Artificial Intelligence & Expert System
CT-361
Complex Computing Problem

Autonomous Wildlife Monitoring System

REPORT

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Complex Computing Problem Assessment Rubrics

Course Code: CT-361		Course Title: Artificial Intelligence & Expert System	
Criteria and Scales			
Excellent (3)	**Good (2)**	**Average (1)**	**Poor (0)**
Criterion 1: Understanding the Problem: How well the problem statement is understood by the student			
Understand the problem clearly and identify the underlying issues and functionalities.	Adequately understands the problem and identifies the underlying issues and functionalities.	Inadequately defines the problem and identifies the underlying issues and functionalities.	Fails to define the problem adequately and does not identify the underlying issues and functionalities.
Criterion 2: Research: The amount of research that is used in solving the problem			
Contains all the information needed for solving the problem	Good research leads to a successful solution	Mediocre research which may or may not lead to an adequate solution	No apparent research
Criterion 3: Code: How complete the code is along with the assumptions and selected functionalities			
Complete the code according to the selected functionalities of the given case with clear assumptions	Incomplete code according to the selected functionalities of the given case with clear assumptions	Incomplete code according to the selected functionalities of the given case with unclear assumptions	Wrong code and naming conventions
Criterion 4: Report: How thorough and well-organized is the solution			
All the necessary information is organized for easy use insolving the problem	Good information organized well could lead to a good solution	Mediocre information which may or may not lead to a solution	No report provided

Total Marks: ______________

Teacher's Signature:__________________

Table of Content

Introduction

The Autonomous Wildlife Monitoring System is designed to observe and analyse wildlife activities autonomously. By employing AI techniques such as object detection, speech recognition, and graph theory, the system aims to accurately identify animals and interpret their behaviours using real-time image and audio data. This technology is particularly useful in environments like safari parks and zoos, where constant and detailed monitoring can enhance both animal welfare and visitor experience.

Purpose of the Project

The main problem addressed by this project is the need for an efficient, automated system to monitor wildlife activities. Traditional methods are labour-intensive and prone to human error, making it difficult to maintain continuous and accurate surveillance. Our system seeks to overcome these limitations by leveraging advanced AI technologies.

Overview of the System

The Autonomous Wildlife Monitoring System comprises three main components:

- Image and Video Detection
- Sound Analysis
- Graph-Based Movement Tracking

1) Image and Video Detection

Objective:

Develop algorithms to detect and identify various animals in photos and videos.

Approach:

Initial Use of HAAR-like Features:

In the initial stages of development, Haar-like features were chosen to meet project requirements. These features utilize basic rectangular patterns to detect specific characteristics within images, making them suitable for preliminary object detection tasks.

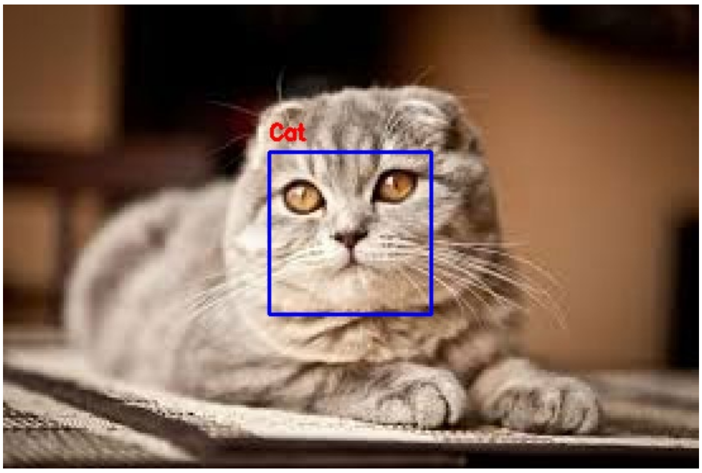
Limitations of HAAR-based Methods:

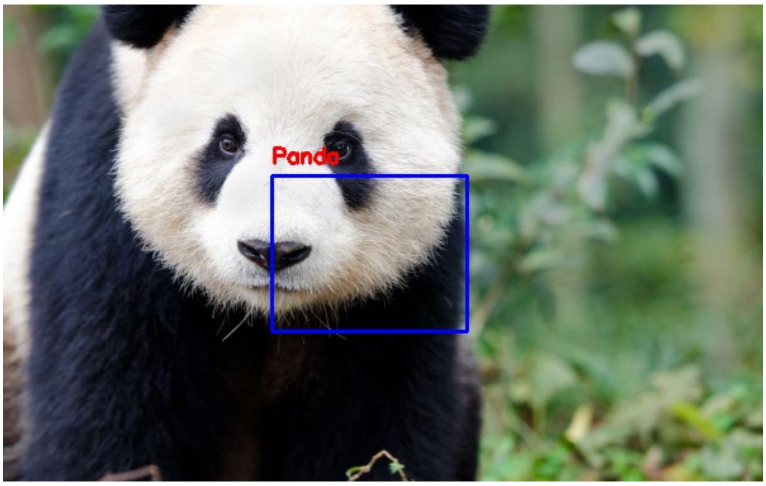
HAAR-based methods, however, have inherent limitations, especially when it comes to accurately distinguishing between different animal species, particularly in video footage. These methods heavily rely on grayscale differences and predefined patterns, which may not sufficiently capture the diverse characteristics and complexities present in wildlife images, especially when animals are in motion.

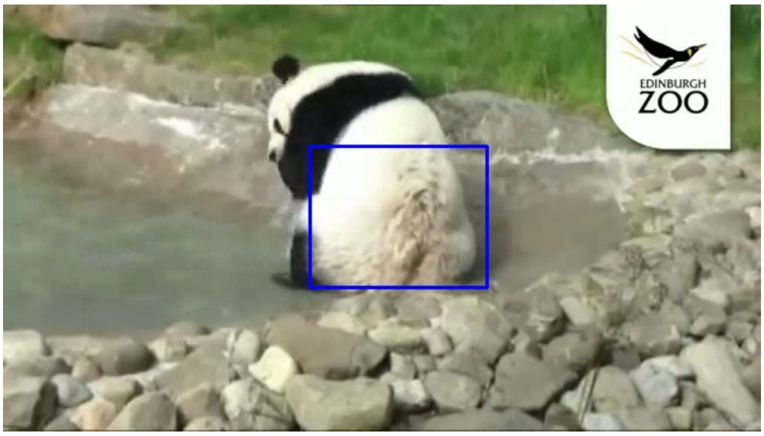
Results of HAAR-based Detection:

Identified Images / Video Frame:

Include a selection of images where HAAR-based detection successfully identified animals. These images can showcase instances where the algorithm accurately localized and recognized animal species within the monitored environment.

