**REPORT**

**Experiment Summary**

In this experiment, two primary approaches were explored: a classification-based pipeline and a segmentation-based pipeline. Each was designed to leverage state-of-the-art architectures while addressing the constraints of a relatively limited dataset.

**Classification Approach**

The classification methodology employed a modular model design, utilizing CLIP-based backbones and allowing for variable numbers of trainable parameters. Two configurations were tested:

1. **ViT-B/32 Architecture**:
   * Integrated through CLIP.
2. **ConvNeXt-Base-W Backbone**:
   * Also provided by CLIP.

This modular design enabled dynamic adjustment of network complexity relative to the dataset size, effectively preventing overfitting and ensuring efficient parameter utilization.

**Results:**

* Both configurations achieved competitive precision and accuracy, demonstrating the robustness of the classification approach.
* The flexible design allowed for easier fine-tuning of the model to match the dataset’s scale and complexity.

**Conclusion:**

* The classification strategy’s performance metrics suggest that it can be readily adapted and improved upon with minimal computational overhead.

**Segmentation Approach**

The segmentation-based approach utilized a U-Net architecture, enhanced with the following features:

* **Custom Activations**: To improve non-linear representation.
* **Attention Blocks**: For selective feature focus.
* **Novel Skip-Connection Design**: To strengthen feature propagation.

The model was more complex and parameter-heavy, with approximately three million parameters to be tuned.

**Challenges:**

* The relatively small dataset size posed a significant challenge.
* The complexity and high parameter count made it difficult to achieve optimal convergence and generalization.

**Conclusion:**

* Although the architecture demonstrated theoretical benefits in feature refinement and spatial precision, the segmentation approach did not perform as favourably as the classification approach under the given constraints.

**Overall Conclusion**

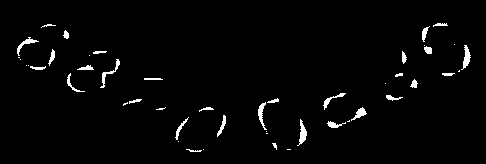
* The classification pipeline outperformed the segmentation approach, likely due to its modular nature and parameter flexibility, which better suited the modest dataset size.
* While the segmentation approach offers richer feature extraction and spatial detail, its parameter-intensive architecture and insufficient data hindered its effectiveness.

**Future Directions:**

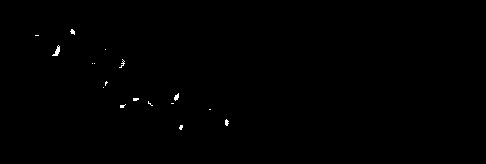
* Reduce the parameter count for the segmentation pipeline.
* Explore more aggressive regularization strategies.
* Incorporate data augmentation or transfer learning techniques to enhance model generalization.

The attached results and images illustrate the respective outcomes and highlight areas for further refinement.

**SEGMENTATION RESULTS**

PREDICTION ACTUAL

PREDICTION ACTUAL

**CLASSIFICATION RESULS**

**Class: scratches**

|  |  |  |
| --- | --- | --- |
| Models | **VIT-B-32** | **Convnext\_base\_w** |
| Precision | 0.8333 | 0.8750 |
| F1 Score | 0.7895 | 0.8235 |
| Recall | 0.7500 | 0.8485 |

Actual: scratches Predicted: scratches Actual: scratches Predicted: scratches