deep learning has been defined as a subset of artificial intelligence that utilizes algorithms to learn from data and make predictions. It can be used in ecology and evolution to analyze large datasets, identify useful patterns, and make predictions about natural phenomena. This may aid in the understanding and conservation of species, as well as in anticipating evolutionary trends and phenomena. (Besson et al., 2022) have explained the monitoring of ecological communities as a fully automated practice, where technology and sophisticated methods are employed to gather and process information about the health of various species or the status of their habitats (Hota et al., 2025). This methodology provides continuous and real-time tracking for informed decisions and effective management to sustain and preserve these settlements. (Dyo et al., 2012) have considered an energy-efficient sensor network for wildlife monitoring. This involves developing and deploying a network of sensors across the park that has a minimal footprint but is highly effective in gathering data on wildlife. This may entail employing energy-efficient sensors, deploying green power supplies, and positioning sensors in a way that minimizes their impact on local ecosystems. (Benzekri et al., 2020) have presented an Early Forest fire detection system based on wireless sensor networks and deep learning. This system utilizes intelligent sensors and sophisticated algorithms to identify and locate potential fires in remote regions rapidly. It can greatly reduce the response time of the fire department and effectively curb the spread of wildfires. (Norouzzadeh et al., 2018), Massive automatic counting and description of wild animals in camera-trap images using deep learning have been discussed. This involves using sophisticated computer algorithms to sift through millions of images taken by camera traps in the wild and accurately identify and define the animals in them. This technology can be used to manage wildlife populations more effectively or track them more accurately. (Li et al., 2022) have presented deep learning-based techniques that have demonstrated great results in automatic fish detection, tracking, and counting for use in aquaculture facilities. Methods such as convolutional neural networks and recurrent neural networks have enhanced the accuracy and efficiency of fish recognition and fish behavior analysis, contributing to better regulation and control of fish populations. (Urbano et al., 2010) have presented the management of wildlife tracking data, which involves capturing, organizing, storing, and analyzing data concerning the movement and behavior of animals in their natural environment. This information is vital for conservation, understanding animal stocks and migration routes, and making informed management decisions. It requires implementing dedicated tracking technology and software to collect and leverage the data. (Alshahrani et al., 2021). We have presented an automatic, deep learning-based satellite remote-sensed image analysis system that utilizes different algorithms and artificial intelligence techniques for satellite image analysis purposes in ecological management (Nazir & Kaleem, 2021). The in-time and efficient monitoring of land use changes, such as vegetation, human activities, and other kinds of ecological data, can facilitate, to some extent, environmental management decisions and adjustments. (Gonzalez-Rivero et al., 2020) have described an achievable and cost-effective method, which is a method that is practical and not too expensive to be successfully carried out. This method takes into account variables that include available resources, time schedules, and potential risks to accomplish the end goal feasibly within a time constraint. Table 1 Displays the general/Comprehensive Analyses.

Table 1: Comprehensive Analysis

Author	Year	Advantage	Limitation
Villon et al.,2020	2020	Better accuracy and reliability in species identification with reduced false positive and false negative results.	Inaccurate species identification when dealing with rare or poorly represented species in the training dataset.
Petso et al., 2022	2022	One advantage of review on methods used for wildlife species and individual identification is increased accuracy and reliability of data.	One limitation is that some methods may require specialized equipment and training, making them less accessible or feasible in certain environments or for certain individuals.
Jung et al., 2021	2021	The model can accurately classify different vocalizations in real-time while reducing errors resulting from noisy background farm sounds.	One limitation is the lack of generalizability of the model to other species or environments due to training on a specific dataset.
Widya et al., 2023	2023	Efficient and accurate identification and management of potential areas for raccoon dog habitats to prevent negative ecological and economic impacts.	A limitation of this study is that the accuracy of the mapping may be affected by the quality of the input data and potentially biased due to human error.
Neethirajan et al., 2020	2020	Improved efficiency and productivity through data-driven decision making and automation in farm operations.	Dependence on electricity and technology, which may not be available in all farming settings or during power outages.
Høye et al., 2021	2021	Deep learning and computer vision will help automate and speed up insect identification and tracking, improving efficiency and accuracy in entomology research.	Requires a large amount of labeled data, which can be expensive and time-consuming to acquire.
Dikow et al., 2022	2022	Deep learning can efficiently process large and complex datasets, making it a powerful analysis tool for ecology and evolution studies.	One limitation of deep learning in ecology and evolution is the potential for overfitting and lack of generalizability due to small sample sizes.
Besson et al., 2022	2022	Increased efficiency and accuracy in data collection, allowing for more comprehensive understanding and management of ecosystems.	One limitation is the lack of reliable machine learning algorithms for accurately identifying and categorizing complex and diverse species within ecological communities.
Dyo et al., 2012	2012	Improved data collection and analysis allowing for more accurate and timely monitoring of wildlife populations and their behaviors.	Limited access to remote and harsh environments for maintenance and data collection.
Benzekri et al., 2020	2020	Improved response time and accuracy in detecting forest fires, leading to quicker containment and reduced damage.	One limitation is the potential for false alarms or inaccurate predictions due to environmental conditions or malfunctioning sensors.
Norouzzadeh, et al., 2018	2018	Increased accuracy and efficiency in wildlife population monitoring, leading to better conservation management and decision-making.	Difficulty in accurately identifying rare or non-standard species due to limited training data and potential class imbalance.
Li et al., 2022	2022	Improved classification accuracy and speed allowing for more precise and efficient monitoring of fish health and behavior in aquaculture systems.	Some deep learning algorithms may not be suitable for certain aquatic conditions or species, thus limiting their application in aquacultural machine vision systems.
Urbano et al., 2010	2010	Efficiently monitor and protect species, understand behavior, and make informed management decisions for conservation and survival of wildlife.	Insufficient funding and resources hinder the implementation and maintenance of comprehensive wildlife tracking data management systems.
Alshahrani et al., 2021	2021	Increased speed and accuracy of processing large amounts of data, allowing for more efficient and timely decision making in ecology management.	Difficulty in accurately identifying and classifying complex and rare ecological features in satellite imagery due to limited training data.
Gonzalez-Rivero, et al., 2020	2020	One advantage is that it allows for efficient resource allocation while also being practical and achievable within budget constraints.	A limitation of a feasible and cost-effective approach is that it may sacrifice quality or long-term sustainability for short-term gains.

