Content-Based Retrieval of Mars Images

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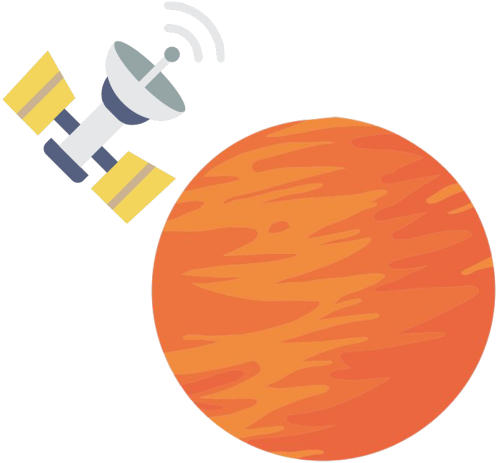

Project Overview

Motivation

- Mapping **planetary surfaces** is essential for mission planning
- Increasing amount of Remote Sensing (RS) image data

  → Need for Content Based Image Retrieval Systems (CBIR)

- Use CBIR for **automatic information discovery** from Mars’ surface

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Motivation

- Conventional systems use **hand-crafted features**
  - → **Semantic-Gap**
- Traditional retrieval methods are **time consuming** and **inefficient**
  - → Bad **scalability**
- Massive amounts of unlabelled data / **Labelled data is scarce**
  - → Supervised approaches have **limited applications**

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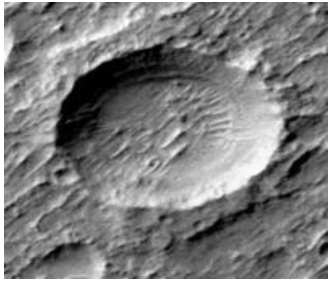
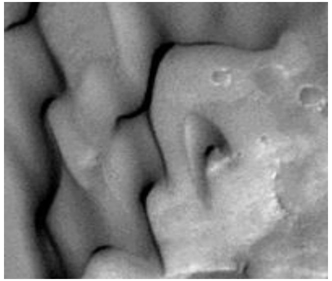
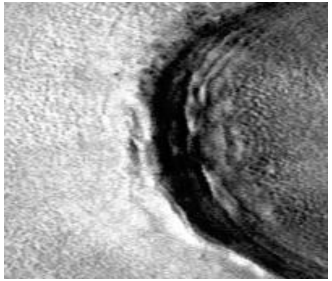
Project Topic & Objective

- Develop a **Content-based remote sensing image retrieval** (CBIR) on Mars Images
    - **Scalable** architecture design
    - Both **Unsupervised** Learning and **Supervised** Learning approaches
    - Integrate methods to ensure **high generalisation capability**

