[Samsung PRISM] Mid Review Report

Synthetic-to-real Domain Adaptation (Unsupervised)

Team

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Synthetic-to-real Domain Adaptation (Unsupervised) | Description

SAMSUNG

Problem Statement

Context

Most deep networks-based approaches require large training datasets which can be expensive to obtain. Synthetic datasets are easier to generate and many have explored supplementing real datasets with synthetic datasets. In some applications it is challenging to obtain the ground truth data on real images, such as albedo estimation. In these scenarios we can train a model solely on synthetic datasets. However, these models do not generalize to real data due to a domain shift between synthetic and real datasets. In this task, we intend to explore possible unsupervised algorithms for domain adaptation.

Statement

Given a model trained on synthetic dataset, design unsupervised algorithm that would enable generalization to real images.

Work let Details

6	4	Abhishek Mishra Dr. Pidaparthy Hemanth
Duration (Months)	**Members Count**	Mentors

Pre-Requisite

- Good knowledge and background in computer vision and deep learning
- Familiar with Python and OpenCV
- Familiar with PyTorch or any other deep learning frameworks

Expectations

Undertaken Tasks

- Review literature on synthetic-to-real domain adaptation for various applications such as segmentation, portrait relighting etc.
- Evaluate algorithms for unsupervised domain adaptation.
- Evaluate limitations of existing approaches and design an algorithm for unsupervised domain adaptation.
- Show proof-of-concept(python) on either image segmentation or portrait relighting tasks.

KPI

- Proof-of-concept solution on either image segmentation or portrait relighting.
- Metrics (MSE or IOU) of the model is comparable on both real and synthetic datasets.

Timeline

Kick Off < 1st Month >	**Milestone 1** < 2nd Month >	**Milestone 2** < 3rd & 4th Month >
• Literature Review • Evaluating existing solutions	• Evaluate unsupervised algorithms for synthetic-to-real domain adaptation.	• Evaluate limitations of current approaches. • Design an algorithm to overcome these limitations