- For instance, data collection and transmission efficiency in animal-sensing systems: The animal-sensing systems collect sensory data in large quantities, which need to be transmitted in real-time to the CPS central unit. Even so, poor data gathering and transmission can cause such delays and dropped packets, resulting in inaccuracy and inefficiency within the system. This issue can be addressed by improving data collection, such as compressing the data before transmission or by utilizing different wireless communication protocols.
- Many animal sensing applications are designed to be battery-powered, battery-powered, so power consumption is an important metric. The sensors never shut down, and the information is being sent. This. This can drain batteries, so you'd have to change them often, and then the system is down. Power management mechanisms, ranging from duty cycling to energy harvesting or low-power storage schemes, must react to the information processing requirements.
- Both the quality and accuracy of animal-sensing systems are vital to the computational algorithms that process the data produced. This would lead to inaccurate outputs and increased computational power overhead, as well as inefficient resource use if the algorithms are outdated. Data processing algorithms can also be enhanced with machine learning and artificial intelligence techniques to improve the accuracy and efficiency of these systems. Frequent updates and improvements to the algorithms can keep pace with changes in sensing capabilities, thereby enhancing the overall system performance.
- Maintaining the integrity of these habitats is crucial to their preservation; however, the traditional method for habitat monitoring is often time-consuming and labor-intensive (Kudeshova, 2025). As a result, the emerging advances in DDNs render the monitoring of habitat even more expensive for the researchers and facilitate an increase in the precision of the evaluation. Technically, what has changed is the capability of these algorithms to handle a massive amount of data used in training them and to learn increasingly complex features from the images (i.e., habitat and animal behavioral patterns) throughout the entire learning process. This can be achieved using deep learning techniques, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to analyze images and videos for species identification and activity recognition, respectively. They even pick up and improve through AA's discovering ways to predict stronger and strategically, and, in theory, of course. They even enable real-time processing of the data, allowing for quick responses and real-time interventions, if necessary. Cumulatively, these technical advances have revolutionized the way we monitor habitats, offering a habitat monitoring tool that is more cost-effective, practical, and competitive for widespread adoption by conservationists and researchers.

3 Proposed System

1) Construction Diagram

- **Orchestration**

In computer systems, including distributed systems, orchestration is a key concept. Less commonly, it is used to describe the coordination and management of several disparate services to combine and carry out a higher-level function. From a small web app to a large enterprise system – it may encompass anything relevant to them; it's essential to ensure they are functioning correctly and are well-optimized. A central master or orchestrator is the core of orchestration. The third part serves as a mediator between the other two parts and the services. Acts as a center of control, allocating resources and determining priorities in a top-down manner; enables efficient action.

$$Q_{a,y}^{*}(f)=\exp\left(\frac{-\left|f-h_{a,y}\right|_{2}^{2}}{\sigma}\right) \tag{1}$$

$$Q_{a}^{*}(f)=\max_{y} Q_{a,y}^{*}(f) \tag{2}$$

$$t=\frac{\left(h_{a_{2}y}-h_{a_{1}y}\right)}{\left|h_{a_{2}y}-h_{a_{1}y}\right|_{2}} \tag{3}$$

The orchestrator accomplishes this through a combination of mechanisms, including message passing, service discovery, and resource management. Message passing is a crucial aspect of orchestration, as it enables communication and coordination among the various complex elements of the system.

- **Data Sources**

Any particular place or mechanism from which data is collected and/or stored. It's a cornerstone of any data system, allowing data-informed decision-making and analytics. At a very basic level, a data source is a mechanism that transports data and enables users to access it. It's responsible for the extraction, transformation, and loading of information to make it usable for analysis. Figure 1 Shows The construction diagram has shown in the following

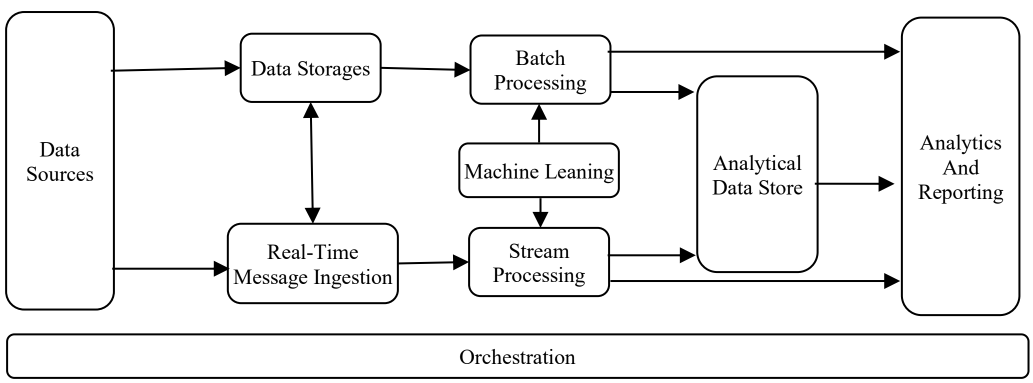

Figure 1: Construction Diagram

This process (a.k.a. ETL) includes several steps that guarantee the quality, correctness, and evenness of the data. Data extraction is the initial step in data source processes. This includes extracting the data from wherever it resides, such as a database, a data warehouse, cloud storage, or another application. This is where the data is processed in some way, using a computational that runs functions and extracts the data being analyzed. The extraction approach used shall highly depend on the data source type, i.e., API, direct connection, or file transfer. The data can be structured, such as numbers and text, or unstructured, including images, videos, social media posts, and other multimedia content.

- **Data Storages, Real-Time Message Ingestion**

Data storage is one of your most valuable resources as an organization, whether it's the data critical to your finances or the vast amounts of data analytics power. Data storage, also known as storage, is the process of recording and storing information in a storage medium. In the age of digital transformation, data is being produced continuously and randomly, so smooth means to store and access it are the priority of the day. The data storage variants, including databases, file systems, and global cloud storage, also carry specific attributes and purposes.

The bipartite graph's key points can be utilised as nodes, and the possibility G of joining the two key points and the trunk can be computed using

$$G = \int_{o=1}^{o=1} R_d\left(\left(1-o\right)c_{a1} + oc_{a2}\right) \cdot \frac{c_{a2} - c_{a1}}{\left\| c_{a2} - c_{a1} \right\|_2} co \tag{4}$$

The symbol for the bone vector is.The values of the horizontal and vertical cosines are, respectively

$$\begin{cases} \sin\alpha^b = \dfrac{\left(G_h^b - I_h^b\right)}{\sqrt{\left(G_h^b - I_h^b\right)^2 + \left(G_h^b - I_h^b\right)^2}} \\ \sin\beta^b = \dfrac{\left(G_h^b - I_h^b\right)}{\sqrt{\left(G_h^b - I_h^b\right)^2 + \left(G_h^b - I_h^b\right)^2}} \end{cases} \tag{5}$$

Databases are the most popular way of storing data, as they allow the data to be structured and also maintainable. A database is a structured digital data organizing system comprising data entries stored in a computer system, arranged in the form of records and fields, such that the data entries can be queried by a computer program or a user to retrieve specific information. These contain Tables that represent the different elements in the data. Columns represent the properties of each component. ACID (Atomicity, Consistency, Isolation, Durability) compliance ensures the most popular promise to maintain accurate and truthful data for everyone who uses the system, among other features. There are various degrees of data consistency among databases.

