A PROJECT PROPOSAL ON PRINTABLE AREA MAPPING IN THE UPPER GARMENTS CONSIDERING THE OBSTACLES

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Motivation

- Consumer preferences for unique and individualized fashion items.
- Manual identification of printable areas is time-consuming and prone to errors.
- Current garment mapping methods lacks optimization and hinder production speed and accuracy.
- Existing automated systems lack robust obstacle detection capabilities, leading to inaccuracies.
- Addressing these challenges with an advanced, automated solution can streamline garment production processes, reduce errors, and enhance overall efficiency.

Background

- Fashion industry requires efficient design and production processes.
- Current methods, often manual, rely on templates and measurements, struggle with obstacle detection.
- Garment mapping, identifying printable areas with the identification of shape and dimensions, is vital for precise printing.
- Need for automated solutions, leveraging deep learning, to improve efficiency and accuracy.

Problem Statement

- Existing garment mapping systems often overlook obstacles, leading to inaccuracies in printable area mapping, resulting in increased production time and potential errors.
- Challenge will be to accurately map and optimize printable area, and to ensure high-quality prints and efficient fabric use.
- Dealing with irregular shapes, fabric properties, and design constraints, and detecting and avoiding non-printable areas.
- Automated Solution is necessary to address these challenges and improve current practices systematically.

Objectives of Project

- To classify the male upper garments and integrate obstacle detection solution to accurately identify and delineate obstacles such as seams, pockets, and zippers on male upper garments.
- To develop an automated system for precise mapping of standard obstacle free printable areas on upper garments using faster RCNN.

Scope of Project

- Development of deep learning-based solution for automated garment mapping with obstacle detection capabilities.
- Evaluation will be conducted using diverse datasets of male upper garments to assess accuracy and performance under various garment types and environmental conditions.
- Development of a prototype system and the demonstration of its feasibility in real-world garment production scenarios.
- Assumes high-quality images and measurements on construction of dataset, and may not address highly complex garment designs.

Originality of Project

- Novel approach to overcome existing traditional manual methods.
- Manually annotated six categories of garment with 100 annotated each for upper male garments.
- Utilizes two staged detection mechanism of Faster R-CNN for upper body garment classification of male, detecting obstacle as well as mapping obstacle free print area.
- Potential to significantly improve print quality and efficiency, setting new standards in the industry.

Potential Applications

- Automated digital garment printing.
- Quality control in textile manufacturing.
- e-Commerce industries.
- Could be adapted for industries requiring precise pattern placement, such as automotive interiors or custom upholstery.

Literature Review

- Significant potential in revolutionizing the fashion industry by streamlining the design and production processes.
- Existing systems often overlook obstacles such as seams, pockets, and zippers, resulting in inaccuracies in printable area mapping.
- Several studies have aimed to address this limitation by developing obstacle detection algorithms.

Literature Review[1]

Author	Title	Model Used	Result	Publication
Ma et al. (2021)	Detecting Garment Landmarks for Fine-Grained Fashion Similarity	CNN	Achieved state-of-the-art performance on garment landmark detection	Journal of Computer Vision and Pattern Recognition
Chen et al. (2021)	Pocket Detection in Garment Images Using Convolutional Neural Networks	CNN	Proposed an effective CNN-based model for pocket detection in garment images	Journal of Computer Vision and Pattern Recognition
Li et al. (2021)	A novel approach to garment mapping using machine learning algorithms	SVM, Decision Trees	Developed a novel approach for garment mapping using ML algorithms with promising results	International Journal of Clothing Science and Technology

Literature Review[2]

Author	Title	Model Used	Result	Publication
Wang et al. (2020)	Seam Detection in Garment Images	(CNN, RNN)	Achieved state-of-the-art performance on garment landmark detection	Pattern Recognition
Zhang et al. (2019)	Automated Garment Pattern Mapping	Edge detection, contour analysis	Proposed an effective CNN-based model for pocket detection in garment images	Journal of Fashion Technology & Textile Engineering,
Delight, D et al.(2021)	Deep Learning based Object Detection using Mask RCNN	Mask R CNN	Masking capabilities to identify the infected cells with Plasmodium Vivax and applicable for detection tasks	International Conference on Communication and Electronics

Dataset Overview: Garment Types

Garment types of classify:

- Shirt
- T-Shirt
- Sweats
- Hoodie
- Jacket
- Polo T-Shirt

Dataset Overview[1]: Obstacle Types

Obstacle Classes for Obstacle Detection:

- **Seam**: Lines where fabric pieces are sewn together.
- **Zipper**: Metal or plastic fasteners used to join two edges of fabric.
- **Pocket**: Small pouches sewn onto or into garments.
- **Button**: Small fasteners, often circular, used for fastening garments.
- **Prints**: Logo and different prints in the garments
- **Text**: Text attached to garments, usually indicating brand or care instructions.
- **Collar**: Collar of the garments.

Dataset overview[2]: Standard Print Area Reference

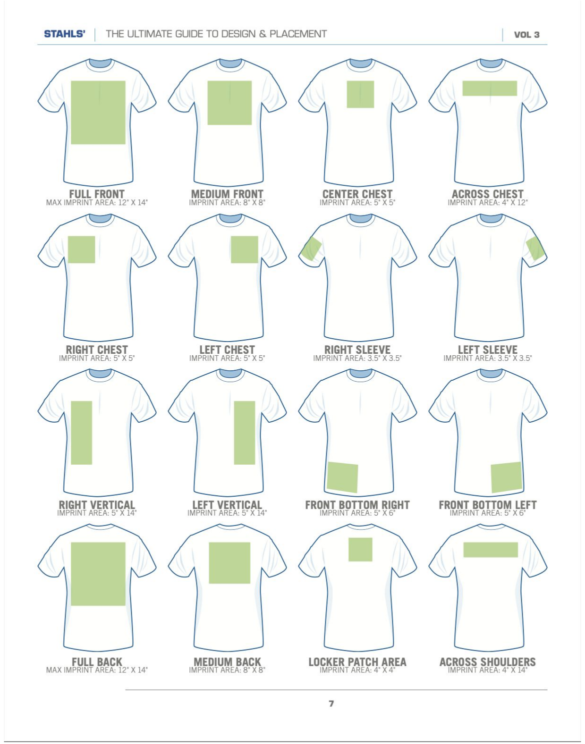


Fig: Print standard for t-shirt [7]

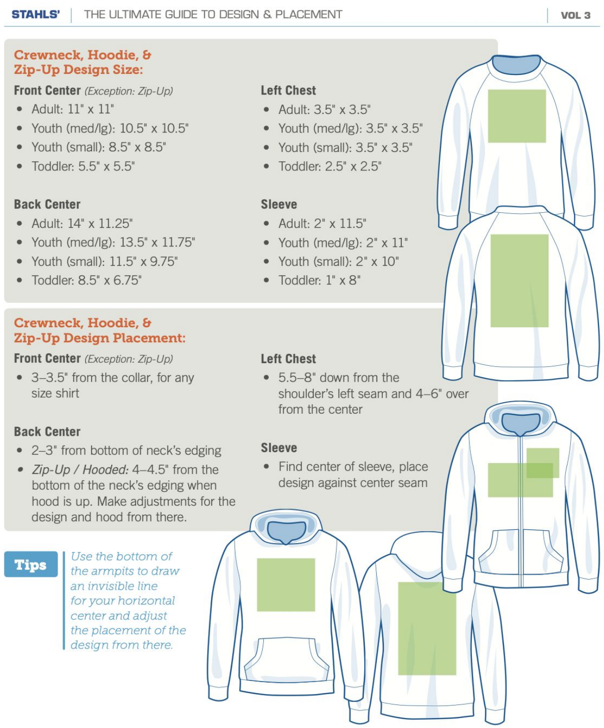


Fig: Print standard for hoodie, and sweatshirt [7]

Dataset OverView[3]: Standard Print Area

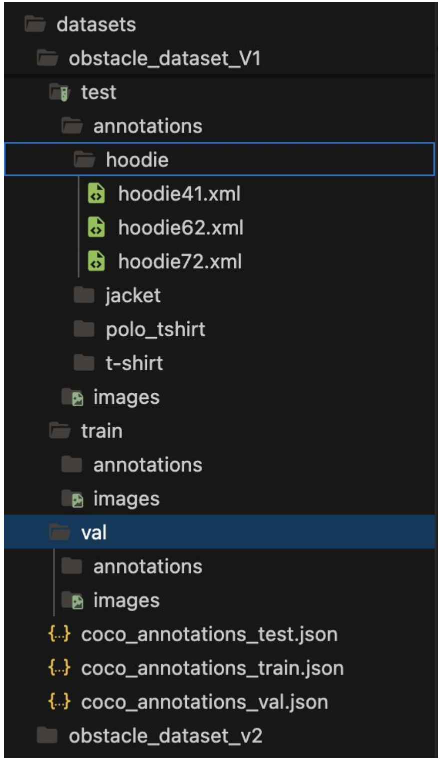
- Standard area on the garment suitable for printing without interference from obstacles.

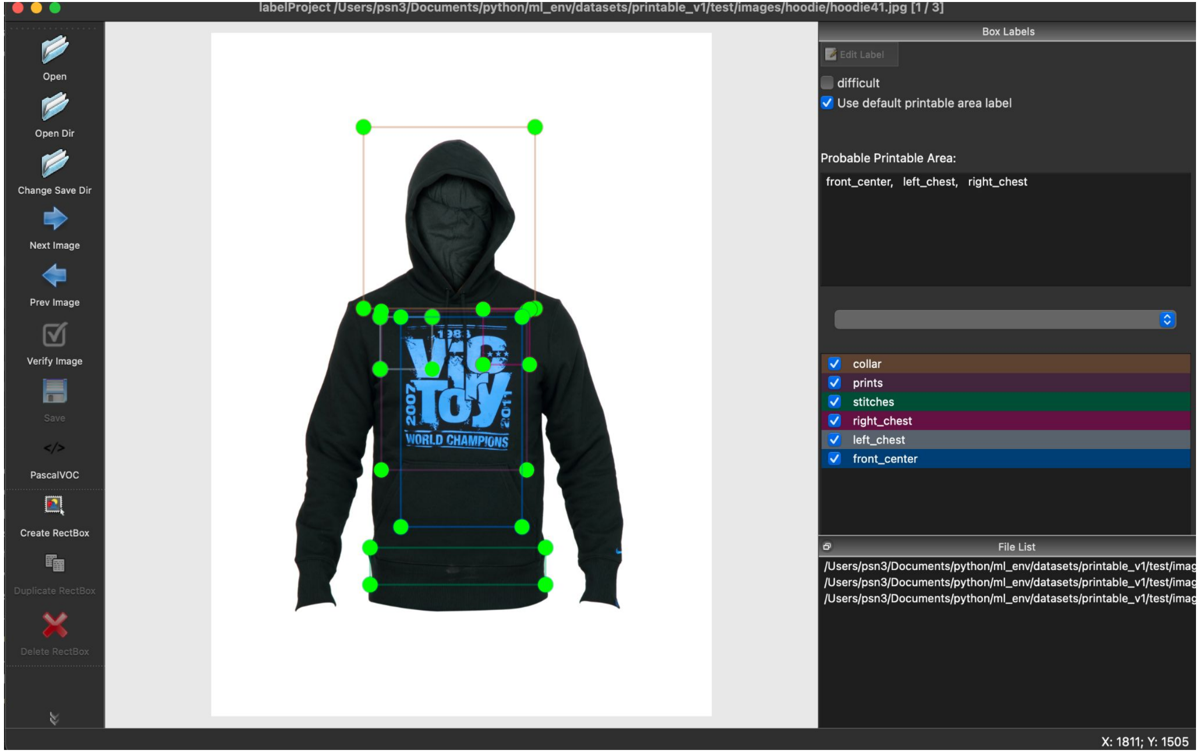
- Garment wise standards:
    - **Shirt**: Left Chest, Right Chest, Center Chest, Across Chest,Left Vertical,Right Vertical, Front Bottom Left, Front Bottom Right, Full Front, Front Center.
    - **Hoodie**: Front Center, Left Chest, Right Chest.
    - **Jacket**: Left Chest, Right Chest.
    - **Sweater**: Front Center, Left Chest, Right Chest.
    - **Polo_tshirt**: Left Chest, Right Chest.
    - **Shirt**: Left Chest, Right Chest.