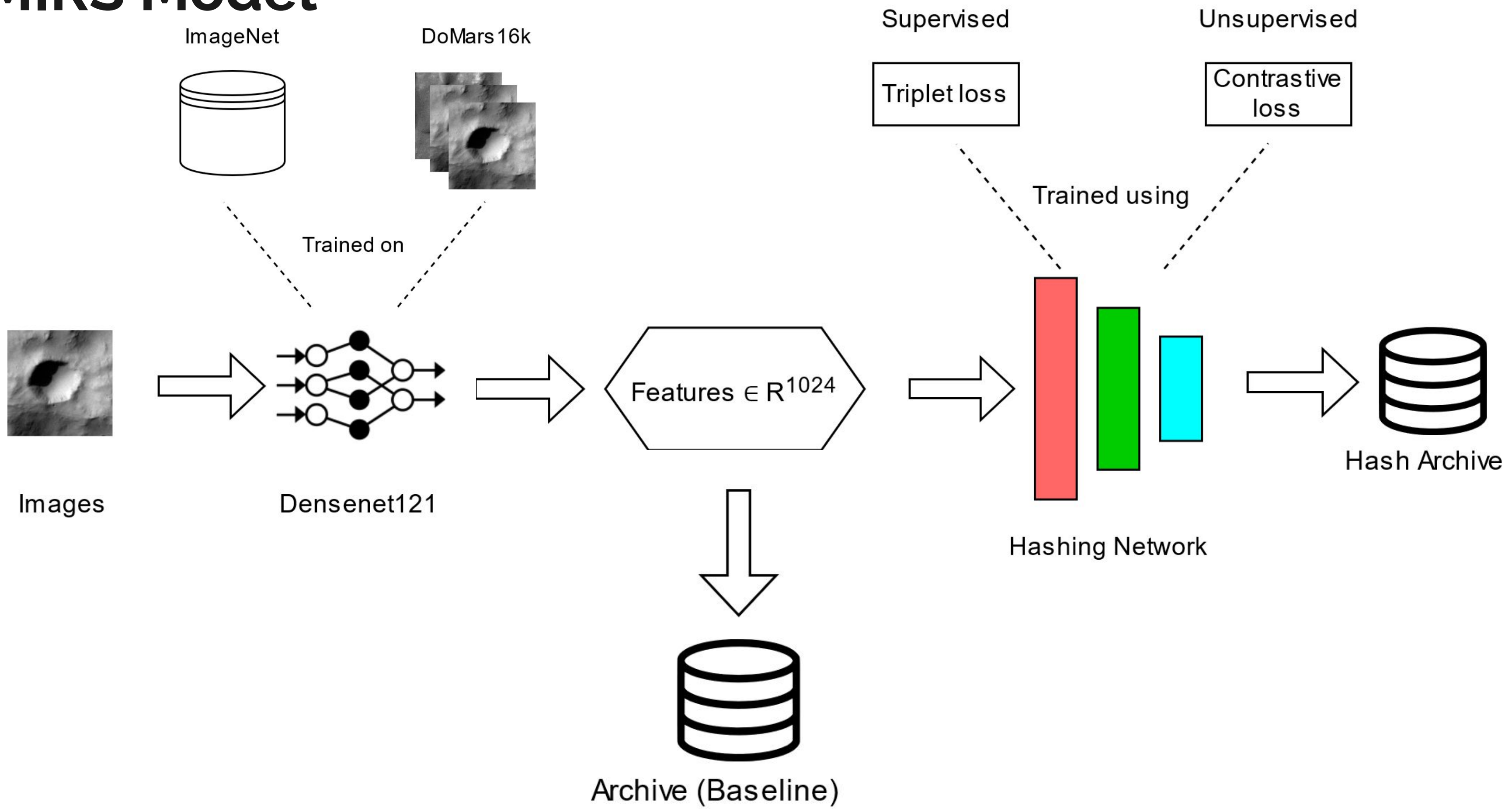






MIRS Model

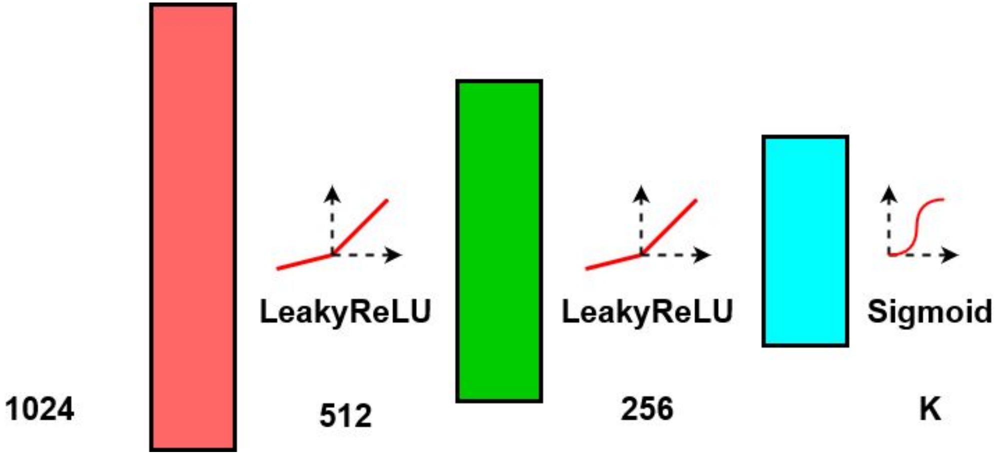
MIRS Model

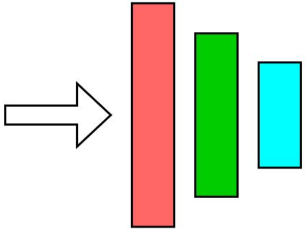

ImageNet
DoMars16k
Trained on
Images
Densenet121
Features $\in R^{1024}$
Archive (Baseline)
Supervised
Unsupervised
Triplet loss
Contrastive loss
Trained using
Hashing Network
Hash Archive

Subtopics

Hashing

- Maps high-dimensional feature vectors into a low-dimensional metric space
- Outputs are converted to binary hash codes with little loss of information
- Reduces image archive size immensely!



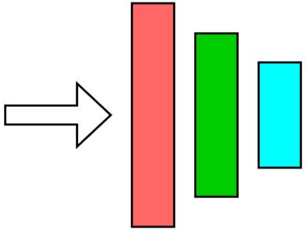


Hashing Network

Hashing

- Loss is **weighted sum** of three losses
    - Main component: **Metric loss**
        - **Supervised** case: On-line **Triplet** loss
        - **Unsupervised** case: **Contrastive** loss
    - **Push loss**: Pushes activations close to the edge of the sigmoid range
    - **Balancing loss**: Results in hash codes with an even number of 0 and 1

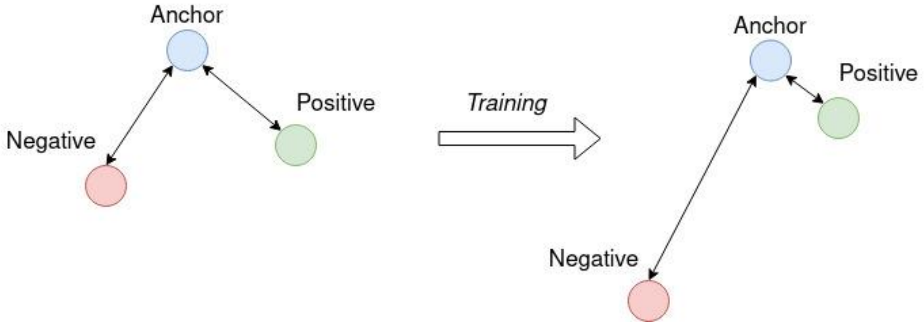
$$\mathcal{L} = \mathcal{L}_{Metric} + \lambda_1 \mathcal{L}_{Push} + \lambda_2 \mathcal{L}_{Balancing}$$

