Particle Shape Classification using ML Based Techniques

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Problem Background:

- In mineral processing (e.g., in a ball mill), knowing the size and shape of mineral particles is key to optimizing processes like grinding, separation, and recovery.
- Manual classification is slow, inconsistent, and error-prone.

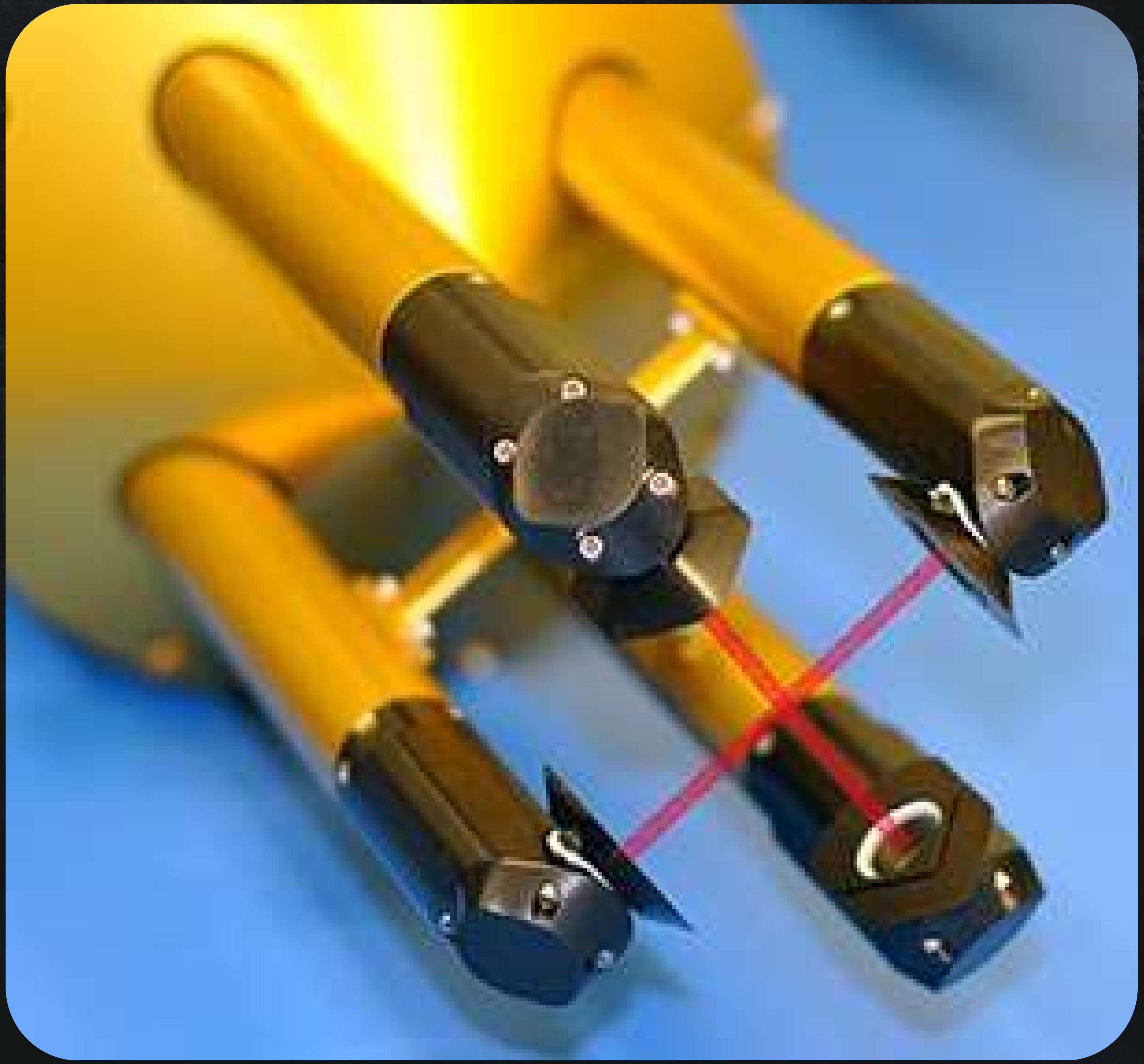
Motivation for Using ML:

- AI and image processing can automate classification with high consistency and speed.
- Machine learning models can identify patterns that are hard to define manually.

Why Cloud Particle Dataset?

- Originally intended to classify mineral particles, but real-world mineral particle image data was unavailable.
- NASA's 2D-S cloud particle imagery resembles mineral particle images in structure — grayscale, varied shapes, overlapping sizes.
- Techniques developed here are directly transferable to mineral particle classification when suitable datasets are available.

NASA 2D-S Probe:



Problem Background:

- Develop a basic unsupervised ML pipeline for particle classification.
- Use image processing techniques to isolate and process individual particles.
- Apply K-Means clustering to classify particles based on physical characteristics like size and shape.
- Evaluate if this approach can be generalized to mineral processing applications.

