Raster Miner: An Open-Source Toolkit for Knowledge Discovery in Satellite Imagery Data

by

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Outline

- Introduction
- Importance of Imputation
- Problem Definition
- Proposed Approach
- Experimental Results
- Conclusions

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Introduction

- Raster Miner is an open-source software for discovering knowledge hidden in Raster Data.
- Availability: GitHub
- Liscence: GNU V3
- Platforms: Windows and Mac
- Type of Execution: GUI, Terminal, and Python.

Knowledge Discovery Tasks

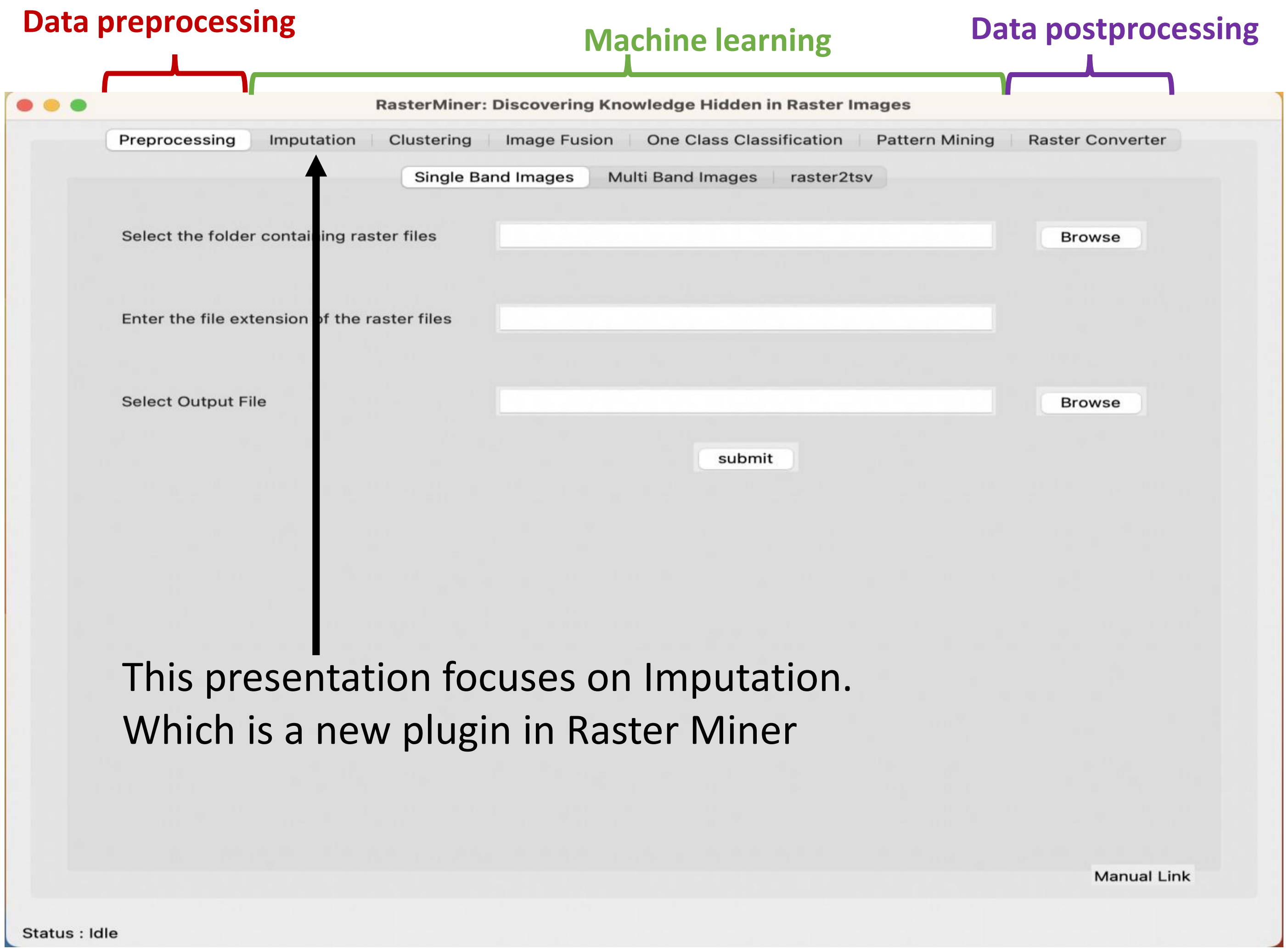

Fig. 1. Front-end of Raster Miner

Data preprocessing:

- Converts raster images into tsv files
- Support various formats of raster images
  - lbl, tiff, geotiff …

Machine learning:

- Contains techniques for various ML tasks
- ML topics currently available are:
  1. Imputation
  2. Clustering
  3. Image Fusion
  4. One Class Classification
  5. Pattern Mining

Data Postprocessing:

Converts the tsv data back into raster/tiff format

Imputation

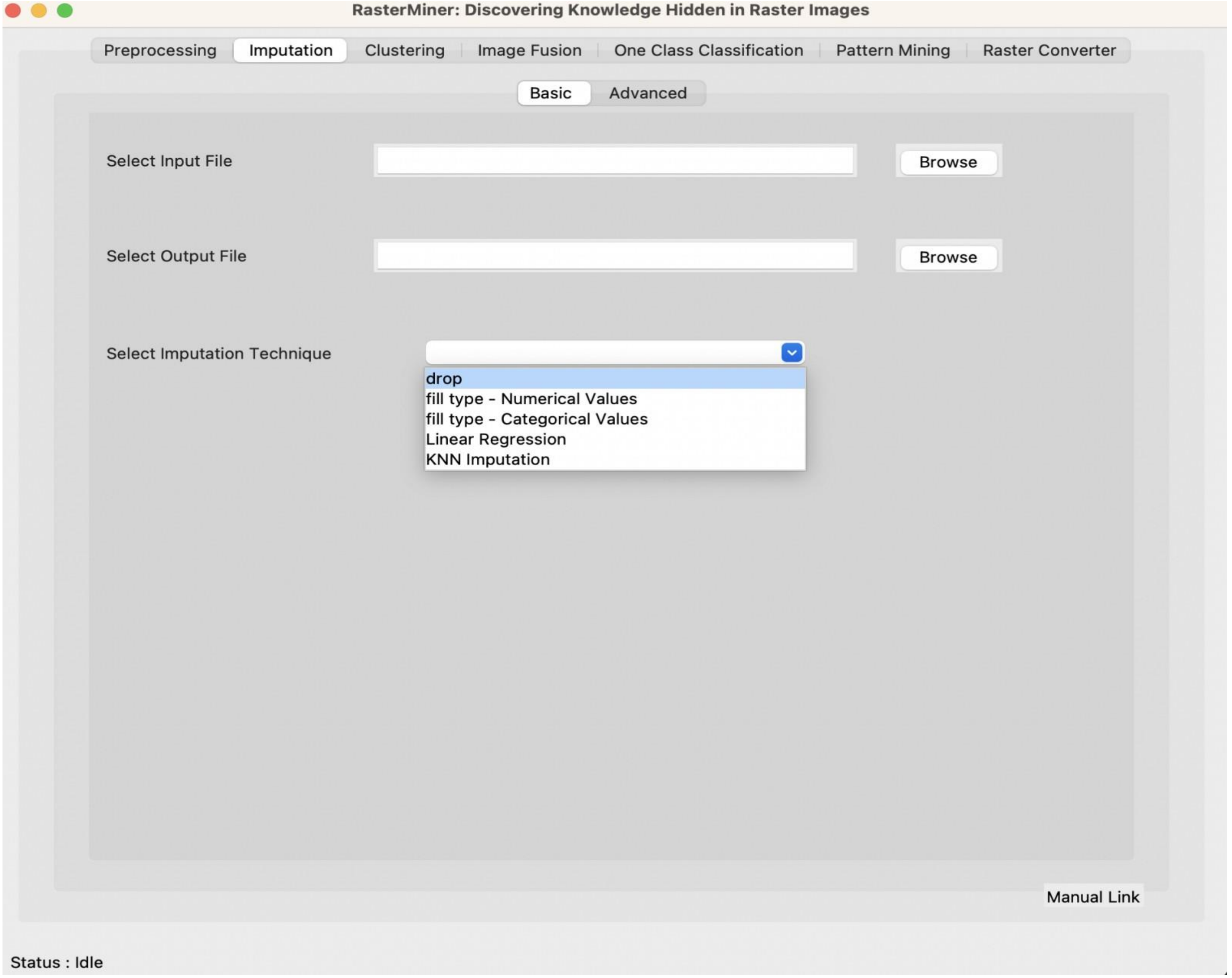

Fig. 2a. Basic Imputation Techniques

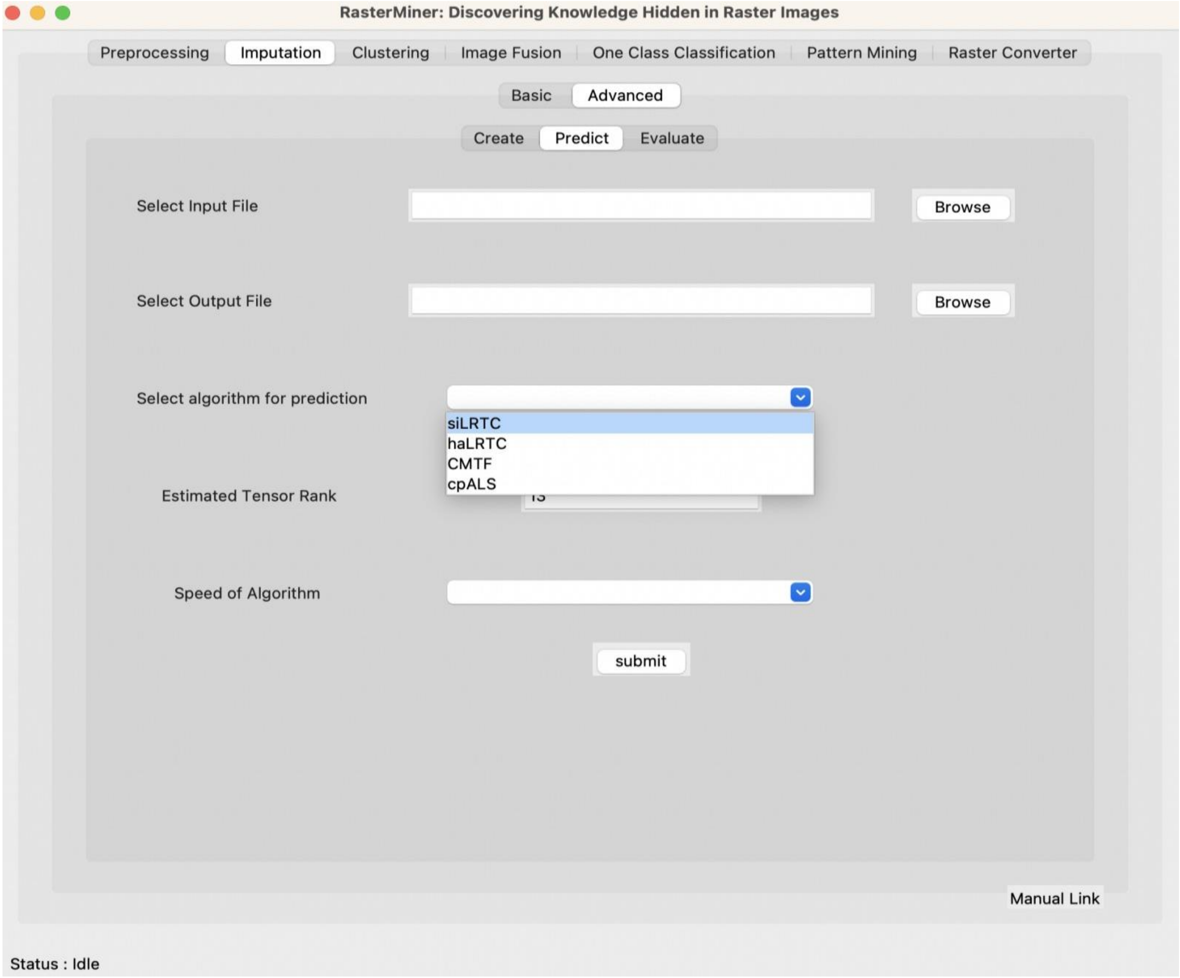

Fig. 2b. Advanced Tensor-based Imputation Techniques

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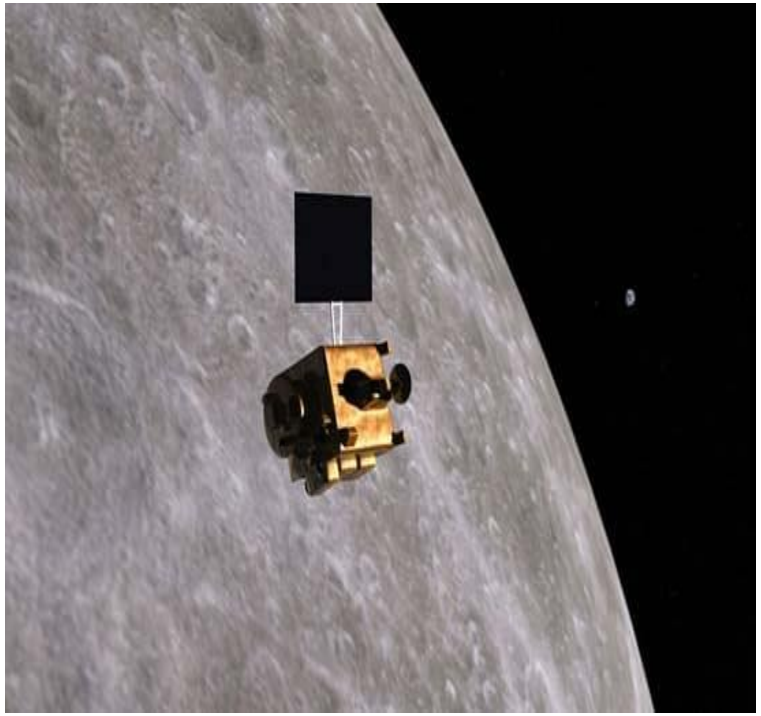
Introduction: A New Space Race

