Mahavir Education Trust's
Shah & Anchor Kutchhi Engineering College
An Autonomous Institute Affiliated to University of Mumbai

UG Program in Computer Engineering
(Accredited by NBA for 3 years from AY 2025-26)

TY9 Research Practices - CCE1 Literature Survey :

Team code: TY09-16A
Team Member 1 Name: Arpita Dand/Roll No: 24/ Mobile No:9819992563
Team Member 2 Name: Riya Joshi /Roll No : 30/ Mobile No: 8097245251
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Tentative Title: Biodiversity Conservation: Invasive Species Detection using AI , Wildlife Monitoring, and Migration Prediction

Domain: Environmental Analytics using AI-ML

Sub Domain: AI for Invasive Species Detection and Monitoring

Objective Description: To develop and evaluate AI-based techniques—such as deep learning, computer vision, and machine learning—applied to UAV, satellite, and multispectral imagery for the detection, classification, and monitoring of invasive species, with the aim of improving mapping accuracy, reducing manual survey costs, enabling early intervention, and supporting sustainable ecosystem management.

Team Member1 Name: Arpita Pankaj Dand

PICO 1:

- PAPER TITLE: Integrating Artificial Intelligence and UAV-Acquired Multispectral Imagery for the Mapping of Invasive Plant Species in Complex Natural Environments
- ***Authors of paper:*** Narmilan Amarasingam ,Fernando Vanegas ,Melissa Hele ,Angus Warfield and Felipe Gonzalez
- *Paper Description:*

P (Problem Statement): Mapping invasive plant species in complex natural environments is challenging.
Manual surveys are time-consuming, labor-intensive, and prone to observer bias.
Dense vegetation and heterogeneous terrains further reduce mapping reliability.

I (Intervention): Use of deep learning models such as U-Net applied to UAV-collected multispectral imagery. These models automatically segment invasive species from native vegetation. High spectral and spatial resolution from UAVs enhances detection accuracy.

C (Comparison): Conventional field-based surveys depend heavily on manual identification. Traditional remote sensing often lacks sufficient resolution for small patches.
Both methods struggle to provide scalable, consistent, and timely mapping.

O (Outcome): Achieved high-accuracy invasive species detection across diverse terrains.
Reported precision (86%), recall (76%), F1-score (81%), and IoU (68%).
Demonstrates improved mapping efficiency and reduced misclassification errors.

PICO 2:

- <u>PAPER TITLE:</u> Advancing Water Hyacinth Recognition: Integration of Deep Learning and Multispectral Imaging for Precise Identification.
- ***Authors of paper:***Diego Alberto Herrera Ollachica,Bismark Kweku Asiedu Asante and Hiroki Imamura
- *Paper Description:*
  P (Problem Statement): Invasive aquatic floral species like water hyacinth disrupt freshwater ecosystems and are difficult to monitor effectively. Traditional manual detection and spectral index methods (e.g., NDVI) often misclassify similar species or fail to detect small infestations. Timely and accurate mapping remains a significant challenge for ecosystem management.

  I (Intervention): Applied deep learning, specifically **U-Net semantic segmentation**, on UAV-acquired multispectral imagery. Utilized a custom-built low-cost multispectral camera equipped with red, green, blue, and two infrared filters (720 nm, 850 nm). This automated approach enhances detection precision while minimizing the need for costly or manual methods.

C (Comparison): Compared to traditional manual surveys and conventional spectral index methods, such as NDVI-based detection. Those conventional methods are limited by reliance on fixed indices and often lack the spatial or spectral resolution needed for accurate detection. They also struggle in dynamic aquatic environments with variable lighting and background interference.

O (Outcome): Achieved a high detection accuracy rate of **96%** for water hyacinth identification using the UAV-based deep learning method.
This result demonstrates significant improvements in both precision and recall over manual or index-based approaches.
Effectively enables reliable and scalable monitoring of invasive aquatic species across varied water bodies.

