**DATA612/MSML612 Assignment 2 Proposal**

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**Problem statement**

Wild animals can present a distinct threat to safety and security, whether of individuals, livestock, or assets. As such, early detection is crucial. A Convolutional Neural Network (CNN) model can provide helpful aid in this endeavor, detecting the presence of a wild animal, in addition to whether it presents a danger. The differentiation of dangerous animals and harmless ones is left up to the user and may differ by his or her goals for the technology, as certain species may present a higher level of danger to human life, while others may pose a greater threat to livestock or assets.

**Background/Significance**

Object detection, a fundamental computer vision task, entails identifying and categorizing objects within digital images. In the early days of object detection, due to limited image representation techniques, most algorithms relied on manually crafted features (Borah, 2020). Traditional methods employed sliding window-based approaches and image classifiers for each segment. However, these approaches were computationally intensive and often lacked accuracy.

In the evolution of object detection, traditional methods relied on handcrafted features and sliding window-based approaches. However, the breakthrough came with deep convolutional networks. These neural networks, equipped with multiple layers, automatically learn powerful feature representations from image data (Borah). This shift opened up new possibilities and significantly improved accuracy in object detection tasks.

Identifying and classifying animals is vital for observing and conserving wildlife. Given the vast number of animal species, manual recognition can be quite difficult. The ability to detect and classify animals can aid in protecting individuals from dangers associated with animals, averting accidents involving animals and vehicles, keeping tabs on animal movements, and preventing the illegal poaching of wildlife.

**Applications**

Object detection has a wide range of applications, including autonomous driving, robotics, and surveillance (“7 Real-Life Use Cases”, 2024). Dangerous animal detection can be most easily applied to surveillance, with early warning systems notifying a user when a surveillance camera has detected an animal which presents a danger. As previously stated, the differentiation of dangerous and non-dangerous animals is flexible (although the model must be re-trained with any redefinition)—in the case of a yard where children play, the “dangerous” label may be applied to bears and wolves, whereas for the protection of livestock, foxes and coyotes may be given the “dangerous” label. In still another use case, sharks and orcas could be the target for underwater cameras.

Utilizing animal detection allows for regular monitoring of wild animals, which is essential for evaluating population shifts and modeling the impact of human activity changes. The ability to detect and classify animals is vital for their continuous monitoring. Over the past few decades, rapid habitat loss, poaching, and environmental degradation have led to significant declines in animal populations, with many species even becoming extinct. Animal detection systems can aid in these conservation efforts. Identifying individual animals and species is crucial for more efficient wildlife monitoring, primarily used for population counts, tracking movements, and controlling health and diseases. By detecting the presence of animals, sensors can provide early warnings to drivers, machine operators, security personnel, and trigger safety measures, thereby reducing the risk of potential incidents.

**Motivation of Using Deep Learning**

Object detection, which relies on large, high-dimensional datasets, benefits significantly from deep learning. Convolutional Neural Networks (CNNs) have excelled in image recognition tasks by automatically learning relevant features from images. These learned features play a crucial role in object localization and classification. Compared to traditional methods, deep learning-based techniques offer superior accuracy and speed. By capturing both low-level and high-level image features, deep learning models enhance detection performance. Moreover, deep learning models learn directly from raw data, eliminating the need for manually crafted features. This end-to-end learning approach enables models to adapt to complex patterns and variations in object appearance.

**Plan of Execution**

We’ll begin by gathering images of wildlife animals from various datasets, including CIFAR-100, African Wildlife, and COCO. These datasets contain a diverse range of animal species, which will help us create a robust model capable of detecting different animals in real-time. To train our model effectively, we need proper labels for each animal. We’ll generate labels such as “Dangerous” or “Not Dangerous” for each animal category. Using a computer vision annotation tool like CVAT.AI, we’ll meticulously annotate the images, associating them with the appropriate labels.

Properly formatted data is crucial for successful training. We’ll ensure that our images and labels match the model’s input requirements. Once ready, we’ll split the data into three sets: training, validation, and testing. This division allows us to evaluate the model’s performance accurately. Our chosen model is YOLO (You Only Look Once). We’ll train it using our custom dataset, which includes images of different animals and their corresponding labels (Dangerous or Not Dangerous). The YOLO model will learn to detect animals in real-time based on these labels.

After training, we’ll assess the model’s performance. Metrics such as F1-scores, confusion matrices, and other relevant measures will help us gauge its accuracy. This evaluation ensures that our model is effective in identifying dangerous and non-dangerous animals. With our newly trained model, we can predict whether an animal is dangerous or not in images or videos. This real-time object detection capability has practical applications, such as wildlife conservation or safety monitoring.

**References**

*7 Real-Life Use Cases of Object Detection*. (2024). Folio3; Folio3 Software, Inc.

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Borah, C. (2020, November 11). Evolution of object detection. *Analytics Vidhya*.

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