Kaguya Satellite



Chandrayan-1 Satellite

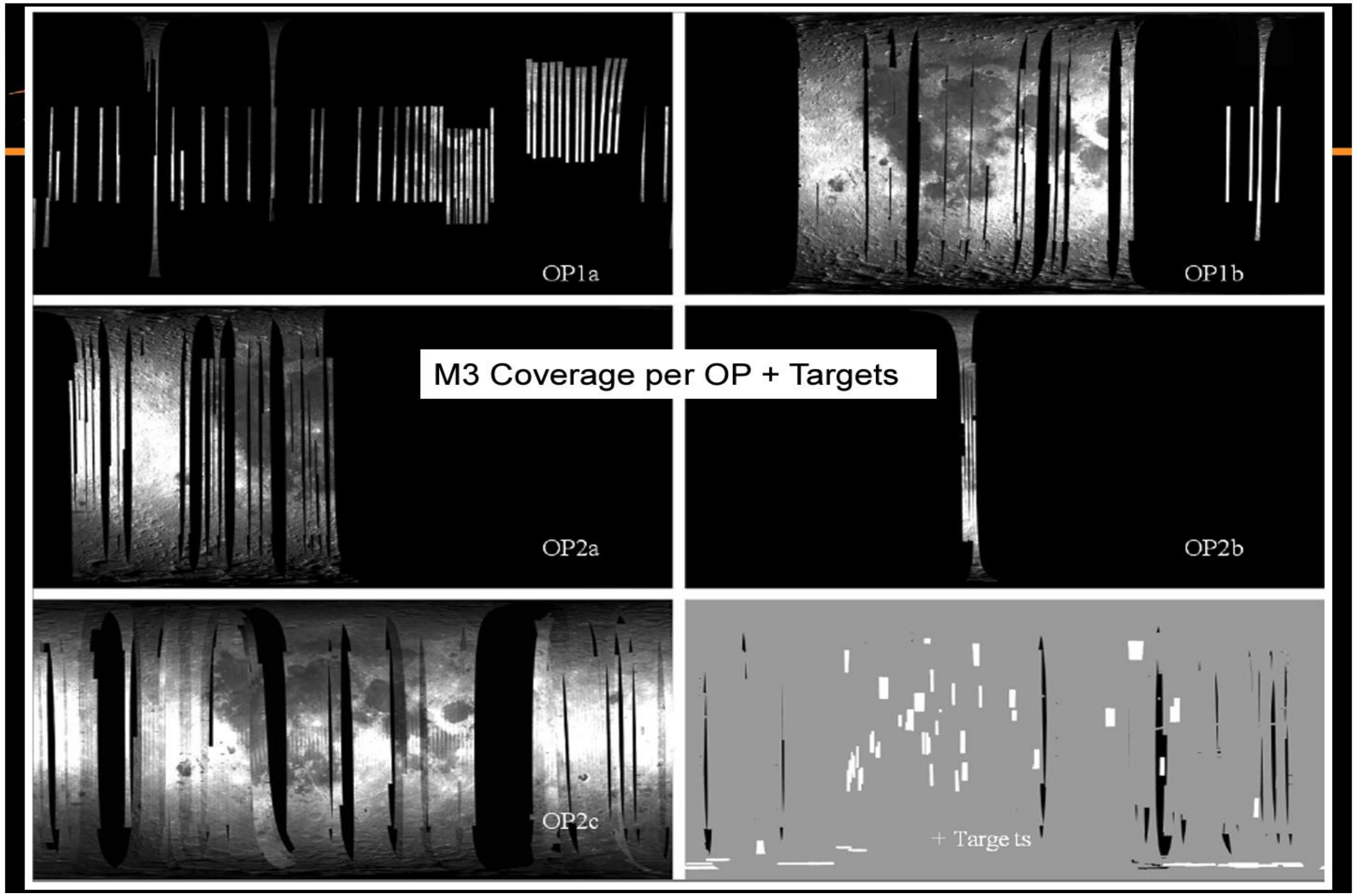
Chandrayan-2 Satellite

Fig. 1. Satellites Collecting Lunar Surface Data

Introduction: Missing Pixel Data Problem

Fig.4. Raster data of Moon’s surface gathered by Kaguya Satellite

Introduction: Missing Pixel Data Problem



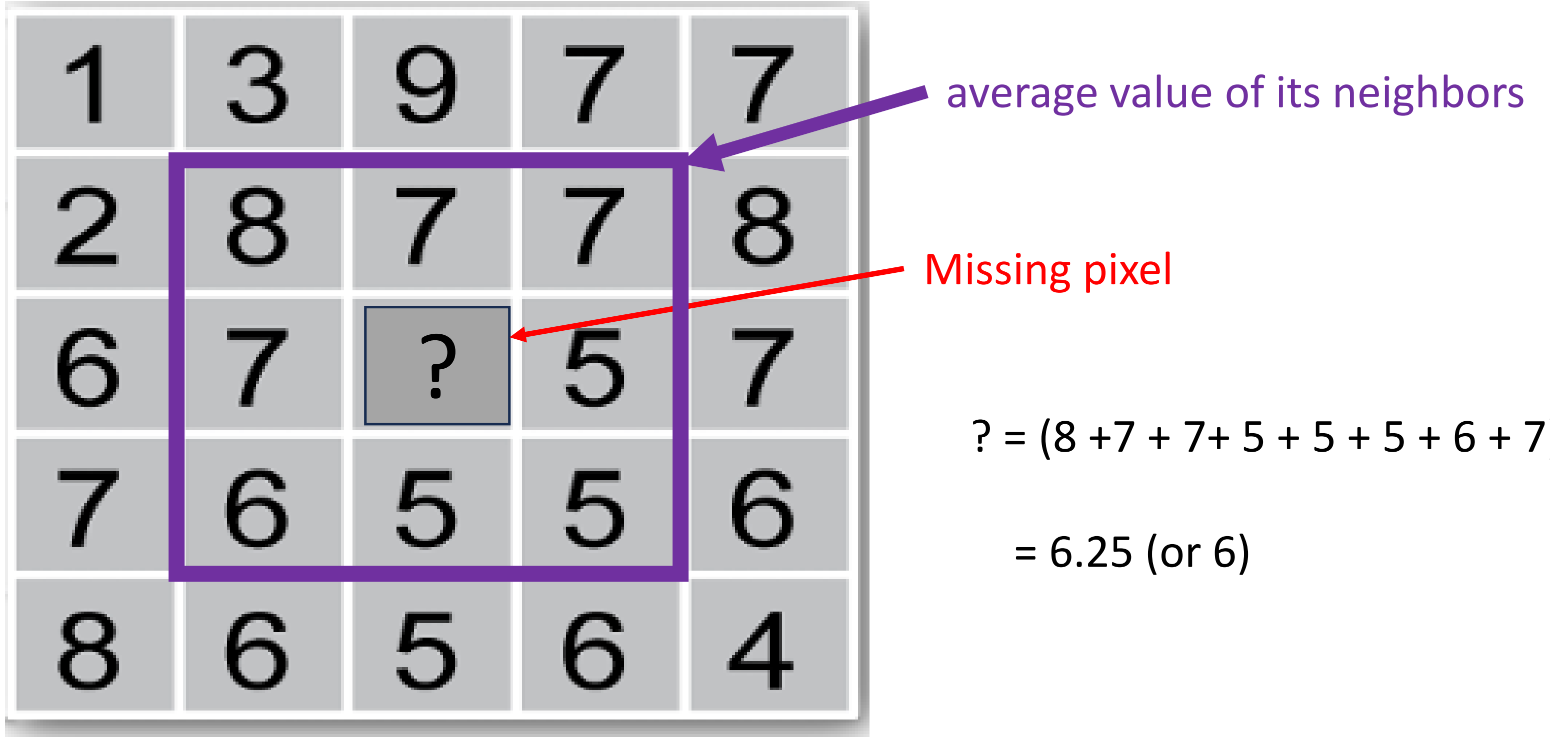
Missing data is shown in black

Fig. 5. Raster data of Moon's surface gathered by Chandrayan Satellite

Source: https://pds-imaging.jpl.nasa.gov/documentation/Isaacson_M3_Workshop_Final.pdf

Introduction: Existing Solutions and Their Limitations

- k-Nearest Neighbors Solution
  - fill in the missing pixel value using its neighbors value



? = (8 +7 + 7+ 5 + 5 + 5 + 6 + 7)/8

= 6.25 (or 6)

- **Limitation:** Cannot be applied if most of the data is missing

Introduction: Existing Solutions and Their Limitations

- Machine Learning
  - Neural Networks
  - GANs

- Limitation:
  - Need much data for model building.
  - Unfortunately, not much data is available