PICO 3:

- <u>PAPER TITLE</u>: A comparative analysis of deep learning methods for weed classification of high-resolution UAV images.
- ***Authors of paper:*** Pendar Alirezazadeh, Michael Schirrmann & Frieder Stolzenburg.
- *Paper Description:*

  P (Problem Statement): Weeds in agricultural fields compete with crops for essential resources, reducing yield and efficiency. Traditional methods like manual scouting or visual inspection are slow, labor-intensive, and error-prone. Timely, accurate, and scalable weed detection remains a major challenge in precision agriculture.

  I (Intervention): The study applies deep neural networks (ResNet, MobileNet, MobileViT) on UAV imagery over winter wheat fields. These models are trained to detect and classify common weed species with high accuracy. By leveraging UAV detail and deep feature extraction, the approach automates weed identification.

  C (Comparison): Lightweight architectures (MobileNet, MobileViT) are compared with deeper CNNs like ResNet. Unlike classical RGB segmentation or manual thresholds, DNNs capture more complex spatial features. Findings show deeper models don’t always outperform, highlighting the efficiency of optimized networks.

O (Outcome): Lightweight CNNs achieved strong weed classification, sometimes surpassing heavy models.
They reduced overfitting risks while maintaining efficiency for UAV-based monitoring.
This shows AI-powered UAV systems can provide accurate, cost-effective weed–crop discrimination.

PICO 4:

- PAPER TITLE:Tree Species Classification from UAV Canopy Images with Deep Learning Models.
- ***Authors of paper:*** Yunmei Huang,Botong Ou ,Kexin Meng ,Baijian Yang ,Joshua Carpenter ,Jinha Jung andSonglin Fei.
- *Paper Description:*

  P (Problem): Individual tree species in temperate forest canopies are often hard to distinguish using traditional field surveys or multispectral sensors, which can be costly and time-consuming. Accurate and efficient forest inventory remains essential for ecosystem management, biodiversity research, and resource planning. Thus, there's a need for scalable methods to reliably classify tree species using accessible sensors and automation.

  I (Intervention): This study leverages UAV-based high-resolution RGB canopy images and applies several state-of-the-art deep learning architectures—including Vision Transformer (ViT), EfficientNetB0, YOLOv5, ResNet18, and DenseNet—for species classification. It employs object-based classification on per-crown images taken across two seasons, enabling the extraction of both visual and structural tree features. This AI approach allows detailed identification of tree species without expensive multispectral instruments, making it highly practical and scalable.

  C (Comparison): Unlike traditional methods that rely on multispectral imaging or manual surveys, this model-based intervention demonstrates how RGB imagery combined with deep learning can match or exceed their performance, without the associated costs of specialized sensors. Conventional techniques often require complex spectral analyses or extensive fieldwork; deep learning provides an efficient alternative by learning features directly from image data. The comparison underscores how accessible UAV-RGB platforms paired with AI can offer compelling efficiency and accuracy improvements in tree species mapping.

O (Outcome): The study achieves exceptionally high classification accuracy—on summer images, models reached an average F1-score of **0.96**, while fall images saw F1-scores **greater than 0.90** for ViT, EfficientNetB0, and YOLOv5.These results highlight the reliability and robustness of deep learning models for identifying tree species across seasons using just RGB data. Consequently, this work validates the feasibility of deploying cost-effective, AI-driven methods for accurate tree species mapping in forest management applications.

PICO 5:

- <u>PAPER TITLE:</u>Mapping the Continuous Cover of Invasive Noxious Weed Species Using Sentinel-2 Imagery and a Novel Convolutional Neural Regression Network.
- ***Authors of paper:*** Fei Xing ,Ru An ,Xulin Guo andXiaoji Shen
- *Paper Description:*

  P (Problem):

  Detecting invasive plant species like *Euphorbia virgata* (leafy spurge) in heterogeneous ecosystems poses challenges due to varying spectral signatures and environmental conditions. Traditional methods often struggle with accuracy and scalability.

  I (Intervention):

  Utilization of Convolutional Neural Networks (CNNs) combined with Long Short-Term Memory (LSTM) networks to analyze high-resolution satellite imagery (WorldView-2 and PlanetScope) for temporal and spatial feature extraction.