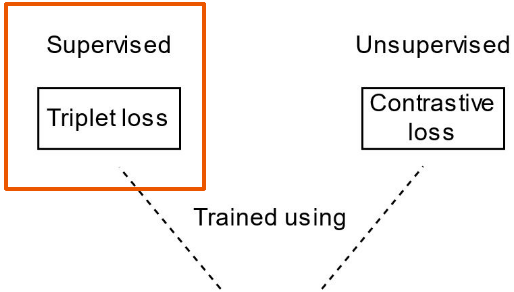


Hashing Network

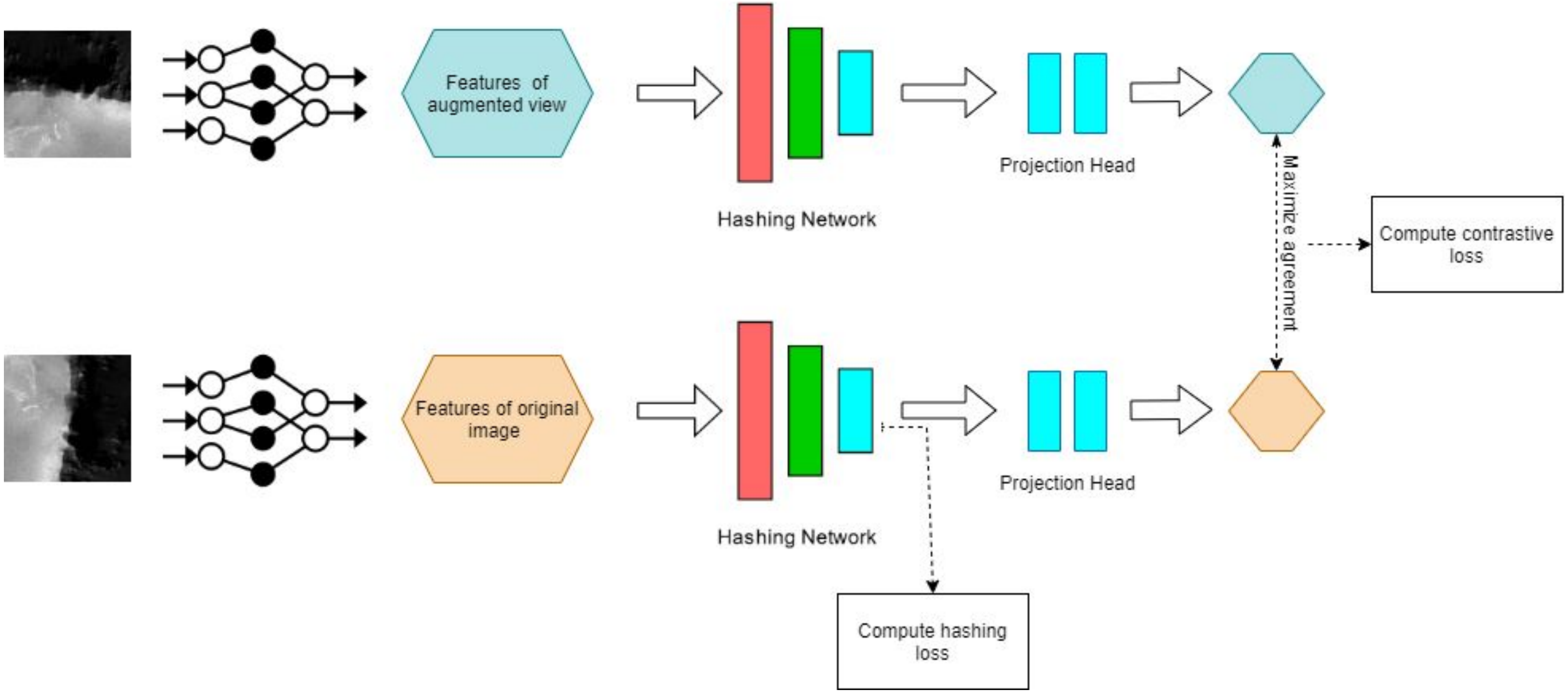
Supervised Approach

- Triplets are sampled from the **MIRS feature outputs** according to class association
- The **anchor** and **positive** belong to the same class and the **negative** belongs to another class
- Model should learn to generate more similar feature outputs for images from the same class