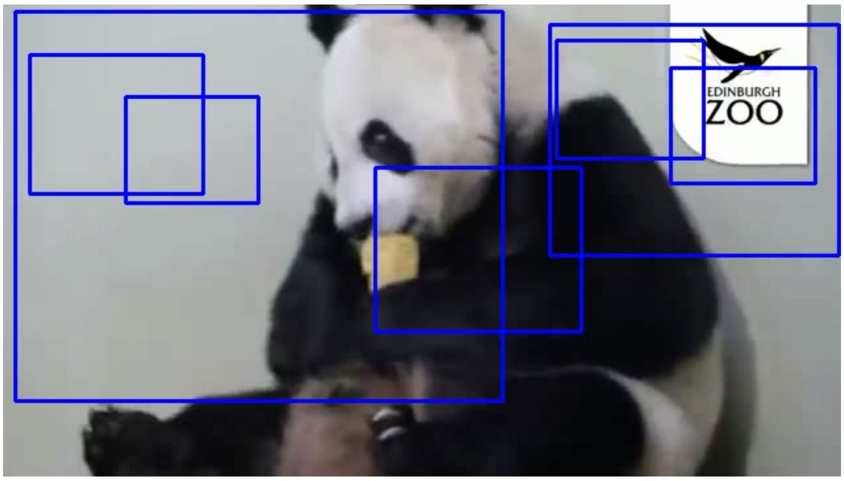


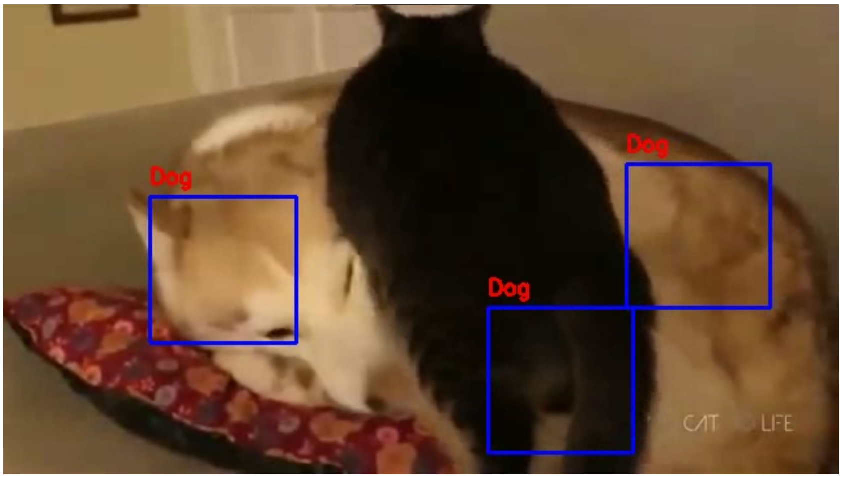




Wrongly Identified Images/Frames:

These examples should highlight scenarios where the algorithm struggled due to the complexity of scenes or variations in animal appearance.





Transition to You Only Look Once (YOLO):

Despite providing foundational insights, HAAR-based detection showed significant limitations in accurately identifying a wide range of animal species, particularly in video footage where animals are in motion and scenes are dynamic. To address these shortcomings and enhance real-time object detection capabilities, we transitioned to more advanced techniques such as You Only Look Once (YOLO)

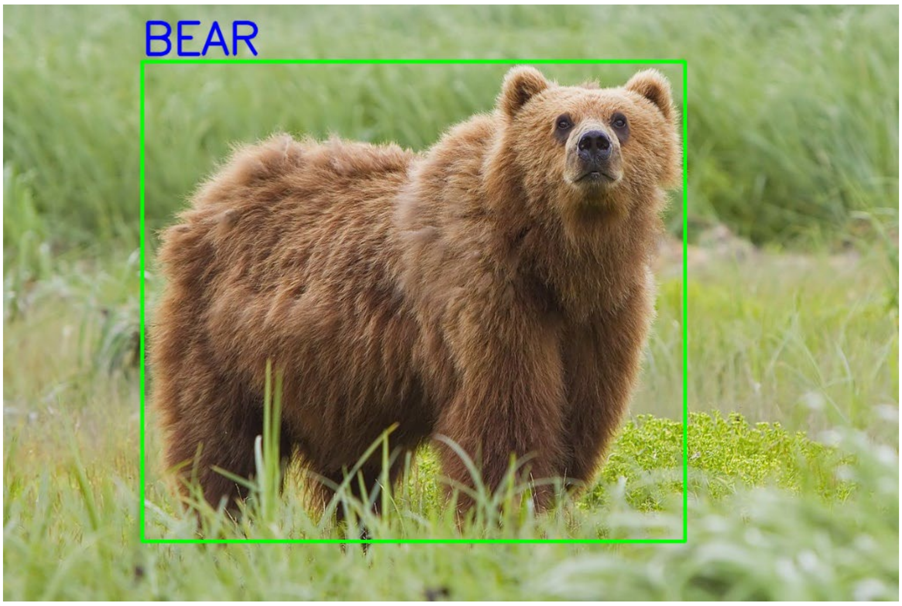
Why YOLO?