K-means clustering:

- Choosing K initial cluster centers (centroids).
- Assigning each point to the nearest centroid.
- Updating centroids as the mean of assigned points.
- Repeating until centroids stabilize.

Workflow Overview

5 | **Output Visualization & Interpretation**

Presenting the processed images for analysis and understanding

4 | **K-Means Clustering**

Grouping similar features into distinct clusters

3 | **Feature Extraction**

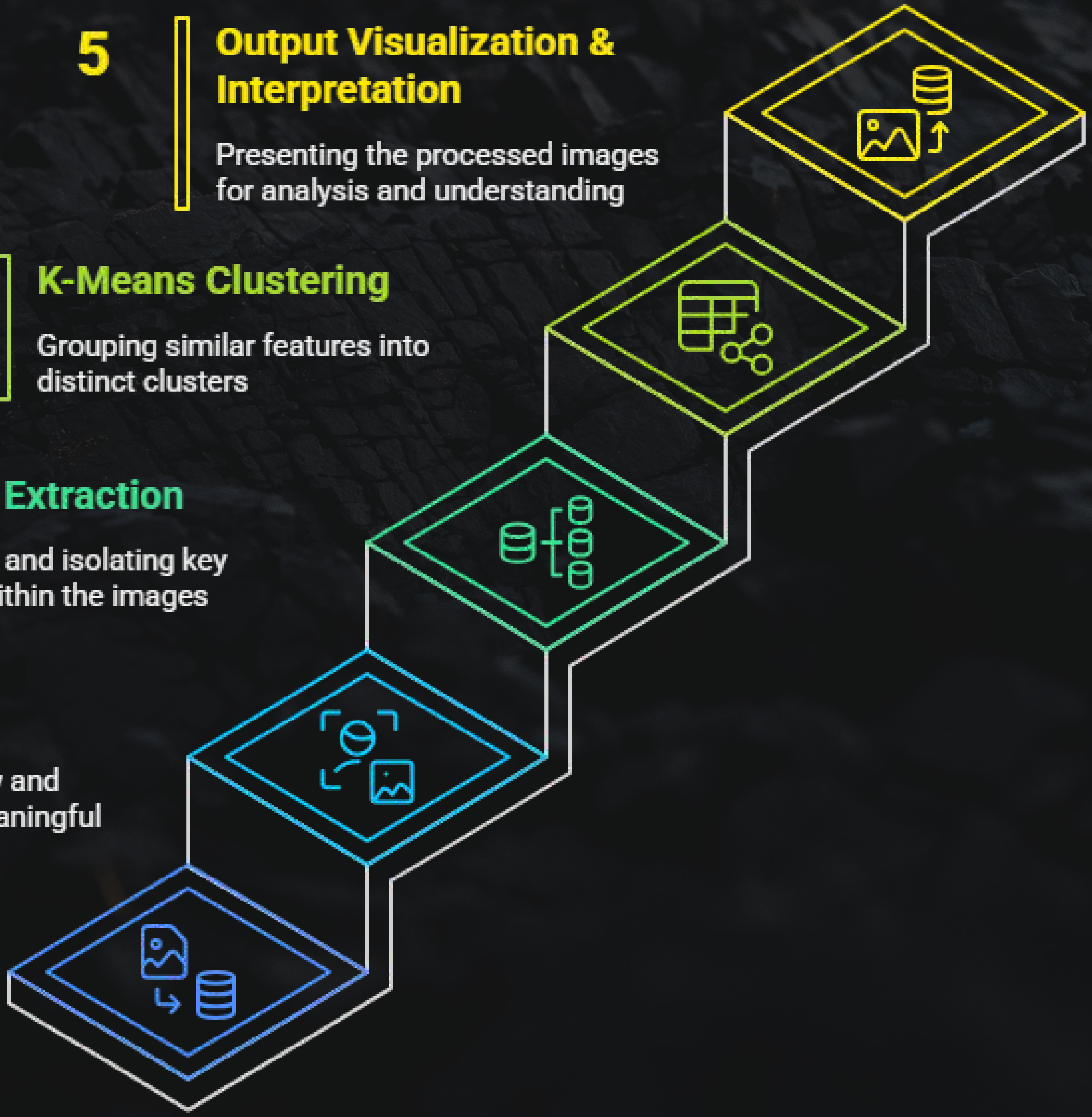
Identifying and isolating key features within the images

2 | **Preprocessing & Segmentation**

Enhancing image quality and dividing images into meaningful segments

1 | **Raw Images**

Initial collection of digital images for processing



Raw Data:

- **Source:** NASA Earth Data – Cloud Particle Images from the 2D-S Probe.
- **Type:** Microscopic imagery of atmospheric ice particles.

Characteristics:

- Each image may contain multiple particles.
- Varying shapes: circular, needle-like, irregular.
- Reason for Choice: Availability, similarity in image characteristics with mineral particles.

