इसरो isro

BHARATIYA ANTARIKSH HACKATHON 2025

Powered by H2S

Team Name : Team Chaitanya

Team Leader Name : Palak Meena

Problem Statement : (PS-12) Dual Image Super Resolution for High-Resolution Optical Satellite Imagery and its Blind Evaluation.

Team Members

Team Leader:
Name: Palak Meena
College: Medi-Caps University

Team Member-1:
Name: Divya Vadnere
College: Medi-Caps University

Team Member-2:
Name: Kuhu Vyas
College: Medi-Caps University

Team Member-3:
Name: Pruthviraj Pasee
College: Gujarat Technological University

Past Hackathon Experience

- We were **finalists in Hack'N'Dore**, a National-level hackathon organized by the **Indore Municipal Corporation (Government of MP)**, where we developed a solution aligned with smart city goals.

- Additionally, we successfully **cleared the internal rounds of Smart India Hackathon (SIH) 2024** at the college level, demonstrating our ability to ideate and present scalable, impactful solutions.

- Participated in the **NASA Space Apps Challenge**, focusing on open-data space-tech solutions.

Our Idea

1. **Dual Hyperspectral Inputs :-** Takes two slightly shifted low-resolution images and aligns them using a **learned attention mechanism**, handling motion and parallax effectively.

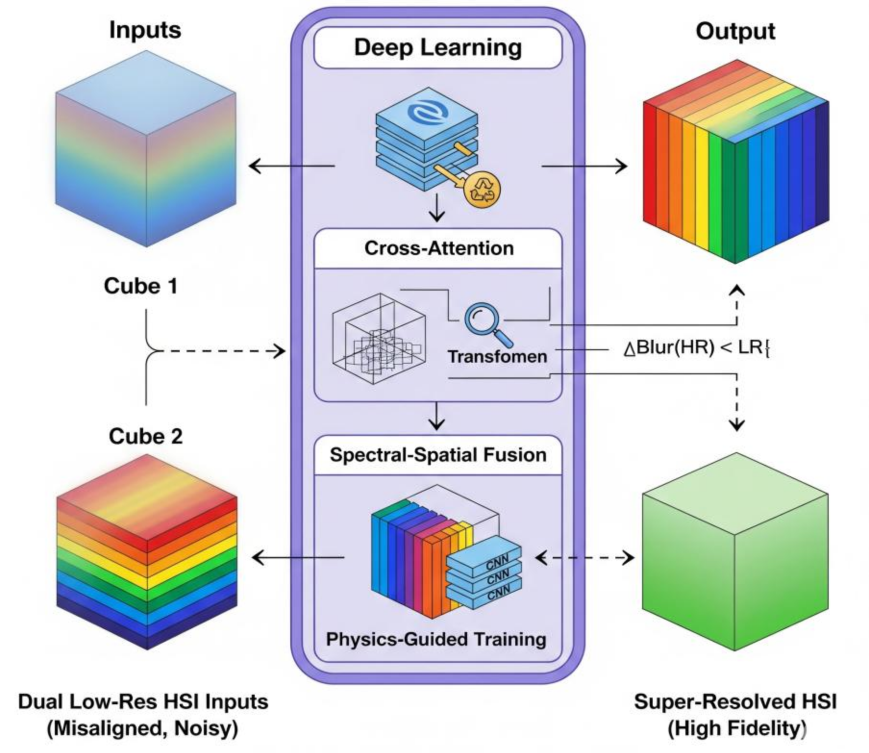
2. **Spectral–Spatial Fusion with Dual Transformer :-** Uses two attention streams one for **spatial detail**, one for **spectral bands** — to reconstruct accurate, high-quality outputs.

3. **Physics-Based Learning : -** Simulates real satellite blur and down sampling during training to ensure outputs are **physically realistic**, not just visually sharp.

4. **Spectral Consistency :-** Applies 1×1×B convolutions and attention to keep all **spectral bands consistent**, reducing color errors and mixing.

5. **Blind Quality Assessment : -** Includes a built-in module to **predict image quality** without needing ground-truth — useful for real-world validation.