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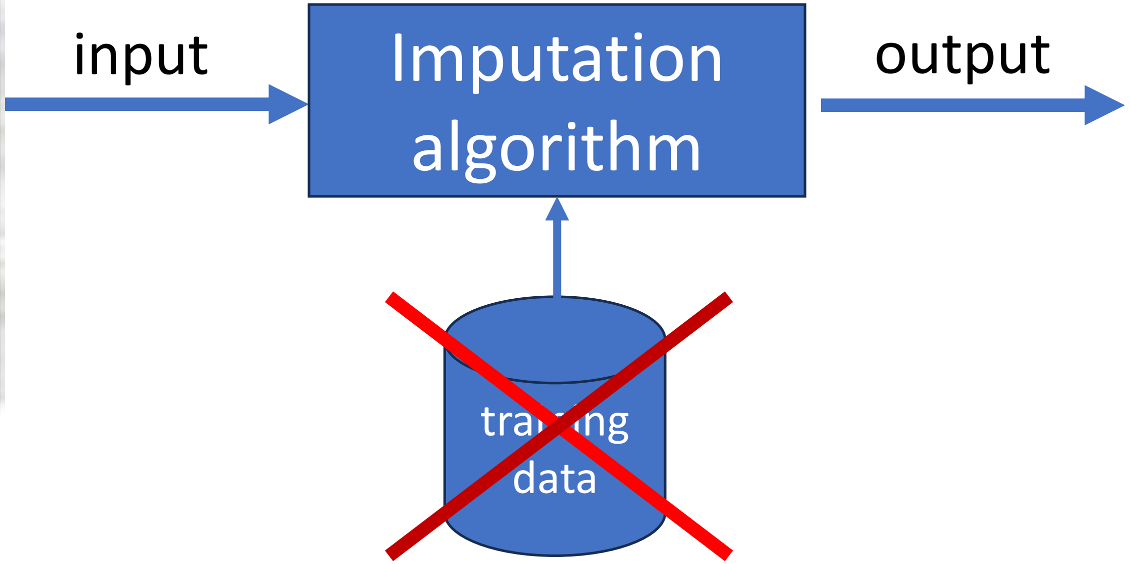
Problem Definition

- Predict the missing data in a highly corrupt image that has little training data

corrupt image



imputed image

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Proposed Approach: Tensor Completion

- Idea:
  - Model raster image as a tensors using Tucker decomposition and Canonical Polyadic decomposition