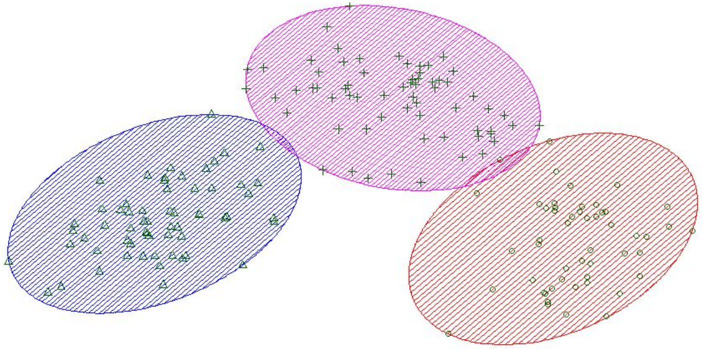


Unsupervised Approach



Generalisation Capability: Inter-class triplets

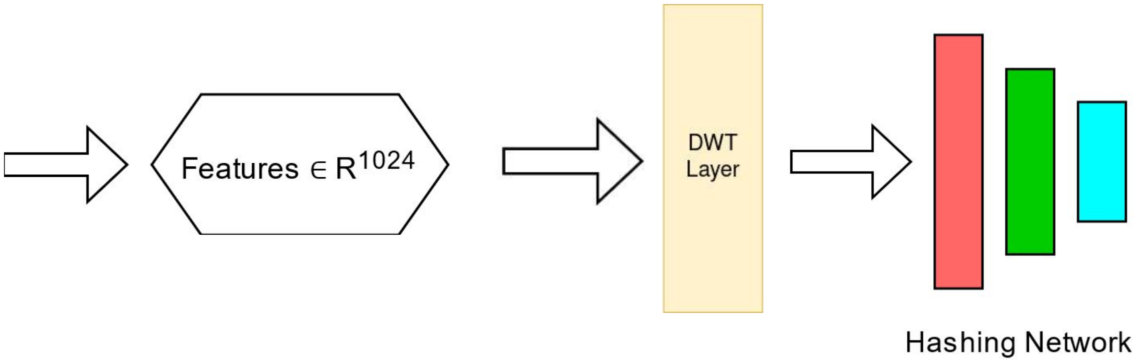
- Apply **K-Means clustering** on feature outputs from the feature extractor
- Sample additional triplets based on the cluster association
- To prevent learning class features again only consider images with shared **features from different classes**



https://towardsdatascience.com/kmeans-clustering-for-classification-74b992405d0a

Generalisation Capability: Domain Whitening Transforms

- Insert DWT layers in between the feature extractor and the hashing model
- Whiten specific features to align feature output between source and target domain
- Train dedicated DWT for the source domain and target domain respectively

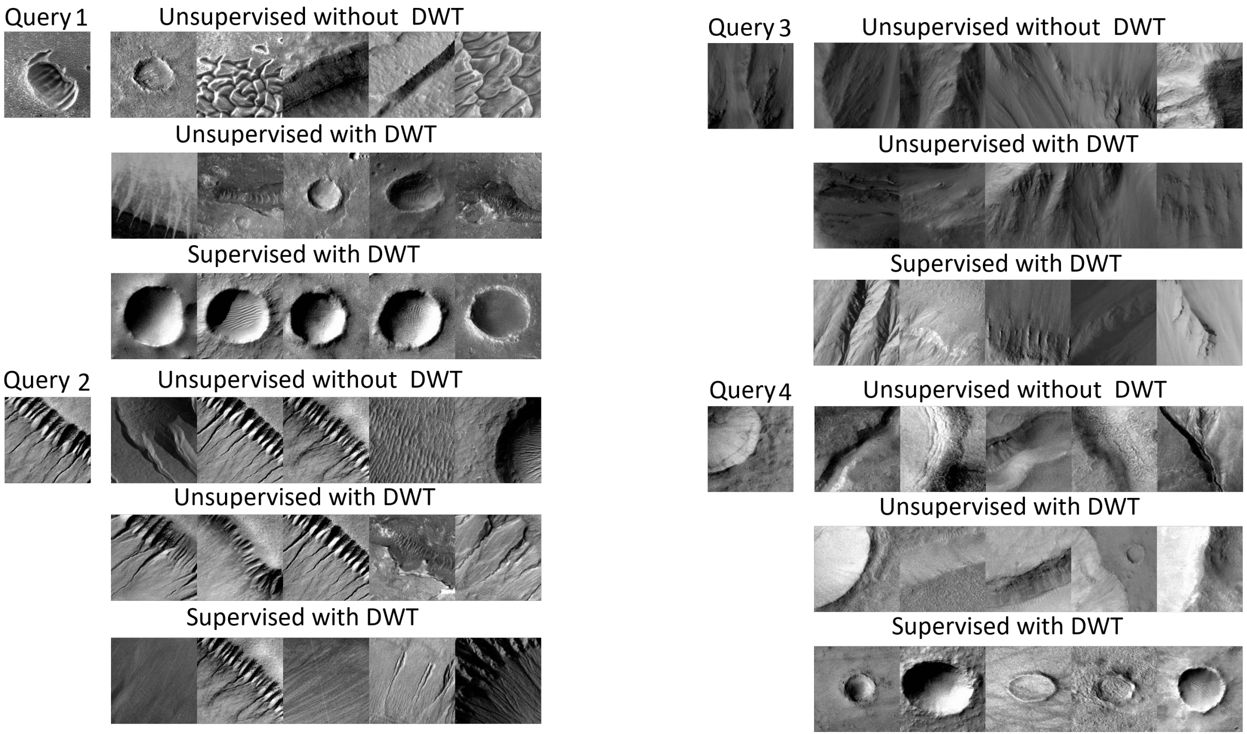


Results

Results: *Supervised vs Unsupervised*

MIRS Model Configuration	mAP@64
Supervised	0.767
Supervised with DWT 32	0.791
Supervised with Interclass	0.678
Unsupervised	0.619
Unsupervised with DWT 32	0.617