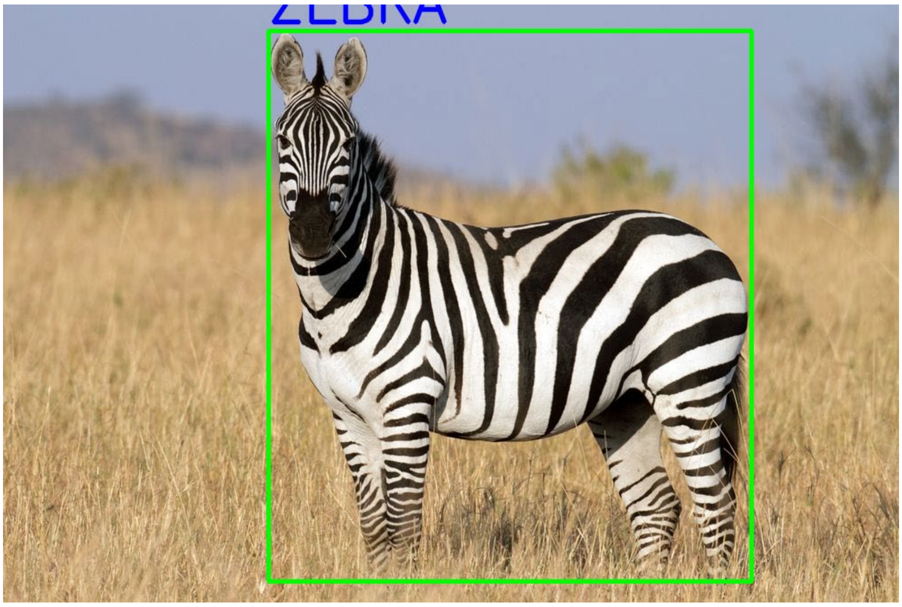
YOLO (You Only Look Once) is a real-time object detection system that predicts bounding boxes and class probabilities simultaneously by dividing images into grids. Its unified architecture uses a single neural network to achieve speed, eliminating complex post-processing.

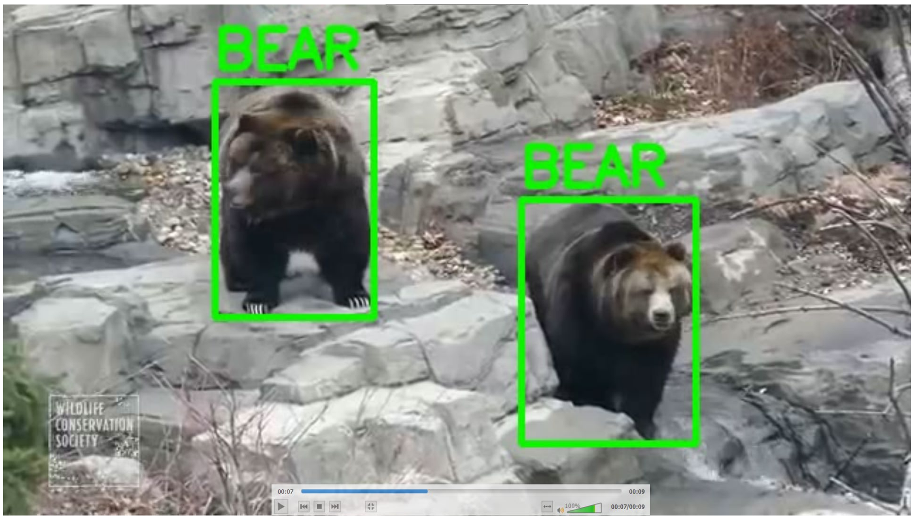
For our Autonomous Wildlife Monitoring System, we opted for YOLOv8 due to its advanced speed and accuracy improvements. YOLOv8 incorporates enhanced network architecture, feature extraction, and training methods, making it ideal for real-time detection and tracking of diverse animal species in safari parks and zoos.