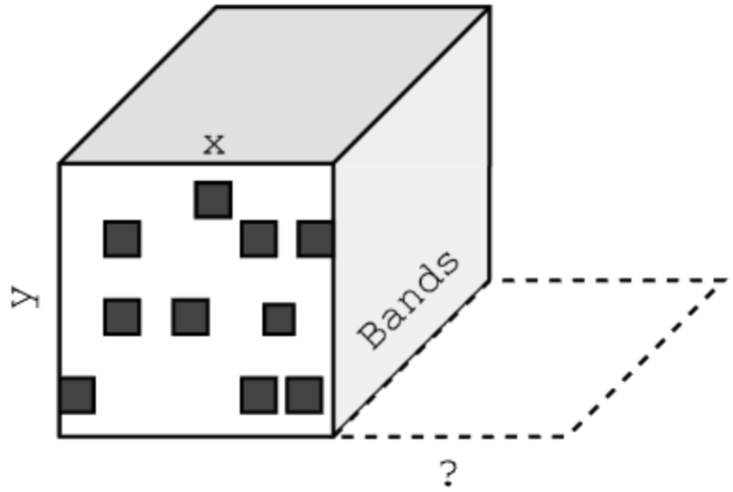


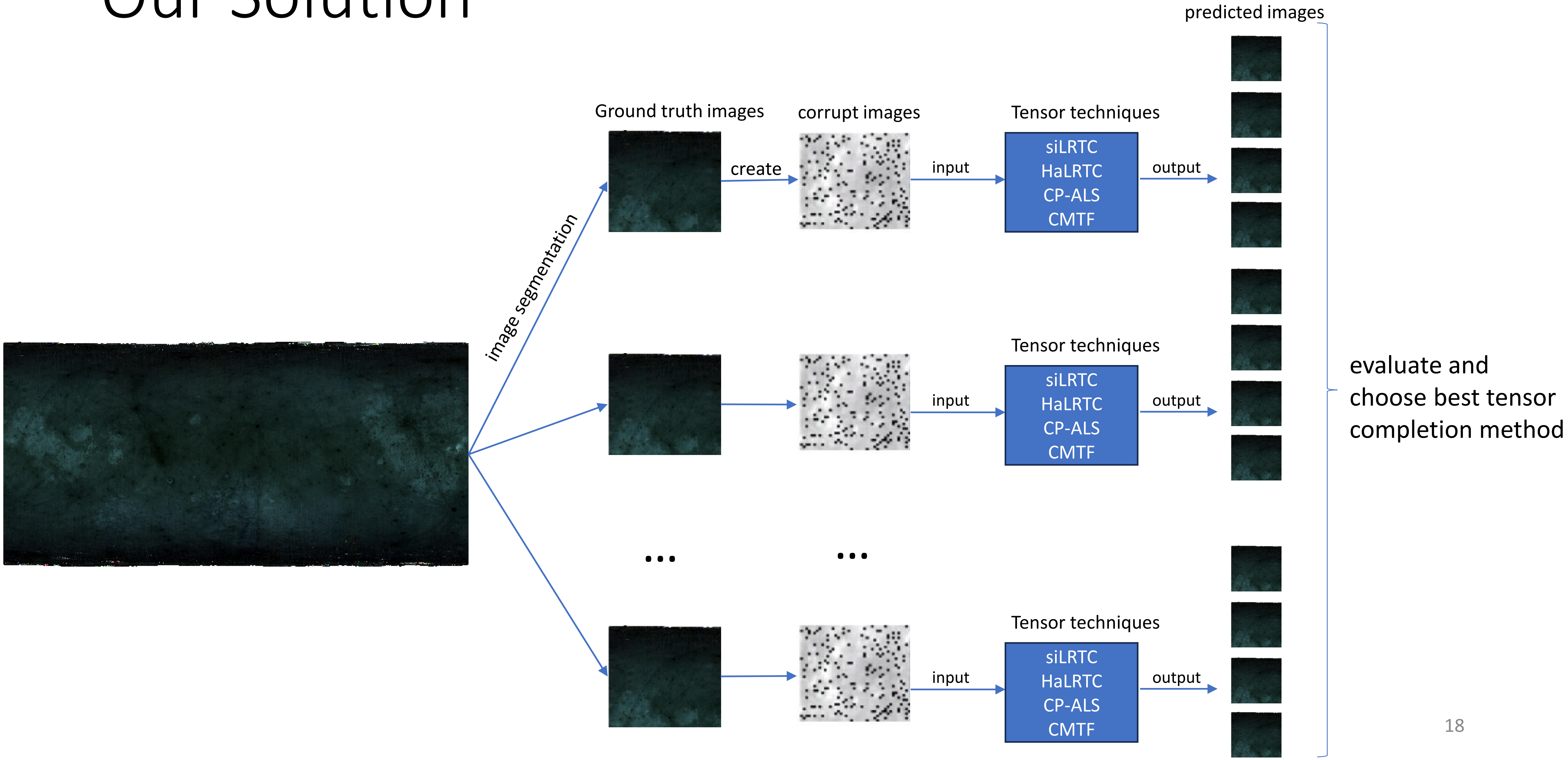
Fig. 6. Raster Data as Tensors

Challenges

- Several Tensor Solutions exists
  - siLRTC (simple Low-Rank Tensor Completion)
  - HaLRTC (High-accuracy Low-Rank Tensor Completion)
  - CP-ALS (Canonical Polyadic - Alternating Least Squares)