Dataset:

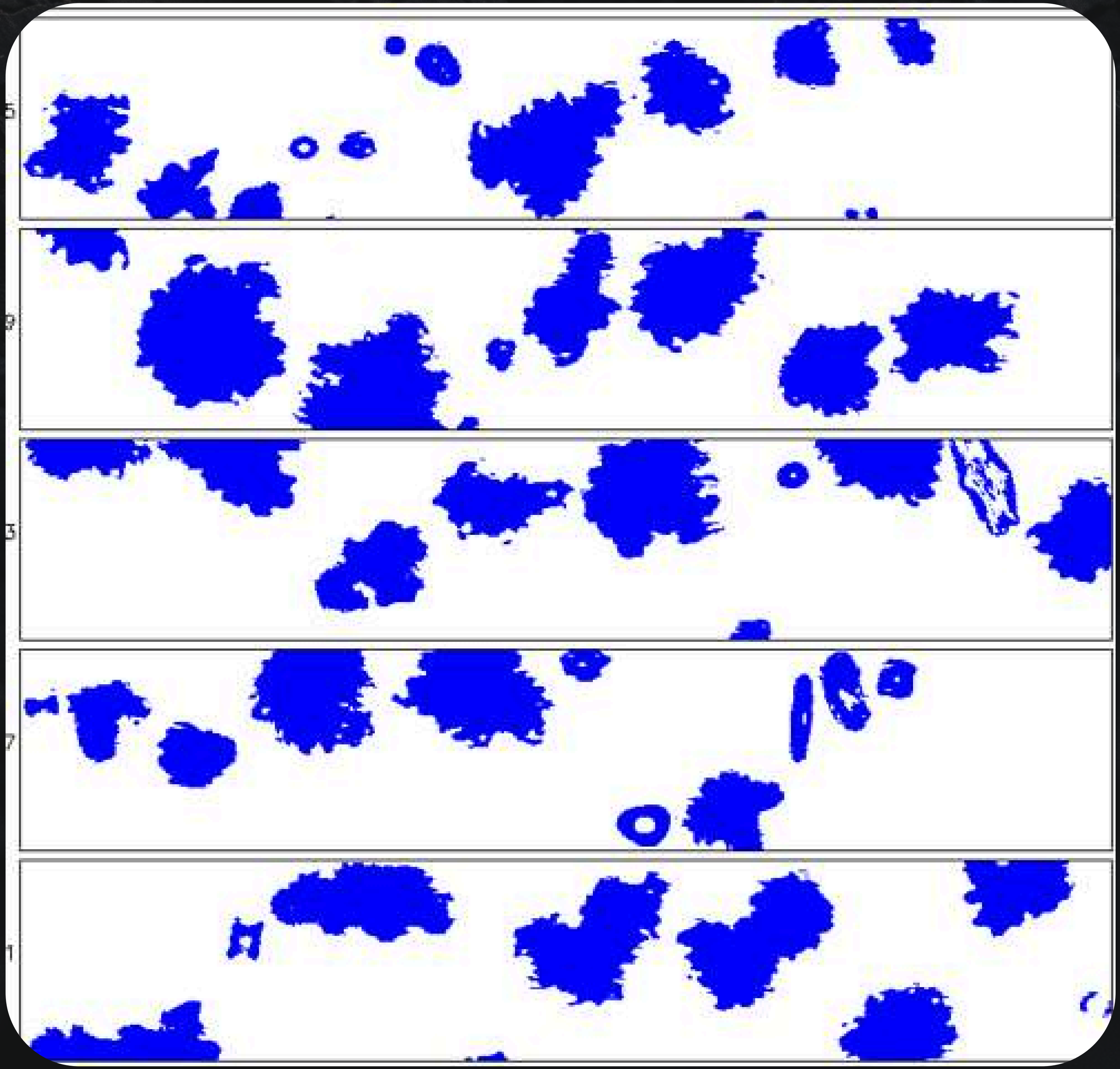


Image Processing:

Image Extraction & Filtering

• Loads images and applies a blue mask (HSV) to detect particles.
• Extracts valid contours (minimum size: 35×35 pixels).