6. **Lightweight and Deployable : -** Runs smoothly on **12 GB GPUs**, supports **batch processing** and **large tile inference**, making it ready for deployment in satellite systems.



How Is It Different From Existing Ideas?

1. Replaces traditional alignment methods with **cross-attention**, which adapts to motion and terrain variation better than affine models.
2. Uses **dual attention streams** to separately learn spatial detail and spectral accuracy, unlike CNNs that treat bands equally.
3. Trains with a **physics-based loss** that mimics how satellites actually capture images, making results more realistic.
4. Includes a **blind quality assessment module**, so outputs can be trusted even without ground-truth references.

USP (Unique Selling Point)

1. Combines **cross-attention alignment**, **spectral–spatial fusion**, and **physics-based learning** in one complete system for hyperspectral super-resolution.
2. Includes a **built-in quality checker** that works without ground-truth, helping assess output reliability in real time.
3. Runs efficiently on **12 GB GPUs** with support for **batch processing** and **large image tiling**, ready for real-world satellite use.
4. Designed using insights from **ISPRS 2020**, **ESSAformer**, and **MUSIQ**, bringing together strong research and practical deployment.

How Does It Solve the Problem?

Uses **cross-attention** (instead of fixed affine alignment) to handle motion and parallax between input frames — inspired by **ISPRS 2020**.

Applies **dual attention** (spatial and spectral) based on **ESSAformer**, to preserve both detail and spectral accuracy.

Trained with a **physics-based loss** to simulate satellite blur and downsampling, making outputs physically realistic.

Evaluated using real **hyperspectral datasets** like **Chikusei** and **Pavia University** for generalization.

Includes a **blind QA head** (inspired by **MUSIQ** and **HSI-QA**) that scores output quality without needing ground-truth.

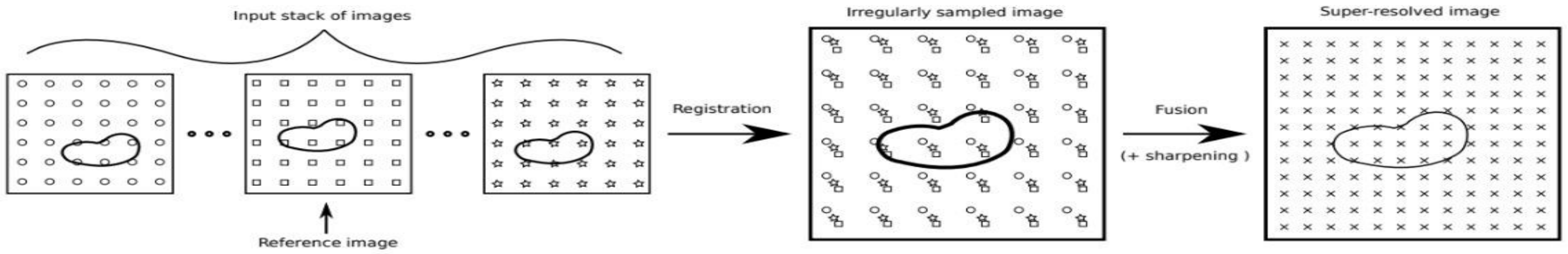


Figure 2. Pipeline of the super-resolution method. Each input image is registered onto a reference image to create an irregularly sampled signal. The uniformly sampled image at the requested resolution is then produced by combining the samples.

List of features offered by the solution

Dual-Frame Hyperspectral Fusion
Uses two slightly misaligned low-res frames to reconstruct one high-resolution image, capturing both spatial and spectral redundancy.

Cross-Attention-Based Alignment
Learns motion-aware alignment instead of relying on fixed geometric transformations, adapting to real-world space scene dynamics.

