DEEP LEARNING FOR MICROPLASTIC CLASSIFICATION

Group 9:

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PROBLEM DEFINITION & HYPOTHESIS

01

Problem: Manual microplastic identification is slow, subjective, and inconsistent.

02

Goal: Develop an automated classification model using deep learning.

03

Hypothesis: Vision Transformer (ViT) will outperform CNNs and classical ML models by capturing global spatial context and texture relationships.

EXPERIMENTAL SETUP

- Dataset: DeepParticle (MICRO) – six classes (foam, hard, line, noise, pellet, reference).
- Preprocessing: resize, normalization, augmentation (flip, rotate, brightness, Gaussian noise).
- Class Balancing: SMOTE oversampling used to balance imbalanced classes.
- Train/val/test: 70/15/15 split, Batch size: 32, Epochs: 100, Optimizer: Adam (1e-4), Loss: CrossEntropy, Early Stopping: 10 epochs
- Metrics: Accuracy, precision, recall, F1 score, per-class IOU Scores, Confusion matrix.
- Explainability Factor: Grad-CAM applied to visualize discriminative image regions.

MODEL OVERVIEW

Model	Type	Implementation Summary
Random Forest Classifier	Classical ML	200-tree ensemble using handcrafted features (GLCM texture, intensity statistics, entropy, edges).
Support Vector Machine (SVM)	Classical ML	RBF kernel (C=10, gamma='scale'), trained on same handcrafted features.
VGG16 (Fine-tuned)	Deep Learning (CNN)	Pretrained VGG16 from ImageNet. Feature extractor layers frozen; fully connected head replaced with Linear(4096 → 6) for six classes.
Resnet-50	Deep Learning (CNN)	Pretrained on ImageNet. Backbone frozen. Fully connected layer replaced with: Linear(in_features → 512) → ReLU → Dropout(0.4) → Linear(512 → num_classes)
ViTs	Deep Learning (Transformers)	Pretrained ViT-B/16, encoder frozen, classification head replaced with Linear(embed_dim → num_classes)

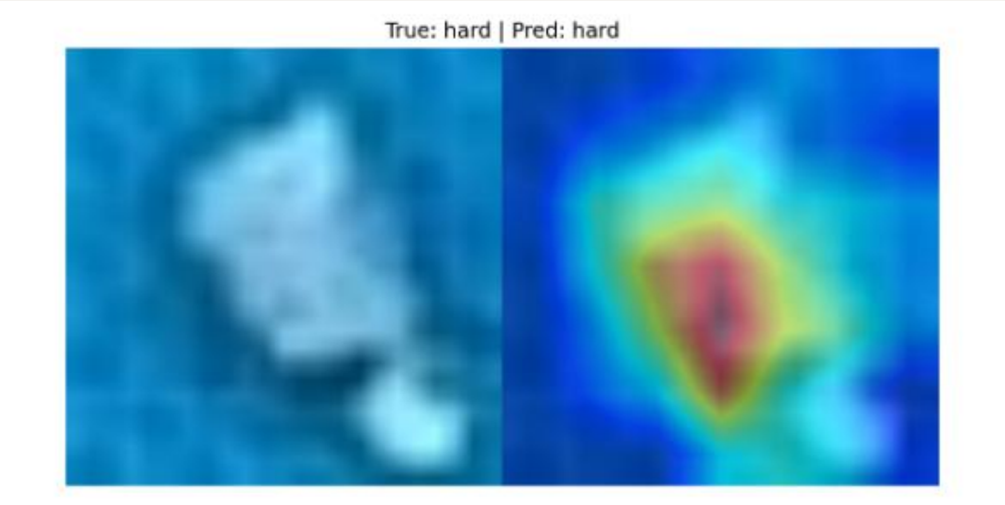
KEY RESULTS (IOU PER CLASS)