Results of YOLO Object Detection:

YOLOv8 demonstrated robust performance in detecting and classifying various animal species within the monitored environment. Below are examples of images and video frames showcasing the successful detections and classifications achieved by YOLOv8.


BEAR

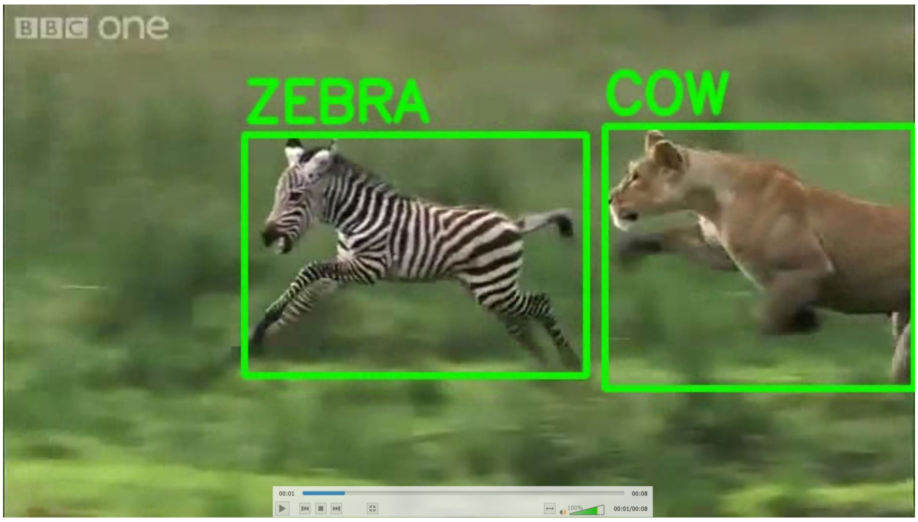



BEAR
BEAR
WILDLIFE
CONSERVATION
SOCIETY

Limitations:

Despite its exceptional localization capabilities, YOLOv8 occasionally misclassifies animals, which can pose challenges in real-life scenarios where accurate species identification is crucial.

Here are examples illustrating instances where YOLOv8 misclassified animals:



Identifying lioness as a Cow by YOLOv8

Identifying Bear as an Elephant by YOLOv8

Identifying Horses as a Person and Cow

Even though these don't happen quite often with animals included in the YOLOv8 class, it is indeed a problem if it is implemented in a real-life scenario.

Proposed Solution:

To mitigate misclassification issues and enhance the accuracy of YOLOv8 in real-world applications, we propose the following solution:

- **Training for Wildlife Environment:**
  Training YOLOv8 with a comprehensive dataset covering all zoo or wildlife species enhances its ability to accurately distinguish between different animals based on unique features and appearances.

- **Providing Clear Image of Animal:**
  Supplying clear, high-quality images of each animal species supports YOLOv8 in achieving better training and classification accuracy, encompassing diverse poses, lighting conditions, and environmental contexts for robust real-time detection and classification.

2) Sound Analysis

Objective:

Classify animal sounds to determine their mood (e.g., Angry, Normal).

Approach:

To detect and classify animal moods based on sound, we will primarily focus on analysing the amplitude of the audio signals. Amplitude provides a measure of the sound wave's intensity, which correlates with the emotional state of the animal.

Classification Criteria:

- **Normal Mood:**
  Amplitude around 50% indicates a normal mood state.
- **Angry Mood:**
  If the amplitude exceeds a certain threshold (e.g., 68%), the mood will be classified as Angry. This threshold is set based on initial observations and may be adjusted during tuning and testing phases.
- **Quiet/Sad Mood:**
  Amplitude below a specified threshold (e.g., 40%) indicates a quiet or sad mood state.

Implementation Steps:

- **Data Processing:**
  The audio signal is read from the WAV file and normalized to ensure consistent amplitude analysis across different audio formats.
- **Amplitude Analysis:**
  The maximum amplitude of the normalized audio signal is calculated. This value represents the intensity of the sound wave, which correlates with the animal's mood.
- **Mood Classification:**
  Based on predefined thresholds (angry_threshold = 0.68 and normal_threshold_low = 0.40), the mood is classified as Angry/Irritated, Normal/Happy, or Sad/Quiet. These thresholds have

been determined through experimentation and validation with real-world data.