Dataset overview[4]: Preview of Datasets

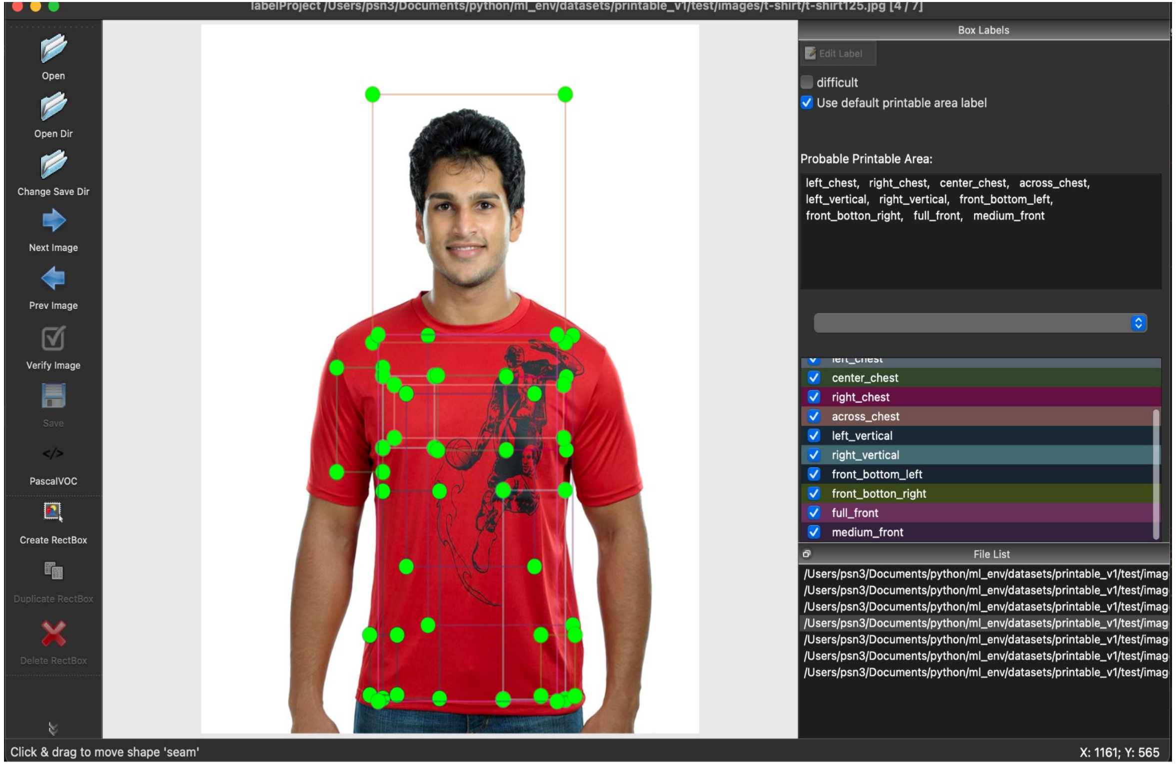
Fig: Dataset showing different garment types: Hoodie, T-shirt, Jacket, Sweatshirt, Polo T-shirt, and Polo Shirt

Dataset overview[6]: Dataset Structure





Dataset overview[7]: Annotation of t-shirt



Dataset overview[8]: Annotation Distribution

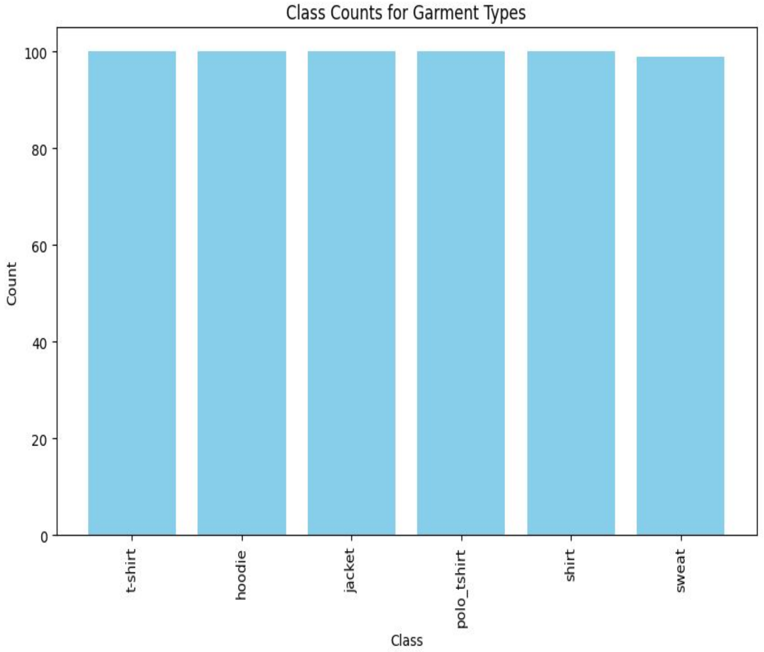


Fig: Garment wise dataset distribution

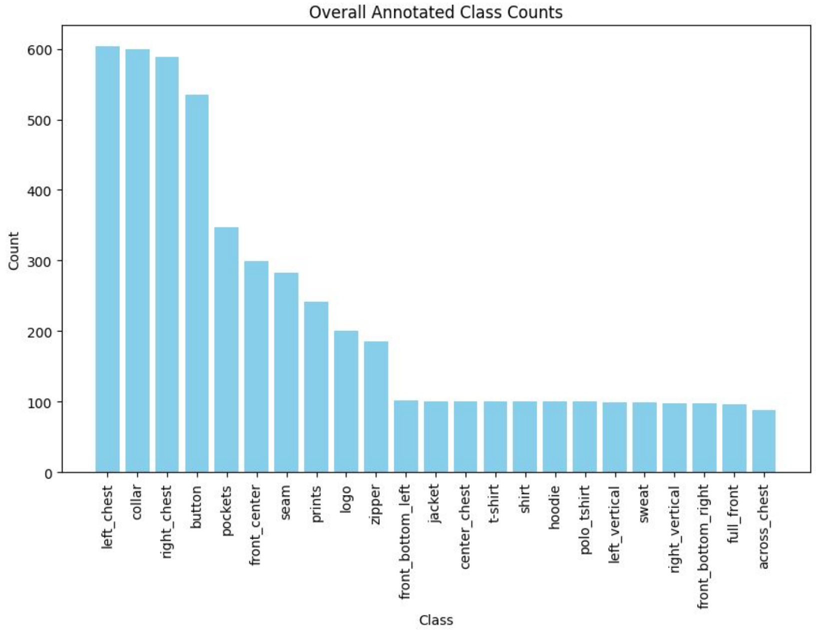


Fig: Category or Label wise distribution

Methodology: Overview

- Data Collection: Collection of garment images and manual annotation with obstacles and printable areas.
- Preprocessing: Image normalization, resizing, and data augmentation.
- Using Faster R-CNN to detect obstacles like seams, zippers, and pockets.
- Garment classification and obstacle and printable area detection.
- Assessing model performance using metrics such as nms, precision,mAP, recall, and IoU.
- Filtering the overlapping bounding boxes of obstacle and printable area.

Methodology[1]: Block Diagram

Fig: System Block Diagram for Printable Area Mapping

Methodology[2]: Flow Chart

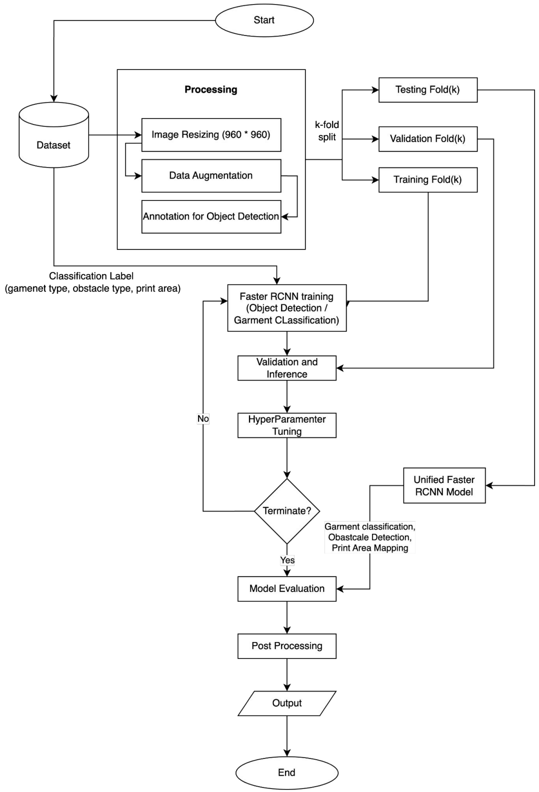


Fig: Flow Chart Printable Area Mapping

Methodology[3]: Data Collection

- Images collected from the different sources and categorized into previous discussed garment types.
- Annotation for images of mentioned **garment type**, **obstacle type**, **printable area** according to garment type is performed.
- Annotated xml is converted into the coco JSON standard required by the Faster RCNN.
- Divided into training, testing, and validation in k-fold cross-validations.

Methodology[4]: Dataset Flow Chart

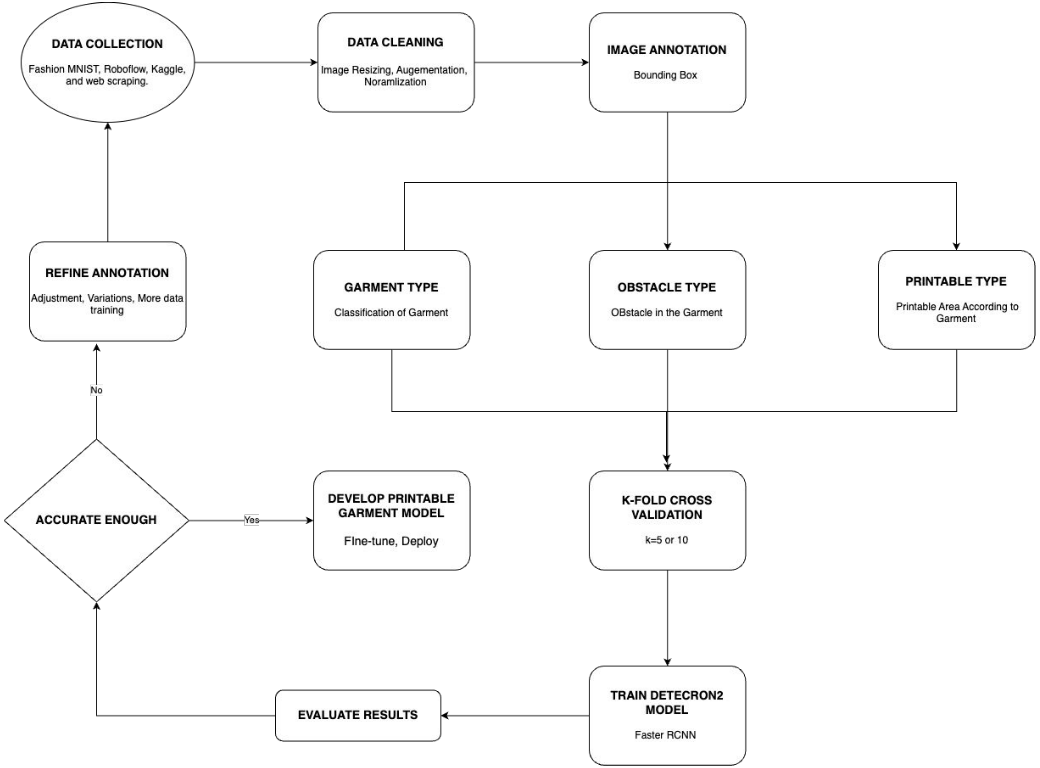


Fig: Data Collection work flow

Methodology[5]: Data Collection Techniques

- Annotated dataset for each class is around 20 for now and will extend up to 100-200 per class.
- Selected Annotation Tools:
    - **CVAT**: Rich annotation capabilities, support for collaborative work, and semi automated annotation will be efficient.
    - Preferred choice but docker images not supported in M1 architecture
    - **LabelImg**: Open Source,easy to use, and customizable.
    - Customized LabelImg to effectively annotate according to garment types.
    - Increased efficiency and quality of annotation obstacle type and printable area

