Creating awareness about security and safety on highways to mitigate wildlife-vehicle collisions by detecting and recognizing wildlife fences using deep learning and drone technology

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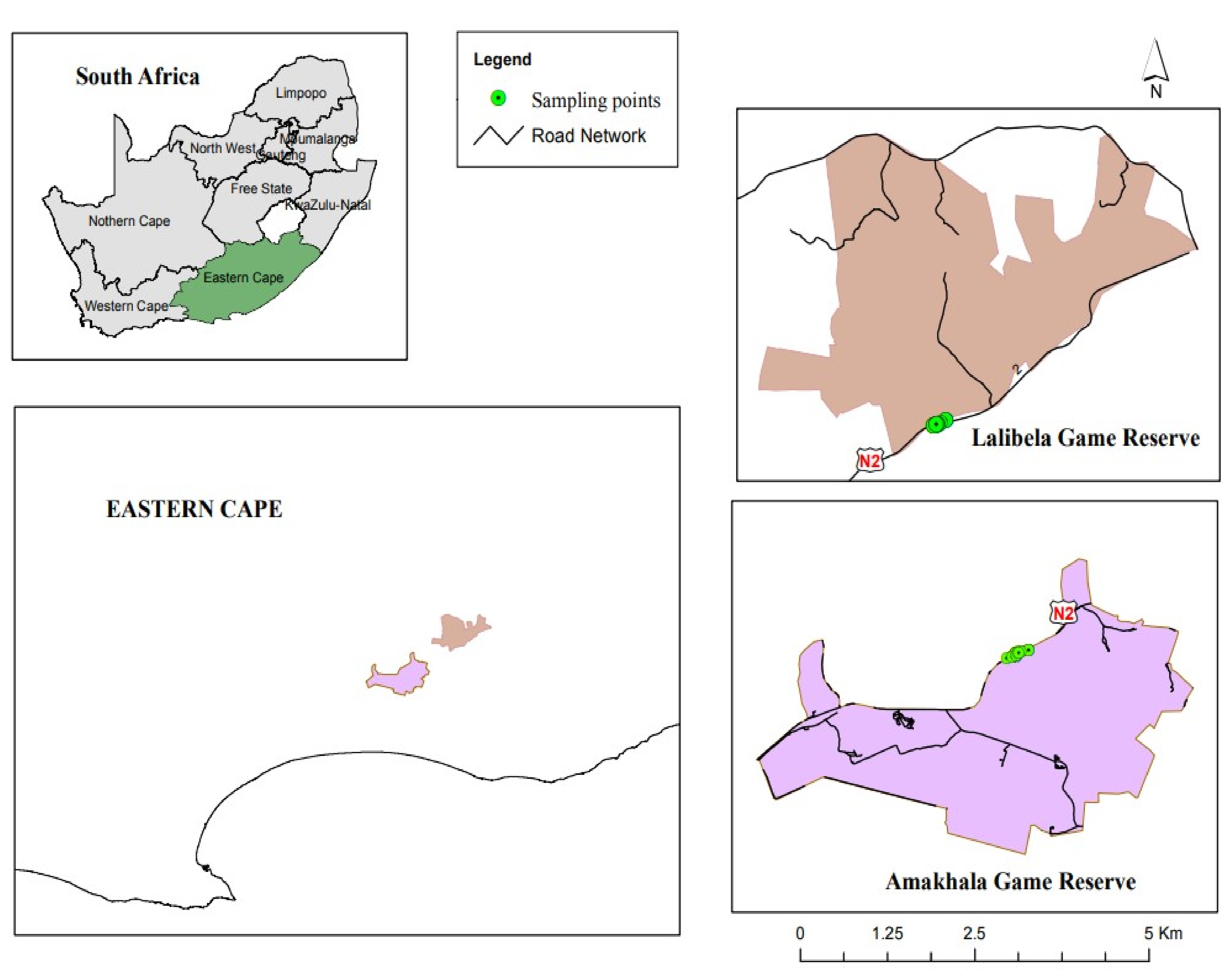
Abstract