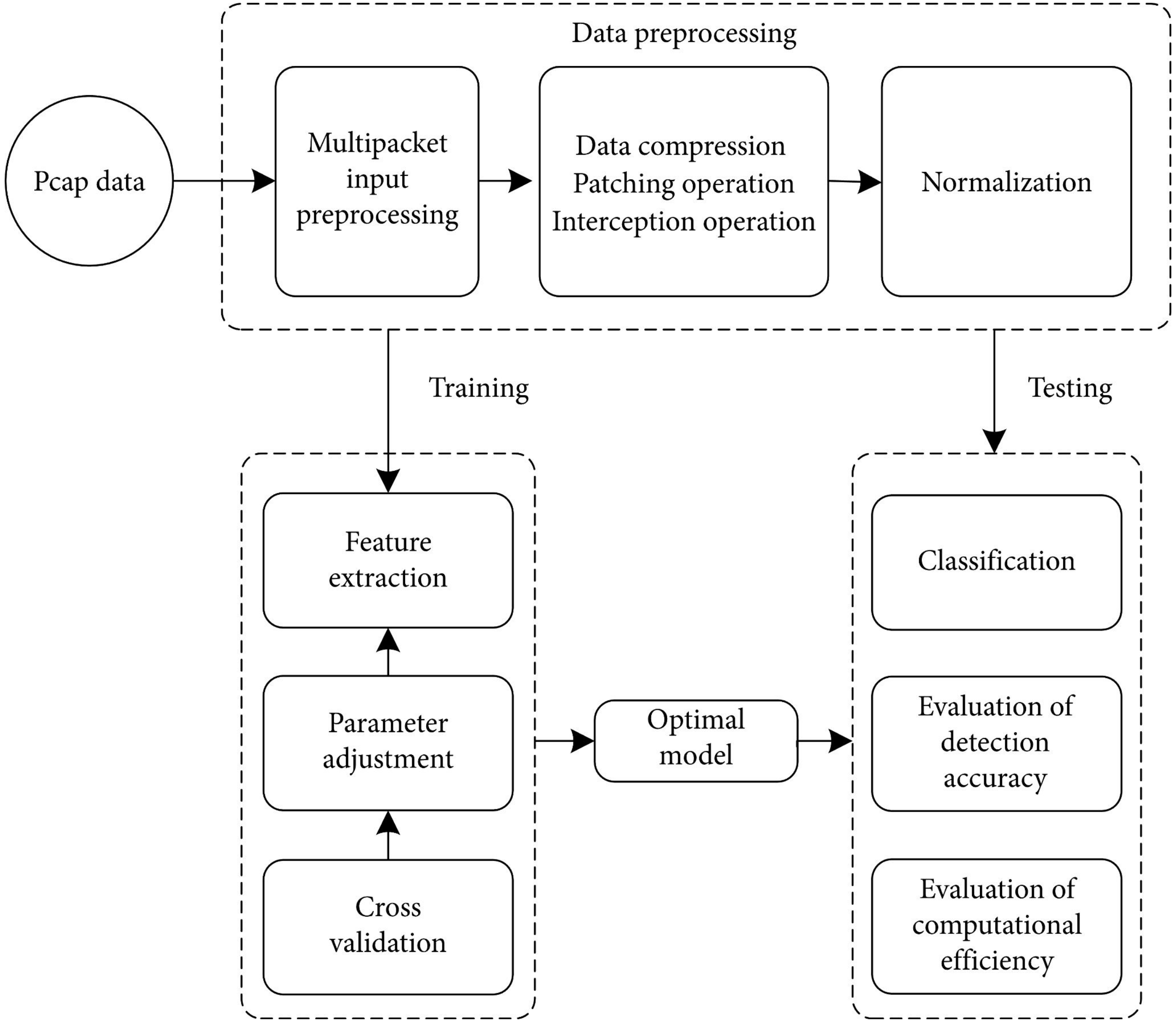
Proposed Approach / Solution

- **Concept Diagram** :
  (Clear detailed schematic / block diagram / flow chart depicting the proposed concept / solution)

FCNN

To address the challenges in image segmentation, a proposed concept involves the use of encoder-decoder architectures. The encoder extracts high-level features from the input image, while the decoder upsamples these features to generate dense pixel-wise predictions. Skip connections are often used to preserve spatial information and aid in accurate segmentation.

Furthermore, incorporating additional techniques such as batch normalization, dropout, and data augmentation can improve the robustness and generalization of the FCNN model. These techniques help in reducing overfitting, increasing model performance, and enhancing the network's ability to handle variations in input data.



Dataset(s) Analysis / Description

- **Dataset Capture / Preparation / Generation** :
  (Discuss the dataset generation process or if downloaded data provide details of what data & from where it was obtained etc… - 2 to 3 bullets only)

  - Synthetic Data Generation: Synthetic data can be generated using computer graphics techniques or simulation environments. This involves creating 3D models, rendering scenes, and generating labeled annotations
  - Real-world Data Collection: Real-world data can be obtained from various sources such as sensors, cameras, or publicly available datasets. This involves capturing data from different environments, conditions, and perspectives
  - Data Augmentation: Another approach is to augment existing datasets to simulate domain shift. This involves applying various transformations or perturbations to the data to mimic the characteristics of the target domain

- **Dataset Understanding / Analysis** :
  (Provide 2 to 3 bullets about what is your understanding of the data / opinion about the data)

  - The dataset is likely to contain a combination of synthetic data and real-world data. The synthetic data is generated using computer graphics techniques or simulation environments, while the real-world data is collected from various sources such as sensors or cameras.
  - The dataset is expected to exhibit a domain shift, meaning that there will be differences in the characteristics and distribution of data between the synthetic and real-world domains
  - The dataset analysis may involve comparing and contrasting the statistical properties, visual appearance, and label distributions between the synthetic and real-world data

- **Dataset Pre-Processing / Related Challenges (if any)** :
  (List out the challenges you fore see in data handling wrt problem definition – 2 to 3 bullets only)