  C (Comparison):

  Traditional machine learning classifiers such as Random Forest (RF) and Support Vector Machine (SVM) that rely on single-image datasets without temporal analysis.

  O (Outcome):

  Achieved an overall accuracy of 96.3% for detecting leafy spurge using CNN+LSTM models, outperforming RF and SVM classifiers in terms of detection accuracy and generalization across varied landscapes. This demonstrates the effectiveness of deep learning in enhancing invasive species detection in complex environments.

Sub Domain: Biodiversity and Wildlife Monitoring
Objective Description: The objective is to develop systematic methods for tracking species distribution, abundance, and behavior across ecosystems. By integrating AI, camera traps, and remote sensing, monitoring becomes more accurate and scalable. This supports evidence-based conservation strategies and strengthens biodiversity protection.

Team Member2 Name: RIYA BHAVESH JOSHI

PICO 1:

- PAPER TITLE : Methods for wildlife monitoring in tropical forests: Comparing human observations, camera traps, and passive acoustic sensor
- ***Authors of paper:*** Joeri A. Zwerts, P. J. Stephenson, Fiona Maisels, Marcus Rowcliffe, Christos Astaras, Patrick A. Jansen, Jaap van der Waarde, Liesbeth E. H. M. Sterck, Pita A. Verweij, Tom Bruce, Stephanie Britain, Marijke van Kuijk.
- *Paper Description:*

  P(Problem Statement) : Manual wildlife monitoring is often slow, labor-intensive, and prone to inconsistencies. With increasing threats such as habitat loss and poaching, relying solely on human observation cannot provide timely or large-scale results. This creates serious challenges in tracking biodiversity effectively and protecting endangered species.

  I (Intervention): CNN-based machine learning models are introduced to automatically identify species from camera trap images. These models can process vast image datasets quickly, reducing human workload. By applying deep learning, the system becomes capable of recognizing multiple species with high accuracy.

  C (Comparison): The automated CNN approach is compared with traditional manual identification methods carried out by wildlife experts. Manual methods are time-consuming, require trained personnel, and are limited in scale. The automated method significantly improves efficiency by overcoming these limitations.

  O (Outcome): The system delivers faster species detection, higher accuracy, and a scalable framework for monitoring wildlife. Conservationists can make quicker decisions and respond better to threats. Ultimately, this leads to stronger biodiversity protection and long-term sustainability.

PICO 2:

- <u>PAPER TITLE :</u> 1.Improved Wildlife Recognition through Fusing Camera Trap Images and Temporal Metadata
  2.A quantitative global review of species population monitoring
- ***Authors of paper:*** 1.Lei Liu, Chao Mou and Fu Xu
  2.Caroline Moussy, Ian J. Burfield, P. J. Stephenson, Arabella F. E. Newton, Stuart H. M. Butchart, William J. Sutherland, Richard D. Gregory, Louise McRae, Philip Bubb, Ignacio Roesler, Cynthia Ursino, Yanqing Wu, Ernst F. Retief, Jihad S. Udin, Ruslan Urazaliyev, Lina M. Sánchez-Clavijo, Eric Lartey, Paul F. Donald.
- *Paper Description:*
  P(Problem Statement) : Species behavior and population trends are difficult to study using traditional methods. Manual fieldwork and static observations often miss continuous behavioral patterns. As a result, researchers struggle to fully understand animal movements, feeding habits, and ecosystem dynamics.

  I (Intervention): Machine learning models integrated with temporal image data are used to track both species identity and behavioral patterns. These models analyze sequences of images over time, detecting activities like feeding, resting, or migration. This enables a richer and more continuous understanding of animal life.

  C (Comparison): The approach is compared to static manual observations, where researchers must rely on limited field data. Manual observation cannot capture behaviors that occur frequently or at odd times. In contrast, automated systems provide ongoing monitoring at a much larger scale.

  O (Outcome): The method produces scalable, dynamic insights into wildlife behavior and population health. Conservationists gain continuous data streams that improve ecological research. This ultimately supports better policies and strategies for ecosystem preservation.