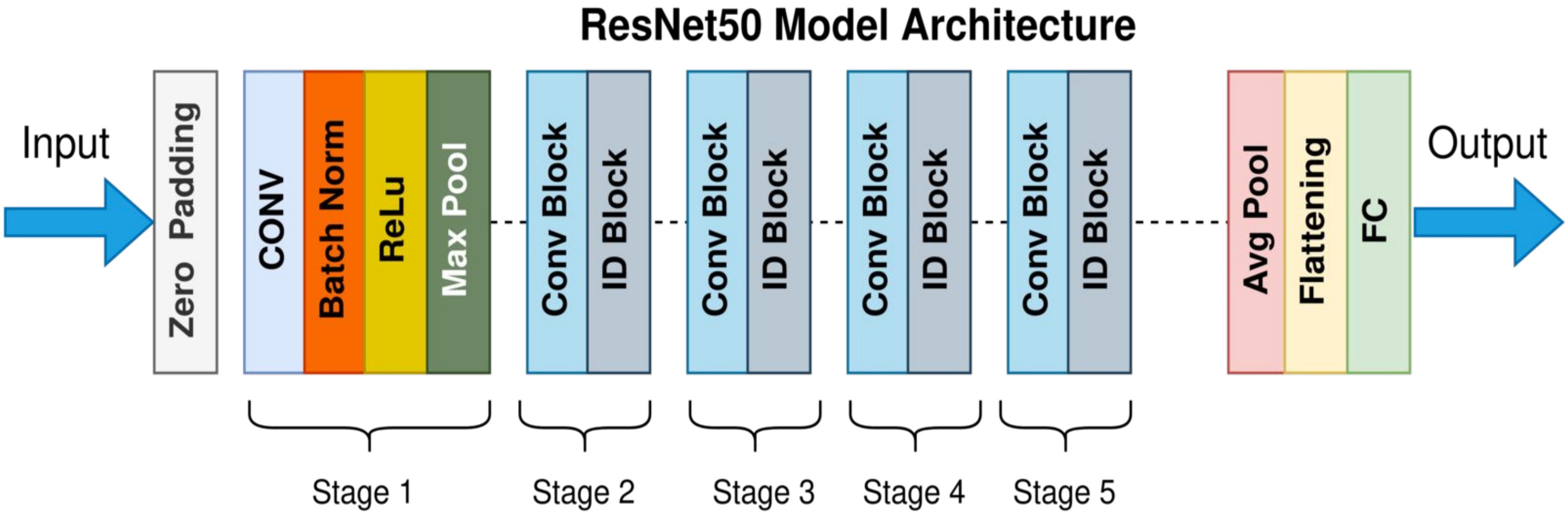
Methodology[6]: Preprocessing

- Image normalization to ensure uniformity in pixel values.
- Image resizing to a standard size for consistency.
- Data augmentation techniques such as rotation, flipping, and brightness adjustments to increase dataset diversity.
- Split data into training, validation, and test sets using k-fold cross validation.
- Pre-trained model on dataset for knowledge transfer.

Methodology[7]: Faster R-CNN

- Detect the classes of objects in the images and the bounding boxes of these objects
- Feature extraction from the input images with selective search.
- Each region given as an input to a CNN model and the prediction process is performed for classes and bounding boxes.
- Region Proposal Network (RPN) for generating region proposals.
- Classification and bounding box regression for obstacle detection.

Methodology[8]: RCNN Backbone



Methodology[9]: Faster RCNN Architecture

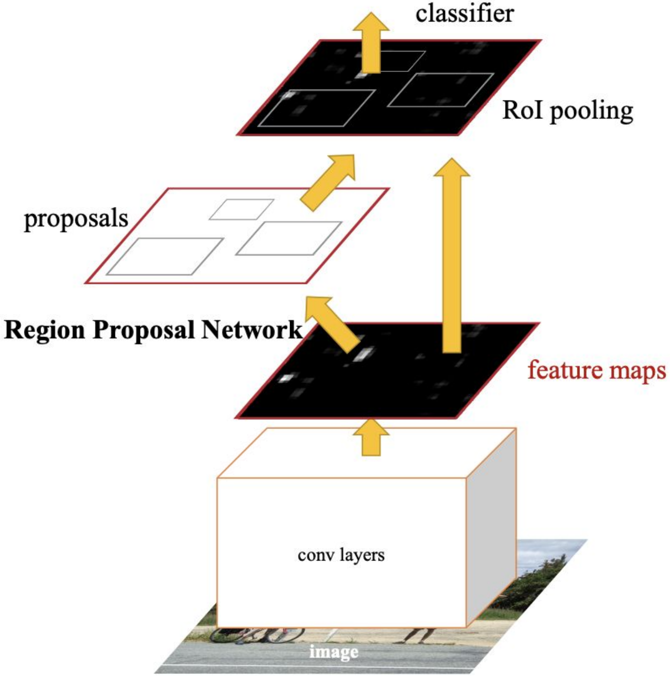


Fig: RCNN architecture [8]

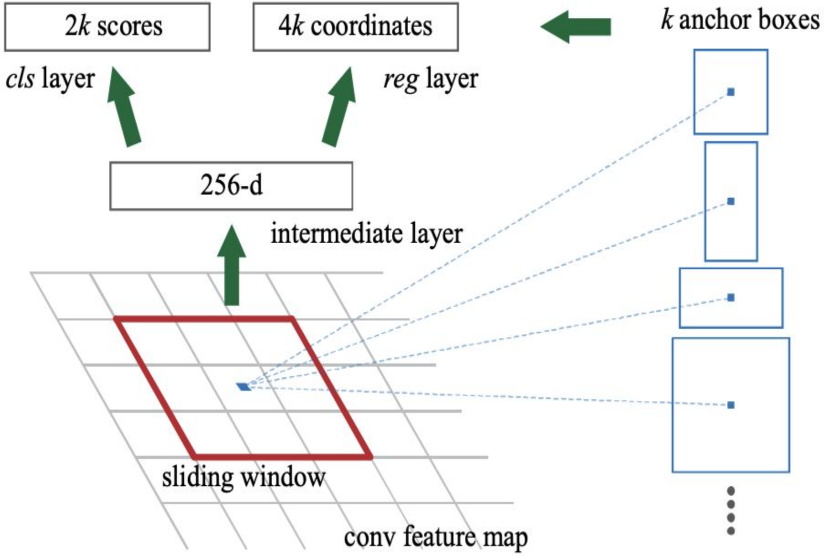


Fig: Region Proposal Network (RPN) [8]

Methodology[10]: Base-RCNN-FPN Visualization

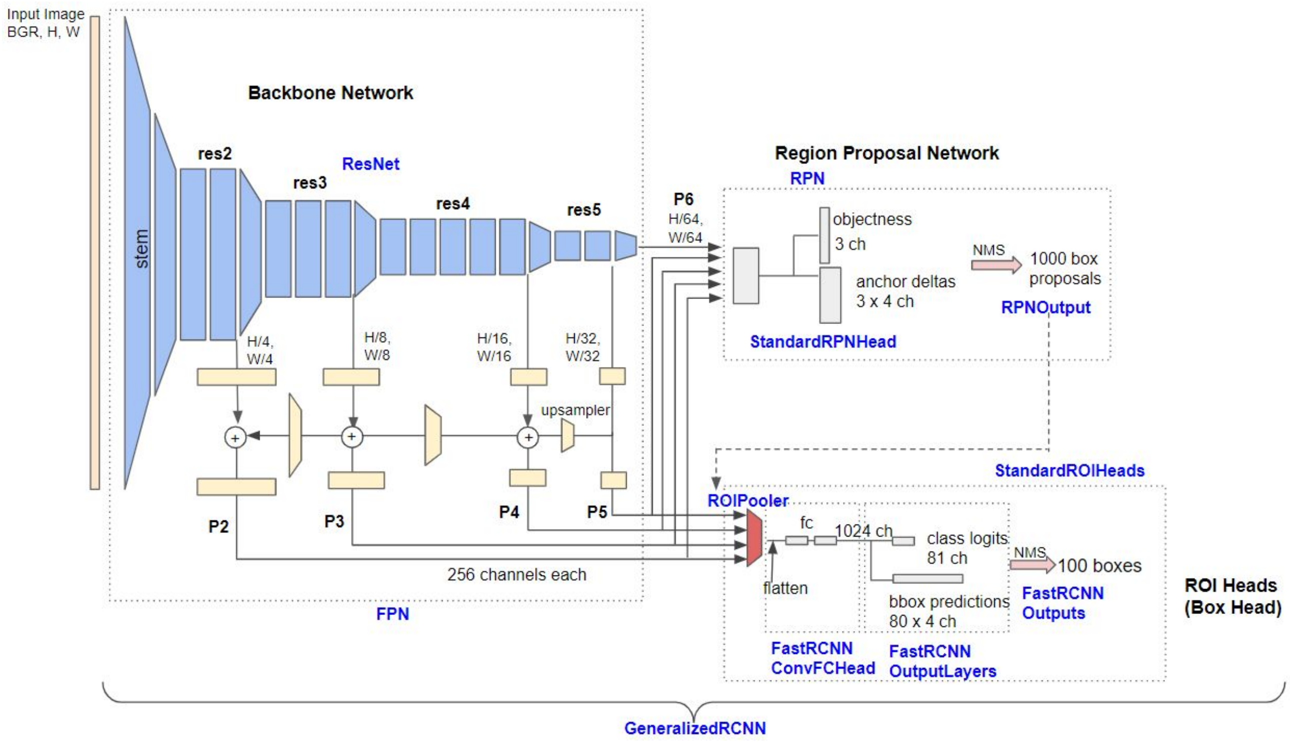


Fig: Detailed architecture of Base-RCNN-FPN [10]

Methodology[11]: Faster RCNN Customization

- Training on annotated dataset with labeled garment type, obstacle type and printable area .
- Two options of training the model to detect and map obstacle free printable area.
- First, training different model for each of the garment classification, obstacle detection, and printable area mapping and combining all to remove the overlapping printable area with obstacle.
- Second,single model training to classify garment and detect the obstacle, garment and print area, reducing the computational overhead.

