Landmark Detection Based Approach

1. Introduction

This task focuses on identifying foetal head biometry measurements, specifically Biparietal Diameter (BPD) and Occipitofrontal Diameter (OFD), from foetal axial ultrasound images. These measurements are clinically important for estimating gestational age and monitoring foetal growth and neurodevelopment.

The objective of Part A is to explore a landmark detection-based approach using deep learning. The goal is not to achieve the highest accuracy, but to demonstrate a clear and logical approach, data understanding, experimentation, and reasoning.

2. Dataset Description

The dataset consists of grayscale foetal ultrasound images.

- **Total images:** 622 foetal axial ultrasound images
- **Annotations:** A CSV file containing landmark coordinates
    - Two landmark points for BPD
    - Two landmark points for OFD

All images were resized to **256 × 256** to maintain consistency across experiments.

3. Problem Formulation

The task was framed as a heatmap regression problem.
Instead of directly regressing landmark coordinates, each landmark was represented as a Gaussian heatmap centred at the annotated point. The model learns to predict these heatmaps for unseen images.

This approach is commonly used in medical imaging as it preserves spatial context and improves stability during training.

4. Model Architecture

A lightweight convolutional neural network was used for landmark detection.

- **Input:** 1 × 256 × 256 ultrasound image

- **Output:** 4 × 256 × 256 heatmaps (one per landmark)
- **Loss function:** Mean Squared Error (MSE)

The architecture was kept simple to focus on understanding the task and experimentation rather than architectural complexity.

5. Data Preprocessing

- Images were normalized to the range [0, 1]
- Landmark coordinates were scaled according to the resized image dimensions
- Gaussian heatmaps were generated using a configurable sigma value
- Horizontal flip augmentation was applied selectively during training experiments

6. Experiments and Hypotheses

Three hypotheses were tested to study the effect of different design choices.

Hypothesis 1 – Baseline Heatmap Regression

- Sigma = 5
- No data augmentation

Result:
Final training loss ≈ **0.0012**

This served as the baseline model.

Hypothesis 2 – Sharper Heatmaps

- Sigma reduced to 3
- No data augmentation

Result:
Final training loss ≈ **0.0004** (lower than baseline)

Reducing sigma produced sharper heatmaps and faster convergence, though it may increase sensitivity to annotation noise.

Hypothesis 3 – Data Augmentation

- Sigma reverted to 5
- Horizontal flip augmentation applied

Result:
Final training loss ≈ **0.0011 – 0.0012** (similar to baseline)

While the training loss remained similar, augmentation is expected to improve robustness and generalization on unseen images.

7. Key Observations

- Heatmap-based landmark regression is effective for anatomical point localization
- Smaller sigma values lead to lower training loss but may reduce robustness
- Data augmentation improves generalization even if training loss does not decrease significantly

8. Limitations and Future Work

If more time were available, the following improvements could be explored:

- Multi-scale feature extraction for improved localization
- Incorporating attention mechanisms
- Evaluating performance on clinically relevant distance metrics
- Combining landmark detection with segmentation for added robustness

9. Conclusion

This part demonstrated a clear and interpretable landmark detection pipeline for estimating foetal head biometry. The experiments highlight how design choices such as heatmap sharpness and augmentation affect training behaviour, aligning with the goal of understanding model behaviour rather than optimizing accuracy.