- **Visualization:**
  A plot of the audio signal over time is generated to visually represent the classified mood and provide further insights into the signal characteristics.

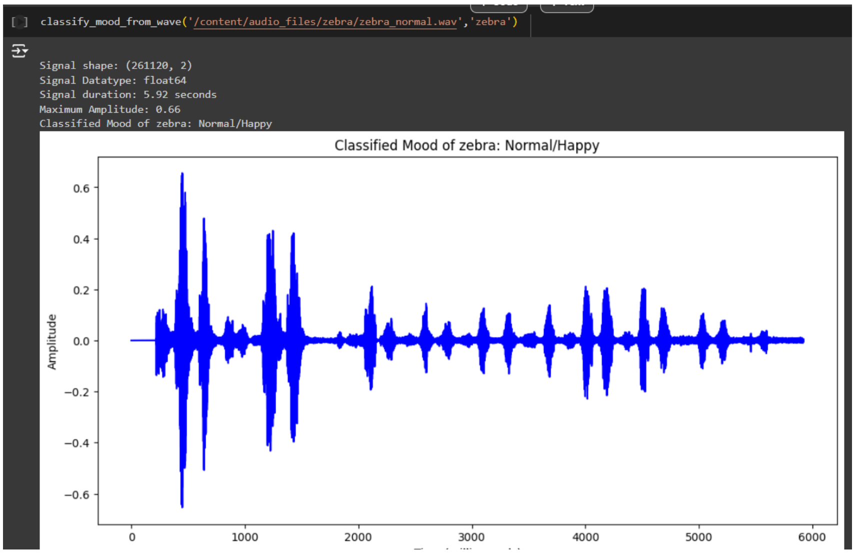
Output of the Procedure:

After implementing the above procedure, the system outputs the following information for each analyzed audio signal:

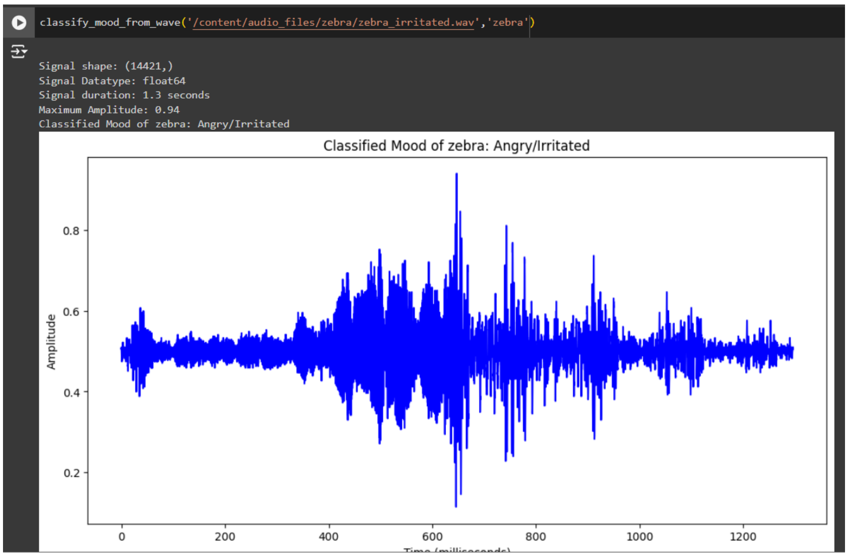
- Signal shape and duration
- Signal datatype
- Maximum amplitude calculated
- Classified mood of the animal (Angry/Irritated, Normal/Happy, or Sad/Quiet)

Example:

Mood analysis on Zebra Normal noise.



Mood analysis on Zebra being irritated



The provided above graphs showcase the mood analysis based on the max amplitude.