Results: *Supervised vs Unsupervised*



Results: *Different Supervised Approaches*

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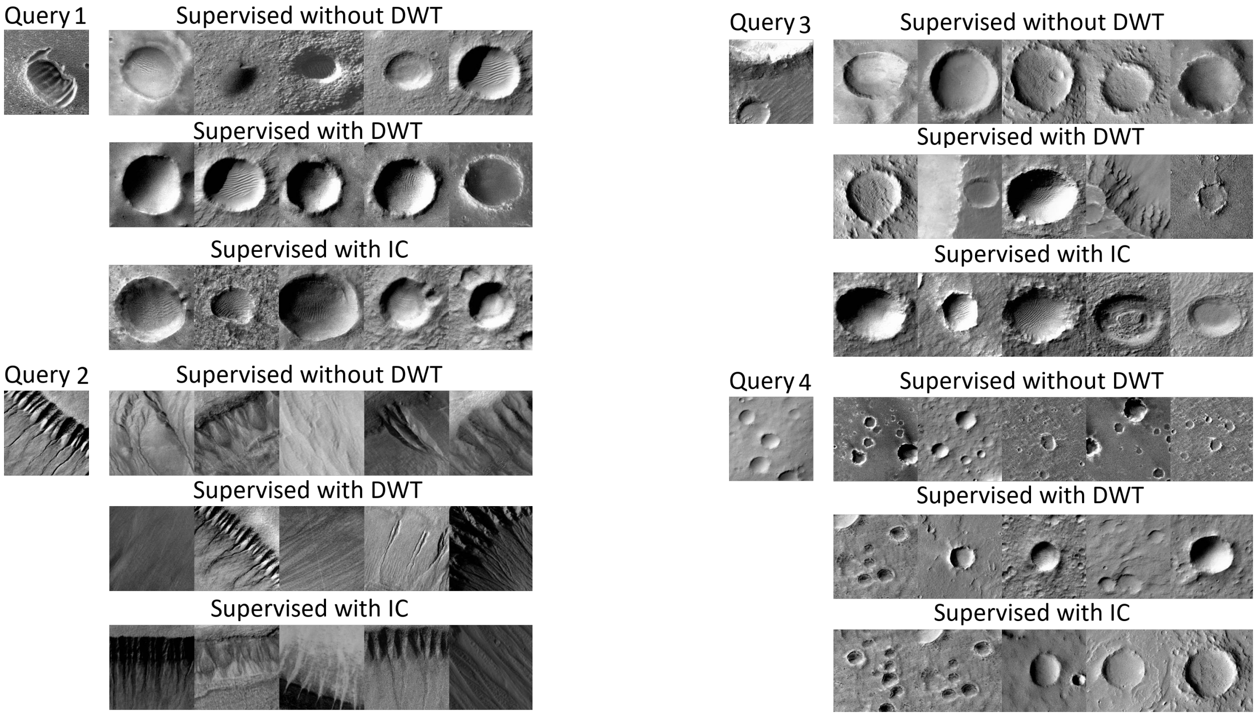
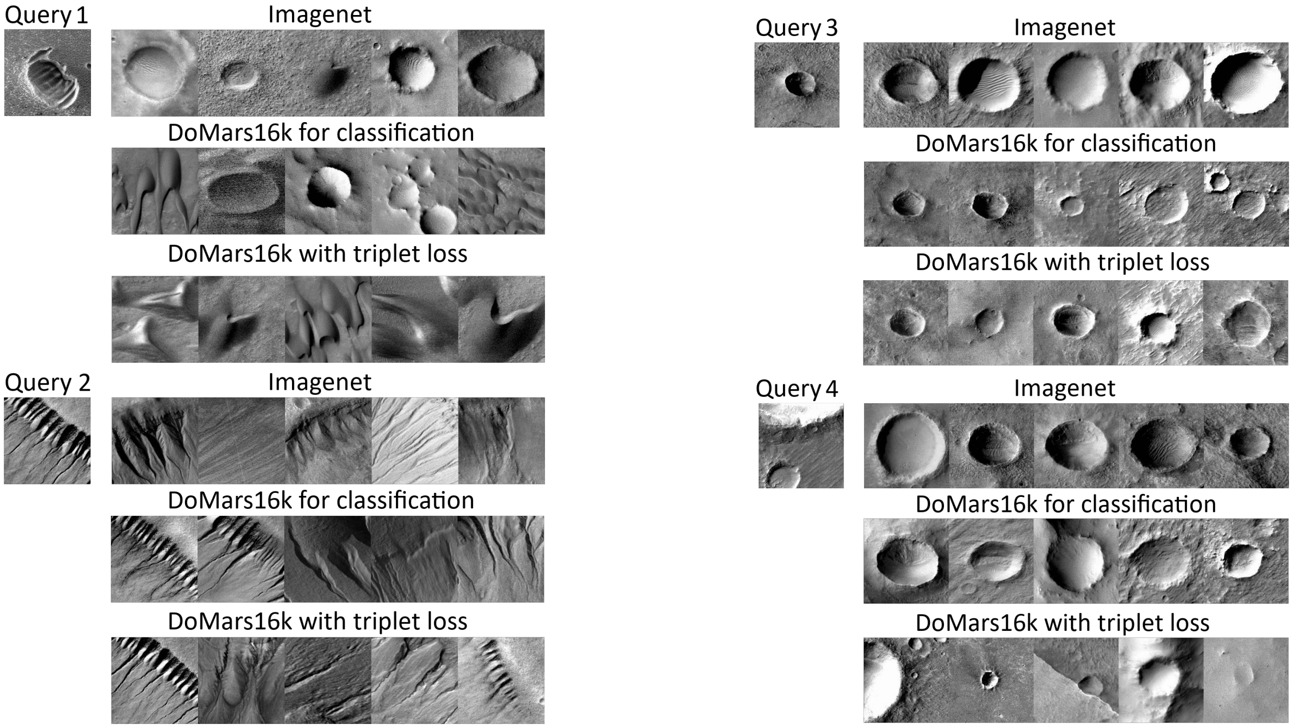