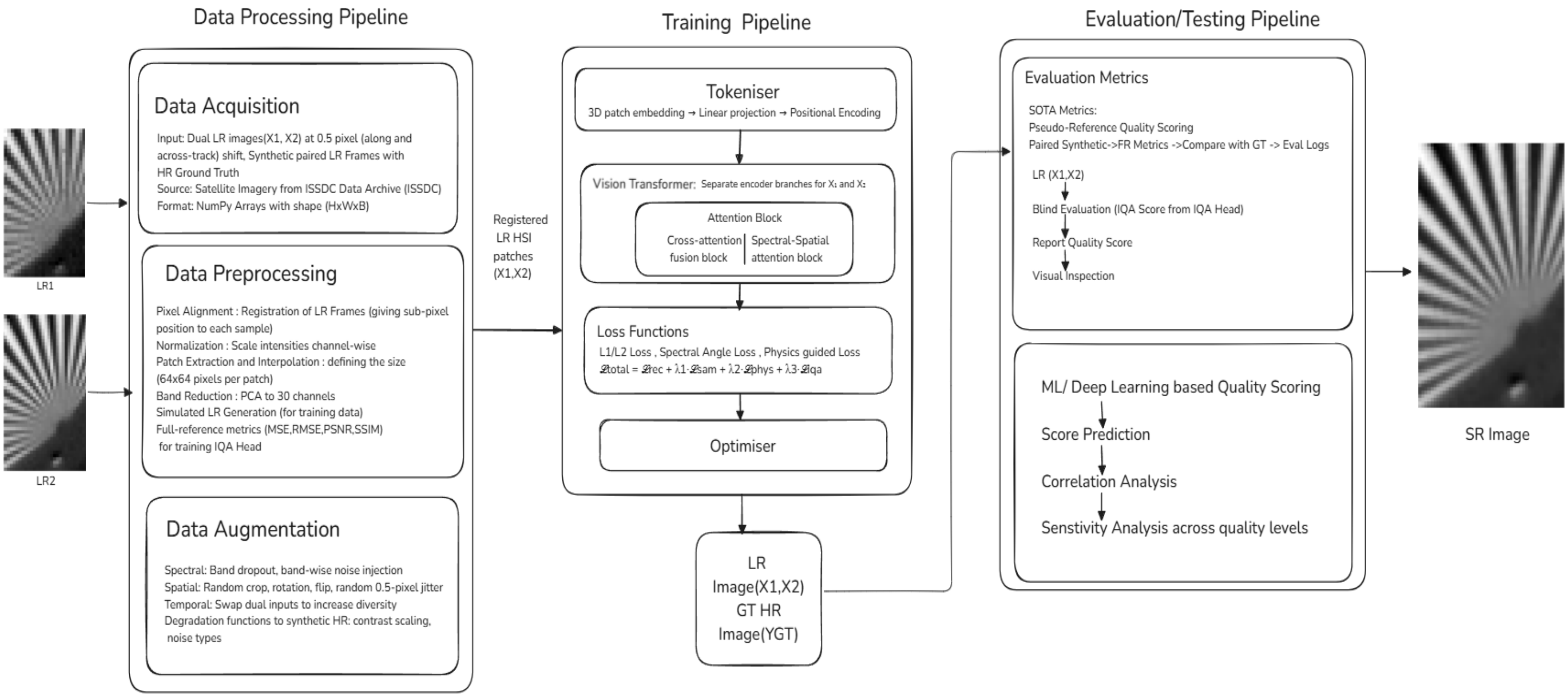
Spectral–Spatial Transformer Design
Separates spectral and spatial attention paths to preserve fine details across bands, crucial for hyperspectral fidelity.

Physics-Constrained Training
Incorporates sensor-specific physics (like blur and downsampling) in training, reducing the chance of unrealistic or hallucinated outputs.