Methodology[12]: Faster RCNN Configuration

- Configured Detectron2 to use pre-trained Faster R-CNN .
- Garment dataset with annotations converted into COCO dataset for training, testing and validation.
- Detectron2's data loaders to load and preprocess the garment dataset.
- Applied data augmentation techniques such as horizontal flipping and random cropping to enhance model robustness.
- Employed Detectron2's Default Trainer class for training the models.

Methodology[13]: HyperParameter Tuning

- **Learning Rate:** Initially set to 0.00025, and ater varied to 1e-3, 1e-5 and dropped on certain iteration cycle such as (1000, 2000) by 10 percent or 0.1.
- **Batch Size:** Set to 2-4 images per batch.
- **Number of Iterations:** Initially set to 500, 700, 1,500, 3000 and so on .
- **Optimizer:** Adam or SGD with momentum for training stability.
- **Weight Decay:** Initially set to 0.0001 to prevent overfitting.
- **ROI Heads Batch Size Per Image:** Number of ROIs per image (128/ 256) for fine-tuning region proposals.
- **ROI Head No. of Class:** 3 including garment type, obstacles and printable areas.

Methodology[14]: Integration and Evaluation

- Combining obstacle detection outputs with printable area segmentation masks.
- Evaluation and inference after each training.
- Precision, recall, and Intersection over Union (IoU) used to assess model performance.
- Rigorous evaluation for validating the effectiveness of the methodology.
- Feedback loop and continuous improvement.

Methodology[15]: Post Data Processing

Bounding Box Filtering

- Select the most representative garment bounding box.
- **Size Filtering:** Choose the largest or nearly largest bounding box.
- **Confidence Score Threshold:** Set to **0.5** to ensure high reliability.

Obstacle Detection

- Identify obstacles that may interfere with printable areas.
- **Confidence Threshold:** Obstacles are detected with a threshold of **0.6**.
- **Validation:** Obstacles below this threshold are ignored to reduce false positives.

Methodology[16]: Post Data Processing

Printable Area Overlap Calculation

- Validate printable areas based on overlap criteria.
- Areas failing to meet overlap thresholds are adjusted or discarded.

Garment Bounding Box Adjustment

- Refine garment areas by excluding obstacles.
- **Bounding Box Subtraction:** Automatically subtracts obstacle areas.
- **Area Validation:** Ensures the remaining area is ≥ 50% of the original garment area.

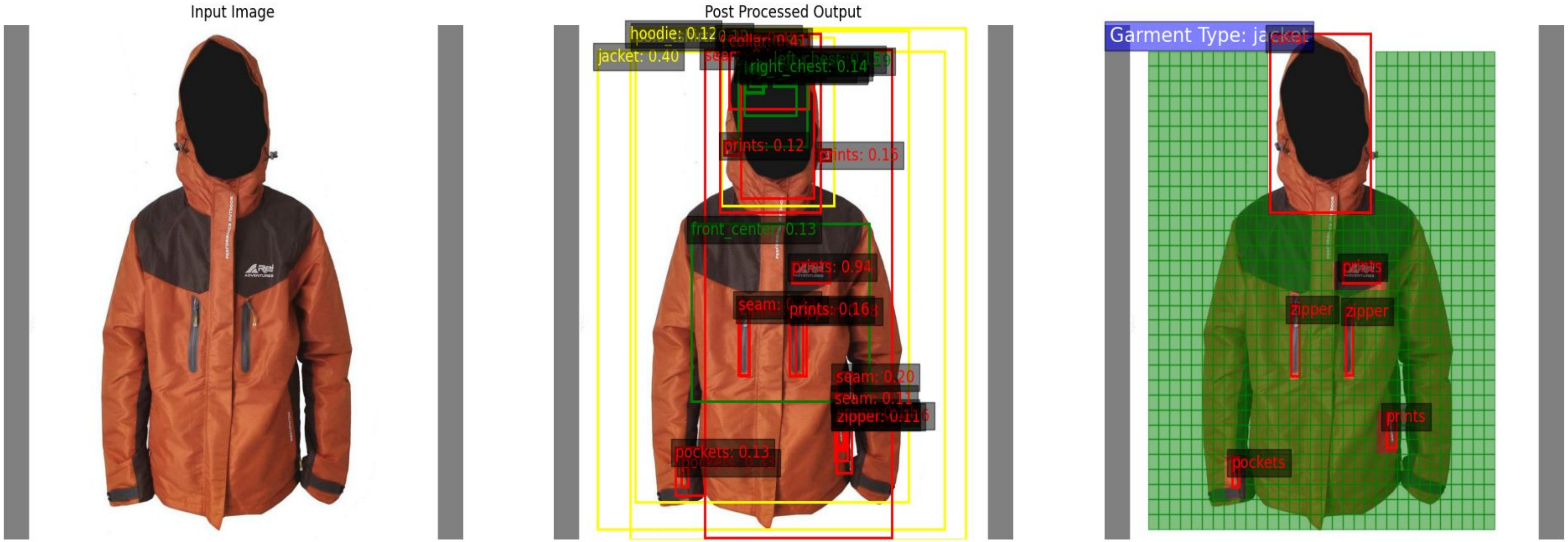
Methodology[14]: Post Data Processing

- **Post-Processing Parameters:**
  - Threshold for NMS set to 0.7 during training to filter overlapping region proposals.
  - To improve the accuracy of the detections, category-specific score thresholds were set:
    - Garment Types: 0.5
    - Obstacles: 0.4
    - Printable Parts: 0.3
  - Overlapped print area with the obstacle are filtered and obstacle free print are is mapped.

Results: Summary of Experiments

Exp.	Dataset	Batch	Iterations	k-fold	LR
1	120 (20/class)	2	500 iters	-	0.025
2	1200 (100/class)	2	700 iters/fold	5	0.025
3	1200 (100/class)	2	3000 iters/fold	10	0.025
4	1200 (100/class)	4	1500 epochs	3	1e-5

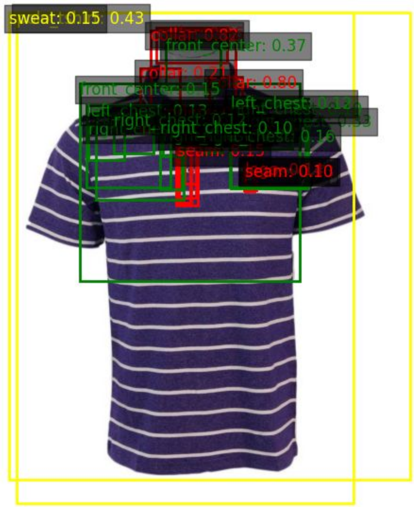
Results[1]: Printable Area on Jacket



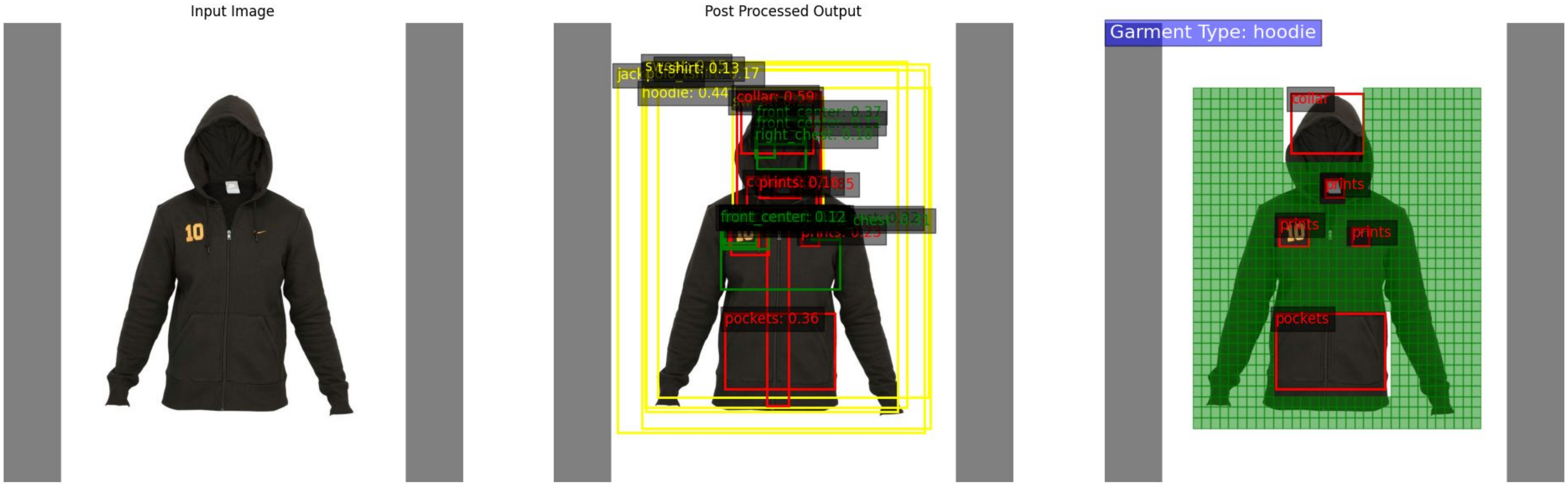
Results[2]: Printable Area on Polo T-shirt