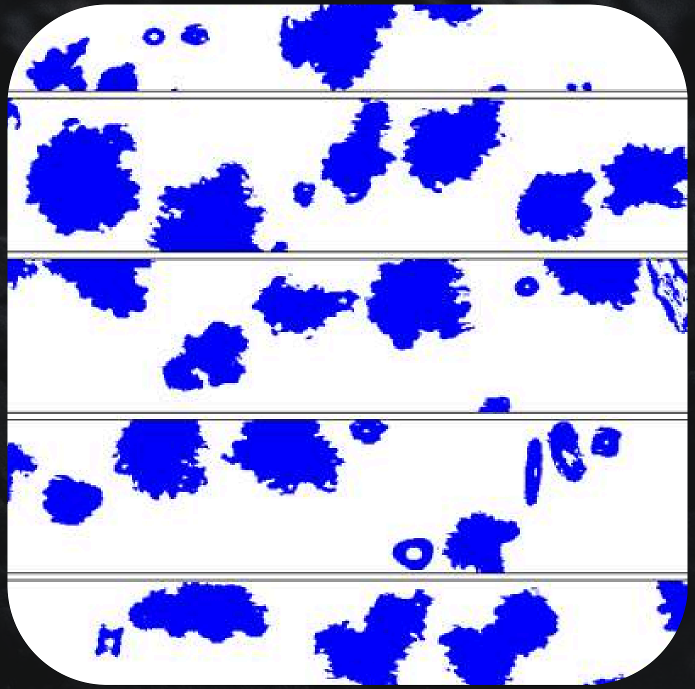
Preprocessing & Enhancement

• Padding & Resizing – Enlarges 5×, resizes while maintaining aspect ratio.
• Grayscale & Sharpening – Enhances clarity.
• Final Output – Placed on a 64×64 white canvas and stored in particles.csv.

ViT Preprocessing

• Converts 64×64 grayscale images to:

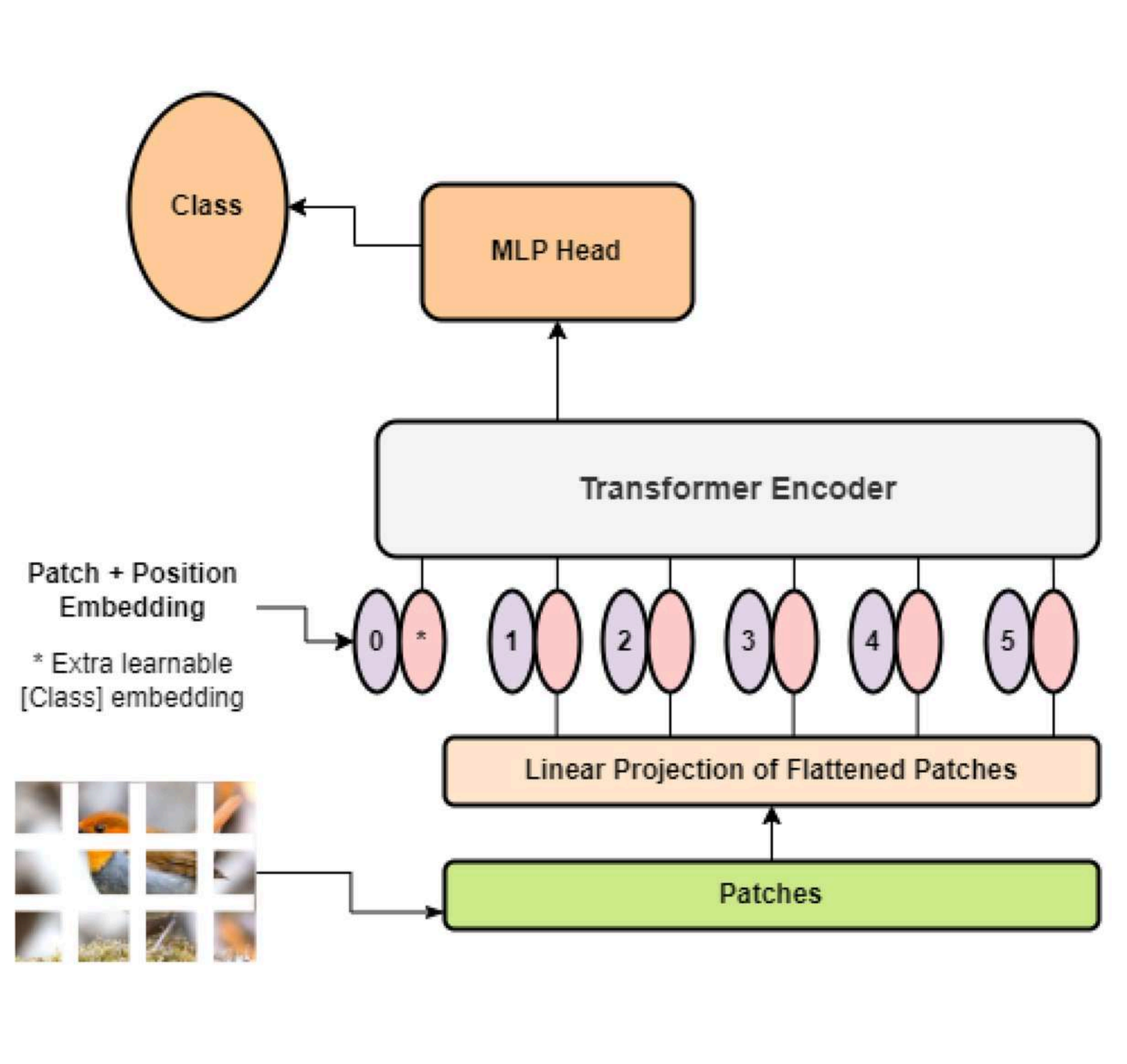
- 224×224 resolution
- 3-channel format
- Normalized range [-1, 1]



Feature Extraction:

Vision Transformer (ViT)

ViT is a deep learning model that processes images using transformers instead of convolutional neural networks (CNNs), treating image patches similarly to words in natural language processing.