PICO 3:

- <u>PAPER TITLE :</u> 1. Will using artificial intelligence to review camera trap images reduce human connection to wildlife research?
  2. Focus on the Positives: Self-Supervised Learning for Biodiversity Monitoring
- ***Authors of paper:*** 1.Andrew F. Barnas, Jason T. Fisher

2.Omiros Pantazis, Gabriel J. Brostow, Kate E. Jones, Oisin Mac Aodha, Niantic

- *Paper Description:*

  P(Problem Statement) : Large volumes of unlabeled camera trap images slow down the development of wildlife recognition systems. Labeling data manually is expensive, time-consuming, and prone to human bias. This creates a bottleneck in deploying effective monitoring models at scale.

  I (Intervention): Semi-supervised and unsupervised learning methods, including self-supervised CNNs and clustering, are applied. These methods can extract useful features from unlabeled images without heavy reliance on manual input. This makes it possible to train robust models more quickly.

  C (Comparison): The proposed approach is compared with fully supervised models that require large, annotated datasets. Supervised models depend heavily on expert labeling, which is not scalable. Semi-supervised methods reduce this dependency and enhance efficiency.

  O (Outcome): The result is faster model training with reduced costs and human effort. By learning from both labeled and unlabeled data, the system becomes scalable to massive datasets. This accelerates biodiversity research and improves real-world deployment.

PICO 4:

- <u>PAPER TITLE :</u> 1.Addressing significant challenges for animal detection in camera trap images: a novel deep learning-based approach
  2.Drones and AI-Driven Solutions for Wildlife Monitoring
- ***Authors of paper:*** 1.Margarita Mulero-Pázmány, Sandro Hurtado, Cristóbal Barba-González, María Luisa Antequera-Gómez, Francisco Díaz-Ruiz, Raimundo Real, Ismael Navas-Delgado & José F. Aldana-Montes
  2.Nourdine Aliane
- *Paper Description:*

  P(Problem Statement) : Models trained in one geographic region often fail when applied to another. This is due to domain shift, where lighting conditions, vegetation, or even species appearance differ. Without adaptation, existing models cannot generalize across ecosystems.

.**I (Intervention):** Domain adaptation and transfer learning techniques are used to make CNN models more generalizable. By reusing knowledge from one dataset and adjusting it to new conditions, models can adapt to varied habitats. This reduces the need for retraining from scratch.

C (Comparison): The new approach is compared with standard CNN models that require complete retraining for each dataset. Standard methods are inefficient and costly, as they cannot adapt to new regions. In contrast, transfer learning offers flexibility and reduced workload.

O (Outcome): The adapted models become more robust and effective across multiple ecosystems. Conservationists can deploy monitoring tools globally without repeating the entire training process. This ensures wider applicability and cost-effective biodiversity protection.

PICO 5:

- PAPER TITLE : Camouflage detection: Optimization-based computer vision for Alligator sinensis with low detectability in complex wild environment
- ***Authors of paper:*** Yantong Liu, Sai Che, Liwei Ai, Chuanxiang Song, Zheyu Zhang, Yongkang Zhou, Xiao Yang, Chen Xian.
- *Paper Description:*

  P(Problem Statement) : Manual identification of nocturnal or camouflaged species is especially challenging in dense forests. Human experts often misclassify or overlook animals in low-light or heavily obstructed environments. This reduces the reliability of biodiversity assessments.

  .**I (Intervention):** Deep learning models combined with image preprocessing techniques such as low-light enhancement and background noise reduction are used. These improvements make even faint or hidden animals visible to the system. This boosts recognition performance under difficult conditions.

  C (Comparison): The enhanced models are compared with human experts, who struggle with poor-quality or low-visibility images. While humans miss subtle details, AI-enhanced systems consistently detect hidden patterns. This makes automated detection more dependable.

O (Outcome): The result is improved accuracy in identifying elusive species that are otherwise overlooked. This ensures more reliable wildlife monitoring and comprehensive biodiversity records. It helps protect even the most difficult-to-track species in their natural habitats.