Input Image

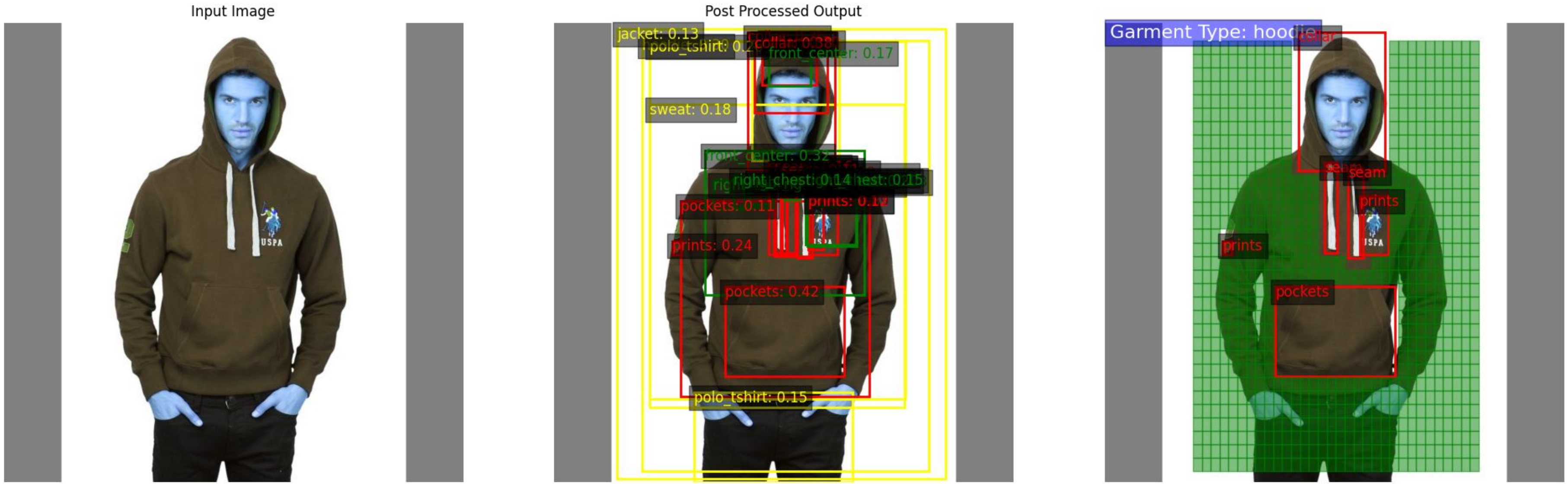
Post Processed Output



Results [3]: Printable Area on Hoodie



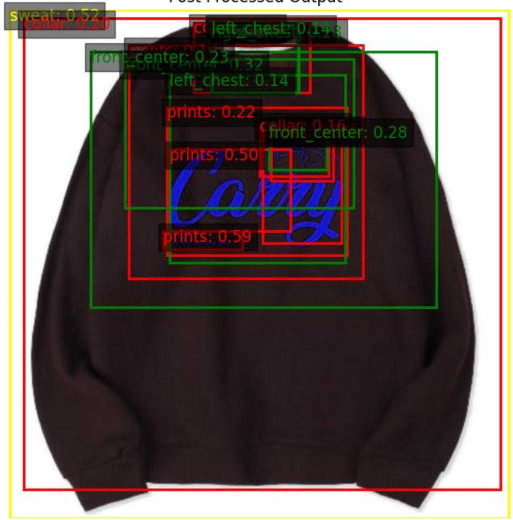
Results [3]: Printable Area on Hoodie



Results[4]: Printable Area on Sweat

Input Image

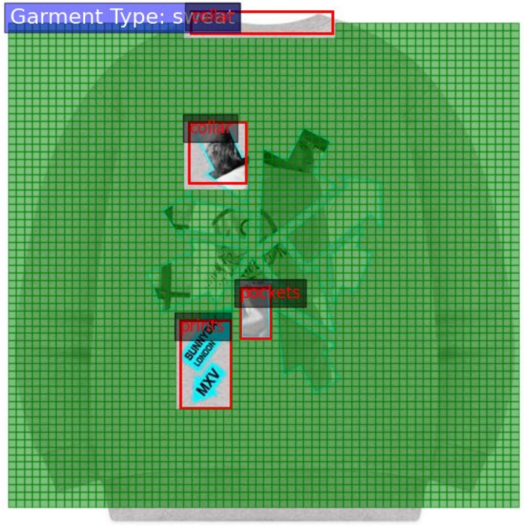
Post Processed Output



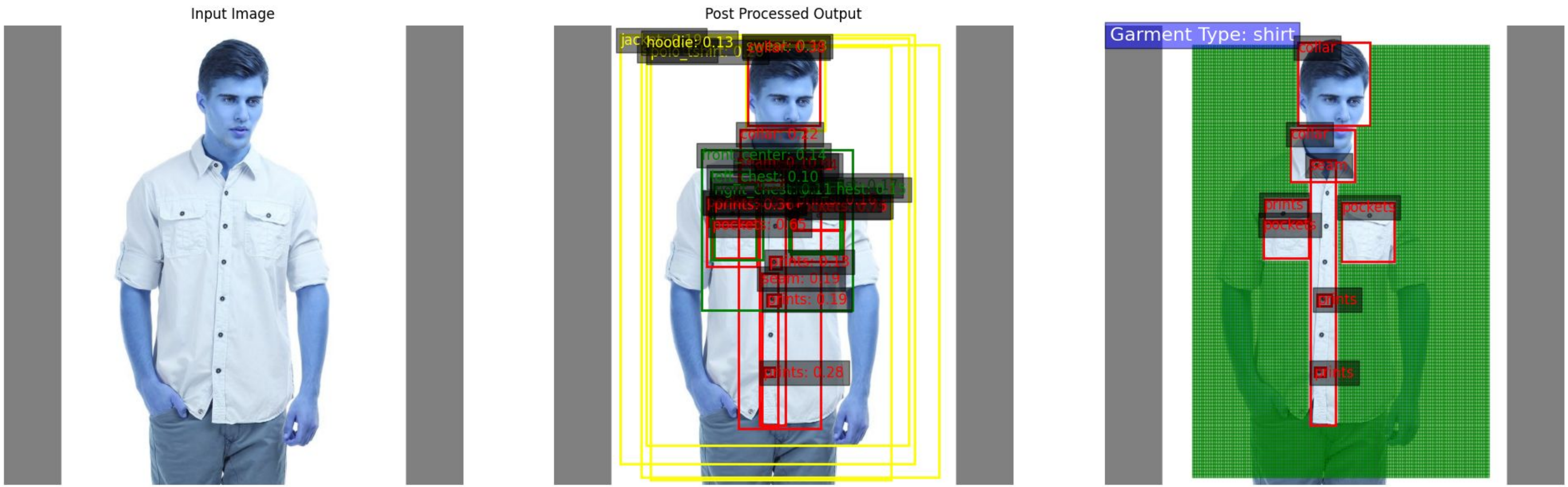
Results[4]: Printable Area on Sweat

Input Image

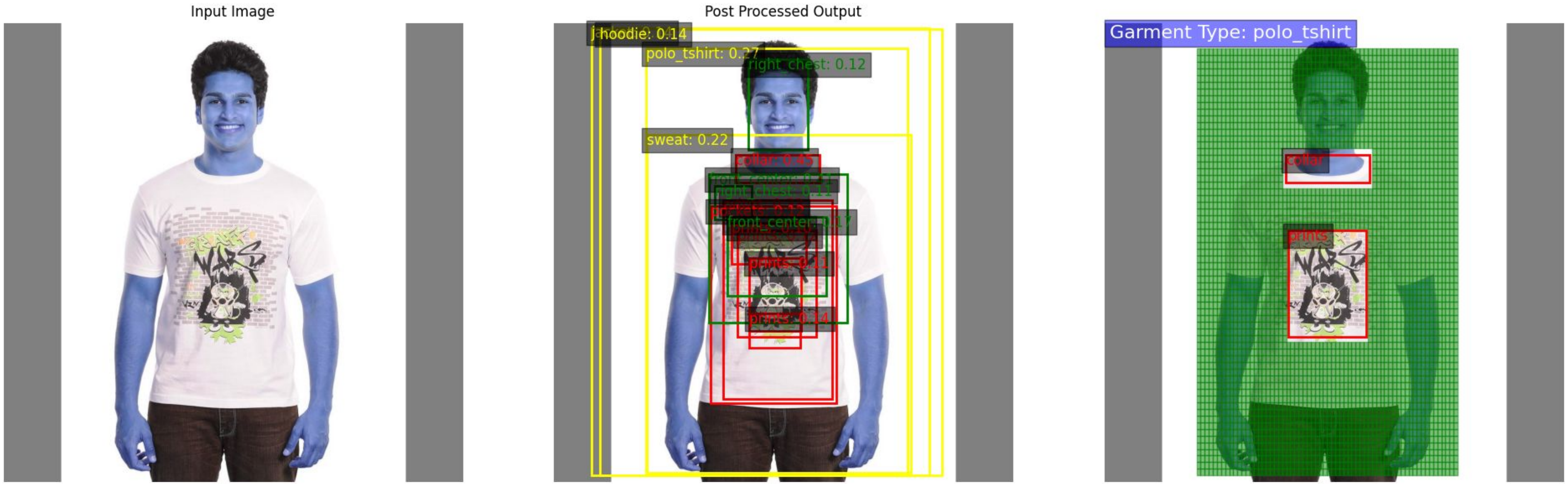
Post Processed Output



