Robust Multi-Label Classification of MRI Artifacts in Low-Field Neonatal Brain Imaging via View-Conditional Dual-Task Learning

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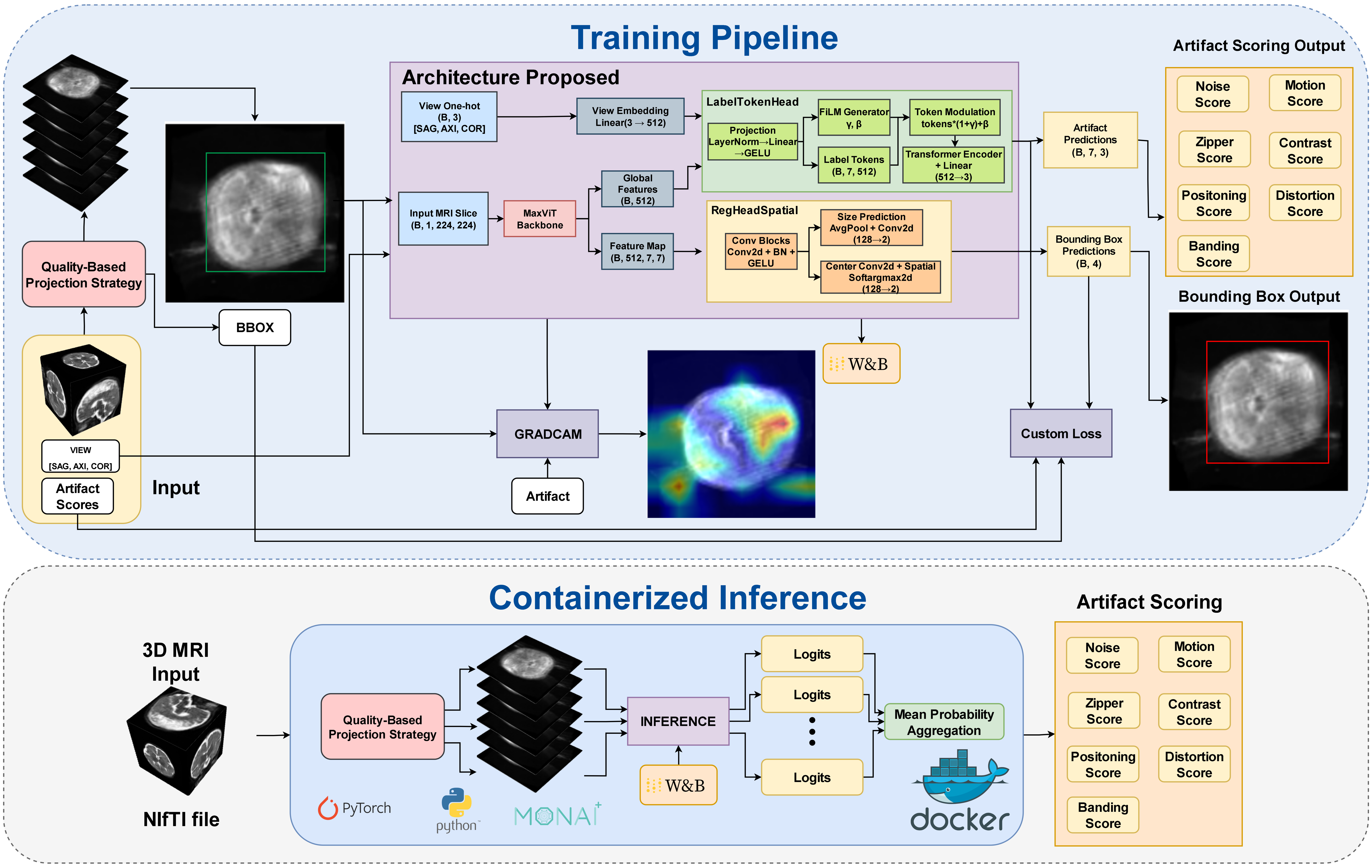

Figure 1. Training and inference pipelines for multi-label artifact classification with spatial attention and containerized deployment.

1. Introduction

LISA Challenge: LISA Task 1 - Multi-label ordinal classification of 7 MRI artifacts (Noise, Zipper, Positioning, Banding, Motion, Contrast, Distortion) in 0.064T pediatric brain scans **(per view: sagittal, axial, or coronal)**.

Key Innovation: Quality-aware 3D-to-2D projection with view-conditional modeling and implicit spatial attention through auxiliary bounding box prediction.

