

PET POSE DETECTION

A MINI PROJECT REPORT

18CSC305J - ARTIFICIAL INTELLIGENCE

Submitted by

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BONAFIDE CERTIFICATE

Certified that Mini project report titled “**Pet Pose Detection**” is the bonafide work of **Tapesh Chandra Das (RA2111003010206)**, **Sangini Trivedi (RA2111003010223)**, **Harshit Nautiyal (RA2111003010236)** and **Devesh (RA2111003010255)** who carried out the minor project under my supervision. Certified further, that to the best of my knowledge, the work reported herein does not form any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

This report outlines the development of a robust pet pose detection system achieved through fine-tuning YOLOv8 pose models for animal pose estimation. Leveraging the Pet Pose Detection Dataset from Roboflow Universe, the system incorporates advanced data preprocessing techniques and employs the Ultralytics library for model training. Key aspects include:

- Dataset Utilization: The utilization of the Pet Pose Detection Dataset facilitated diverse pet image analysis with keypoint annotations, ensuring comprehensive model training.
- Methodological Approach: Implementation of data preprocessing techniques involves metadata download, organization, and visualization, ensuring optimal data utilization for model training.
- Model Training and Evaluation: Training YOLOv8 models with tailored settings such as epochs, batch size, and augmentation probabilities led to optimized performance. Model evaluation using validation metrics and visualized predictions showcased the system's efficacy in accurately detecting pet poses.
- Real-world Application Scenarios: The report delves into various real-world applications of pet pose detection, including health monitoring, training, rehabilitation, and enhancing pet services industry practices.
- Challenges and Motivation: Addressing challenges like data variability, keypoint annotation quality, real-time processing efficiency, model fine-tuning complexities, and integration challenges, the report emphasizes the system's adaptability and reliability.

- Conclusion and Future Prospects: The report concludes by highlighting the significant strides made in pet pose detection technology, its potential impact on pet care and behavior analysis, and avenues for future research and enhancements.

This comprehensive report encapsulates the development journey of the pet pose detection system, offering insights into its methodology, challenges, applications, and future prospects.

ABSTRACT

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ABBREVIATIONS

1. **PPD**: Pet Pose Detection
2. **CV**: Computer Vision
3. **ML**: Machine Learning
4. **YOLOv8**: You Only Look Once version 8
5. **ROBU**: Roboflow Universe
6. **DA**: Data Augmentation
7. **UL**: Ultralytics Library
8. **DNN**: Deep Neural Networks
9. **KP**: Keypoint
10. **AP**: Average Precision
11. **CNN**: Convolutional Neural Network
12. **DO**: Data Organization
13. **MP**: Model Performance
14. **GD**: Gradient Descent
15. **EM**: Early Stopping

INTRODUCTION

Pet pose detection has emerged as a vital area within computer vision, catering to the growing demand for intelligent systems capable of understanding and analyzing animal behavior. This project delves into the development of a sophisticated pet pose detection system, leveraging cutting-edge technologies and methodologies to achieve accurate and reliable results.

By fine-tuning YOLOv8 pose models specifically for animal pose estimation, this project aims to address the complexities associated with diverse pet breeds, sizes, and poses encountered in real-world scenarios. The utilization of the Pet Pose Detection Dataset from Roboflow Universe provides a rich and diverse set of pet images with keypoint annotations, facilitating robust model training and evaluation.

Through meticulous data preprocessing, including image and keypoint metadata organization and visualization, this project ensures data quality and consistency, laying a strong foundation for subsequent model training. The training process involves configuring various parameters such as epochs, batch size, and augmentation probabilities using the Ultralytics library, known for its efficiency in deep learning model development.