- **Machine Learning, Batch Processing, Stream Processing**

While ML is the purely scientific study of algorithms and statistical models, where it has no instructions provided for any task other than informing the model about what it needs to do, it learns from data and figures out something that works. Still, AI is a broader concept encompassing various systems, machines, robots, and many self-learning systems that perform and act independently of human intervention in tasks. Rather, some conscience is there. The data selection and data cleaning are the first steps of an ML process, ultimately leading to model construction using a learning algorithm. Then, the data is trained on this model, which has recognized these patterns and relations, and, ultimately, this model predicts values for new data. The complexity of the ML model is, however, an iterative factor, meaning that the amount and type of data to be used to feed the chosen algorithm. Batch Processing is based on the approach of processing large volumes of data, which can be broken down into manageable chunks or batches. Here is how it works: Data is accumulated on an ongoing basis until it's time to do something with that data collectively. Batch processing is widely used in companies with large datasets, such as Banking, Finance, and retail.

- **Analytics and Reporting**

Analytics and reporting are the two fundamental components of any business, providing insights into the performance and progress of a particular operation. Analytics is all about the science of collecting, storing, and analyzing data in a way that identifies patterns and trends, drawing insights to inform decisions and drive success.

$$U(Q_C, Q_V) = \exp\left(\sqrt{\sum_{b=1}^{13} \zeta\left(\left(\sin\alpha_C^b - \sin\alpha_V^b\right)^2 + \left(\sin\beta_C^b - \sin\beta_V^b\right)^2\right)}\right) \tag{6}$$

The specific calculation formula is

$$k_a = \left(\sum_{b=1}^{m} \omega_b h_b + I_a\right) \tag{7}$$

Output: the ability of a neuron's outcome to be utilised as an input by another neuron. The following equation illustrates the input layer and the hidden layer.

$$D_{b:b+1} = \left(h_{b+1}\right)^{h_b} \tag{8}$$

The following equation displays its mathematical representation.

$$p(h) = \frac{1}{1 + -g^{-h}} \tag{9}$$

Any value can be transformed into a value in the [0, 1] interval using the sigmoid function. Here is its mathematical expression displayed in the equation.

$$p(h) = \frac{g^h - g^{-h}}{g^h + g^{-h}} \tag{10}$$

The sigmoid function and the tanx function are comparable. Despite the fact that it is symmetrical around the origin and meets the requirements of zero means. The ReLU function, also called the "modified linear unit," has an equation that expresses its mathematical form.

$$p(h) = \max(0, h) \tag{11}$$

The basis of analytics is collecting pertinent and quality data from various sources, including customer transactions, web interactions, social media, and other business transactions. This is the first step in the process. The information is stored in a centralized database or warehouse for quick and easy access and analysis. The use of new technologies, such as cloud computing and big data systems, has made it easier and more economical to store and process large sets of data. The analytics process begins after the data is collected and stored. It requires multiple methods and algorithms to process raw data into meaningful and actionable information.

2) Functional Working Model

- **Encoder RNN (Sec 4.3,4.4)**

The Encoder RNN is a crucial component of the Seq2Seq (sequence-to-sequence) model for natural language processing (NLP) applications, such as machine translation and text summarization. It then has the task of 'looking' at the input sequence of words and converting it to a fixed length, context-sensitive representation, referred to as the encoding. The first step of the Encoder RNN is to tokenize the input sentence into words and then convert each word into an integer index representing it, called an embedding.

Positive values are immediately output as-is by the ReLU function, whereas negative integers are set to 0.

The following equation displays the mathematical expression.

$$A_{MAE} = \frac{1}{N}\sum_{b=1}^{M}\left|\left(k_b - \hat{k}_b\right)\right| \tag{12}$$

The simplest version of this loss function, which is most frequently employed in regression tasks, is displayed in the following equation.

$$A_{MAE} = \frac{1}{N}\sum_{b=1}^{M}\left(k_b - \hat{k}_b\right)^2 \tag{13}$$

There are two primary ways that Mae and MSE differ from one another. (1) By deriving equations (12) and (13), MSE can converge more quickly than Mae. The following equation illustrates how hinge loss is calculated.

$$A_{Hinge} = \sum_{b=1}^{M}\max\left(0, 1 - k_b, \hat{k}_b\right) \tag{14}$$

The positive and negative samples are represented as ±1 for both categories and ∈ (−1, 1).

These are the word embeddings that express word relationships and are computed using Word2Vec or GloVe. After tokenizing and converting your text to numbers, you pass the data through the RNN layer. The RNN consists of two elements: the recurrent state and the hidden state. The recurrent state retains information from past words of the sequence, and the secret state summarizes the information from the recurrent state.

- **Attention (Sec 4.5)**

Attention is a Technology used in neural networks to concentrate on a particular part of the input data while processing it; it is much like how the human brain works, making mental calculations and prioritizing to use resources efficiently. It is widely used in sequence-to-sequence models, such as machine translation and speech recognition, where a model must examine the entire input sequence to produce an appropriate output. The foundation of attention is to compute a dynamic weighted average of the hidden states of the input sequence, where the weights are conditioned on the current state of the model. Figure 2 Shows The functional block diagram has shown in the following