Key Processing Steps:

1. Image Patching – The image is divided into fixed-size patches (e.g., 16×16 pixels).
2. Embedding & Positional Encoding – Each patch is converted into a vector with positional information.
3. Transformer Encoding – Self-attention mechanisms identify relationships between patches.
4. [CLS] Token – A special classification token represents the entire image for downstream tasks..

Advantages of ViT for Particle Image Analysis:

- Captures fine-grained details and long-range dependencies.
- Pretrained on large datasets (e.g., ImageNet) for transfer learning.
- Performs effectively even with limited training data

Model Used	ViT Base Patch16-224 (pretrained on ImageNet)
Feature Output Shape	768-dimensional vector per image (768 Number of Features per Image)
Features' Meaning	High-level image patterns learned by the model's attention mechanism
Key Aspects Captured	Shape, texture, edges, spatial relationships, and abstract visual patterns
Human Interpretability	No — features are numerical embeddings optimized for similarity comparisons

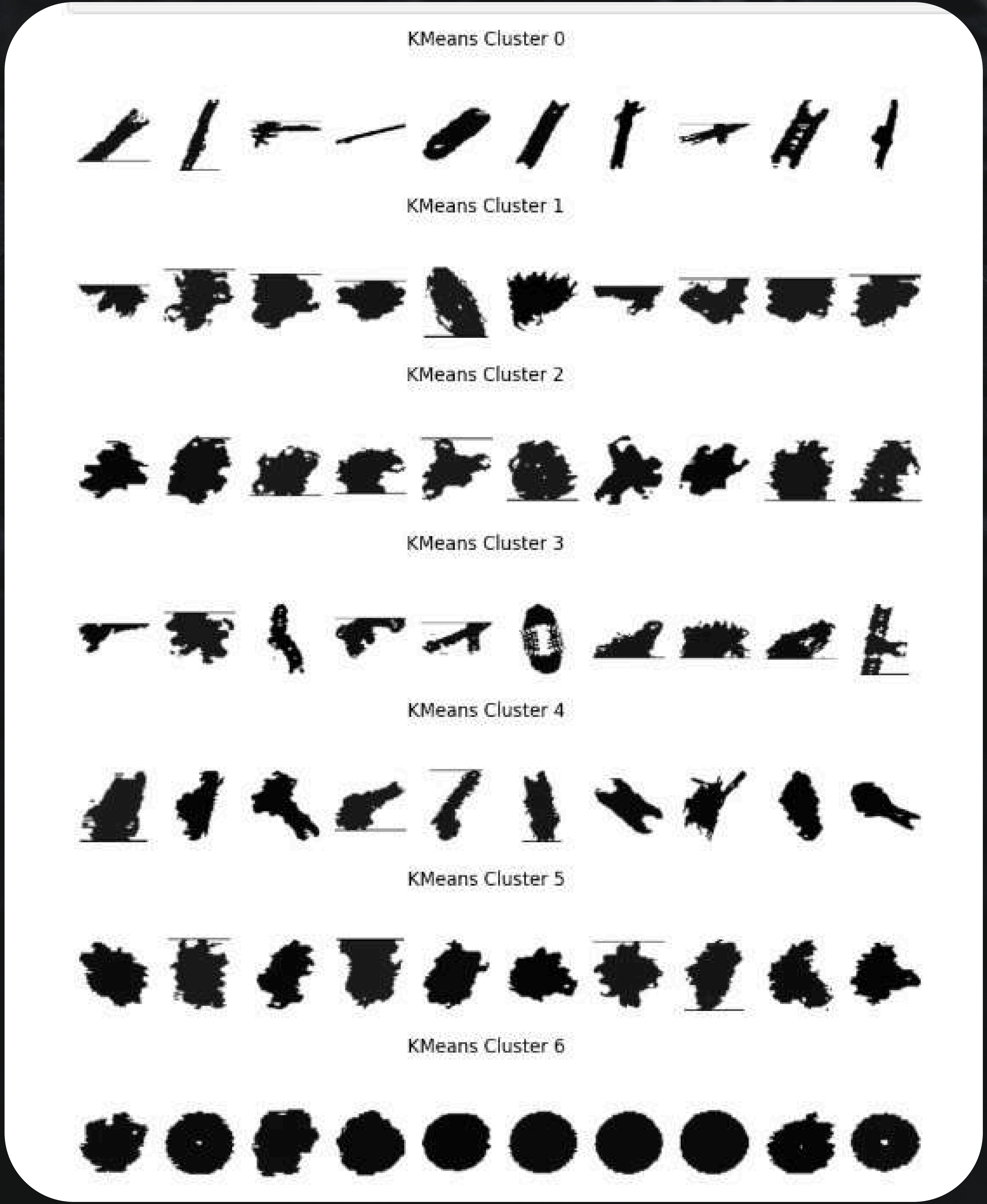
Cluster (K) evaluation metrics used

Metric	Significance	Value Found
Silhouette Score	Measures how well-separated clusters are by comparing intra-cluster similarity to inter-cluster separation. Higher values (closer to 1) indicate better-defined and well-separated clusters.	0.4309
Davies-Bouldin Index	Evaluates cluster compactness and separation by measuring the average similarity between each cluster and its closest neighboring cluster. Lower values indicate better clustering.	0.8073
Calinski-Harabasz Score	Assesses the ratio of between-cluster variance to within-cluster variance. Higher values indicate more compact and well-separated clusters.	29,874.8313

Output Analysis:

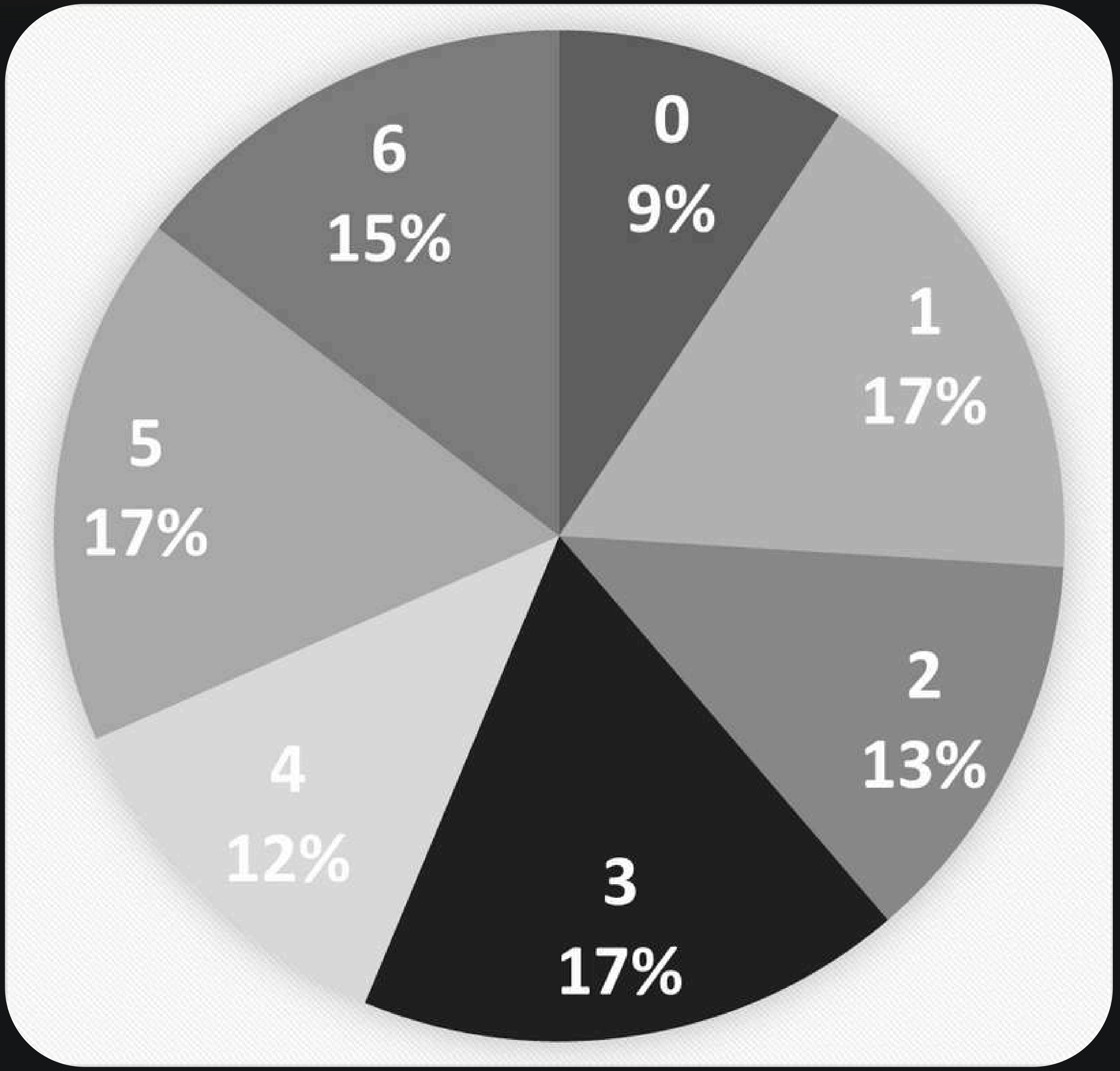
The particles were classified into various clusters based on shape. The clusters can be named as follows:

- Cluster 0 : Linear
- Cluster 1 : Aggregate
- Cluster 2 : Graupel
- Cluster 3 : Dendrite
- Cluster 4 : Irregular
- Cluster 5 : Plate
- Cluster 6 : Spherical



Clustering results

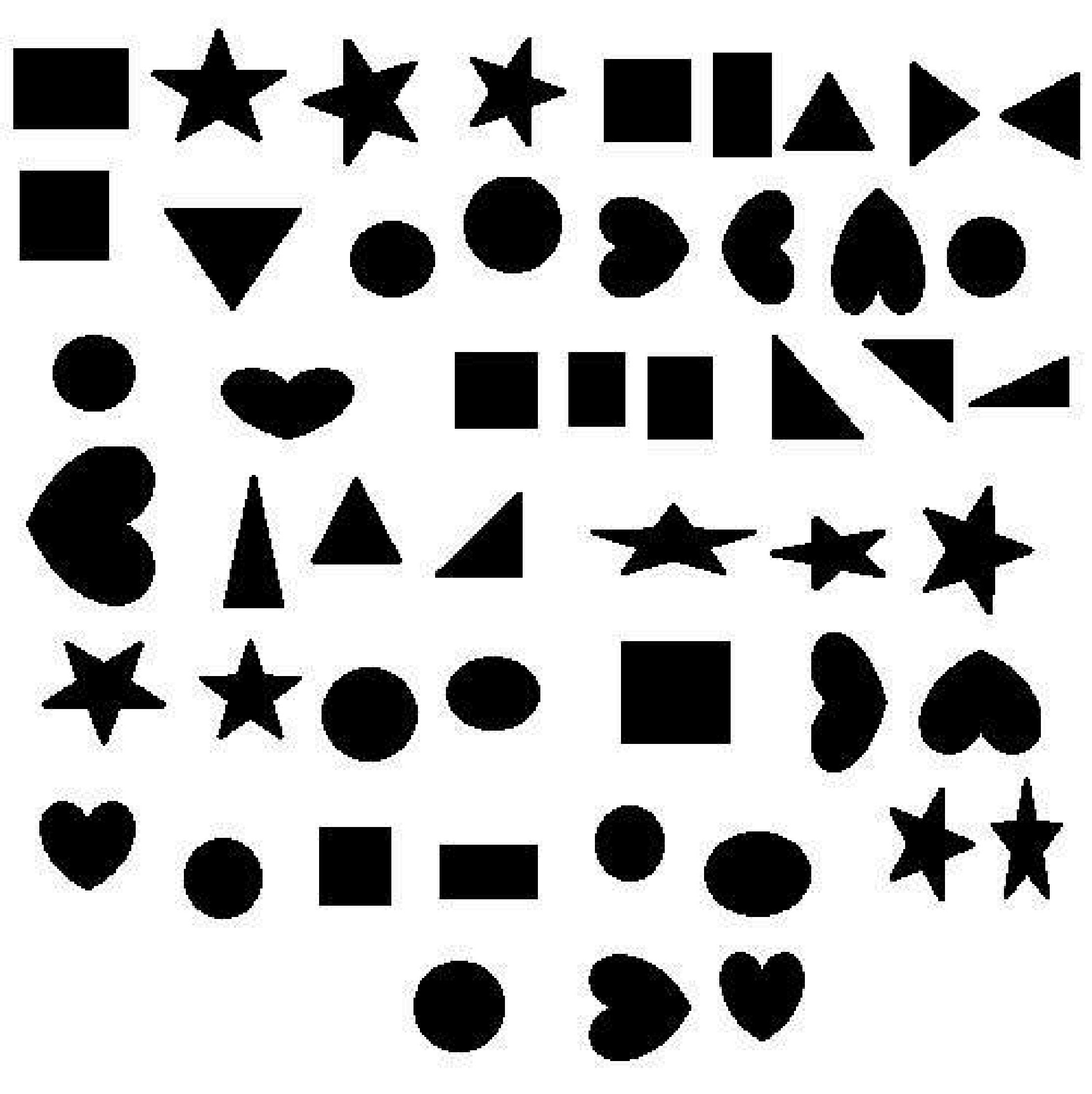
Cluster	Shape	% Distribution
0	Linear	9%
1	Aggregate	17%
2	Graupel	13%
3	Dendrite	17%
4	Irregular	12%
5	Plate	17%
6	Spherical	15%