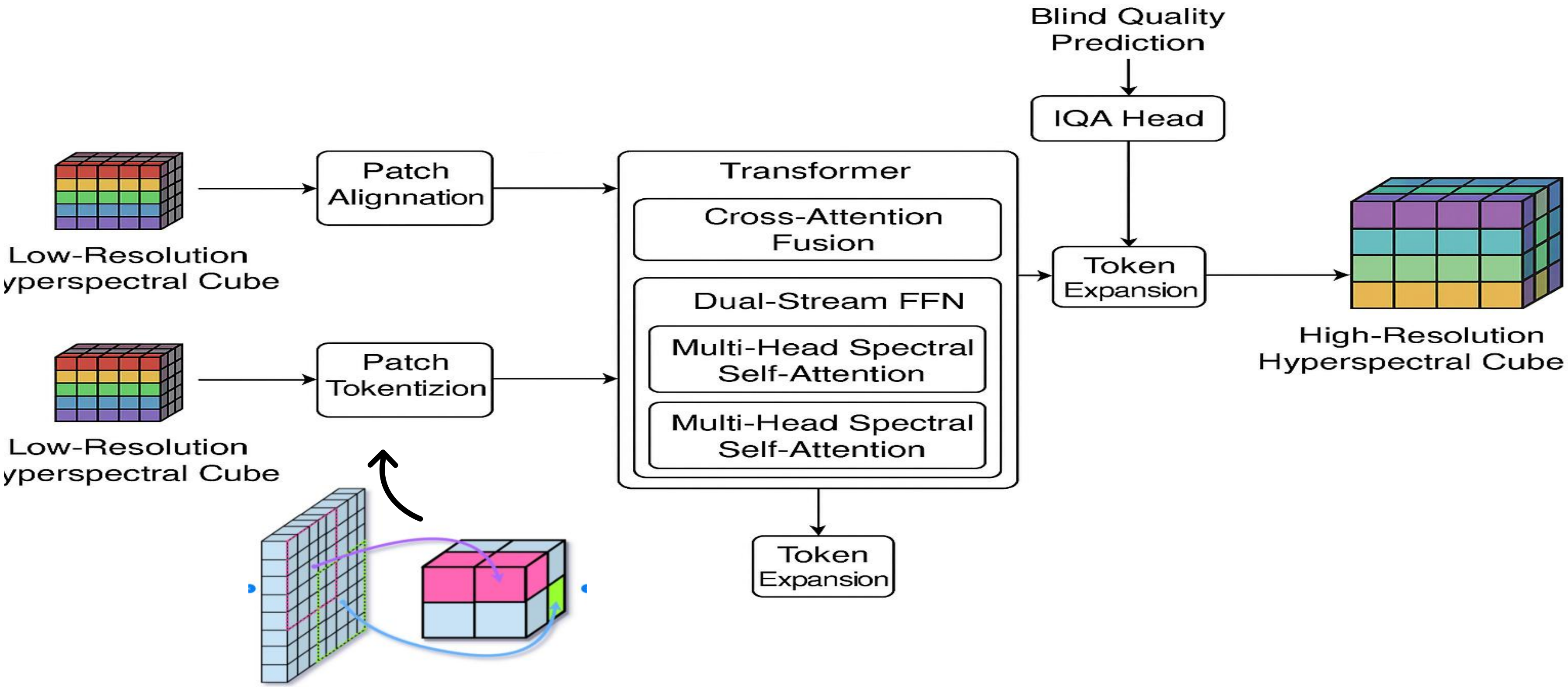
Blind Quality Estimation Head
Predicts image quality in real-time using BRISQUE, NIQE, and DeepIQA scores. No need for reference data — ideal for satellite operations and fast decision-making.

Spectral Fidelity Preservation
Maintains consistency across spectral bands using lightweight convolutional refinement to prevent color distortion.