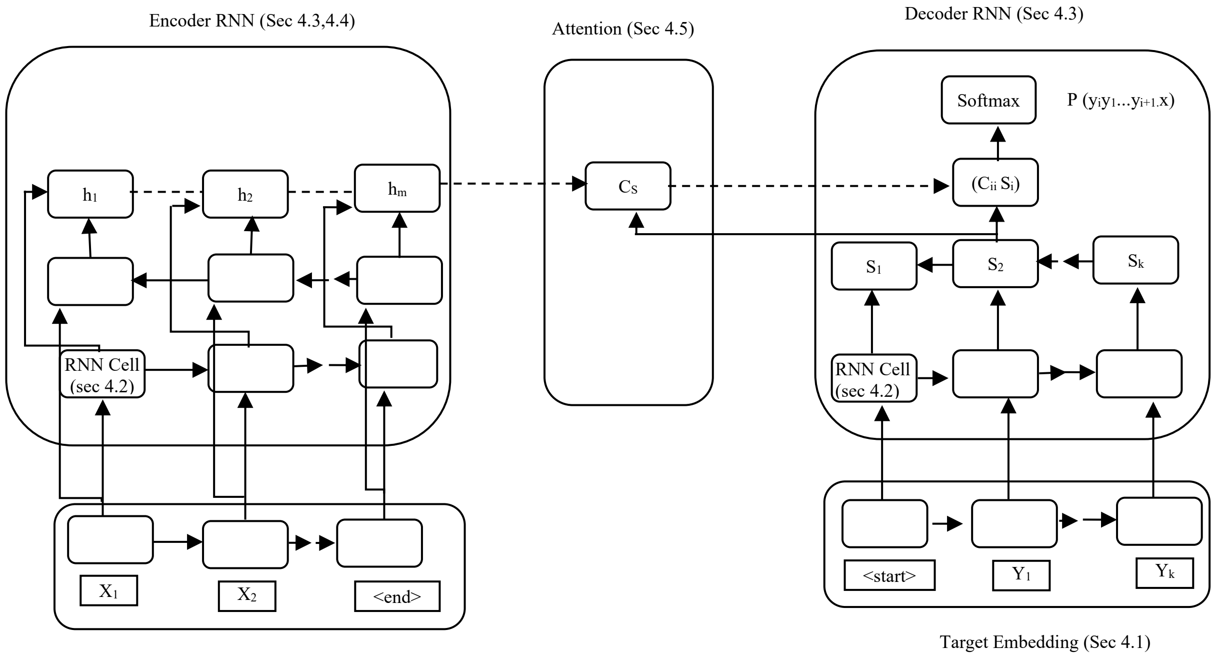

Figure 2: Functional Block Diagram

It enables the model to focus more on specific parts of the input sequence during output generation, which improves its ability to handle long sequences. These weights are obtained from attention scores, which quantify how much we care about each input hidden state about the current state.

- **Decoder RNN (Sec 4.3)**

The Decoder RNN (Recurrent Neural Network) Christin et al., (2019) is a component in a deep learning system. It is widely used for seq2seq problems, such as machine translation, text summarization, and speech recognition. RNNs can capture sequence information more effectively for this kind of operation than typical ANNs. The Decoder RNN's main function is to generate the output sequence from the input provided by the Encoder RNN.

Cross-entropy can be used to express the difference in information between them, as demonstrated by the following equation.

$$X(f,s)=\sum f(h)\log\left(\frac{1}{s(h)}\right)=-\sum f(h)\log s(h) \tag{15}$$

The CNN output is frequently processed using the sigmoid function in the binary classification problem. Its output is mapped to a probability value between [0, 1], and its loss is then computed.

$$A_{DG}=A_{sigmoid}=-\sum_{b=1}^{M}k_b\log\left(\hat{k}_b\right)+\left(1-k_b\right)\log\left(1-\hat{k}_b\right) \tag{16}$$

Two classification tasks are expanded upon by multiclassification. Its true value, y, is a single hot vector in contrast to the two classifications.

Equation (18) illustrates how to construct the Softmax loss function by combining equations (15) and (17).

$$Q(h_b) = \frac{g^{h_b}}{\sum_{a=1}^{M} g^{h_b}} \tag{17}$$

The Encoder RNN takes the input and outputs a fixed-size context vector (the first-time step of the decoder) for our Decoder 2. The Decoder RNN Decoder uses the context vector to produce the output sequence. The Decoder RNN is asked to predict one sequence element at a time. At every step of the input sequence, the RNN is given the current input and its hidden state from the previous step. The secret state is an aggregate of all inputs seen so far, helping the RNN not forget the signal from a distant point in the sequence.

- **Source Embedding (Sec 4.1)**

Source Embedding is a module in an NMT system that transduces an input text in a source language to a hidden layer. The sentence encoder reads the input source sentence (in the source language) and outputs a vector of fixed length. It is this vector that is then fed to the NMT model, which, after being trained, will generate a sequence of words in the target language. The source Embedding Process is composed of two steps: tokenization and embedding. In the tokenization process Here, as the tokens are the smallest units of a language, the input sentence (source sentence) is converted into a sequence of tokens (or words).

$$R_{DG} = R_{soft\max} = \frac{1}{M}\sum_{b=1}^{M}\log\left(\frac{g^{x_b}}{\sum_{a=1}^{D} g^{x_b}}\right) \tag{18}$$

$$\hat{D}_a^b = \max\left\{h_{a:a+\omega}^{b:b+x}\right\} \tag{19}$$

$$\bar{D}_a^b = \mathrm{m}ean\left\{h_{a:a+\omega}^{b:b+x}\right\} \tag{20}$$

When is the input characteristic matrix, the sub matrix in the correlating window of the input matrix is represented by parameters Z and x, respectively,

These tokens also contain some pieces of text in the vicinity of the word, which can be words, characters, or subwords, depending on the tokenization. This is because the model needs a structured input that it can use to refer to and make sense of any unseen input. Once the sentence is tokenized, it is ready to convert tokens into numbers, in other words, an embedding.

- **Target Embedding (Sec 4.1)**

Target Embedding is a technique in NLP that embeds target words in a continuous space, where the meanings of similar words tend to be close to each other. This is highly relevant to sentiment analysis and opinion mining, where sentiment orientation towards a target (e.g., a product or service) must be detected. The first phase in target embedding methods involves creating a large text corpus (e.g., product reviews and social media posts) that contains the target words. and the size of the pooling window is indicated by these parameters.

$$K = p\left(Z_p H + i_p\right) \tag{21}$$

Where is the activation function, is the offset, and is the weight.

$$F = soft\max\left(Z_q K + i_q\right) \tag{22}$$

$$\sum_{b=1}^{Y} F_b = 1 \tag{23}$$

This work uses the embedded Gaussian function, a straightforward modification of the conventional Gaussian function, for the similarity computation.

$$E\left(h_b, h_a\right) = g^{h_b^V h_a} \tag{24}$$

The target words are then extracted from the corpus. The context words associated with the target word are also collected. These context words may encode valuable semantic information about the target word and can facilitate its discrimination from neighboring words whose meanings may be shared. Once there are target and context words, a pre-trained neural network model, such as Word2Vec or GloVe, can be used to train the corpus.