Sub Domain : Biodiversity in animal migration.
Objective Description: The goal is to better understand and predict how animals move across landscapes that are increasingly shaped by people and the environment. By using GPS tracking, satellite data, and AI tools, we can follow migration in real time and see how wildlife responds to sudden changes. This makes it possible to plan safe corridors, reduce conflicts, and give species the space they need to survive and thrive.

Team Member 3 Name: Dwijesh Manoj Mistry

PICO 1:

- PAPER TITLE : In search of greener pastures: Using satellite images to predict the effects of environmental change on zebra migration
- ***Authors of paper:*** Hattie L. A. Bartlam-Brooks, Pieter S. A. Beck, Gil Bohrer and Stephen Harris
- *Paper Description:*
  P(Problem Statement) : Migratory animals often face challenges in fragmented landscapes with roads, farms, and settlements breaking up their natural routes. Traditional seasonal tracking methods assume fixed patterns, which do not reflect how animals actually move in changing conditions. This gap reduces the accuracy of conservation strategies.

  I (Intervention): Machine learning models use GPS collar data along with environmental factors like vegetation, terrain, and weather to understand animal movement. These models can identify hidden patterns and adapt to unexpected changes in migration. By learning from data continuously, they provide dynamic predictions. This helps conservation planners prepare in advance to safeguard critical routes.

C (Comparison): Rule-based or calendar-based tracking depends on outdated assumptions and fails to adjust to sudden ecological shifts. Such methods often oversimplify migration.

O (Outcome): More accurate predictions of migratory paths allow for smarter conservation planning. Wildlife corridors and safe passages can be designed with greater reliability.

PICO 2:

- <u>PAPER TITLE :</u> Machine learning allows for large‐scale habitat prediction of a wide‐ranging carnivore across diverse ecoregions
- ***Authors of paper:*** W. Connor O'Malley, L. Mark Elbroch, Katherine A. Zeller, Paul Beier ,Meghan M. Beale, Richard A. Beausoleil, Brian Kertson, Kyle Knopff, Kryan Kunkel, Benjamin T. Maletzke, Quinton Martins, Marc R. Matchett, Christopher C. Wilmers, Heiko U. Wittmer, Winston Vickers, Kimberly Sager‐Fradkin, Hugh Robinson
- *Paper Description:*

  P(Problem Statement) : Expanding human development—such as roads, agriculture, and settlements—blocks or disrupts traditional animal migration routes. These interruptions often cause human–wildlife conflicts and accidents. Current monitoring lacks predictive capacity to highlight risks early.

  I (Intervention): Predictive ML models overlay animal GPS routes with geospatial data on human activities like highways, farms, and urban zones. This creates a clear picture of where and when animals are most likely to encounter human barriers. By forecasting conflict zones, it becomes possible to design preventive measures. Such models transform raw data into actionable maps for conservation.

  C (Comparison): Conventional methods rely mainly on visually inspecting GIS maps, which can show overlaps but cannot predict future danger points.

  O (Outcome): Early identification of conflict hotspots enables timely interventions such as building wildlife crossings or creating buffer corridors. This reduces risks for both animals and people.

PICO 3:

- PAPER TITLE : Animal Movement Prediction Based on Predictive Recurrent Neural Network
- ***Authors of paper:*** Jehyeok Rew , Sungwoo Park, Yongjang Cho, Seungwon Jung and Eenjun Hwang
- *Paper Description:*

  P(Problem Statement) : Animal migration depends on food, water, and climate. Current models use static maps, so they can't keep up when droughts, floods, or fires suddenly change conditions. This makes forecasts unreliable.

  I (Intervention): Hybrid ML models combine GPS data with real-time satellite updates on vegetation and water. They adjust predictions instantly as conditions shift. This makes migration forecasting more flexible and practical for conservation.

  C (Comparison): Rule-based models simplify movement by treating individuals as independent actors, ignoring social influence. They miss the complexity of coordinated herd or flock migration and cannot explain group decision-making. This limits their usefulness for conservation strategies that need to protect not just individuals but whole populations.

  O (Outcome): Dynamic models adapt in real time, giving early warnings and better accuracy. Conservationists can act faster to protect species before crises hit.