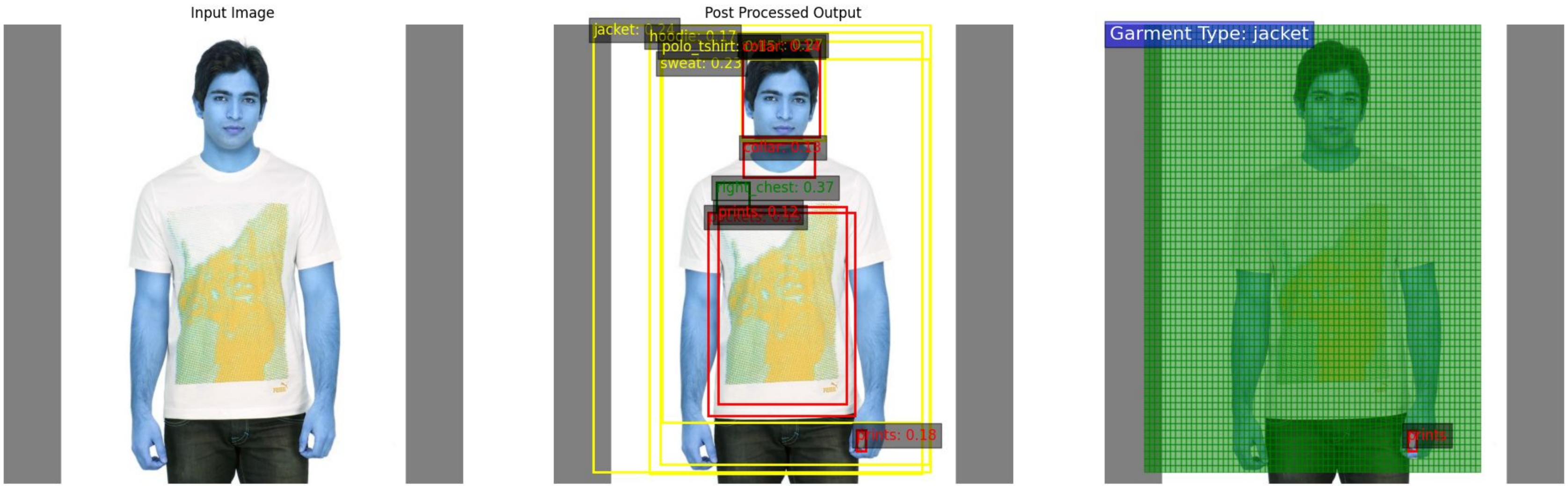
Results[5]: Printable Area on Shirt



Results[6]: Obstacle Detection on T-Shirt

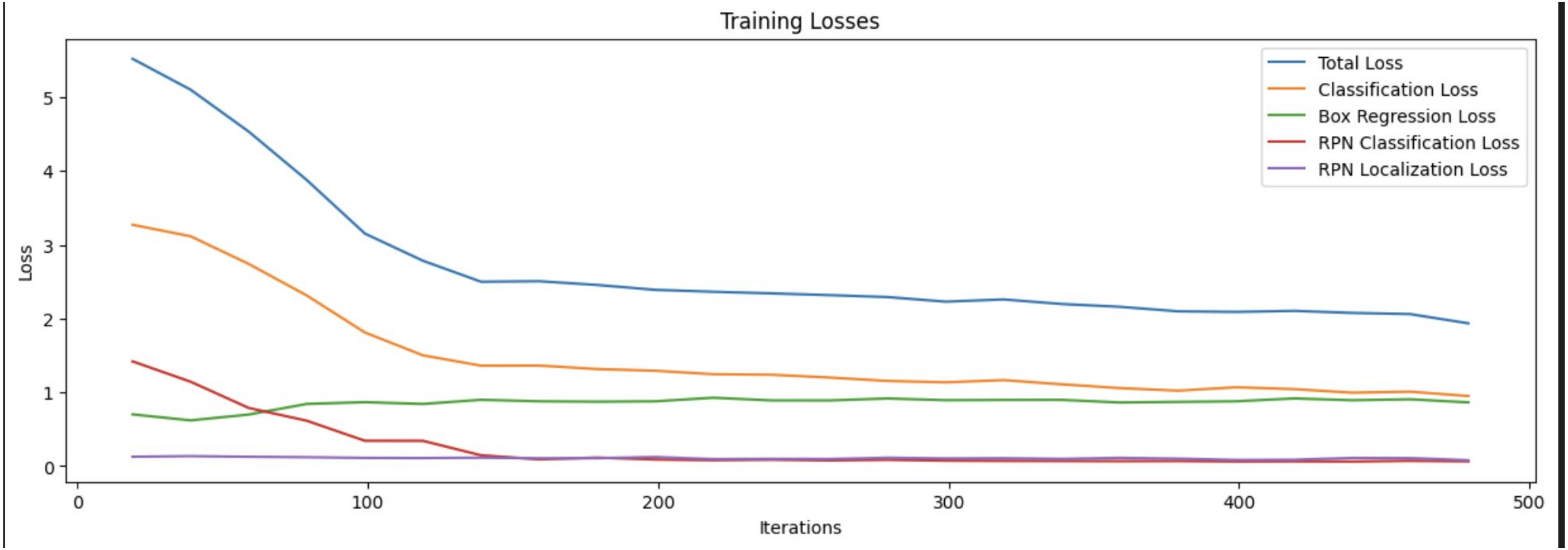


Results[7]: Printable Area on T-Shirt on Man

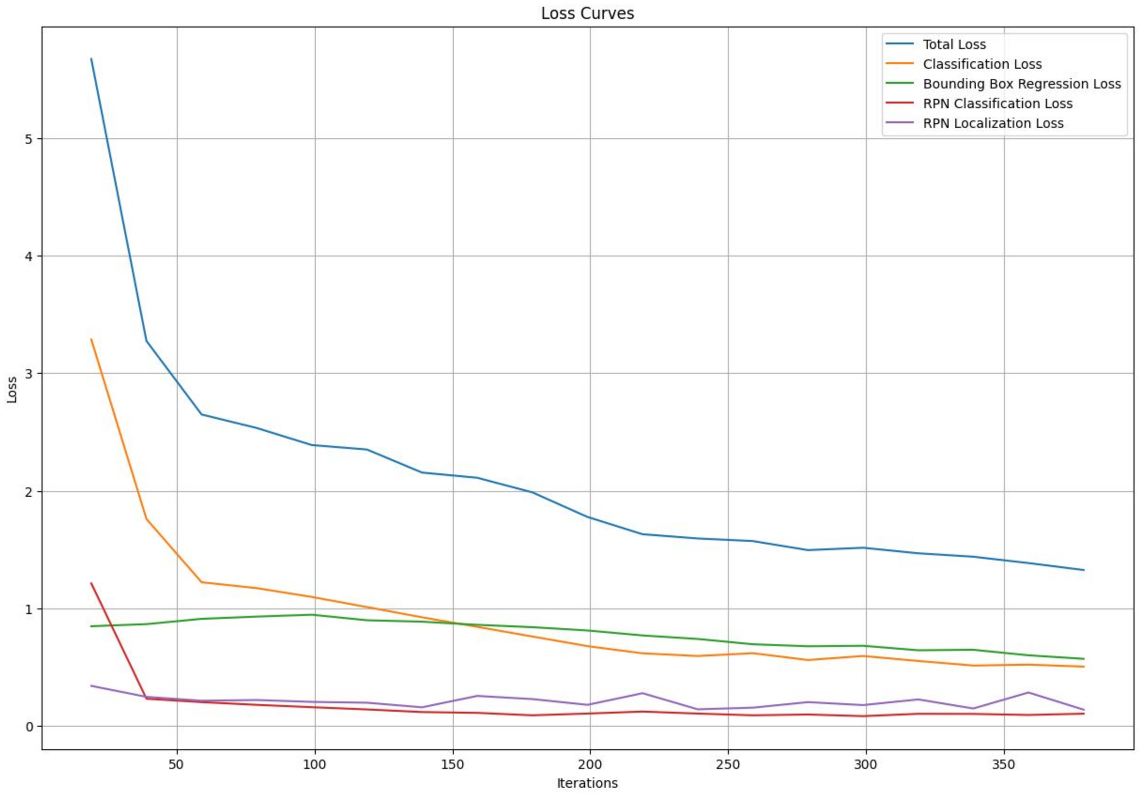


Results[8]: Loss Curve on 250 Iterations

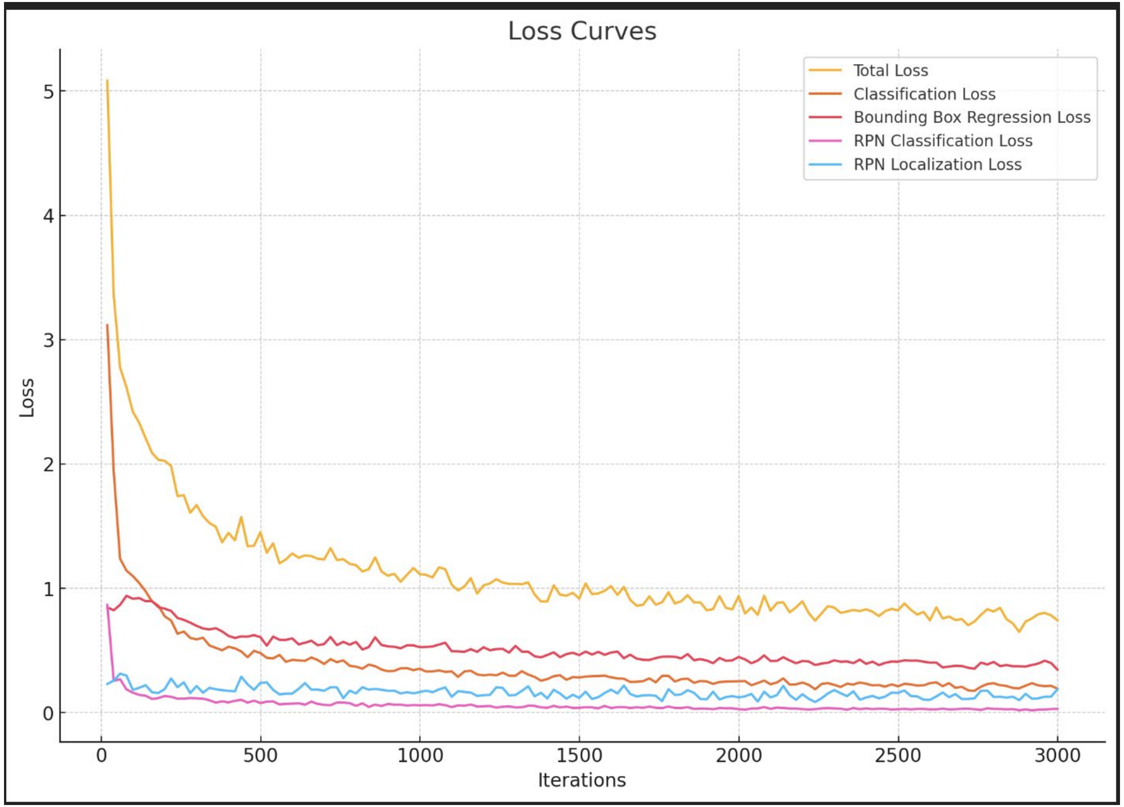
Results[9]: Loss Curve on 500 Iterations



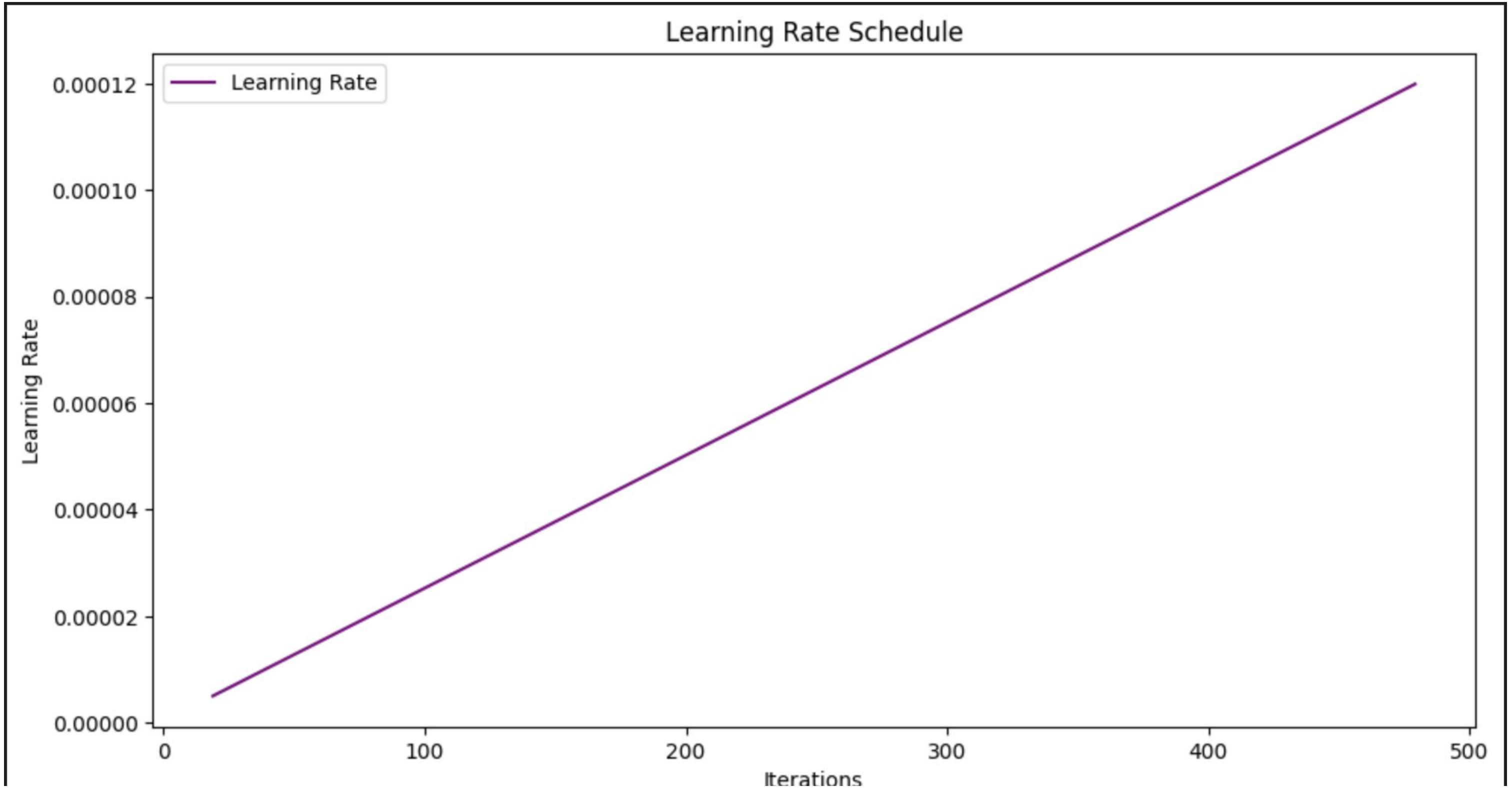
Results[10]: Loss Curve k-fold 5 and 700 iterations