Results: *Different Feature Extractors*

DenseNet121 trained on	mAP@64 without generalisation	mAP@64 with inter-class triplets	mAP@64 with DWT
ImageNet	0.767	0.677	0.791
DoMars16k for classification	0.819	0.819	0.860
DoMars16k using Triplet Loss	0.884	0.877	0.889

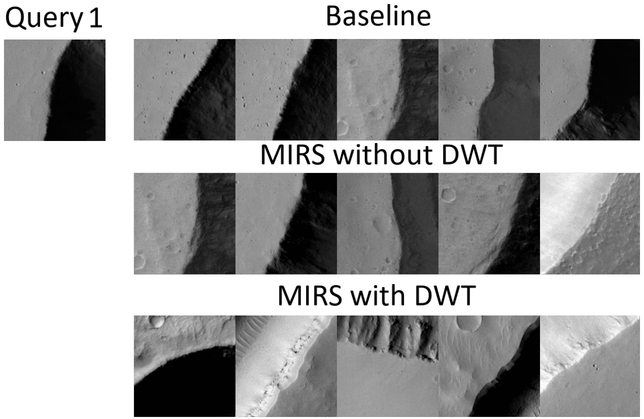
Results: *Different Feature Extractors*

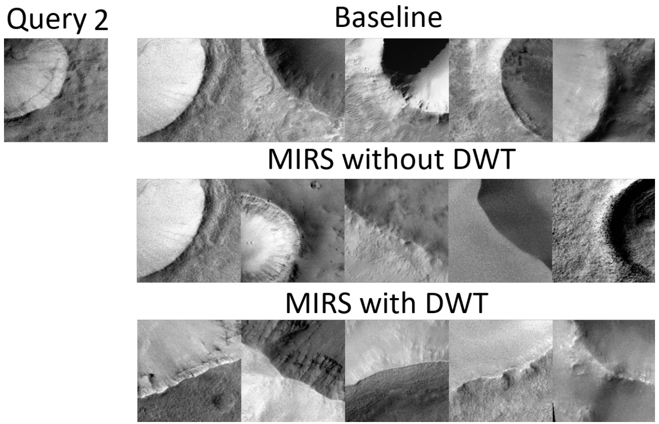


Results: *Baseline Comparison*

	Baseline	Supervised without DWT	Supervised with DWT	Unsupervised with DWT
ImageNet	0.668	0.767	0.791	0.617
DoMars16k for classification	0.844	0.819	0.860	-
DoMars16k using triplet loss	0.871	0.884	0.889	-