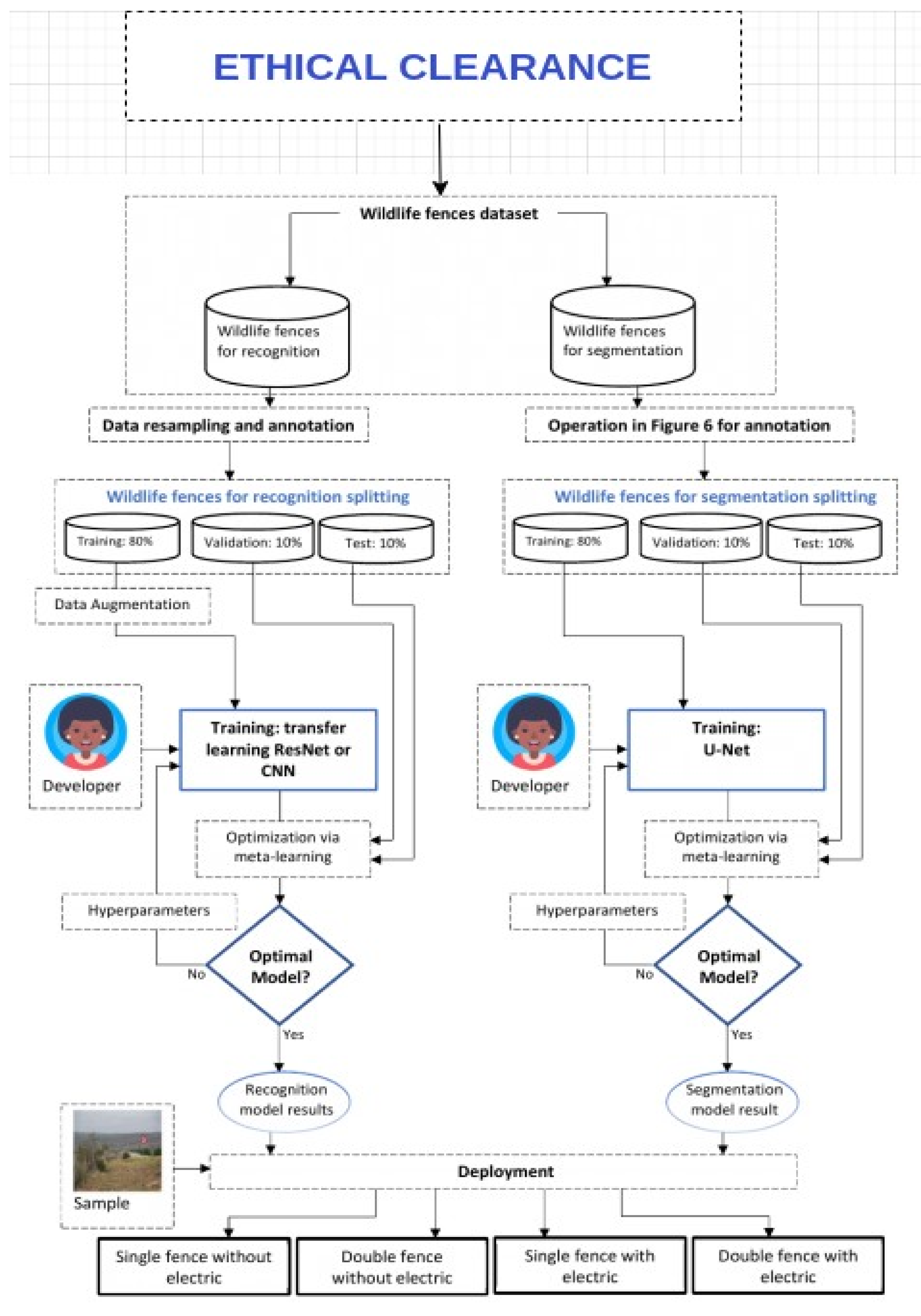
In South Africa, it is a common practice for people to leave their vehicles beside the road when traveling long distances for a short comfort break. This practice might increase human encounters with wildlife, threatening their security and safety. Here we intend to create awareness about wildlife fencing, using drone technology and computer vision algorithms to recognize and detect wildlife fences and associated features. We collected data at Amakhala and Lalibela private game reserves in the Eastern Cape, South Africa. We used wildlife electric fence data containing single and double fences for the classification task.

Additionally, we used aerial and still annotated images extracted from the drone and still cameras for the segmentation and detection tasks. The model training results from the drone camera outperformed those from the still camera. Generally, poor model performance is attributed to (1) over-decompression of images and (2) the ability of drone cameras to capture more details on images for the machine learning model to learn as compared to still cameras that capture only the front view of the wildlife fence. We argue that our model can be deployed on client-edge devices to inform people about the presence and significance of wildlife fencing, which minimizes human encounters with wildlife, thereby mitigating wildlife-vehicle collisions.