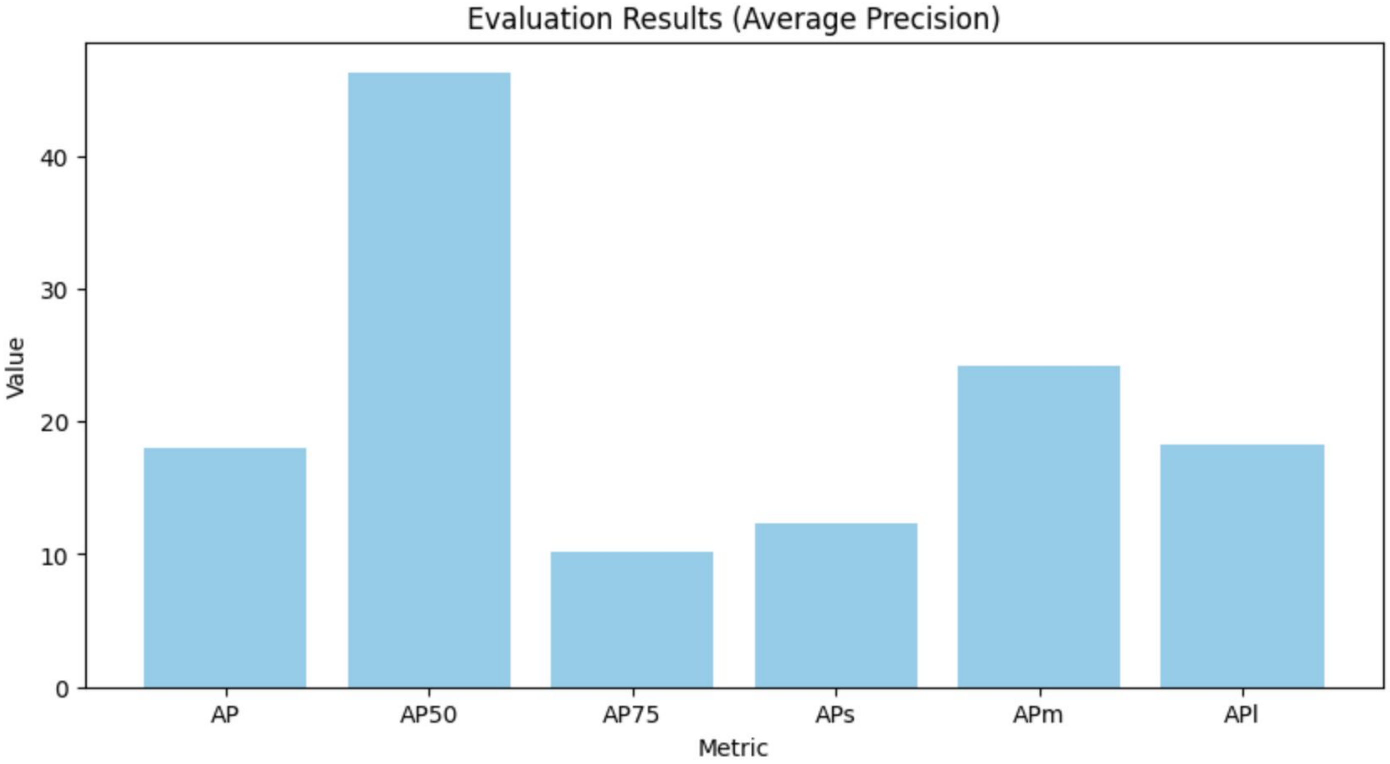
Results[11]: Loss Curve k-fold 10 and 3000 iterations



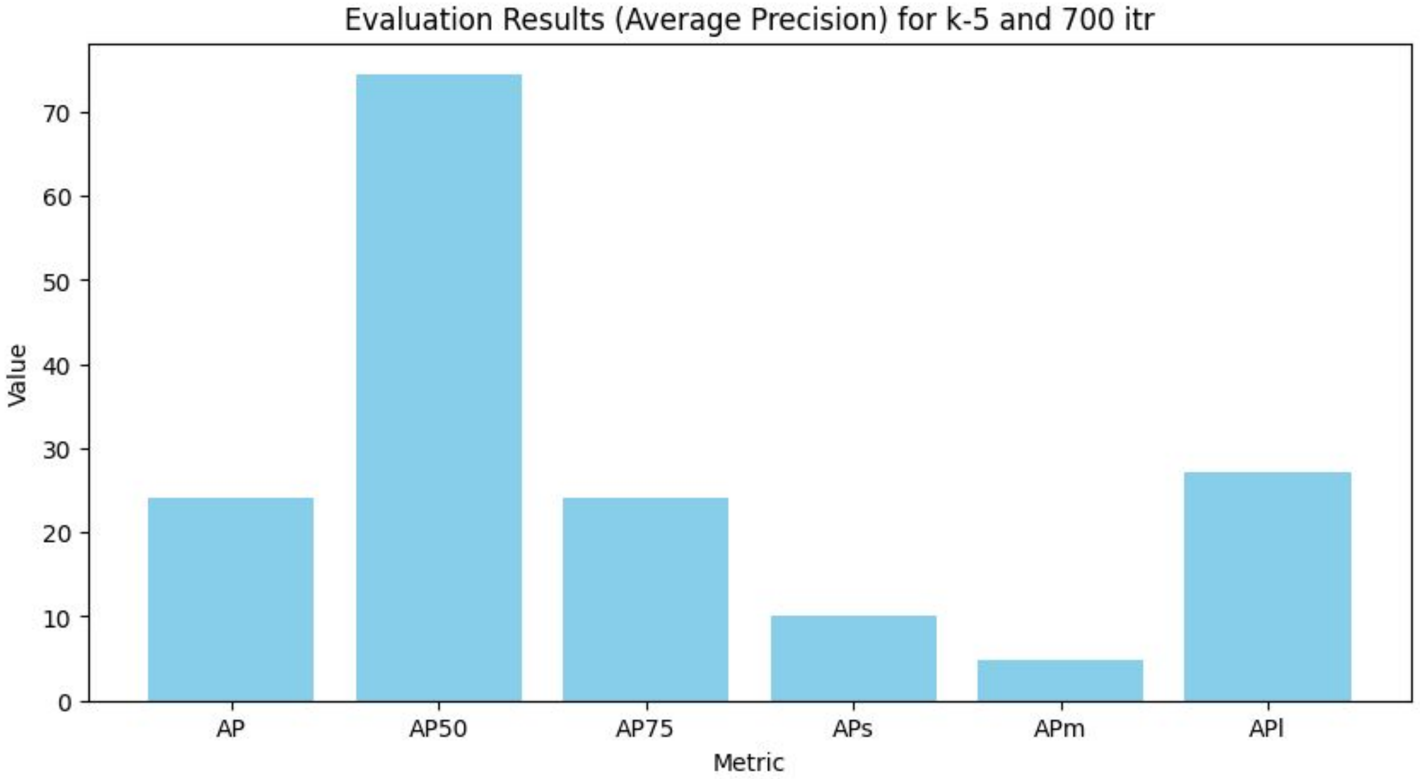
Results[12]: Learning Rate Curve



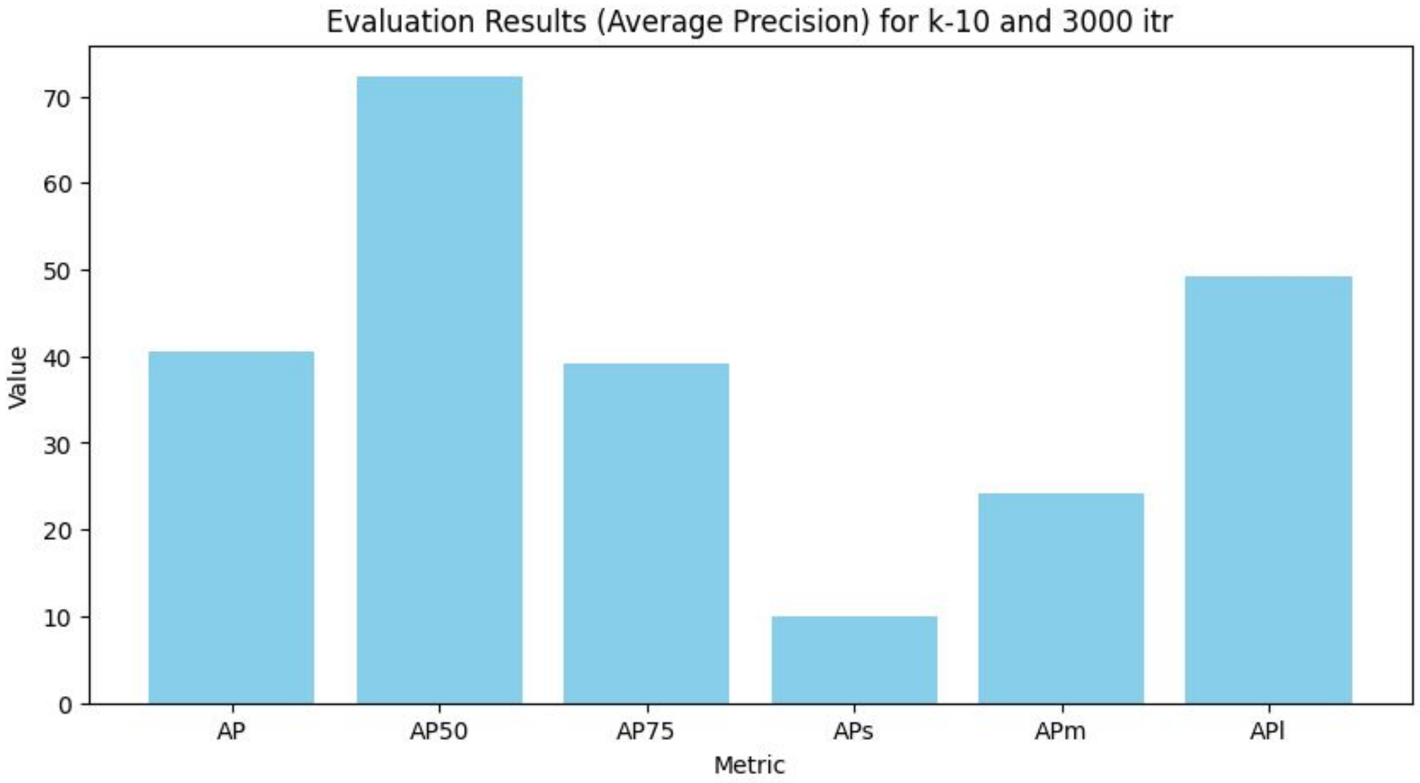
Results[13]: mAP for 500 iteration



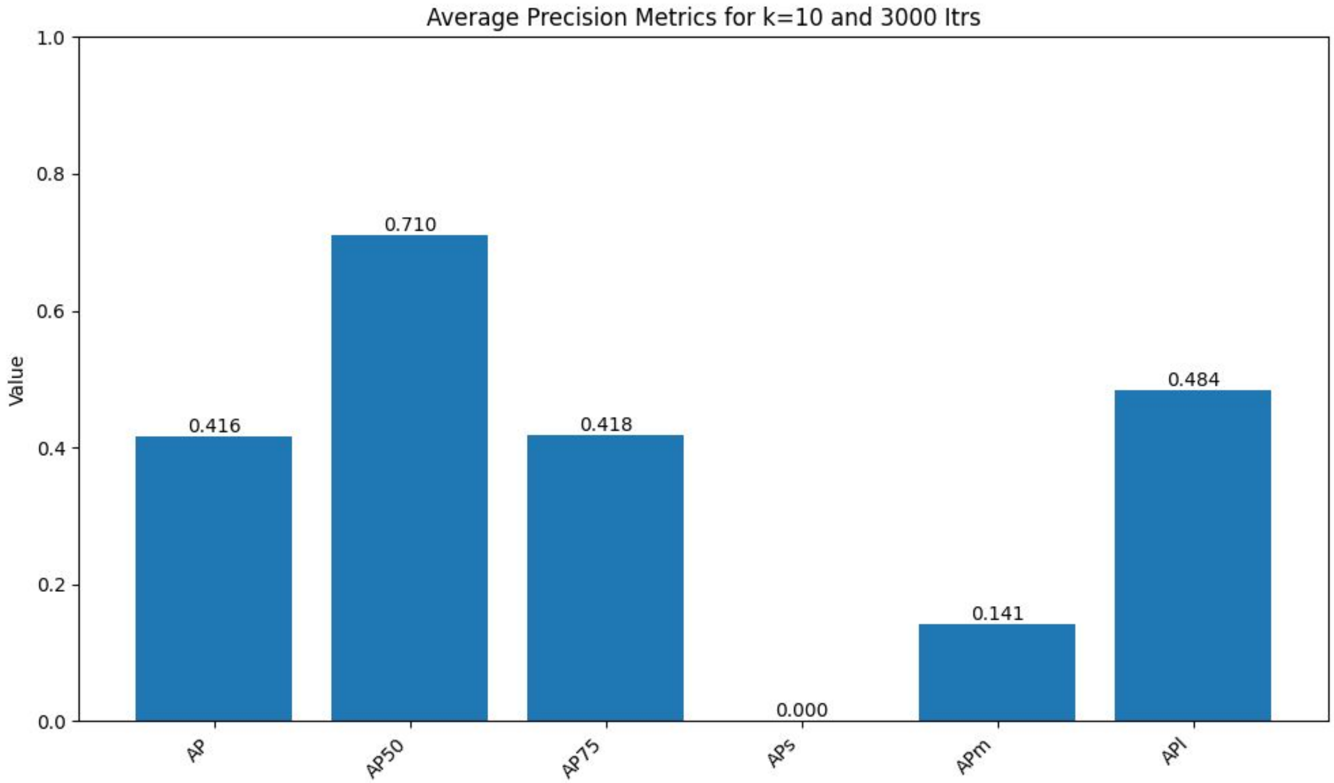
Results[14]: mAP for k=5 and 700 iteration



Results[15]: mAP for k=10 and 3000 iteration



Results[15]: mAP for k=10 and 3000 iteration



Evaluation Metrics Overview

Introduction to Metrics

- **AP (Average Precision)**: A critical metric that evaluates the model's precision-recall balance across different confidence thresholds.