3) Operating Principle

- **Capture Image**

Capture Image is the moment when the camera creates an electronic image of a subject or scene. This is a multi-stage process, and a kit is needed to produce high-quality batches of it. A sensor within the camera performs the process of recording light and converting it into a digital signal. The sensor is typically a CCD (Charge-Coupled Device) or CMOS (Complementary Metal-Oxide-Semiconductor) device, comprising millions of tiny photodetectors. These photosites are responsive to (sense) and measure the intensity and color of the light that is projected onto or passes through them.

$$E_{end}\left(h_b, h_a\right) = g^{\theta(h_b)^V \phi(h_a)} \tag{25}$$

$$h' = J\left(h\right) \tag{26}$$

$$k = p_2\left(p_1\left(\omega_{conv} h + i_{conv}\right) + h'\right) \tag{27}$$

K is the bias parameter in the convolution kernel, J is the attention feature presentation operation, and p1 and p2 are the activation functions of the Reed function. T is a variable that represents different places.

The camera's processor then writes the sensor data into a raw digital photo file. It is a series of complex routines and algorithms that apply sharpening to enhance color and sharpen sharpness - it sounds complicated, but the result is pleasing to the eye. It also discusses aspects such as understanding exposure settings, the type of lens we own, and whether we want to take the camera one stop more to push the image a little, providing an effective enhancement. Quality: The digital image is registered and stored in a memory card within the camera body after it is captured.

- **Transfer Data to BS**

Data Transfer to a Base Station (BS) refers to the process of transferring data from one device (for example, a WSN sensor node) or location to a base station. It is a crucial operation in various wireless communication systems, including cellular systems, Wi-Fi networks, and satellite networks. Figure.3 Shows The operational flow diagram has shown in the following.

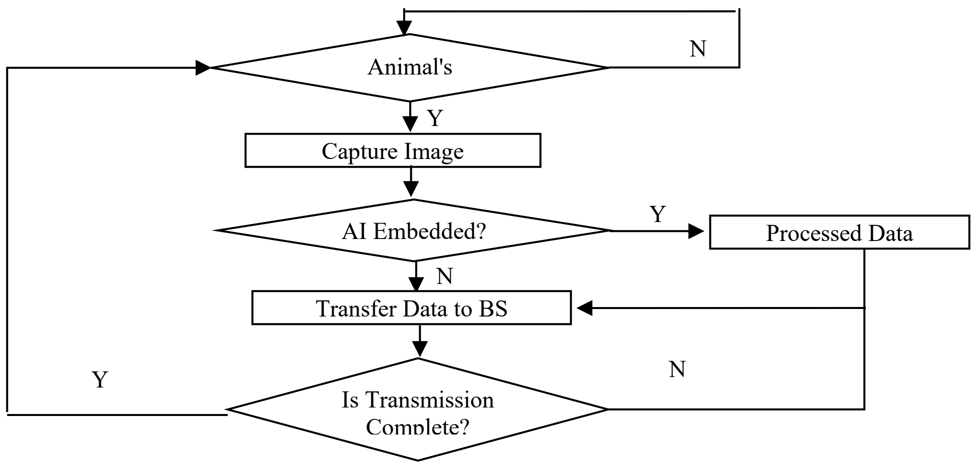

Figure 3: Operational Flow Diagram

User-BS (Base Station): Information transfer between the terminal and the Base Station (BS). This transmission is performed using radio waves, (Ditria et al., 2020). optical signals, or a wired Ethernet connection. Data is sent to it from the base station (BS), demodulated and processed by the BS receiver, decoded, and so forth. Then, the base station (BS) will send the obtained data to the core network, which will then take over the transmission along the proper path (destination). Another part of the 5G network, the core network, handles other, though smaller, components — such as routers, switches, and gateways — which all help ensure that your data finds its way to the right place intact.

- **Processed Data**

Processed Data (a.k.a. manipulated data) is data that has been translated into a more easily understood form, which is typically easier to work further with. This is the information produced by algorithms, calculations, and the processing of raw data that communicates actionable insights and supports decision-making. Data and Processing: The process begins by gathering raw data and organizing it.

The attention mechanism is then assigned to acquire the final output feature k through the 3Dattention mechanism module, as shown in equation.

$$h_{res} = p\left(\omega_{res} h + i_{res}\right) \tag{28}$$

$$k = J\left(h_{res}\right) \tag{29}$$

The tracking target's prediction range and boundary regression will change depending on the following thresholds:

$$IOU = \frac{area(D) \cap area(E)}{area(D) \cap area(E)} \tag{30}$$

Target location and tracking are steps in the process of recognising an athlete's behaviour. To begin with, every video clip is separated into an arbitrary number of frames.

$$C_{YR}\left(f \| s\right) = \sum_{b=1}^{M} F\left(h_b\right) \log\left(\frac{f\left(h_b\right)}{s\left(h_b\right)}\right) \tag{31}$$

The real location distribution is denoted by and the target approximate distribution by in the formula.

$$p_N\left(h, w\right) = \varphi\left(h\right) * \varphi\left(W\right) + i * 1 \tag{32}$$

The training target module's feature point representation is learned using one branch variable in the formula, while detection is accomplished by using the other branch variable.

This could be text, numbers, images, video, or any other file type. Data is cleaned and filtered; irrelevant or inaccurate data is suppressed. This is done to ensure the processed data is reliable. Manipulating data through tasks such as sorting, aggregating, and summarizing. These operations can help uncover patterns, trends, or relationships that were previously hidden within the raw data. It might be easier to understand your data.

4 Result and Discussion

The proposed model AISDM - Artificial Intelligence for Species Detection and Monitoring. has been compared with the existing PGNN - Population Growth Neural Network, DHHM - Deep Learning for Habitat Mapping and DIMAT - Deep Learning for Image Analysis and Tracking.

1) Speed

Therefore, fast online applications, such as real-time computer vision, require the computational velocity of the deep learning algorithm to be accelerated to achieve efficient data processing of latency-sensitive data. This will provide a simple means of conducting regular, accurate detection of animal habitats. Table 2 shows the comparison of Speed between existing and proposed models. Figure 4 Shows the Computation of Speed.