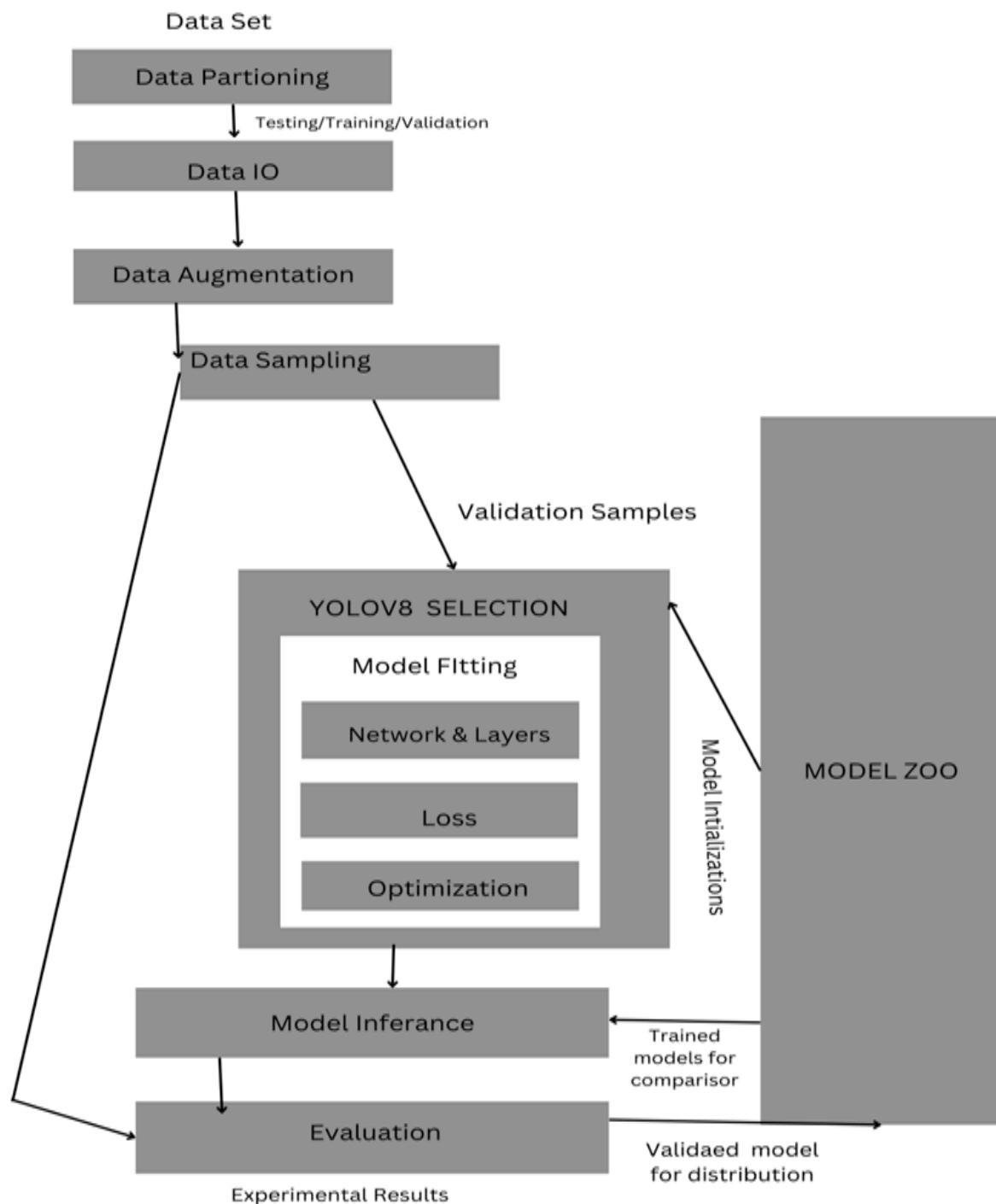
Model performance evaluation is a critical aspect, encompassing validation metrics and visualized predictions on sample images to assess accuracy and effectiveness. The project's outcomes showcase the system's ability to accurately detect pet poses, paving the way for enhanced applications in pet care, behavior analysis, and related domains.

This introduction sets the stage for a comprehensive exploration of the project's methodology, results, challenges, and future prospects, highlighting the transformative potential of pet pose detection in advancing pet care practices and research endeavors.

LITERATURE SURVEY

Authors	Title	Dataset	Methods	Remarks
Aishwarya D Shetty Soumya Ashwath	Animal Detection and Classification in Image & Video Frames Using YOLOv5 and YOLOv8	No specific Dataset provided	The research employs YOLOv5 and YOLOv8, two state-of-the-art object detection models, for animal detection and classification tasks. YOLOv5 and YOLOv8 are deep learning-based architectures known for their efficiency and accuracy in real-time object detection.	The utilization of YOLOv5 and YOLOv8 showcases the effectiveness of modern deep learning techniques in animal detection and classification. However, the paper lacks detailed information on experimental setup, dataset characteristics, and performance evaluation metrics
Kunal Dawn	Animal Pose Estimation: Fine-tuning YOLOv8 Pose Models	http://vision.stanford.edu/aditya86/ImageNetDogs/	Various methods are employed for animal pose estimation, including transfer learning from human pose datasets like COCO, augmentation techniques to address dataset scarcity, and specialized architectures such as "DeepPoseKit" and "OpenPose."	The article highlights challenges in dataset diversity and annotation quality, underscoring the need for standardized benchmarks and larger annotated datasets for effective model training and evaluation in animal pose estimation.