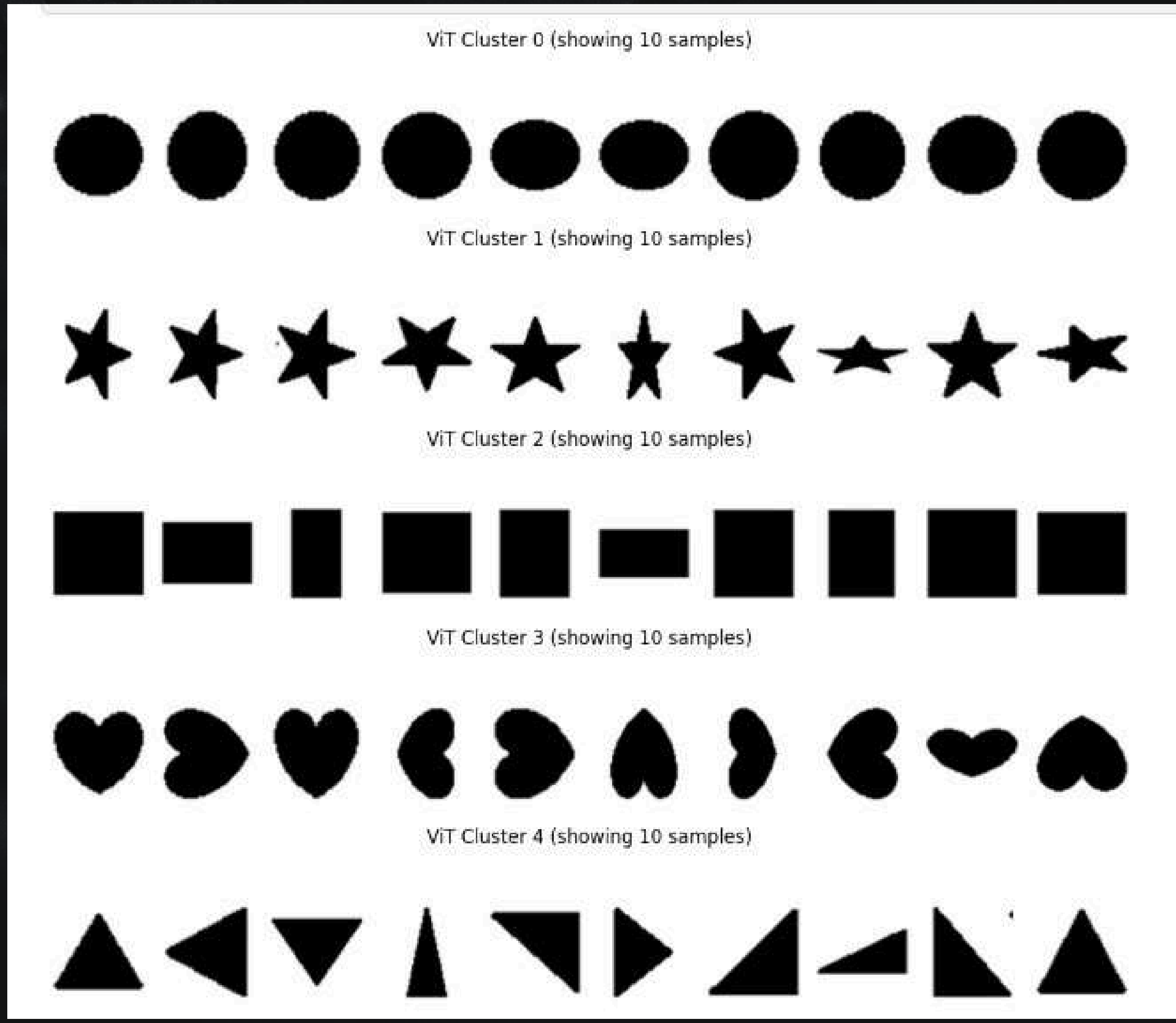


- Clusters are well-distributed, with high representation of Aggregate, Dendrite, and Plate shapes (17% each).
- Clear morphological trends help in automated particle classification—a key requirement in both cloud particle and mineral classification applications.

Proof of Concept

We took 5 sets of shapes (10 images each) and ran our model on it - resulting in all of them being clustered accurately, with the following scores on our evaluation metrics:
Silhouette Score: 0.8441 (higher is better)
Davies-Bouldin Index: 0.2144 (lower is better)
Calinski-Harabasz Score: 10491.6900 (higher is better)





References

- Find our code attached here: GitHub Repository
- https://airbornescience.nasa.gov/instrument/2D-S_Stereo_Probe
- http://www.mineraltech.com/Downloads/CLSchneider_Dissertation.pdf
- https://www.researchgate.net/publication/373694643_Shape_Classification_of_Cloud_Particles_Recorded_by_the_2D-S_Imaging_Probe_Using_a_Convolutional_Neural_Network
- https://search.earthdata.nasa.gov/search/granules?p=C1995868627-GHRC_DAAC&pg[0][v]=f&pg[0][gsk]=-start_date&g=G2903518361-GHRC_DAAC&q=cloud%20particle%202d-s&tl=1628484480!4!!&lat=-0.0703125

Thank you for your Attention

Your Questions are Welcome!