  - Domain Shift
  - Labeling and Annotation
  - Data Quality and Variability
  - RGB shift in the obtained data histograms

Experimental Results / Simulations / Observations

- **Results** :
  (provide numerical data / bar charts / plots / images / videos / tabulated results etc. Use full slide or multiple slides up to max 3 slides to demonstrate the results)

FCNN

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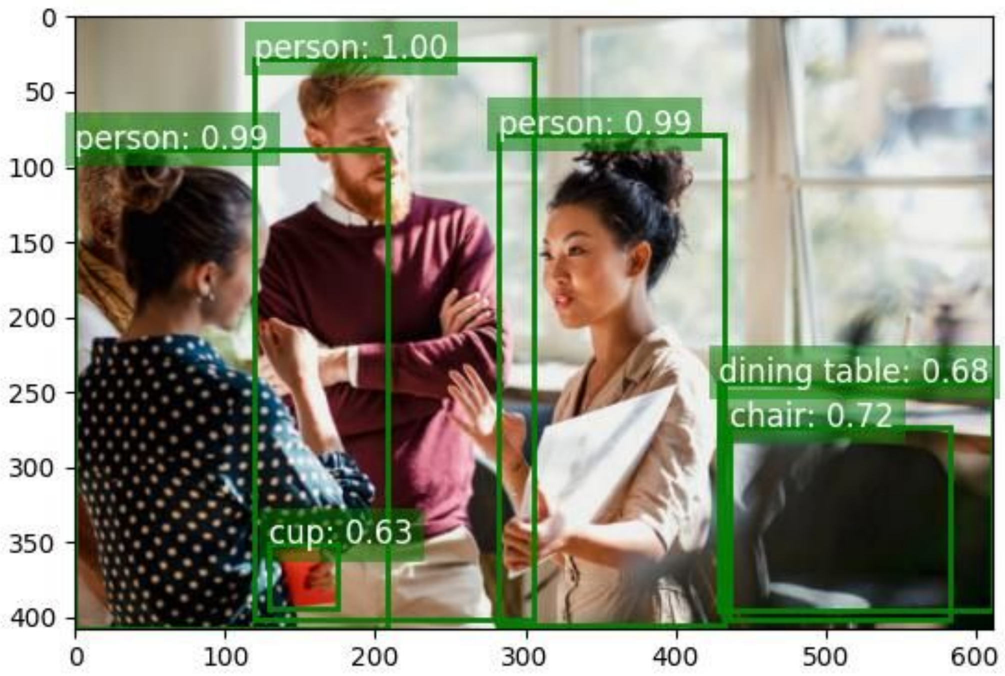
FCNN



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FCNN GPU INPUT

1

2

3

Experimental Results / Simulations / Observations

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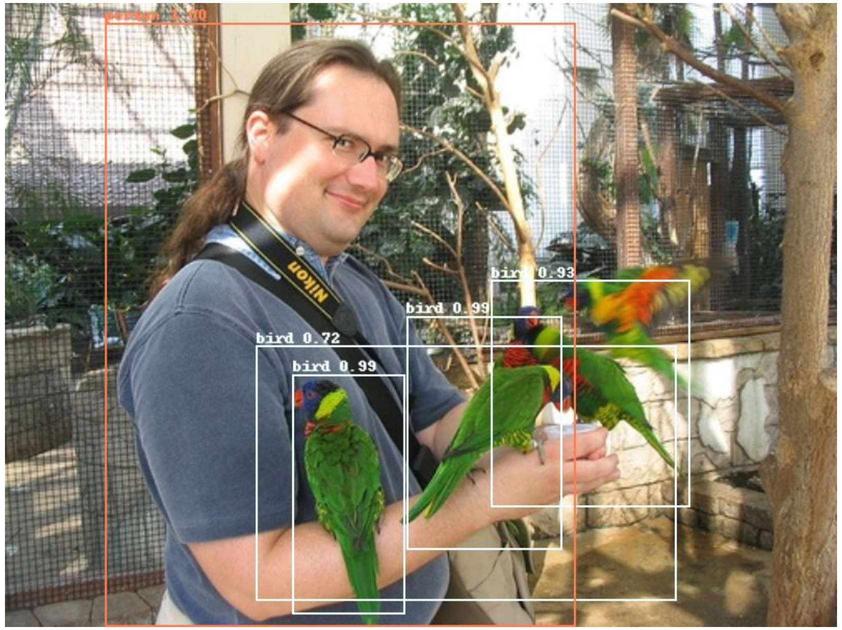