- **AP50, AP75**: Specific thresholds that measure precision at 50% and 75% Intersection over Union (IoU), providing insights into the model's ability to localize objects with varying degrees of overlap accuracy.

- **APs, APm, APl**: These metrics denote Average Precision for small, medium, and large objects, respectively, reflecting the model's robustness across different object scales.

Evaluation Metrics Overview

- **Total Loss:**
  - Steady decline indicating successful learning and convergence
- **Classification Loss:**
  - Reduction over iterations shows improved model accuracy in distinguishing between classes
- **Bounding Box Regression Loss:**
  - Lowering values reflect better localization of objects within images
- **RPN (Region Proposal Network) Losses:**
  - Measures the performance of the region proposal stage, essential for accurate object detection

Evaluation Metrics Overview

Learning Rate: Controls step size in loss function optimization

- Critical for model convergence and performance

Learning Rate Schedule: Predefined plan for adjusting learning rate

- Common schedules: step decay, exponential decay, cosine annealing

Learning Rate Warm-Up: Gradually increases learning rate

- Stabilizes early training
- asures the performance of the region proposal stage, essential for accurate object detection

Evaluation Metrics Overview

Precision-Recall Curve: Shows precision-recall trade-off

- Visual representation of performance across confidence levels

Loss Curves: Plots of classification, bounding box regression, and total loss

- Identifies trends and issues during training

Learning Rate Curve: Plots learning rate changes over time

- Illustrates learning rate adjustments during training

Learning Rate Interpretation

Config (500 and 700 iterations):

- **Advantages**:
  - **Fewer folds** reduce computational overhead, making the process faster.
  - **Shorter training period** may prevent overfitting by not allowing the model to overlearn from the training data.

- **Disadvantages**:
  - **Less robust estimate of performance** due to fewer folds, potentially increasing variance.
  - **Risk of underfitting** if the model doesn't have enough time to learn, especially with complex datasets

Learning Rate Interpretation

Config (3000 iterations):

- **Advantages**:
  - **More folds** in cross-validation provide a robust estimate of model performance by reducing variance and giving a better picture of generalization.
  - **Longer training period** (3000 iterations) allows the model to learn more thoroughly, capturing complex patterns in the data.
- **Disadvantages**:
  - **Higher computational cost and time** due to more folds and iterations.
  - **Increased risk of overfitting** if the model learns too much from the training data without proper regularization or early stopping.

Comparative Analysis for k=5 (700 iterations)

Graph Analysis

- **AP Scores:**
  - Achieved a baseline performance with moderate AP scores.
  - AP50 shows the highest value, indicating good detection accuracy at lower IoU thresholds.
- **Observations**
  - The model demonstrates reasonable precision in detecting obstacles and garments
  - Room for improvement, particularly in handling small objects (APs).

Comparative Analysis for k=10 (3000 iterations)

Graph Analysis

- **AP Scores**:
  - Significant improvement in AP, AP50, and AP75 scores, highlighting better precision and recall across all categories.
  - APm and APl show notable increases, indicating enhanced performance for medium and large objects.

Observations

- The increase in iterations and folds (k=10) has positively impacted the model's learning, resulting in better generalization and precision.

Detailed Loss Curve Analysis

- **Total Loss**:
  - Steady decline indicating successful learning and convergence.
- **Classification Loss**:
  - Reduction over iterations shows improved model accuracy in distinguishing between classes.
- **Bounding Box Regression Loss**:
  - Lowering values reflect better localization of objects within images.
- **RPN (Region Proposal Network) Losses**:
  - The decline in RPN Classification and Localization losses suggests more accurate proposal generation and localization.

Average Precision Interpretation

Interpretation:

- **AP50** shows the highest value, indicating that the model performs well at a lower IoU threshold.
- **APm** and **APl** are relatively higher compared to **APs**, suggesting that the model performs better on medium and large objects than small objects.
- **AP75** is lower than **AP50**, which is expected because the criteria for correct predictions are stricter.

Key Findings and Implications

Performance Insights

- **Training and Generalization**:
  - The significant gains in AP metrics suggest the model's enhanced ability to generalize across different garment types and obstacle detection tasks.
- **Overfitting Considerations**:
  - Close monitoring of the loss curves ensures that the model does not overfit the training data, especially as the total loss plateaus.

Key Findings and Implications[1]

Challenges Identified

- **Small Object Detection**:
  - The relatively lower APs scores indicate challenges in detecting smaller obstacles or details, necessitating targeted improvements in training data or model architecture.
  - Losses suggests more accurate proposal generation and localization.

Optimization

Data Augmentation:

- Techniques: Horizontal flipping, rotation, scaling, color jittering
- Enhanced dataset diversity, improved model robustness, and better generalization

Learning Rate Scheduling:

- Techniques: Step decay, cosine annealing
- Prevented overfitting, improved convergence, and achieved optimal training dynamics

Batch Normalization:

- Integrated batch normalization layers
- **Impact:** Stabilized training and accelerated convergence

Optimization

Hyperparameter Tuning:

- Optimal values: Learning rate, batch size, momentum
- **Impact:** Improved performance and fine-tuned model behavior

Transfer Learning:

- Utilized pre-trained models
- **Impact:** Reduced training time and improved accuracy

Regularization Techniques:

- L2 regularization and dropout
- **Impact:** Prevented overfitting and improved generalization

Future Enhancements[1]

Dataset Enhancements:

- Polygonal or Pixel-Wise Annotations
- Attribute-Based & Landmark Detection:**Advanced Model Architectures:**
- Mask R-CNN
- Attention Mechanisms
- Hyperparameter Optimization:

Future Enhancements

Methodologies:

- Domain Adaptation & Transfer Learning
- Modular & Iterative Development

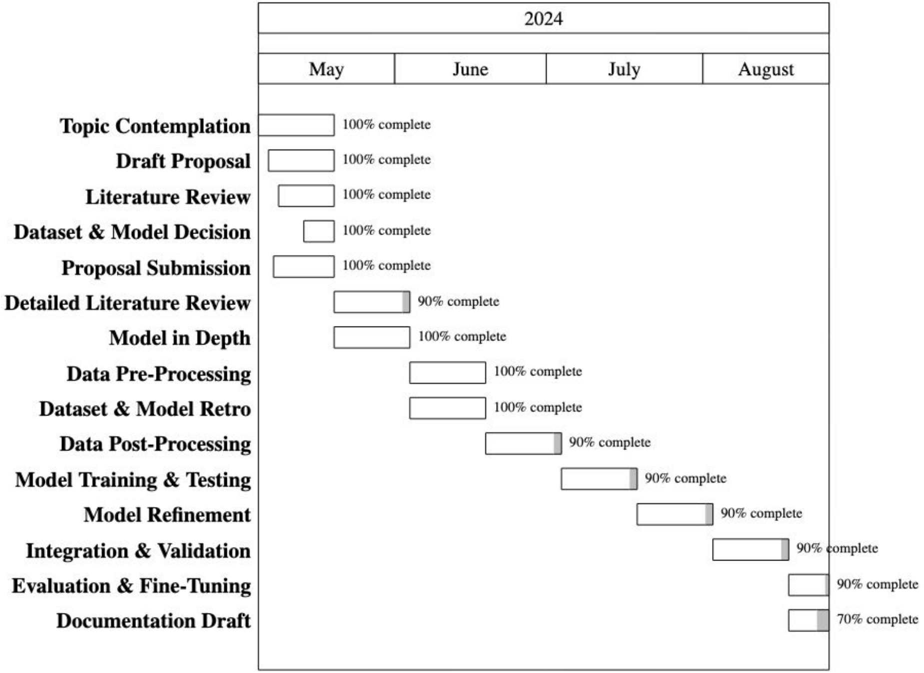
Recommendations for Future Researchers:

- Comprehensive Dataset Curation
- Incremental Model Development
- Model Explainability

Conclusion

- Successfully detected key obstacles (e.g., zippers, buttons, pockets) using Faster R-CNN with Detectron2.
- Post-processing techniques ensured precise mapping and segmentation of printable areas after obstacle filtering.
- Evaluated using Average Precision (AP), the model demonstrated strong performance across various garment types.
- Met goals of improved detection accuracy, generalization across garments, and reliable obstacle identification.
- The project offers valuable insights for developing advanced detection systems in automated garment printing.

Project Timeline (Gantt Chart)



References

[1] Z. Ma, Y. Dong, et al., Detecting Garment Landmarks for Fine-Grained Fashion Similarity, *Journal of Computer Vision and Pattern Recognition*, vol. 15, no. 2, pp. 78-91, 2021.

[2] X. Chen, et al., Pocket Detection in Garment Images Using Convolutional Neural Networks, *Journal of Computer Vision and Pattern Recognition*, 2021.

[3] S. Li, J. Wang, and Y. Chen, A novel approach to garment mapping using machine learning algorithms, *International Journal of Clothing Science and Technology,* vol. 43, no. 3, 2021.

[4] L. Wang, J. Zhang, and Y. Shi, Seam detection in garment images using deep learning, *Pattern Recognition*, vol. 98, 2020.

[5] Y. Zhang, B. Xu, and X. Tao, Automated garment pattern mapping using computer vision, *Journal of Fashion Technology & Textile Engineering*, vol. 7, no. 2, 2019.

References

[6] Delight, D and Velswamy, Karunakaran, Deep Learning based Object Detection using Mask RCNN, *International Conference on Communication and Electronics,* pp. 1684-1690, vol.6, 2021.

[7] Stahls. Design placement, https://www.stahls.com/design-placement-guide, 2024. Accessed: 2024-07-09.

[8] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. In Advances in Neural Information Processing Systems, volume 28, 2015.

[9] K. He, G. Gkioxari, P. Dollár and R. Girshick, "Mask R-CNN," 2017 IEEE International Conference on Computer Vision (ICCV), Venice, Italy, 2017, pp. 2980-2988, doi: 10.1109/ICCV.2017.322.

[10] Hiroto Honda, “Digging into Detectron 2—Part 1”, “https://medium.com/@hirotoschwert/digginginto-detectron-2-47b2e794fabd”, 2024.

Thank You !!!