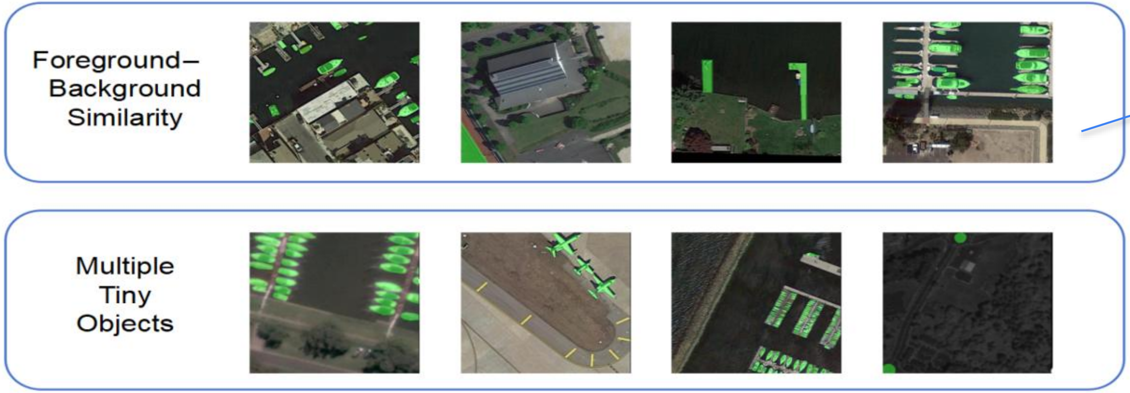
Process Flow Diagram



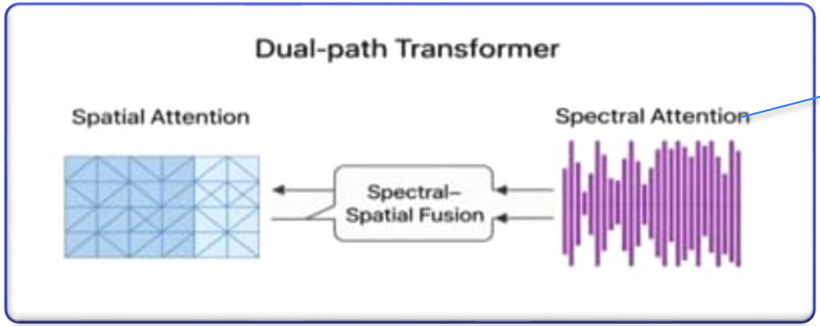
Architecture diagram of the proposed solution



Mock diagrams of the proposed solution



Our model uses **cross-attention** to “look” at both images and learn **which parts match,** even if there is **motion**, terrain **depth**, or **angle change**.



Hyperspectral images have many color bands. Our model uses two attention paths, one finds shapes and edges **(spatial),** and the other understands colors and materials **(spectral).** This helps create clear and accurate images.

Powered by H2S

Technologies to be used in the solution

Data Preparation

We use **Python** and **OpenCV** to extract patches from low-resolution hyperspectral images. PCA is applied to reduce the number of spectral bands.

Tokenization & Encoding

Patches are embedded into 3D tokens using linear projection and positional encoding. This prepares the input for transformer attention layers.

Swin-Transformer (Spectral-spatial attention).

Model Training

Spectral–spatial dual attention is implemented via **Vision Transformers (PyTorch)**.

A physics-based loss ensures HR outputs, when blurred and downsampled, resemble the LR input.

Evaluation

A QA head built using PyTorch regresses quality scores from Transformer features.

It's trained on PSNR/SAM using distorted pairs and tested for sensitivity.

We use **NumPy, SciPy, and Seaborn** for evaluation & correlation analysis.

TorchMetrics (PSNR, SSIM, SAM)

- Python
- PyTorch
- OpenCV
- Matplotlib/Seaborn
- Spectral Python (SPy)

Relevant Datasets for Future Validation

- **Chikusei** – Airborne HSI with 128 bands, 2.5 m resolution (Japan).
  https://naotoyokoya.com/Download.html
- **Pavia University** – Urban HSI with 103 bands, 1.3 m resolution (Italy)
  https://www.ehu.eus/title=Hyperspectral
- **PROBA-V (ESA)** – Multi-frame satellite data with 300 m LR and 100m HR Images.
  https:/Hyperspectral_Remote_Sensing_Scenes
- **Indian Space Science Data Center-** https://www.issdc.gov.in/isda.html

Estimated Implementation Cost

Component	Est. Cost (INR)
GPU Usage (Cloud)	₹35K–₹50K
Dataset Handling	₹5K–₹10K
Model Dev + QA	₹70K–₹1L
Deployment Prep	₹5K–₹10K

Can be reduced using academic credits, Colab Pro, or open-source tools

Citation

Xie et al., *Dual-frame Hyperspectral Image Super-Resolution via Attention-based Fusion*, ISPRS Annals, 2020.

- This setup is scalable, cost-aware, and designed for real-world deployment and validation using publicly available satellite datasets
- In case of limited hyperspectral datasets, we simulate realistic low-res/high-res image pairs using **sensor-specific** degradation models for training.

Powered by H2S

BHARATIYA ANTARIKSH HACKATHON 2025

THANK YOU