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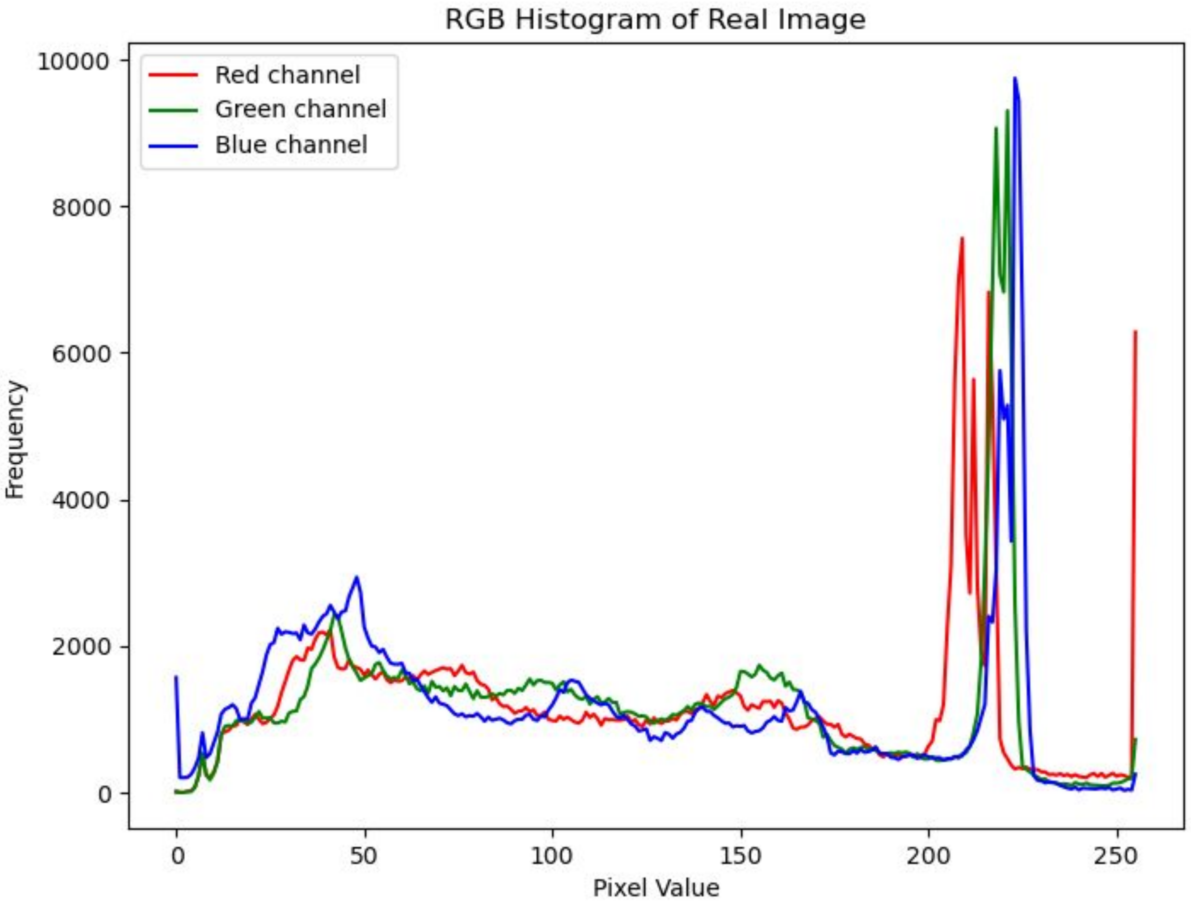