2. Dataset Analysis & Challenge

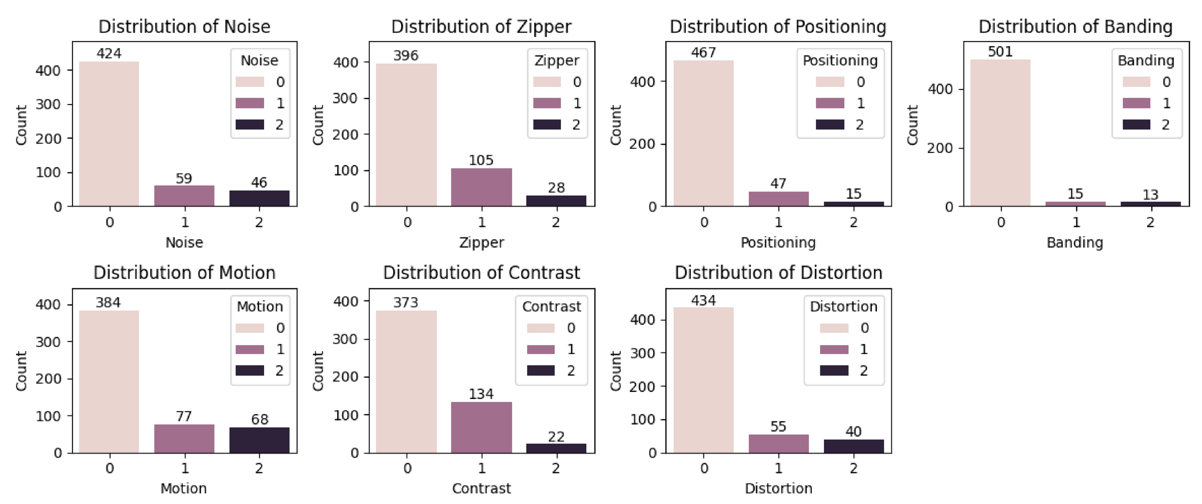

Figure 2. Extreme class imbalance and limited severe examples.

3. Methodology

Quality Projection: Optimal 2D axis (sagittal, 1.5mm).

Brain Localization: Threshold≥0.15 → erosion → dilation.

Dual-Task Net: MaxViT + view embedding,Classification: LabelTokenHead + FiLM , Spatial: RegHeadSpatial (bbox)

Training: 5-fold CV (by patient labels) + Augmentations (gamma, rotation, elastic) + Class-weighted sampling loss

Brain-Focused Processing

Design Choice: Threshold-based brain segmentation.
- Removes background
- Improves bbox init
- Focus on diagnostic regions

Impact:
- Filter slices <10% brain
- Remove 15% non-informative data
- Preserve clinical info

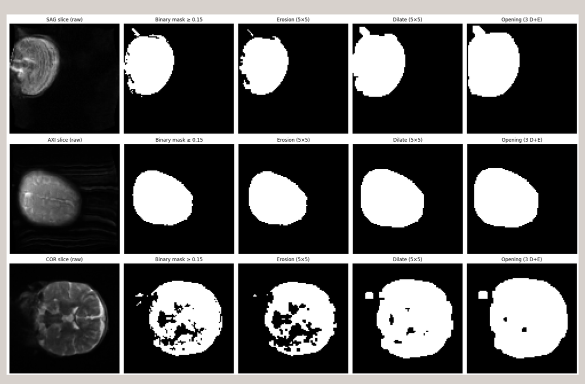

Figure 3. Brain segmentation.

Loss Functions:
- Classification: Dynamic Focal Loss (α=[0.25,0.75,1.0], γ=2.0)
- Localization: Smooth-L1 + GIoU Loss
- Combined: $\mathcal{L} = \mathcal{L}_{\text{focal}} + 0.2(\mathcal{L}_{\text{L1}} + \mathcal{L}_{\text{GIoU}})$

4. Results

Method	F1-macro	F1-micro	F2
Baseline (no conditioning)	0.582	0.791	0.498
+ View conditioning	0.634	0.815	0.549
+ Bounding box task	0.659	0.826	0.568
+ Probability Agg (Full model)	**0.691**	**0.834**	**0.597**

Table 1. Performance comparison showing progressive improvements.

Metric	Noise	Zipper	Position	Banding	Motion	Contrast	Distortion
F1-macro	**0.797**	**0.709**	0.432	0.596	0.594	0.443	**0.754**

Table 2. Per-artifact F1 scores, challenges with Positioning due to extreme imbalance.

5. Key Contributions

- **Quality-aware projection** automatically selects optimal 2D view based on resolution
- **View-conditional modeling** learns view-specific artifact patterns
- **Implicit spatial attention** via auxiliary bounding box task guides focus to brain regions
- **Robust to extreme imbalance** through Stratified Sampling, Data Augmentation, and Focal Loss with dynamic class weights

6. Acknowledgments & Code

Acknowledgments: We thank the RISE-MICCAI 2025 organizers for providing this valuable challenge and dataset.
Open Science Contribution: In the spirit of reproducible research and to support teams working in resource-limited settings, our complete implementation is publicly available:

References

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[2] Lin et al. (2017) Focal loss for dense object detection. ICCV.
[3] Tu et al. (2022) MaxViT: Multi-axis vision transformer. ECCV.