Table 2: Comparison of Speed (in %)

No. of Inputs	PGNN	DHHM	DIMAT	AISDM
100	76.59	76.06	73.28	81.34
200	78.08	78.03	75.70	83.54
300	78.88	79.16	76.11	84.34
400	81.21	80.37	77.71	85.01
500	82.22	80.74	80.03	86.44

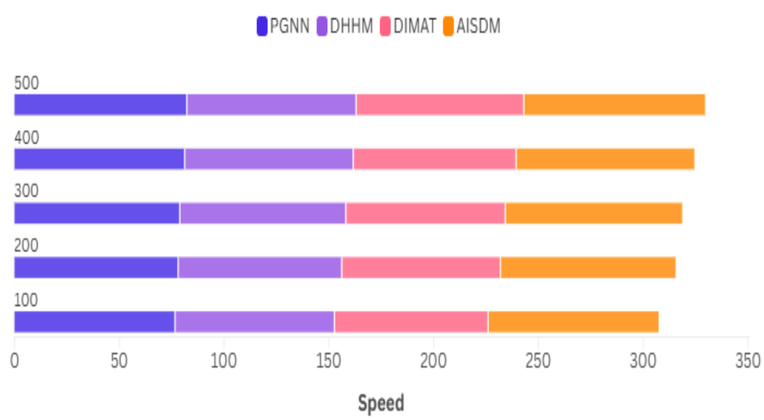

Figure 4: Computation of Speed

2) Accuracy

The accuracy of the deep learning method is crucial in monitoring the habitat, as it influences the trustworthiness of the collected data. The protocol must be refined to ensure robustness, which, in turn, contributes to an informed decision-making system and the success of conservation actions. Table.3

shows the comparison of Accuracy between existing and proposed models. Figure 5: Shows the Computation of Accuracy.

Table 3: Comparison of Accuracy (in %)

No. of Inputs	PGNN	DHHM	DIMAT	AISDM
100	79.59	79.06	76.28	83.34
200	81.08	81.03	78.70	85.54
300	81.88	82.16	79.11	86.34
400	84.21	83.37	80.71	87.01
500	85.22	83.74	83.03	88.44

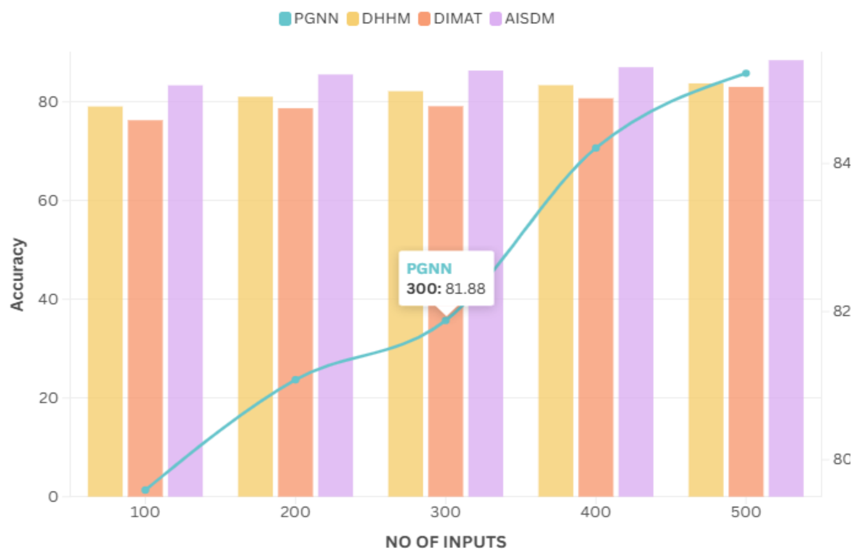

Figure 5: Computation of Accuracy

3) Scalability

The type of information an animal's sensing system records may vary significantly between habitat types and animal species. The deep learning model, therefore, must be adaptable to different kinds of input data and scalable for future rollouts. Table 4 shows the comparison of Scalability between existing and proposed models. Figure 6: Shows the Computation of Scalability.

Table 4: Comparison of Scalability (in %)

No. of Inputs	**PGNN**	**DHHM**	**DIMAT**	**AISDM**
100	84.59	82.06	80.28	85.34
200	86.08	84.03	82.70	87.54
300	86.88	85.16	83.11	88.34
400	89.21	86.37	84.71	89.01
500	90.22	86.74	87.03	90.44

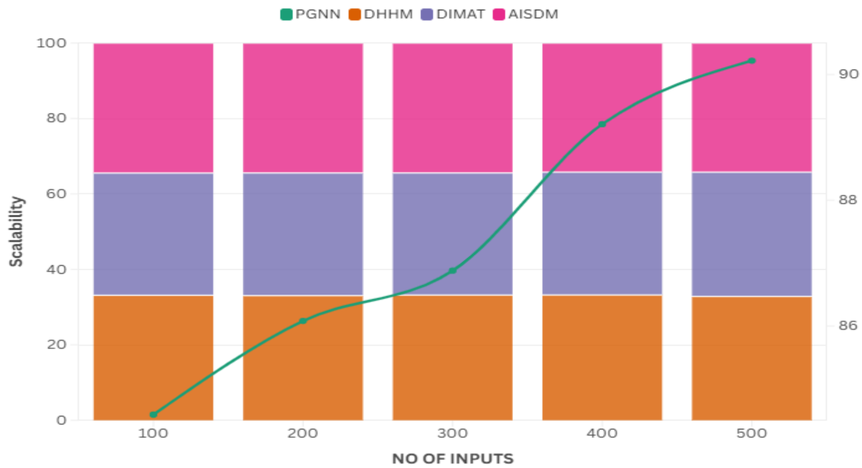

Figure 6: Computation of Scalability

4) Robustness

The algorithm should be robust to noise, missing data, or other artifacts that might be present in the data. This would ensure the data is secure and trustworthy, thus providing accurate views and analysis. Table 5 shows the comparison of Robustness between existing and proposed models. Figure 7 Shows the Computation of Robustness.

Table 5: Comparison of Robustness (in %)

No. of Inputs	PGNN	DHHM	DIMAT	AISDM
100	88.59	86.06	83.28	89.34
200	90.08	88.03	85.70	91.54
300	90.88	89.16	86.11	92.34
400	93.21	90.37	87.71	93.01
500	94.22	90.74	90.03	94.44