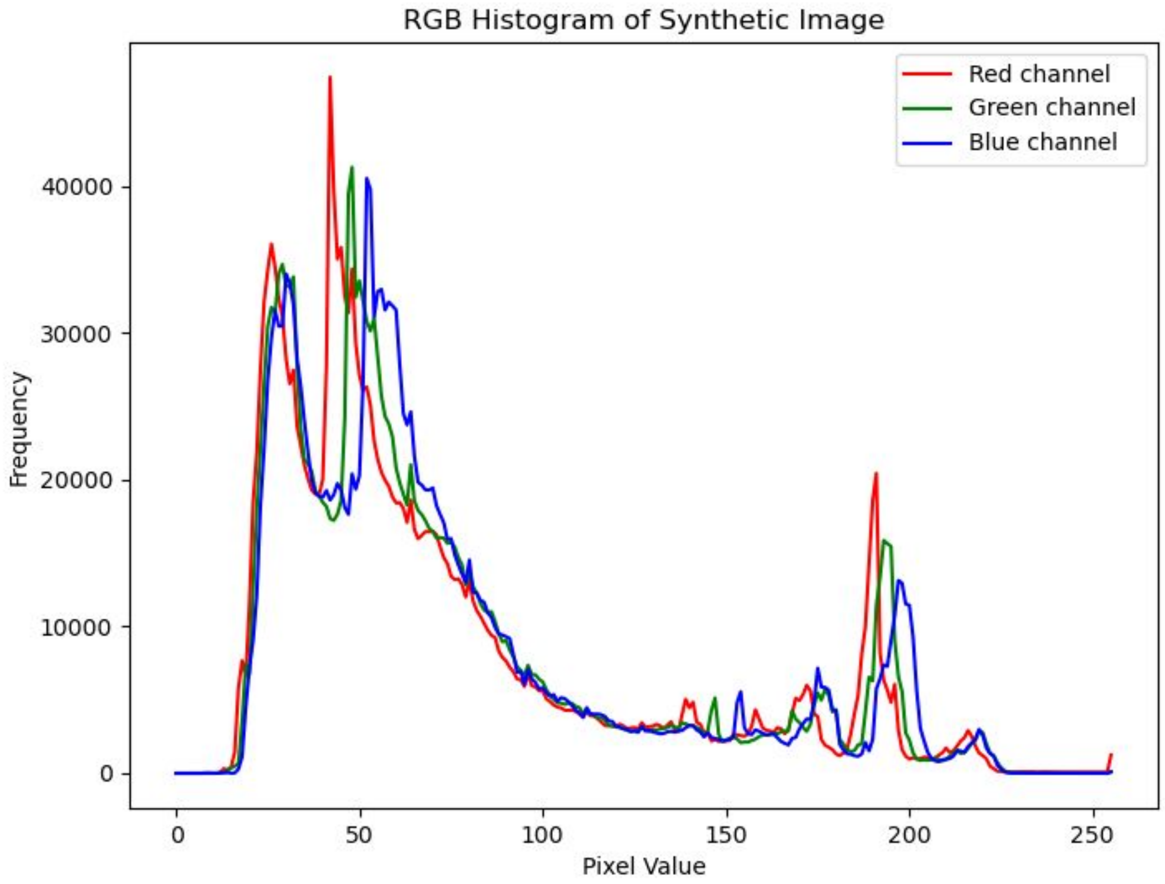

Experimental Results / Simulations / Observations

- **Major Observations / Conclusions & Challenges :**

(provide details about your findings, experimental opinion – Use separate slide if necessary)

Major Observations:

- Domain Shift: The dataset analysis revealed a significant domain shift between the synthetic and real-world data. The statistical properties, visual appearance, and label distributions exhibit notable differences
- Limited Labeled Data: The dataset lacks labeled examples in the target domain, which poses challenges for traditional supervised learning approaches. This necessitates the exploration of unsupervised or weakly supervised techniques for domain adaptation
- Data Variability: The synthetic data, while useful for generating diverse scenarios, may not capture the full complexity and variability present in real-world data. This variation poses challenges