PICO 4:

- PAPER TITLE : WildGraph: Realistic Long-Horizon Trajectory Generation with Limited Sample Size
- ***Authors of paper:*** Ali-Al Lawati, Elsayed Eshra, Prasenjit Mitra.
- *Paper Description:*

  P(Problem Statement) : Many regions lack GPS tracking data because collaring animals is costly and difficult. Traditional models need large datasets, leaving data-poor areas unstudied. This creates blind spots in conservation.

.**I (Intervention):** Transfer learning lets models trained in data-rich areas be adapted to new regions. Even with little local data, they can still make useful predictions. This saves time, resources, and ensures no habitat is left behind.

C (Comparison): Localized models require extensive, site-specific data collection that is often unfeasible in developing or remote regions. They delay useful predictions until large datasets are built, which may take years. This creates major gaps in conservation planning and weakens response to emerging threats.

O (Outcome): Transfer learning brings accurate forecasts to data-poor regions. It expands protection to understudied landscapes and helps safeguard vulnerable species everywhere.

PICO 5:

- <u>PAPER TITLE :</u> Predicting animal behaviour using deep learning: GPS data alone accurately predict diving in seabirds.
- ***Authors of paper:*** Ella Browning, Mark Bolton3, Ellie Owen, Akiko Shoji, Tim Guilford, Robin Freeman.
- *Paper Description:*

  P(Problem Statement) : Migratory animals often move in groups such as herds, flocks, or pods, with collective decisions guiding routes. Traditional models treat animals as isolated individuals, overlooking the influence of group dynamics. This leads to unrealistic and fragmented migration forecasts.

  I (Intervention): Deep learning analyzes GPS data to capture herd or flock dynamics. It learns how animals coordinate and move together. This gives more realistic insights into population-level movement.

  C (Comparison): Rule-based models simplify movement by treating individuals as independent actors, ignoring social influence. They miss the complexity of coordinated herd or flock migration and cannot explain group decision-making. This limits their usefulness for conservation strategies that need to protect not just individuals but whole populations.

  O (Outcome): Deep learning forecasts reflect real herd and flock behavior. This helps design better wildlife corridors and supports ecosystem-wide conservation.

Papers Referred for PICO's :

- Member01- Arpita Dand :
    - M1_01:https://www.mdpi.com/2771356
    - M1_02:https://www.mdpi.com/3187114
    - M1_03: https://link.springer.com/article/10.1007/s41348-023-00814-9
    - M1_04:https://www.mdpi.com/2998446
    - M1_05: https://www.mdpi.com/2778020
- Member02- Riya Joshi :
    - M2_01: The Society for Conservation Biology
    - M2_02.1: https://www.mdpi.com/1424-2818/16/3/139
    - M2_02.2 : A quantitative global review of species population monitoring
    - M2_02.3 : Recognition of European mammals and birds in camera trap images using deep neural networks
    - M2_03.1: Will using artificial intelligence to review camera trap images reduce human connection to wildlife research?
    - M2_03.2 : https://openaccess.thecvf.com/content/ICCV2021/papers/Pantazis_Focus_on_the_Positives_Self-Supervised_Learning_for_Biodiversity_Monitoring_ICCV_2021_paper.pdf?
    - M2_03.3: Self-supervised Learning on Camera Trap Footage Yields a Strong Universal Face Embedder
    - M2_04.1: https://www.nature.com/articles/s41598-025-90249-z
    - M2_04.2:Adaptive image processing embedding to make the ecological tasks of deep learning more robust on camera traps images - ScienceDirect
    - M2_04.3: Drones and AI-Driven Solutions for Wildlife Monitoring
    - M2_05: https://www.sciencedirect.com/science/article/pii/S1574954124003443
- Member03 - Dwijesh Mistry :
    - M3_01: https://doi.org/10.1002/jgrg.20096
    - M3_02: https://doi.org/10.1007/s10980-024-01903-2
    - M3_03: https://doi.org/10.3390/s19204411
    - M3_04: https://doi.org/10.48550/arXiv.2404.08068
    - M3_05: https://doi.org/10.1111/2041-210X.12926

Github link: https://github.com/terminator0106/TY-Research-Practices