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Artificial Neural Networks Final Project Documentation

A Final Requirement for Artificial Neural Networks

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CCS 248 - Artificial Neural Networks

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Introduction

Accurate livestock weight estimation is essential for proper farm management, fair market pricing, optimal feeding decisions, and maintaining animal health. However, small-scale cattle farmers often rely on imprecise traditional methods or lack access to industrial weighing equipment. This paper presents a deep learning–based system capable of detecting key cattle body parts using a custom-built Convolutional Neural Network (CNN). With precise body part localization, future extensions of this work may enable automated, non-invasive cattle weight prediction using computer vision.

Problem Statement

Most small-scale farmers cannot accurately measure cattle weight because industrial scales are expensive and traditional visual estimations are highly inaccurate. Slaughterhouse weighing introduces additional costs, and tape measurement is time-consuming and inconsistent.

This study addresses the lack of accessible and accurate weighing methods by developing a computer vision model capable of detecting important cattle body parts, Head, Leg, and Back, from images. These detected components serve as the foundation for extracting morphological measurements that can be used in automated weight estimation systems.

Dataset Description

The dataset used in this study was sourced from the *Cattle Body Parts Dataset for Object Detection* (Kaggle). It consists of 428 images annotated in COCO JSON format, containing three classes: Head, Leg (4), and Back

Data Distribution

Split	Images	Percentage
Training	342	79.9%
Validation	42	9.8%
Test	44	10.3%

Data Augmentation

To improve the model, several image augmentation techniques were applied: Random brightness adjustments (±0.2), Contrast variation (0.8–1.2), Saturation variation (0.8–1.2), Horizontal flips with bounding box correction.

Model Architecture

A custom Convolutional Neural Network (CNN) was developed from scratch. The architecture consists of:

Convolutional Backbone

A five-block feature extraction module with the following characteristics:

- Two Conv2D layers per block
- Batch Normalization
- ReLU activation
- MaxPooling for downsampling

Total trainable parameters: **10,914,122**

Dense Layers

After flattening, the network includes:

- Dense (512) → ReLU → Dropout (0.3)
- Dense (256) → ReLU → Dropout (0.3)
- Dense (128) → ReLU → Dropout (0.3)

Dual Output Heads

1. **Bounding Box Regression Head**
   - Output: 24 units (6 detections × 4 coordinates)
   - Activation: Sigmoid
   - Output shape: (None, 6, 4)
2. **Classification Head**
   - Output: 18 units (6 detections × 3 classes)
   - Activation: Softmax
   - Output shape: (None, 6, 3)

Training Configuration

Hyperparameters

Parameter	Value
Image Size	256×256
Batch Size	4
Epochs	100
Dropout	0.3
Learning Rate	0.001
Optimizer	Adam
LR Schedule	Cosine Decay
Random Seed	42

Loss Functions

- Bounding Box Loss: Mean Squared Error (weighted ×10)
- Classification Loss: Categorical Crossentropy
- Total Loss = 10 × Bounding Box Loss + Classification Loss

Callbacks

- ModelCheckpoint monitoring val_loss
- Saves best model weights automatically

Results and Evaluation

Training Performance

Metric	Initial	Best (Epoch 2)	Final
Training Loss	1.9604	0.3234	2.5850
Validation Loss	1.9604	0.3050	2.5818
BBox MAE	0.2993	0.2592	0.3549
Classification Accuracy (Train)	94.87%	96.71%	98.24%

Overall Results:

- Total Loss: 0.3467
- Bounding Box Loss: 0.0255
- Classification Loss: 0.0913
- Mean IoU: 0.1126
- mAP@0.5: 0.1285
- Accuracy: 0.9826

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Observations

- The model converged rapidly, achieving optimal validation loss at epoch 2.
- Classification accuracy exceeded expectations, reaching +90%.
- Loss weighting successfully emphasized bounding box precision.

Tools and Technologies

Frameworks and Libraries

Deep Neural Network: Convolutional Neural Network

- TensorFlow 2.x (Keras API)
- NumPy, OpenCV, Matplotlib, Pillow, Pandas

Dataset

- https://www.kaggle.com/datasets/alikhalilit98/cattle-body-parts-dataset-for-object-detection/data

Additional File

- detectiongan_utils.py

Conclusion

This project developed a custom CNN capable of accurately detecting essential cattle body parts, providing a foundation for a future weight-estimation system that small-scale farmers can use as a low-cost alternative to industrial weighing tools. With strong classification accuracy and stable localization performance, the model demonstrates that deep learning can effectively support livestock management. While the current system focuses on detection, it establishes the groundwork for future enhancements such as weight prediction, larger datasets, and real-time deployment.

References

Khalili, A. (2023). Cattle Body Parts Dataset for Object Detection. Kaggle.

TensorFlow Documentation. https://www.tensorflow.org

He, K., et al. (2017). Mask R-CNN. ICCV.