Conclusions:

- Unsupervised domain adaptation techniques are necessary to bridge the gap between synthetic and real-world domains
- Leveraging the available labeled data in the source domain and finding effective ways to adapt the model to the target domain without labels are crucial for achieving satisfactory performance.
- Pre-processing techniques such as feature normalization, data augmentation, and distribution matching should be employed to address the domain shift and align the distributions of synthetic and real-world data.
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Experimental Results / Simulations / Observations

- **Major Observations / Conclusions & Challenges :**

(provide details about your findings, experimental opinion – Use separate slide if necessary)

Conclusions :

1. Trained models to segment the image
2. A precision on the scale of >0.5 was obtained
3. Program built to generate a histogram
4. RGB histogram had not too similar results for both sets
5. Tried and tested data on a set of 8000 Images

Challenges:

- Developing robust unsupervised domain adaptation algorithms that can effectively handle the domain shift between synthetic and real-world data remains a significant challenge.
- Acquiring or generating more labeled data in the target domain is resource-intensive and time-consuming.
- Exploring techniques to utilize the limited labeled data efficiently is a challenge worth addressing.
- Balancing the trade-off between synthetic and real-world data is essential.
- Ensuring that the synthetic data adequately represents the variations and complexities of the target domain while preserving the diversity offered by synthetic data generation techniques is a challenging task.

Further Plan to Complete Project

- **Final Probable Deliverables** :
  (Discuss in the form of bullets, what are the next steps to complete the solution, any road blocks / bottlenecks, any support needed from SRIB)

- Implementation of Domain Adaptation Techniques
- Evaluation and Fine-tuning of Models
- Documentation and Reporting: Prepare a detailed report documenting the methodology, experiments, and findings

Bottle Necks:

- Limited Labeled Data
- Scalability and Generalization

- **IP Target / Plan** :
  (Any possibility of papers / patentable ideas / innovative aspects that can lead to patentable ideas)

- Novel Domain Adaptation Algorithms: Developing new algorithms or techniques specifically designed for unsupervised domain adaptation
- Domain-Specific Data Augmentation: Introducing unique data augmentation strategies that target domain-specific variations and challenges can be patentable.
- Meta-learning for Domain Adaptation: Exploring meta-learning approaches that enable models to quickly adapt to new domains without extensive training can be an innovative aspect
- Transfer Learning Frameworks: Designing novel transfer learning frameworks specifically tailored for synthetic-to-real domain adaptation can be patentable. These frameworks could include methods for knowledge transfer, model initialization
- Evaluation Metrics and Benchmarks: Developing new evaluation metrics and benchmarks for assessing the performance of unsupervised domain adaptation in the context of synthetic-to-real data can contribute to the field

Further Plan to Complete Project

- **KPIs delivered/Expectations Met**:

  (Planned Expectations shared in Work-let vs Delivered Results)

We were able to perform a set of several tasks.

1. **The model got trained on the synthetic datasets of about 8K images.**
2. **Synthetic data used was COCO(Common objects in Context).**
3. **Explored pytorch toolbox of Dassl used in Domain Adaptive Ensemble Learning (DAEL).**
4. **Limitation of the existing GANN's evaluated to find out Color profile separation works the best.**
5. **Proof-of-concept solution on image segmentation was successful Achieved**
6. **Generate the RGB histogram using OpenCV**
7. **We plot the difference in RGB histogram modelled by program**

- **Git Upload details:** All the files with their code and output have been uploaded on git

Work-let Closure Details

- **Code Upload details:**

Items	Details
KLOC (Number OF Lines of codes in 000's)	1.2
Model and Algorithm details	FCNN, CNN, GANN's
Is Mid review, end review report uploaded on Git ?	Mid Review - Yes, End Review will
Link for Git	https://github.com/gaurangagarwal15/samsung-task/tree/master

Note: If data uploaded on google drive, access to be shared to prism.srib@gmail.com

Thank you