Automated Wildlife Monitoring

A. Introduction

Monitoring wildlife in their natural habitats is vital for the planning and execution of conservation strategies. [9] Camera traps are the most favored tool among conservationists to monitor animals, simultaneously not disturbing and keeping the integrity of ecosystems. Yet, manual monitoring presents significant challenges, including the labour and time-consuming process of analyzing vast quantities of data, images, and videos captured by these devices. This approach is not only resource-intensive but also costly. The adoption of automated monitoring systems could substantially alleviate the workload on conservationists by eliminating the need for continuous and repetitive observation.

Automated wildlife monitoring, however, is complex. [8] As of 2022, there are over 2.16 million identified animal species, making it a daunting task to train models to recognize each one accurately. In this project, we aim to develop a prototype capable of identifying a broad range of species, experimenting with datasets that include between 30 to 151 classes of varying sizes. This approach will enable us to refine our model for effective training and implementation in real-world conservation efforts. The potential impact of the project extends beyond easing the workload of conservationists; it aims to minimize costs, reduce human error in wildlife monitoring, enhance the protection and tracking of species populations and changes, and expand the capacity to monitor larger areas comprehensively.

One of the most significant advancements this project seeks to introduce is the use of sophisticated algorithms and machine learning techniques that can adapt to the inherent uncertainties of nature, including variations in visibility, quality of images, and the nuanced differences within the same species. Accurately identifying and tracking wildlife across diverse and changing environments is complex. By addressing these challenges head-on, the project not only aims to improve the efficiency and accuracy of wildlife monitoring but also to contribute valuable insights into biodiversity and ecosystem health [2]. This endeavor represents a critical step forward in the use of technology for conservation, promising to revolutionize how we understand and protect the natural world.

B. Image Dataset Selection

Dataset	Total images	Image size	Total classes
Dataset 1	19000	1024*683	30
Dataset 2	6270	224*224	151
Dataset 3	5400	1200*1200	90

Table 1. Dataset Details

We've selected three distinct datasets for our project. The first dataset is the largest, featuring 19,000 images spread across 30 different classes [11]. The second dataset contains 6,270 images but spans a wider range of 151 classes, offering a deeper dive into species diversity [7]. Our third dataset, although the smallest, includes 5,400 images across 90 classes [4]. This careful selection of datasets provides a robust foundation for our exploration, catering to the varying complexities and scales essential for our project's success.

C. Possible Methodologies

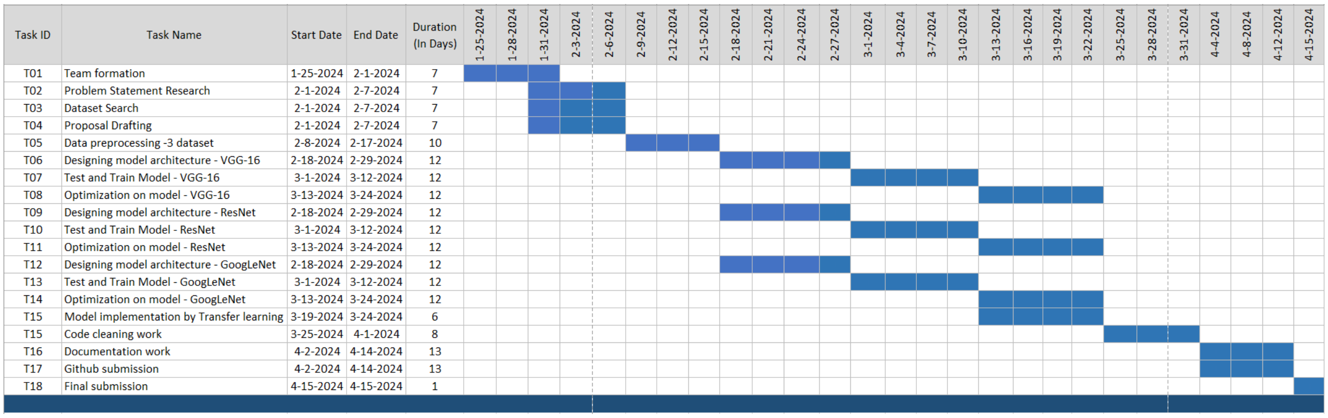
For our project, we have strategically selected VGG16, ResNet, and GoogLeNet, tailoring our approach to the unique goals and challenges at hand. VGG16, with its 16-layer depth, is particularly suited for our smaller datasets. Its architecture excels at capturing detailed features within the 224x224 pixel images of our datasets, negating the need for resizing and thus preserving the original quality. Its renowned efficacy in transfer learning enables us to leverage pre-existing patterns, streamlining the training process and minimizing the requirement for extensive data.