Results: *Baseline Comparison*





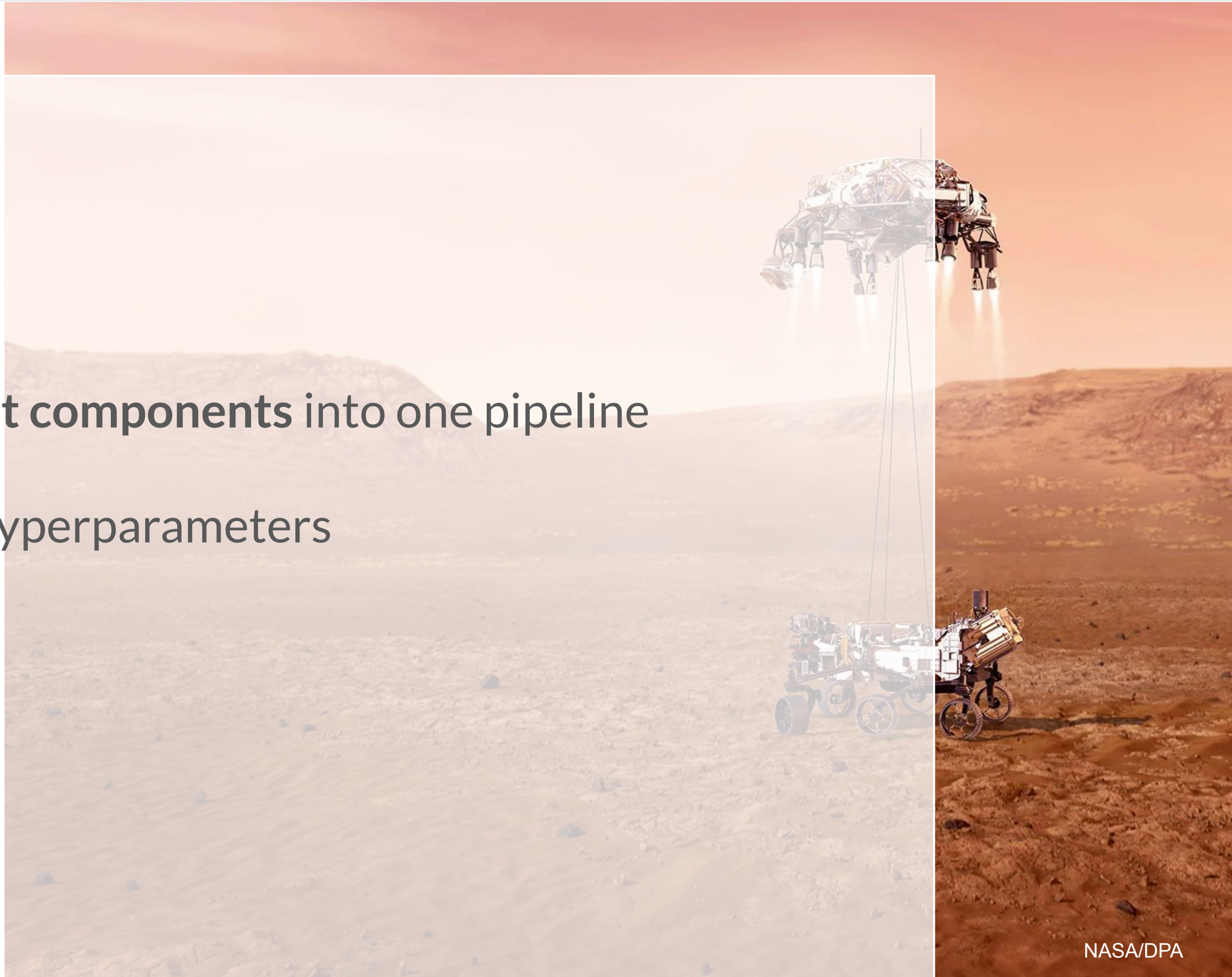
Results: *Baseline Comparison*

	Baseline	MIRS model
Training time per epoch	174s	1s
Total training time for 100 epochs	1740s	159s+100s=259s
Query execution time per image	6s	3s
Archive size	120 Mb	6.7 Mb

Conclusion

Challenges

- **Data set limitations**
- **Integrating different components** into one pipeline
- **Fine-tuning** of the hyperparameters



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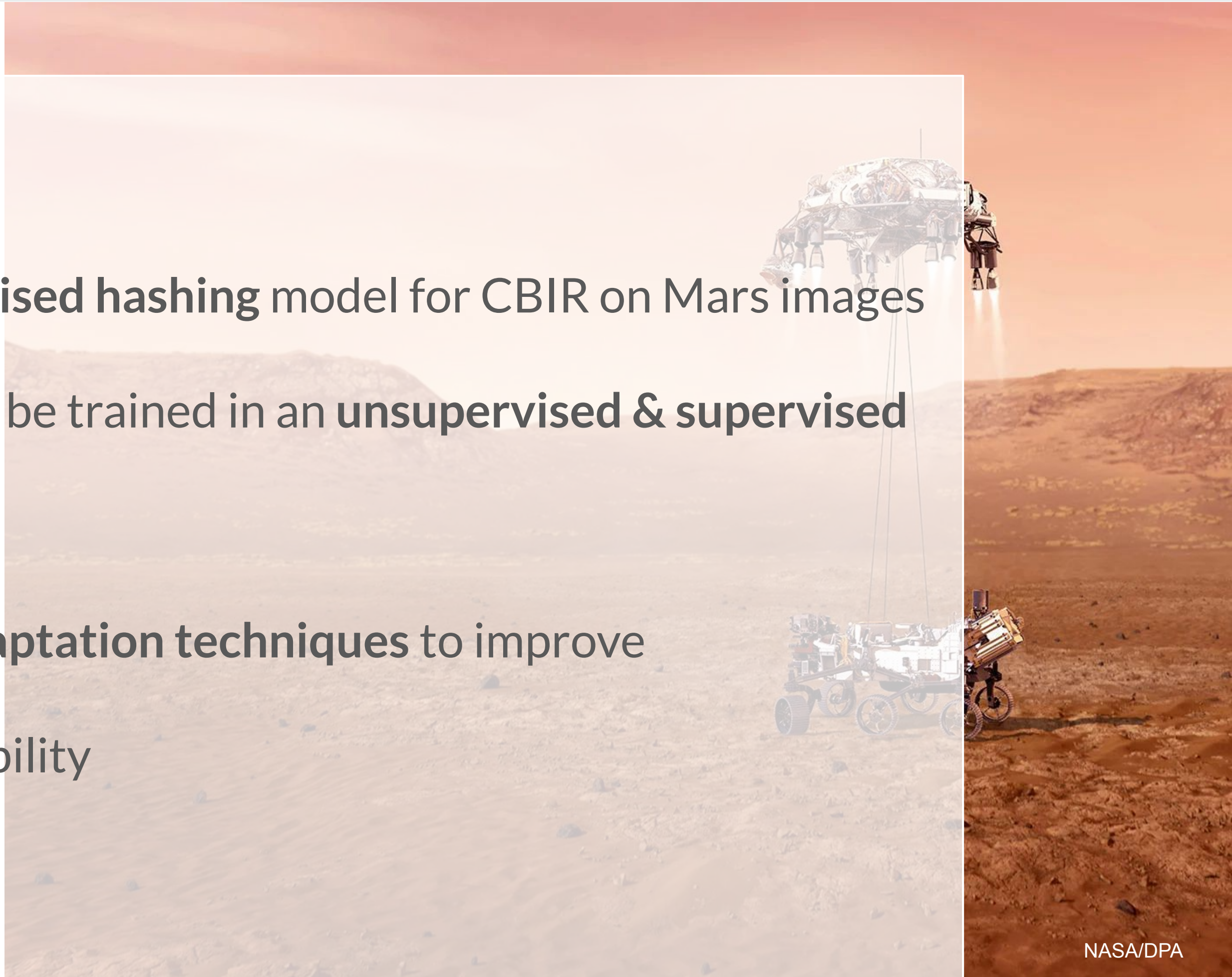
Conclusion