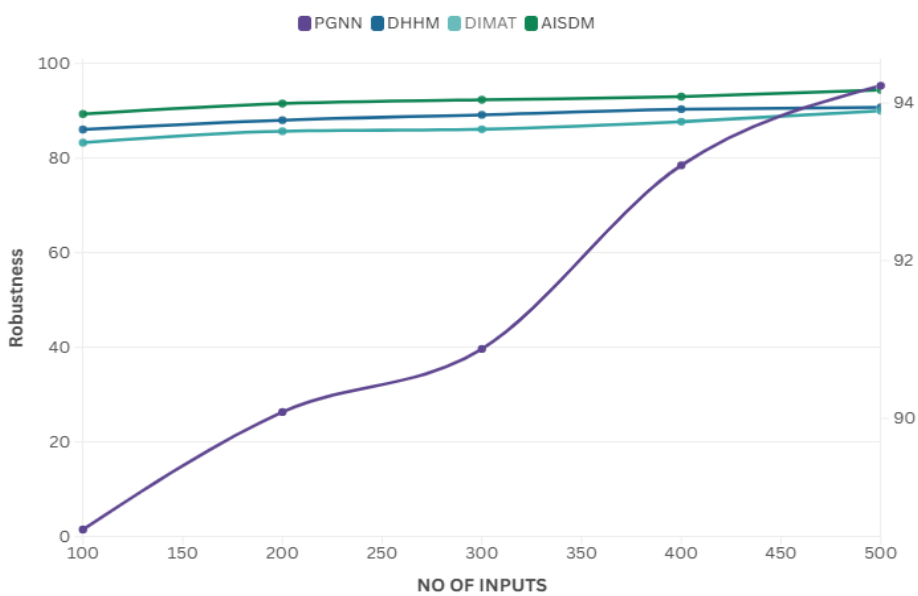

Figure 7: Computation of Robustness

5 Conclusion

Finally, the application of deep learning algorithms to process data in animal sensing systems enables effective lifecycle monitoring in the wild. These algorithms are then learned and refined using complex machine-learning methods that can process and make sense of the enormous amount of data collected from the sensors on the animals in real-time. This enables decreased data processing time and resource utilization, as well as a higher degree of precision and accuracy when monitoring habitats. Additionally, deep learning algorithms can learn and be trained on new data, making them suitable for ongoing strategy development and continuous monitoring of habitats for sustained improvement. With the data enabled by the deep-learning processing of animal sensing systems, we can gain extensive knowledge about the behavioral patterns of animals, on the one hand, and population dynamics, as well as how changing environments affect these, on the other; these are key to conserving endangered biodiversity and species. It can also support biodiversity management, decision-making, and policy formulation, as well as assist policymakers in creating long-term programs for comprehensive habitat management. There should be a greater focus on developing deep learning algorithms for animal sensing systems to provide the most efficient and comprehensive habitat monitoring solutions.

References

[1] AL-Nabi, N. R. A., Laith, A. K. M., Ammar, S. M., Ahmed, R. A., & Laith, A. A. (2024). Design and Implementation of a Low-cost IoT Smart Weather Station Framework. *Journal of Internet Services and Information Security*, *14*(2), 133-144.https://doi.org/10.58346/JISIS.2024.I2.009

[2] Alqaralleh, B. A., Mohanty, S. N., Gupta, D., Khanna, A., Shankar, K., & Vaiyapuri, T. (2020). Reliable multi-object tracking model using deep learning and energy efficient wireless multimedia sensor networks. *IEEE Access*, *8*, 213426-213436. https://doi.org/10.1109/ACCESS.2020.3039695

[3] Alshahrani, H. M., Al-Wesabi, F. N., Al Duhayyim, M., Nemri, N., Kadry, S., & Alqaralleh, B. A. (2021). An automated deep learning-based satellite imagery analysis for ecology management. *Ecological Informatics*, *66*, 101452. https://doi.org/10.1016/j.ecoinf.2021.101452

[4] Benzekri, W., El Moussati, A., Moussaoui, O., & Berrajaa, M. (2020). Early forest fire detection system using wireless sensor network and deep learning. *International Journal of Advanced Computer Science and Applications*, *11*(5). https://doi.org/10.14569/IJACSA.2020.0110564

[5] Besson, M., Alison, J., Bjerge, K., Gorochowski, T. E., Høye, T. T., Jucker, T., ... & Clements, C. F. (2022). Towards the fully automated monitoring of ecological communities. *Ecology letters*, *25*(12), 2753-2775. https://doi.org/10.1111/ele.14123

[6] Borowiec, M. L., Dikow, R. B., Frandsen, P. B., McKeeken, A., Valentini, G., & White, A. E. (2022). Deep learning as a tool for ecology and evolution. *Methods in Ecology and Evolution*, *13*(8), 1640-1660. https://doi.org/10.1111/2041-210X.13901

[7] Christin, S., Hervet, É., & Lecomte, N. (2019). Applications for deep learning in ecology. *Methods in Ecology and Evolution*, *10*(10), 1632-1644. https://doi.org/10.1111/2041-210X.13256

[8] Ditria, E. M., Lopez-Marcano, S., Sievers, M., Jinks, E. L., Brown, C. J., & Connolly, R. M. (2020). Automating the analysis of fish abundance using object detection: optimizing animal ecology with deep learning. *Frontiers in Marine Science*, *7*, 429. https://doi.org/10.3389/fmars.2020.00429

[9] Dujon, A. M., Ierodiaconou, D., Geeson, J. J., Arnould, J. P., Allan, B. M., Katselidis, K. A., & Schofield, G. (2021). Machine learning to detect marine animals in UAV imagery: Effect of

morphology, spacing, behaviour and habitat. *Remote Sensing in Ecology and Conservation*, *7*(3), 341-354. https://doi.org/10.1002/rse2.205

[10] Dyo, V., Ellwood, S. A., Macdonald, D. W., Markham, A., Trigoni, N., Wohlers, R., ... & Yousef, K. (2012). WILDSENSING: Design and deployment of a sustainable sensor network for wildlife monitoring. *ACM Transactions on Sensor Networks (TOSN)*, *8*(4), 1-33. https://doi.org/10.1145/2240116.2240118

[11] Gonzalez-Rivero, M., Beijbom, O., Rodriguez-Ramirez, A., Bryant, D. E., Ganase, A., Gonzalez-Marrero, Y., ... & Hoegh-Guldberg, O. (2020). Monitoring of coral reefs using artificial intelligence: A feasible and cost-effective approach. *Remote Sensing*, *12*(3), 489. https://doi.org/10.3390/rs12030489

[12] Hota, D., Rajasekar, K., Parashar, T., Sobti, S., Roy, A., & Ajitha, P. (2025). Using the MaxEnt Algorithm to Predict Habitat Suitability Under Climate Change Scenarios. *Natural and Engineering Sciences*, *10*(2), 270-283. https://doi.org/10.28978/nesciences.1763921

[13] Høye, T. T., Ärje, J., Bjerge, K., Hansen, O. L., Iosifidis, A., Leese, F., ... & Raitoharju, J. (2021). Deep learning and computer vision will transform entomology. *Proceedings of the National Academy of Sciences*, *118*(2), e2002545117. https://doi.org/10.1073/pnas.2002545117

[14] Jasim, A. T. (2024). Investigating the Potential of Remote Sensing for Sustainable Urban Renewal and Regeneration: A Review. *International Academic Journal of Science and Engineering*, *11*(1), 54-64. https://doi.org/10.9756/IAJSE/V11I1/IAJSE1108

[15] Jeantet, L., Vigon, V., Geiger, S., & Chevallier, D. (2021). Fully convolutional neural network: a solution to infer animal behaviours from multi-sensor data. *Ecological Modelling*, *450*, 109555. https://doi.org/10.1016/j.ecolmodel.2021.109555

[16] Jung, D. H., Kim, N. Y., Moon, S. H., Jhin, C., Kim, H. J., Yang, J. S., ... & Park, S. H. (2021). Deep learning-based cattle vocal classification model and real-time livestock monitoring system with noise filtering. *Animals*, *11*(2), 357. https://doi.org/10.3390/ani11020357

[17] Kudeshova, G. (2025). Fish Habitat Suitability Evaluation Through Habitat Evaluation Procedure Modelling. *Aquatic Ecosystems and Environmental Frontiers*, *3*(2), 11-19.