SYSTEM ARCHITECTURE AND DESIGN



METHODOLOGY

The development of a robust pet pose detection system involves a structured methodology encompassing data acquisition, preprocessing, model training, evaluation, and validation. The following steps outline the methodology employed in this project:

1. Data Acquisition and Preprocessing

- Utilized the Pet Pose Detection Dataset from Roboflow Universe, containing diverse pet images with keypoint annotations.
- Downloaded and organized image and keypoint metadata for training and validation.
- Applied data preprocessing techniques such as resizing, normalization, and augmentation to enhance dataset quality and model robustness.

2. Model Selection and Training

- Selected YOLOv8 as the base model architecture for pet pose detection due to its real-time capabilities and accuracy.
- Fine-tuned the YOLOv8 model using the Ultralytics library, configuring training settings such as epochs, batch size, learning rate, and augmentation probabilities.
- Implemented transfer learning by initializing the model with pre-trained weights on a large-scale dataset to expedite convergence and improve performance.

3. Training and Validation Process

- Split the dataset into training and validation sets to monitor model generalization and prevent overfitting.
- Conducted iterative training sessions, monitoring key performance metrics such as loss, precision, recall, and mean average precision (mAP).

- Implemented early stopping and model checkpointing techniques to ensure optimal model performance and prevent training stagnation or overfitting.

4. Model Evaluation and Validation

- Evaluated the trained model using validation metrics, including precision, recall, F1 score, and mAP, to assess its ability to accurately detect and localize pet poses.
- Conducted qualitative analysis by visualizing model predictions on sample images, identifying areas of improvement, and validating pose estimation accuracy.

5. Performance Optimization

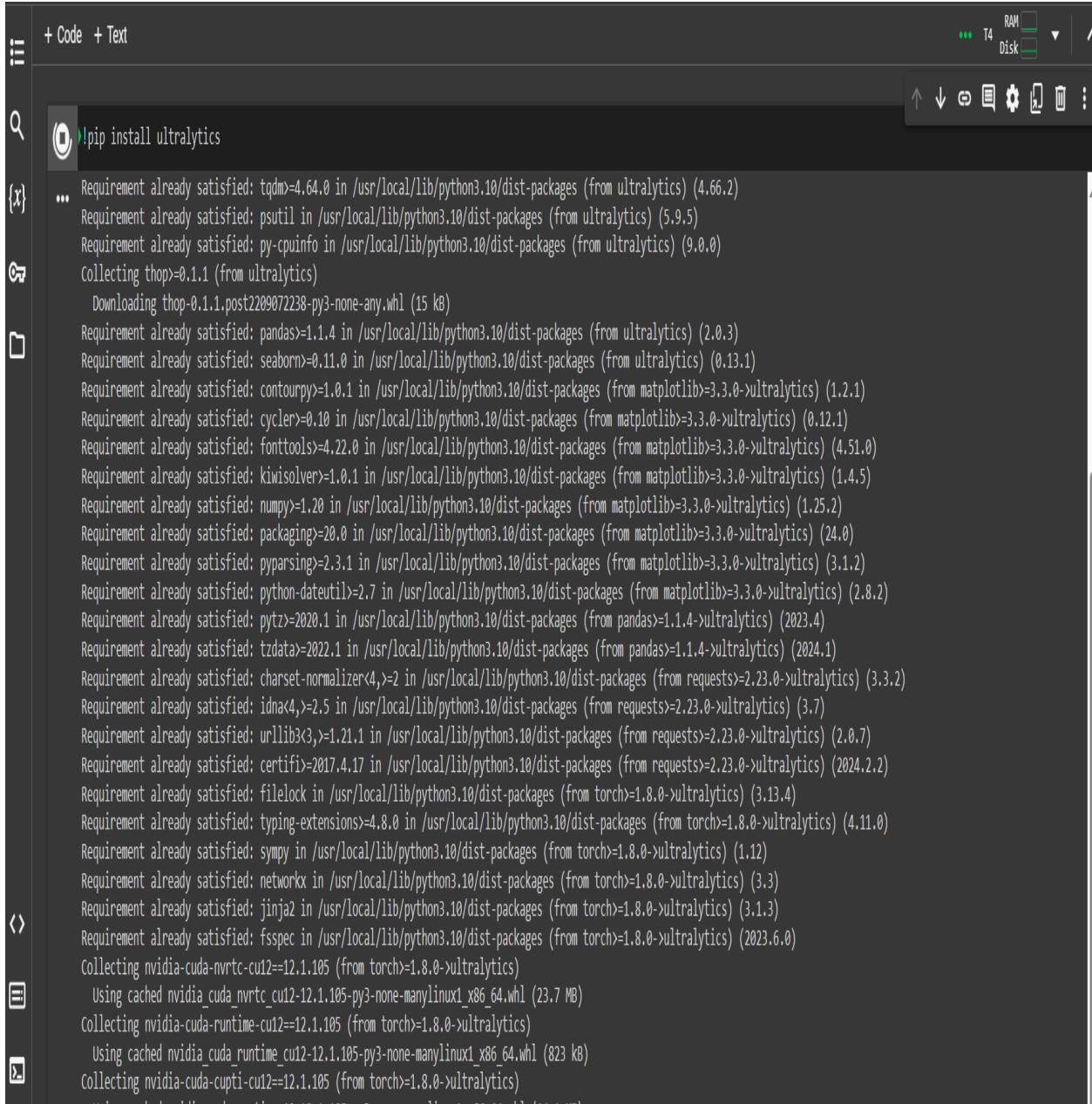
- Optimized model hyperparameters, such as anchor box sizes, input resolution, and model depth, to enhance performance and speed without compromising accuracy.
- Employed techniques like batch normalization, dropout, and gradient clipping to improve model stability, convergence, and generalization.