- Developed a **specialised hashing** model for CBIR on Mars images
- Integrated ability to be trained in an **unsupervised & supervised** way
- Injected **domain adaptation techniques** to improve generalisation capability



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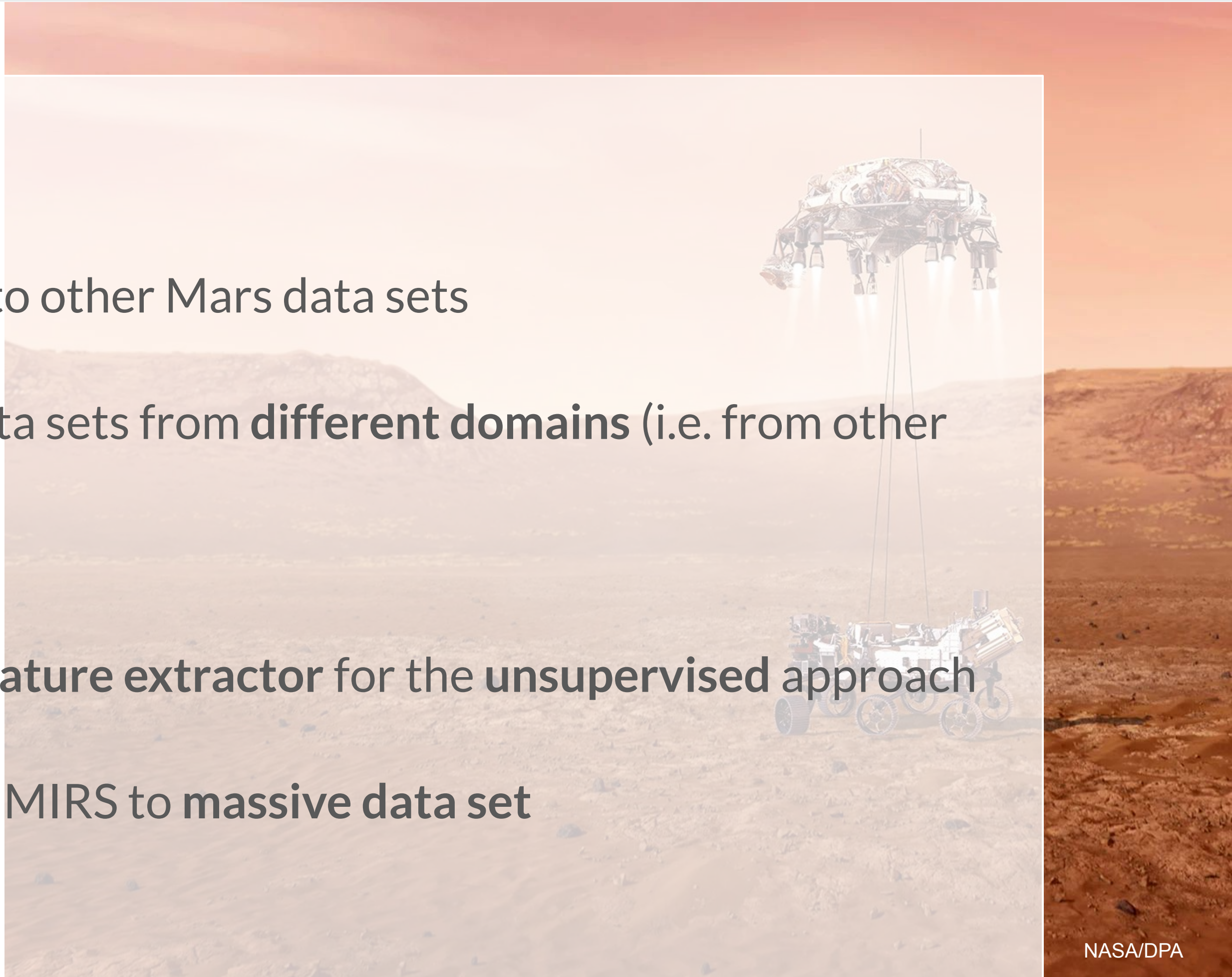
Outlook

- Apply **MIRS Model** to other Mars data sets
- Test the **DWT** on data sets from **different domains** (i.e. from other satellite images)
- **Train a dedicated feature extractor** for the **unsupervised** approach
- Apply unsupervised MIRS to **massive data set**



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Thank you for listening!

Sources

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