  - CMTF-OPT (Coupled Matrix and Tensor Factorization -Optimization)

- No universally accepted best solution exists for predicting missing data for any given dataset

Our Solution



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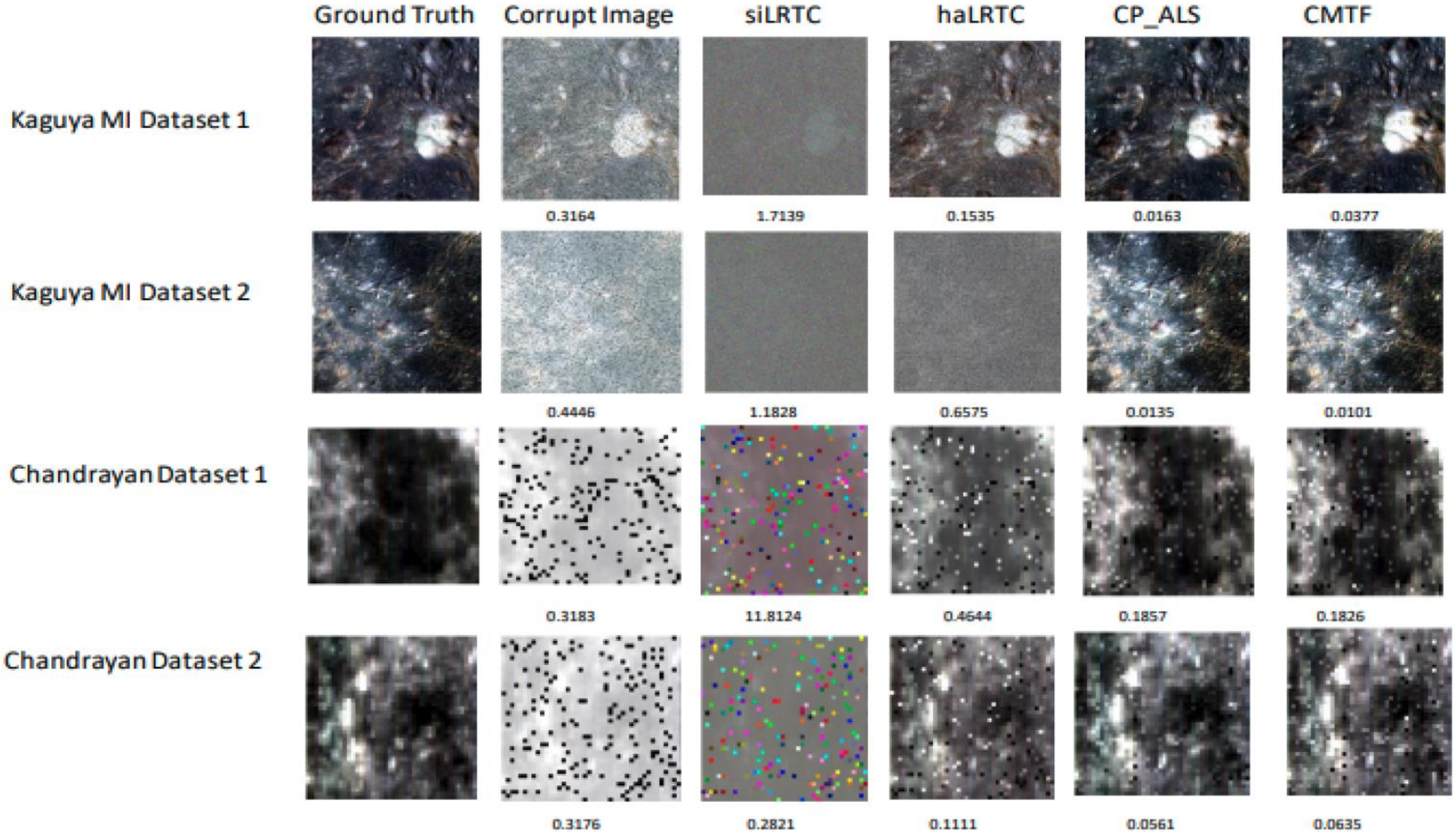
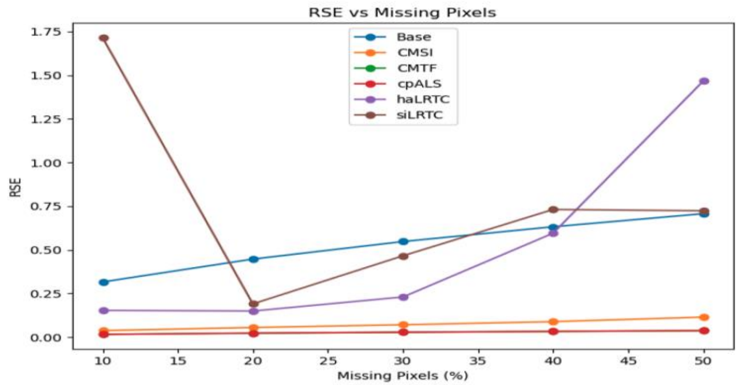
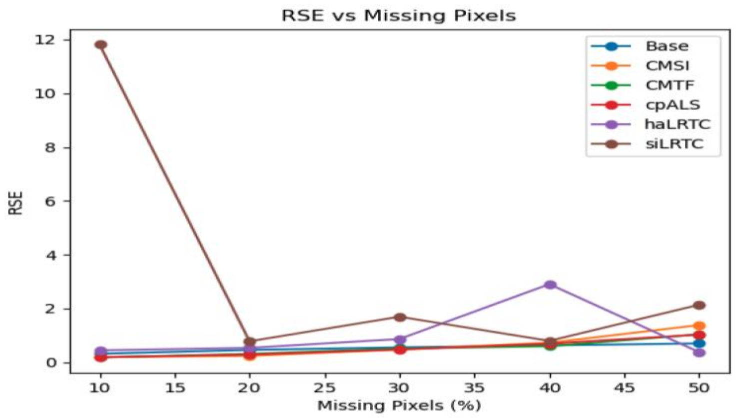
Experimental Results