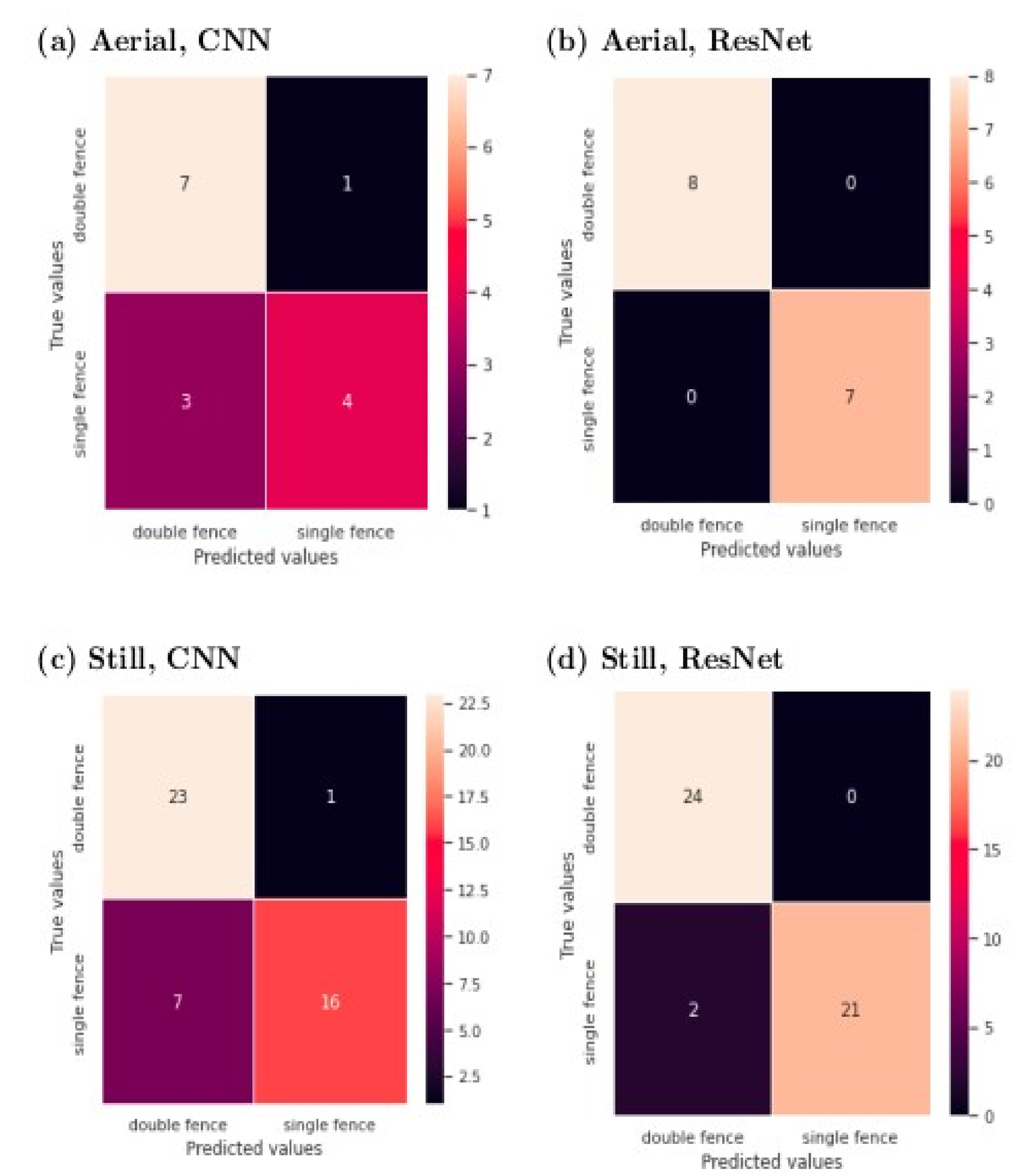
Data Collection

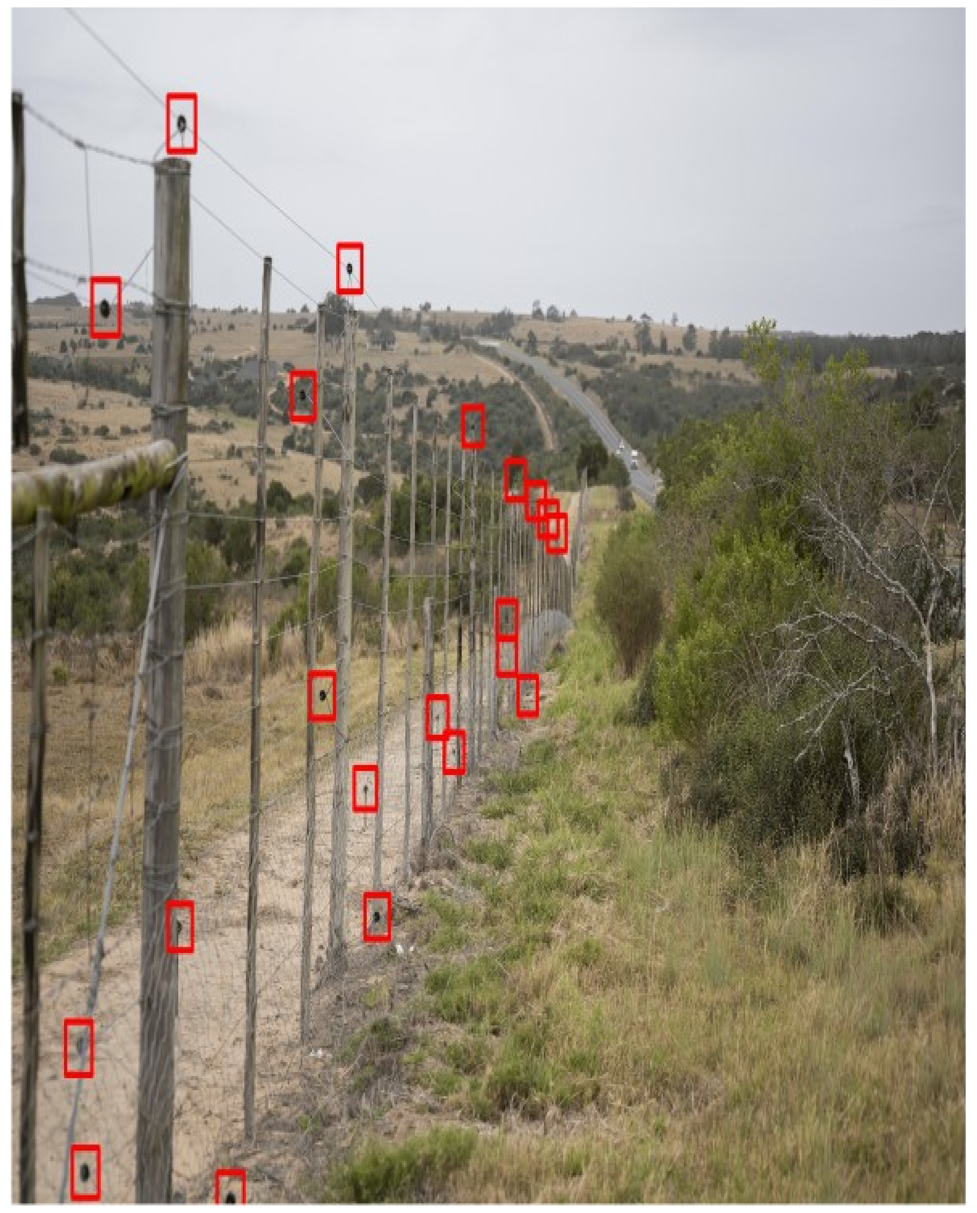


Proposed Methodology



Results





Conclusions

- Comparisons of CNN results and those from the ResNet50 architecture showed that ResNet50 outperforms CNN when applied to aerial and still images.
- Generally, the classification and U-Net models performed better on aerial images than still images because the drone can capture wildlife fences by the front view, back view, and top view, while the standalone camera captures only by front view. Meaning drones capture more details of the fence and its associated features as compared to a standalone camera.
- Besides, image features from the still camera are over-decompressed compared to images from a drone camera. That means more information is lost, which has contributed to the weak performance of these models
- We intend to use data augmentation techniques to improve model performance

- Reference:
- https://arxiv.org/abs/2301.07174