6. Documentation and Reporting

- Documented the entire methodology, including data preprocessing steps, model architecture, training configurations, evaluation metrics, and results.
- Generated comprehensive reports and visualizations, including training curves, validation results, and sample predictions, to communicate findings and insights effectively.

This methodology framework ensures a systematic and rigorous approach to pet pose detection system development, incorporating best practices in data preprocessing, model training, evaluation, and optimization to achieve accurate and reliable pose estimation results.

CODING AND TESTING



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+ Code + Text
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  Using cached nvidia_cuda_cupti_cu12-12.1.105-py3-none-manylinux1_x86_64.whl (1.1 kB)
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SCREENSHOTS AND RESULTS



Class: This could refer to the specific class or category being detected or processed by the convolutional layer.

Images: Total number of images processed.

Instances: Total number of instances detected.

Box(P): Precision for bounding boxes.

Box(R): Recall for bounding boxes.

mAP50: Mean Average Precision at IOU threshold of 0.5.

mAP50-95: Mean Average Precision across IOU thresholds from 0.5 to 0.95.

Pose(P): Precision for pose estimation.

Pose(R): Recall for pose estimation.

Pose mAP: Mean Average Precision for pose estimation.

Here's the breakdown of the provided values:

Class: All

Images: 1703

Instances: 1703

Box Precision (P): 96.5%

Box Recall (R): 98.5%

mAP50: 99.1%

mAP50-95: 92.2%

Pose Precision (P): 92.5%

Pose Recall (R): 92.8%

Pose mAP: 93.7%

Pose mAP50-95: 49.7%

This output suggests high performance across both bounding box detection and pose estimation tasks

CLUSION AND FUTURE ENHANCEMENTS

Conclusion:

The emergence of pet pose detection marks a transformative milestone in pet care, offering unprecedented insights into pet health, behavior, and training. Leveraging advanced machine learning techniques like YOLOv8 and keypoint annotations, these systems have attained remarkable accuracy and reliability, paving the way for revolutionary pet care practices.

Pet pose detection holds immense promise across various domains. It stands to significantly enhance pet health monitoring by detecting subtle changes in posture and movement indicative of potential health issues, enabling timely intervention. Additionally, it aids in behavioral analysis, empowering owners and professionals to address stressors and abnormalities through targeted training interventions, thereby enhancing overall pet well-being.

Future Prospects:

The trajectory of pet pose detection extends towards broader applications in pet safety, security, and social interactions. Integration with surveillance systems or smart pet environments can bolster pet safety by alerting owners to potential dangers or intrusions. Moreover, coupling this technology with wearable devices enables real-time monitoring and feedback, fostering deeper bonds between pets and owners while facilitating proactive management of their well-being.

Collaboration among veterinarians, pet trainers, and behavioral experts is pivotal for harnessing the full potential of pet pose detection. By merging domain expertise with technological innovation, tailored solutions can be developed to address diverse pet care needs effectively. From optimizing training regimes to managing chronic conditions, a multidisciplinary approach promises holistic and personalized pet care solutions.

In summary, the convergence of technology and compassion heralds a new era in pet care. With ongoing research, innovation, and collaboration, pet pose detection is poised to become an indispensable tool in the arsenal of pet care professionals and enthusiasts alike, ushering in proactive and personalized pet care practices on a widespread scale.

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