Limitation:

The limiting factor of this type of analysis is its heavy dependency on amplitude. In scenarios where the animal is in close proximity to the recording device or during periods of heightened ambient noise, the amplitude of the audio signal may be elevated even when the animal is in a normal mood. This can result in misclassification, where the system identifies the animal as Angry/Irritated incorrectly.

Proposed Solution:

To mitigate this limitation, we propose incorporating video feed analysis alongside audio signal analysis. By simultaneously observing the behaviour of the animal through video footage, the system can correlate visual cues with the audio-based mood classification resulting in enhancing the accuracy of mood classification.

3) Graph-Based Movement Tracking

Objective:

Track animal movements within a mapped area using graph theory.

Approach:

For tracking bear movements based on behaviour, we utilize a graph representation specifically tailored to the bear's habitat. Each location (node) in the graph represents a crucial area within the bear's environment, including water sources, forests, dens, and visitor centres. Edges between nodes denote feasible paths or movements that bears can undertake between these locations, forming a structured network that models their potential movements and interactions within their natural habitat. This approach provides a systematic framework for understanding and predicting bear behaviour based on their spatial dynamics and habitat utilization patterns.

Behaviour-based Destination Determination:

To determine where an animal will move based on its behavior, we establish mappings:

- **Hungry:**
  The animal heads towards areas with food sources, typically forests or specific feeding grounds.
- **Thirsty:**
  Water sources become the destination, ensuring the animal can hydrate.
- **Tired:**
  The den or resting areas are targeted for relaxation and safety.
- **Exploring:**
  This behaviour might lead the animal to areas like visitor centres or other less predictable spots, promoting a variety of movement patterns.

Implementation Steps:

- **Graph Construction:** Define the graph structure with nodes representing key locations and edges representing possible paths between them. This is typically based on observed or predefined knowledge of the wildlife habitat.
- **Destination Determination Function:** Implement a function that maps animal behaviours to specific nodes in the graph. This function helps decide where the animal should move based on its current state or needs.
- **Shortest Path Calculation (BFS):** Use BFS algorithm to calculate the shortest path from the animal's current location to its determined

destination. BFS ensures that we find the shortest path in terms of the number of edges traversed, which is efficient for real-time tracking and decision-making.

Why This Approach?

- **Realism and Accuracy:** Graph-based modeling simulates animal movements realistically by integrating spatial relationships and environmental influences, providing a precise portrayal of wildlife behaviors in their habitats.

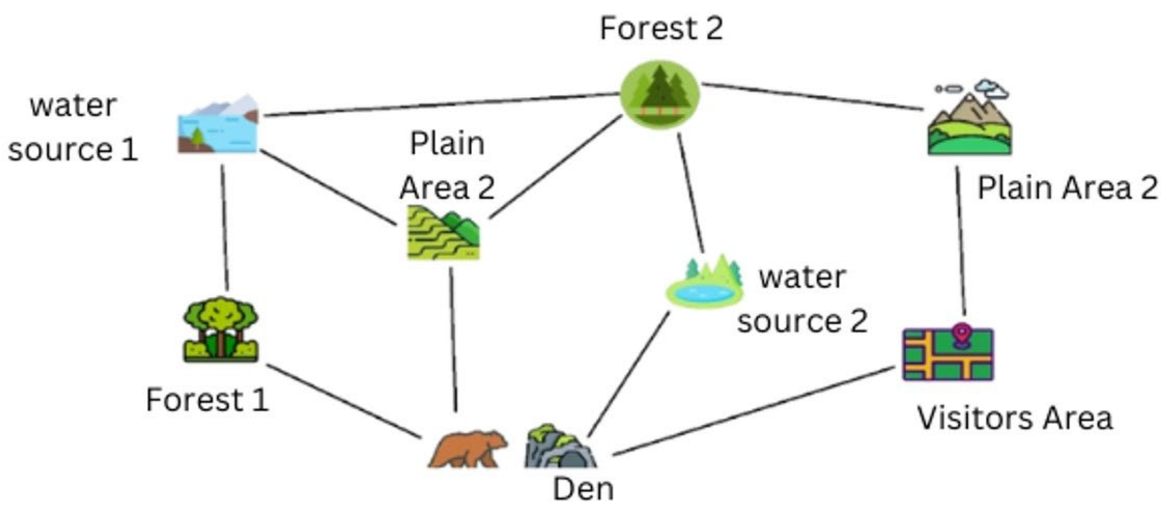
- **Decision Support:** This approach assists wildlife managers and conservationists by predicting animal movement paths, supporting informed decisions on habitat management, conservation planning, and welfare strategies.