[18] Kusuma, W. L., & Fatemah, R. (2023). Mapping the potential distribution of raccoon dog habitats: Spatial statistics and optimized deep learning approaches. *National Institute of Ecology Bulletin, 4*(4), 159-176. https://doi.org/10.22920/PNIE.2023.4.4.159

[19] Lahoz-Monfort, J. J., & Magrath, M. J. (2021). A comprehensive overview of technologies for species and habitat monitoring and conservation. *BioScience*, *71*(10), 1038-1062. https://doi.org/10.1093/biosci/biab073

[20] Lamba, A., Cassey, P., Segaran, R. R., & Koh, L. P. (2019). Deep learning for environmental conservation. *Current Biology*, *29*(19), R977-R982. https://doi.org/10.1016/j.cub.2019.08.016

[21] Li, D., & Du, L. (2022). Recent advances of deep learning algorithms for aquacultural machine vision systems with emphasis on fish. *Artificial Intelligence Review*, *55*(5), 4077-4116. https://doi.org/10.1007/s10462-021-10102-3

[22] Lopez-Vazquez, V., Lopez-Guede, J. M., Marini, S., Fanelli, E., Johnsen, E., & Aguzzi, J. (2020). Video image enhancement and machine learning pipeline for underwater animal detection and classification at cabled observatories. *Sensors*, *20*(3), 726. https://doi.org/10.3390/s20030726

[23] Nayak, A., Lalnunthari, & Rawat, A. (2025). Surveillance of coastal erosion and marine habitat degradation using remote sensing and GIS. *International Journal of Aquatic Research and Environmental Studies*, 5(1), 162–169. https://doi.org/10.70102/IJARES/V5I1/5-1-16

[24] Nazir, S., & Kaleem, M. (2021). Advances in image acquisition and processing technologies transforming animal ecological studies. *Ecological Informatics*, *61*, 101212. https://doi.org/10.1016/j.ecoinf.2021.101212

[25] Neethirajan, S. (2020). The role of sensors, big data and machine learning in modern animal farming. *Sensing and Bio-Sensing Research*, *29*, 100367. https://doi.org/10.1016/j.sbsr.2020.100367

[26] Nguyen, H., Maclagan, S. J., Nguyen, T. D., Nguyen, T., Flemons, P., Andrews, K., ... & Phung, D. (2017, October). Animal recognition and identification with deep convolutional neural networks for automated wildlife monitoring. In *2017 IEEE international conference on data science and advanced Analytics (DSAA)* (pp. 40-49). IEEE. https://doi.org/10.1109/DSAA.2017.31

[27] Norouzzadeh, M. S., Nguyen, A., Kosmala, M., Swanson, A., Palmer, M. S., Packer, C., & Clune, J. (2018). Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning. *Proceedings of the National Academy of Sciences*, *115*(25), E5716-E5725. https://doi.org/10.1073/pnas.1719367115

[28] Petso, T., Jamisola Jr, R. S., & Mpoeleng, D. (2022). Review on methods used for wildlife species and individual identification. *European Journal of Wildlife Research*, *68*(1), 3. https://doi.org/10.1007/s10344-021-01549-4

[29] Sikarwar, T. S., Chauhan, A. S., Jain, N., & Mathur, H. (2025). Application of Predictive Analytics in IOT Data Processing. *Indian Journal of Information Sources and Services, 15(2), 340–348*. https://doi.org/10.51983/ijiss-2025.IJISS.15.2.42

[30] Urbano, F., Cagnacci, F., Calenge, C., Dettki, H., Cameron, A., & Neteler, M. (2010). Wildlife tracking data management: a new vision. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *365*(1550), 2177-2185. https://doi.org/10.1098/rstb.2010.0081

[31] Villon, S., Mouillot, D., Chaumont, M., Subsol, G., Claverie, T., & Villéger, S. (2020). A new method to control error rates in automated species identification with deep learning algorithms. *Scientific reports*, *10*(1), 10972. https://doi.org/10.1038/s41598-020-67573-7

Authors Biography

Dr.K.A. Yashaswini is an Assistant Professor – Senior Scale in the Department of Information Technology at Manipal Academy of Higher Education, Manipal. Her research interests include artificial intelligence, machine learning, and data-driven computing. Dr. Yashaswini has authored several publications in reputed journals and actively mentors students and research projects focused on innovative IT applications and emerging technologies

Saniya Khurana is associated with the Centre of Research Impact and Outcome at Chitkara University, Punjab. Her professional focus includes research assessment, institutional analytics, and innovation management. She contributes to projects aimed at enhancing research visibility, academic performance, and interdisciplinary collaboration. Saniya is actively engaged in initiatives to improve research impact and promote data-driven decision-making in higher education.

Dr. Sagar Gulati is the Director of the Department of Computer Science and Information Technology at JAIN (Deemed-to-be University), Bangalore. His research interests include artificial intelligence, software engineering, and computer systems optimization. Dr. Gulati has numerous publications in peer-reviewed journals and leads academic initiatives, research projects, and mentorship programs in computer science and information technology.

Girish K. Deokar is an Assistant Professor in the Department of Life Sciences at PIAS, Parul University, Gujarat. His research areas include microbiology, molecular biology, and biotechnology. He is actively involved in guiding students, conducting research projects, and publishing in peer-reviewed journals to advance scientific knowledge in life sciences.

Ashmeet Kaur is affiliated with the Chitkara Centre for Research and Development, Chitkara University, Himachal Pradesh. Her professional focus includes research evaluation, academic development, and outcome-based project management. She actively contributes to initiatives that enhance institutional research quality, interdisciplinary collaboration, and innovation in higher education.

Shweta Singh is an Assistant Professor at the Maharishi School of Engineering & Technology, Maharishi University of Information Technology, Uttar Pradesh. Her areas of interest include computer science, data analytics, and emerging technologies. She is engaged in teaching, research guidance, and academic development, focusing on enhancing student learning outcomes and advancing applied research in engineering disciplines.