ResNet introduces an innovative residual learning framework, allowing for the training of significantly deeper networks without the hindrance of vanishing gradients. This capability is crucial for our mid-sized and larger datasets, facilitating the capture of the extensive diversity present across species. The scalability and robustness of ResNet makes it an ideal choice for our dataset comprising 151 classes, ensuring detailed feature extraction across a wide array of classes.

GoogLeNet, with its inception modules, provides a multi-scale processing approach, critical for addressing the varied sizes and appearances of wildlife captured in the same scene. This model's computational efficiency is paramount for our largest dataset, reducing the overall number of parameters required. This efficiency allows for the processing of extensive datasets without an exorbitant demand on resources. Additionally, GoogLeNet's architecture is adept at handling the unpredictable variables inherent in wildlife monitoring, such as fluctuations in lighting, diverse poses, and backgrounds, making it an invaluable tool in our methodology.

Together, these models form the backbone of our approach, each selected for its specific strengths in dealing with the complexities of automated wildlife monitoring. By integrating these advanced algorithms, we aim to enhance the accuracy, efficiency, and scope of our conservation efforts, marking a significant leap forward in the application of technology to protect and understand our natural world.

D. GANTT CHART



Task ID	Task Name	Start Date	End Date	Duration (In Days)
T01	Team formation	1-25-2024	2-1-2024	7
T02	Problem Statement Research	2-1-2024	2-7-2024	7
T03	Dataset Search	2-1-2024	2-7-2024	7
T04	Proposal Drafting	2-1-2024	2-7-2024	7
T05	Data preprocessing -3 dataset	2-8-2024	2-17-2024	10
T06	Designing model architecture - VGG-16	2-18-2024	2-29-2024	12
T07	Test and Train Model - VGG-16	3-1-2024	3-12-2024	12
T08	Optimization on model - VGG-16	3-13-2024	3-24-2024	12
T09	Designing model architecture - ResNet	2-18-2024	2-29-2024	12
T10	Test and Train Model - ResNet	3-1-2024	3-12-2024	12
T11	Optimization on model - ResNet	3-13-2024	3-24-2024	12
T12	Designing model architecture - GoogLeNet	2-18-2024	2-29-2024	12
T13	Test and Train Model - GoogLeNet	3-1-2024	3-12-2024	12
T14	Optimization on model - GoogLeNet	3-13-2024	3-24-2024	12
T15	Model implementation by Transfer learning	3-19-2024	3-24-2024	6
T15	Code cleaning work	3-25-2024	4-1-2024	8
T16	Documentation work	4-2-2024	4-14-2024	13
T17	Github submission	4-2-2024	4-14-2024	13
T18	Final submission	4-15-2024	4-15-2024	1

Figure 1. GANTT Chart

The Gantt chart is used to show the project timeline. Each of our project's milestones is distinct.

Milestone 1: In the first stage, project is initiated with the formation of the team followed by problem research which included the problem statement, proposing the project goals, prerequisites and searching the targeted dataset. The team members are responsible for deciding the goals and objectives for the project and determining the scope as well as the resources required to finish it. This step also includes searching for relevant datasets required to train and test the models.

Milestone 2: In the second milestone, the team focuses on pre-processing the data, This stage is critical as it includes cleansing and removing any unwanted data that may be provide inaccurate results while modelling and analysis. This stage also involves designing the model architecture followed by the training and testing of developed model. Furthermore, optimization on the model will also be conducted to enhance its performance and efficiency.

Milestone 3:: In this stage, the team implements transfer learning models. This is the stage where the pre-trained model is fine-tuned to perform the intended task. Moreover, This stage includes code cleaning that ensures clarity and maintainability and comprehensive documentation that provides details of the functionality and implementation of the project.

Milestone 4: In the final stage, the team collects the intended data and metrics for the final time to produce findings which in turn will be used to compare and evaluate the performance of the model by compiling and analyzing data from the earlier phases. The Github project is then submitted followed by the final project submission.

References

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