- **Scalability and Adaptability:** The graph-based method is scalable to different wildlife environments and adaptable to incorporate variables such as terrain, seasons, and human impacts, ensuring its relevance across diverse conservation contexts.

Assumption:

Before moving on to the demonstration, we assume that bear will always that the smallest path towards its destination

Graph for Bear Tracking:



Example output:

If a bear is at its den and the current behaviour system detects that it's hungry hence he went to Forest-1 to hunt for berries or other foods.

```
Appropriate places for bear (behavior: hungry): ['Forest-1', 'Forest-2']
Bear is currently at Den and its behaviour is hungry hence it will take the following path:
 ['Den', 'Forest-1']
```

In the following example, the bear is at the visitor centre but is thirsty. The path it takes to reach the nearby water source is as follows:

```
Appropriate places for bear (behavior: thirsty): ['Water-Source-1', 'Water-Source-2']
Bear is currently at Visitor-center and its behaviour is thirsty hence it will take the following path:
 ['Visitor-center', 'Den', 'Water-Source-2']
```

Proposed Solution for Enhancement:

Rather than relying on a predefined function, the system would learn the patterns of the bear through years of monitoring, recognizing its habits such as feeding and resting.

Similarly, instead of using a shortest path traversal technique, the system should implement a method to identify the most frequently travelled path by the bear based on its behaviour and current location.

4) Conclusion

The Autonomous Wildlife Monitoring System integrates three essential components: Image and Video Detection, Sound Analysis, and Graph-Based Movement Tracking, each designed to enhance our understanding and management of wildlife habitats

In Image and Video Detection, our objective is to develop algorithms capable of detecting and identifying animals accurately in both photos and videos. Initially, we utilized HAAR-like features but transitioned to YOLOv8 due to its superior real-time object detection capabilities. YOLOv8 overcomes the limitations of HAAR-based methods by predicting bounding boxes and class probabilities simultaneously, thereby improving accuracy in identifying a wide range of animal species across dynamic environments.

Sound Analysis focuses on classifying animal moods based on audio signals. By analysing amplitude thresholds, we categorize mood states such as Angry, Normal, and Sad. To enhance accuracy, we propose integrating video feed analysis to correlate visual cues with audio-based mood classification, providing more nuanced insights into animal behaviors and emotional states.

Graph-Based Movement Tracking utilizes graph theory to map and track animal movements within their habitats. Nodes in the graph represent key locations like water sources, forests, and dens, while edges denote possible paths animals may take. This approach enables behavior-based destination determination, where animals move towards areas suited to their needs such as food, water, rest, or exploration. Implementing BFS ensures efficient calculation of optimal paths, contributing to realistic simulations of animal movements and interactions in their natural environments.

Our proposed enhancements include adopting a learning-based approach to capture long-term behaviour patterns from continuous monitoring data. Additionally, implementing a path selection strategy based on the most frequently travelled routes by animals according to their behaviours and current locations will provide deeper insights into habitual movement patterns, further refining our understanding and management strategies for wildlife conservation.

This comprehensive approach not only enhances the accuracy of wildlife monitoring but also supports informed decision-making in habitat management, conservation planning, and welfare strategies. By leveraging advanced technologies and adaptive methodologies, our system aims to contribute effectively to the preservation and sustainable management of wildlife across diverse environmental contexts.