Experimental Results

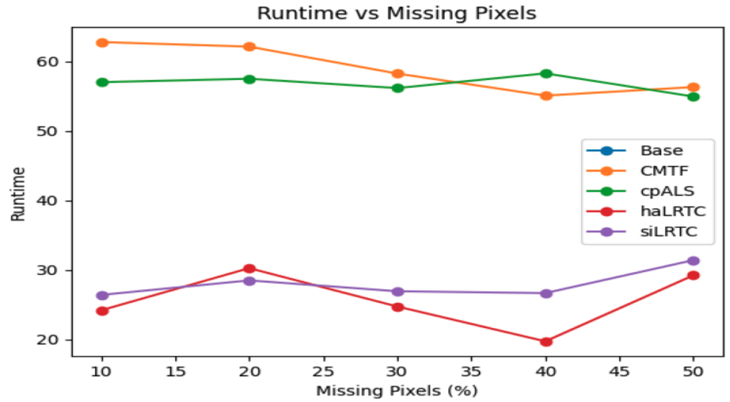


(a) Kaguya Dataset 1

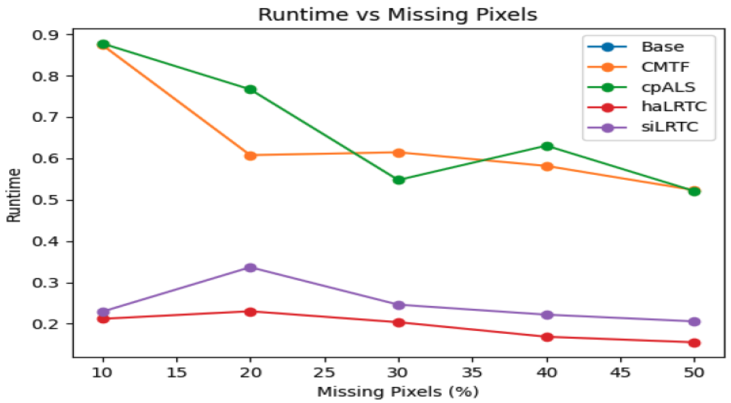


(b) Chandrayan Dataset 1

Fig. 4. Comparison between various approaches on varying the percentage of missing pixels on Kaguya Dataset 1(left) and Chandrayan Dataset 1(right)



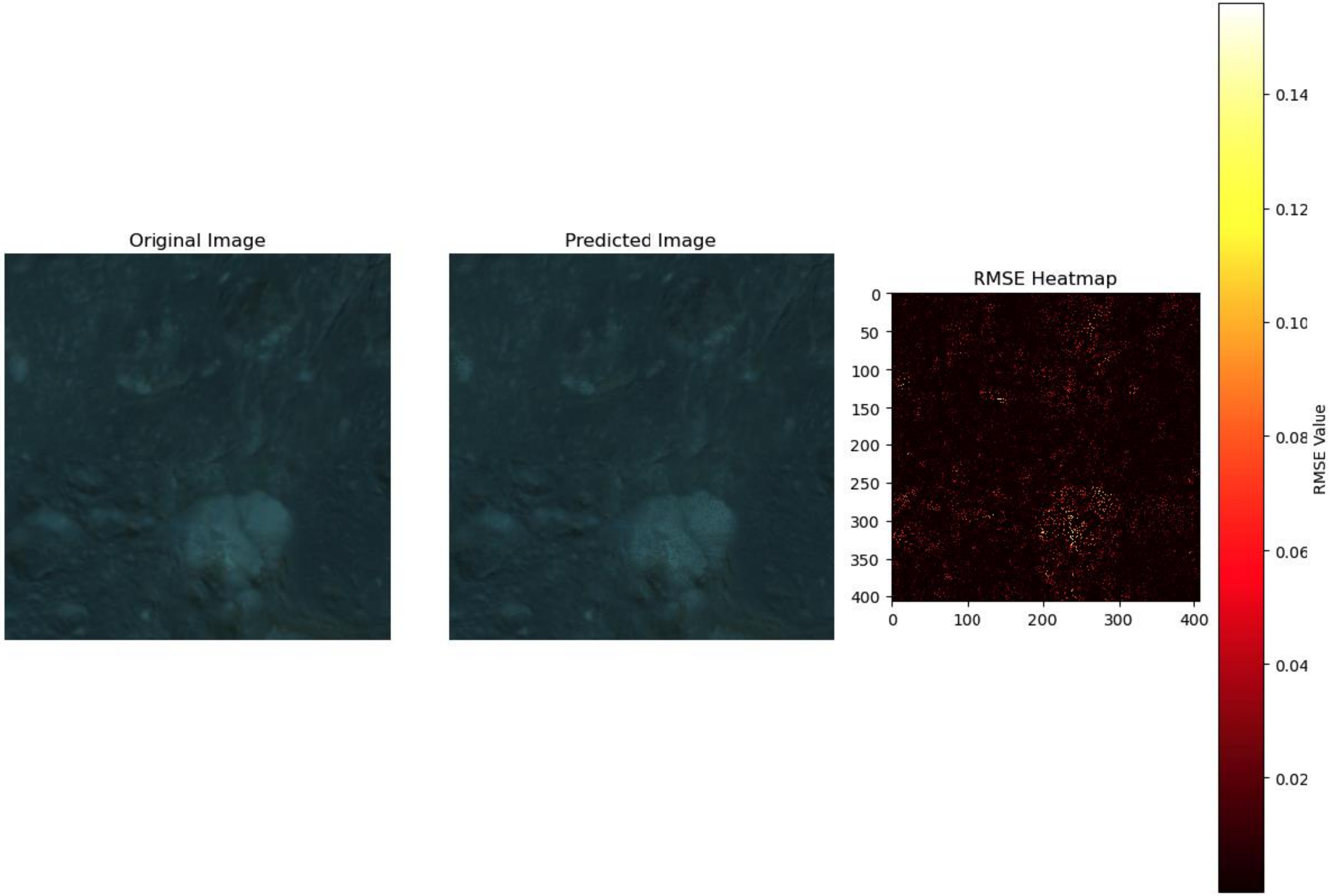
(a) Kaguya Dataset 1



(b) Chandrayan Dataset 1

Fig. 5. Study to compare the run time of different approaches on varying the percentage of missing pixels on Kaguya Dataset 1(left) and Chandrayan Dataset 1(right)

Experimental Results



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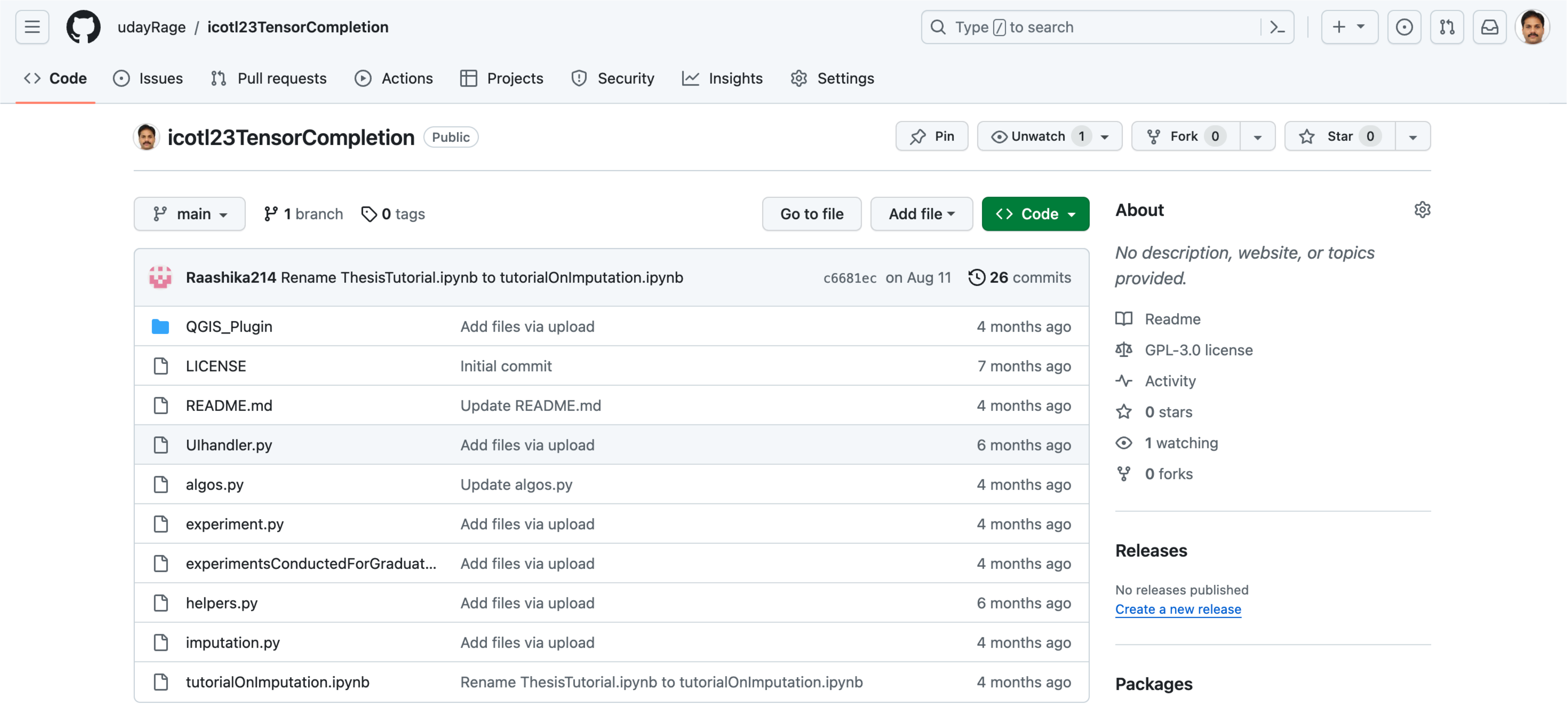
Conclusions

- This paper tackled the missing pixel problem in raster images using Tensor Completion Technique.
- Experimental results demonstrate that CMTF-OPT technique performed better against other imputation techniques.
- CMTF-OPT was found to be computationally expensive than most of the tensor-based imputation techniques.

https://github.com/udayRage/icotl23TensorCompletion



Thank you

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Questions