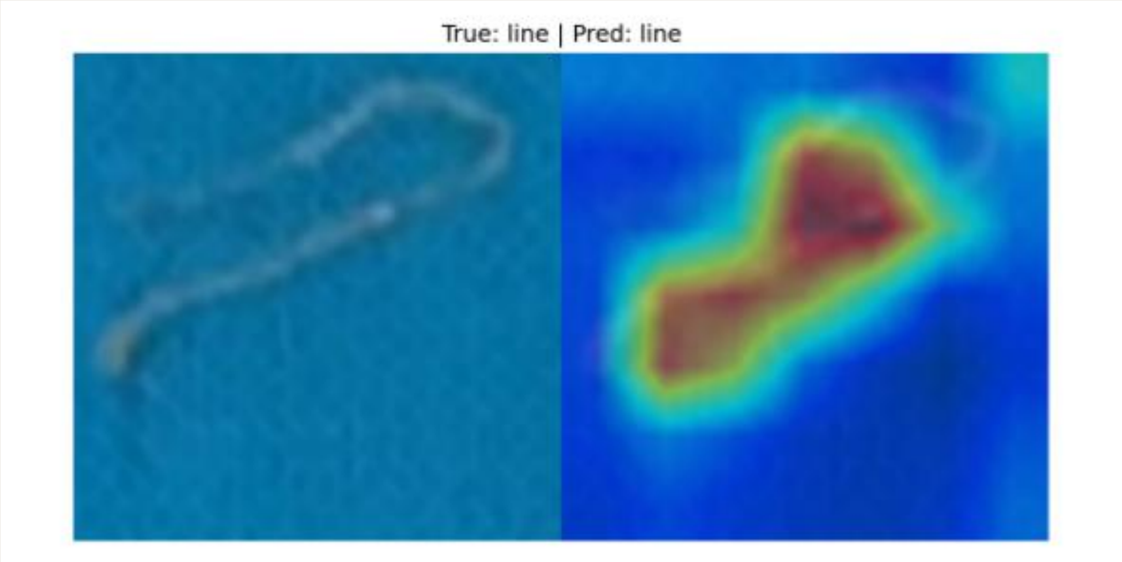
Class	Random Forest	SVM	VGG16	ViTs	ResNet50
Foam	0.3182	0.4762	0.7826	**0.9091**	0.8696
Hard	0.8598	0.8612	0.9478	**0.9593**	0.9106
Line	0.7767	0.7573	0.9038	**0.9216**	0.8288
Noise	0.7885	0.7037	**0.9184**	**0.9098**	0.8148
Pellet	0.2353	0.1406	0.7671	**0.7971**	0.6790
Reference	0.8889	0.8889	1.0000	**1.0000**	1.0000

KEY RESULTS (METRICS)

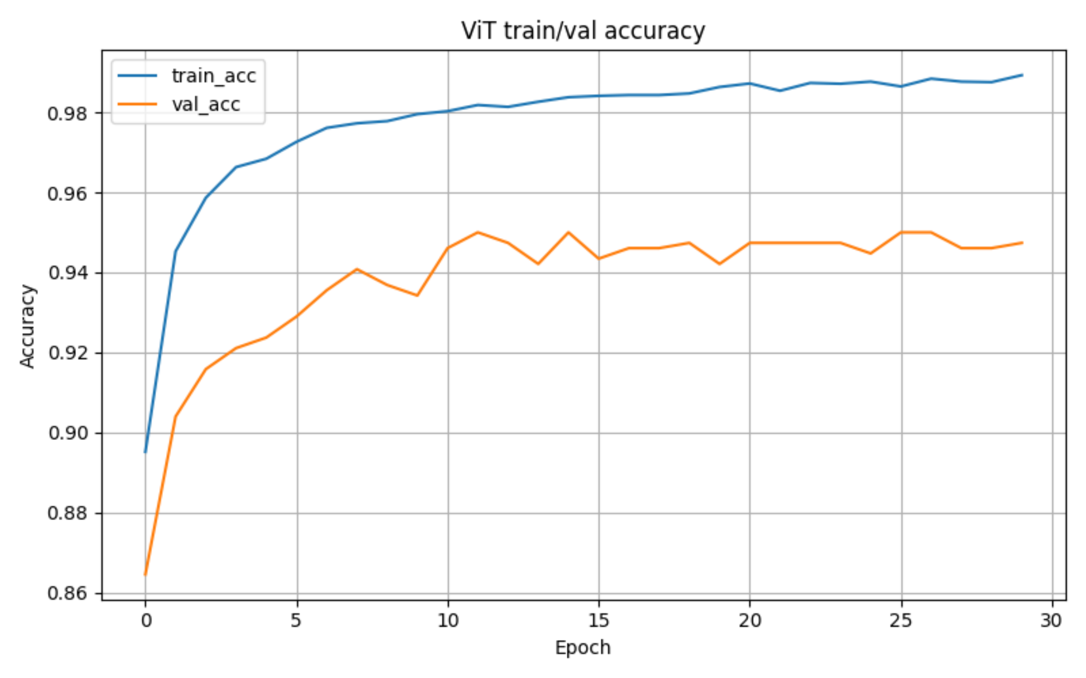
Model	Epochs	Accuracy	Precision	Recall	F1 Score
RF	-	0.87	0.84	0.710	0.748
SVM	-	0.87	0.85	0.718	0.741
Resnet-50	31	0.93	0.88	0.96	0.92
VGG	19	0.97	0.96	0.96	0.96
ViTs	30	**0.98**	**0.97**	**0.97**	**0.97**

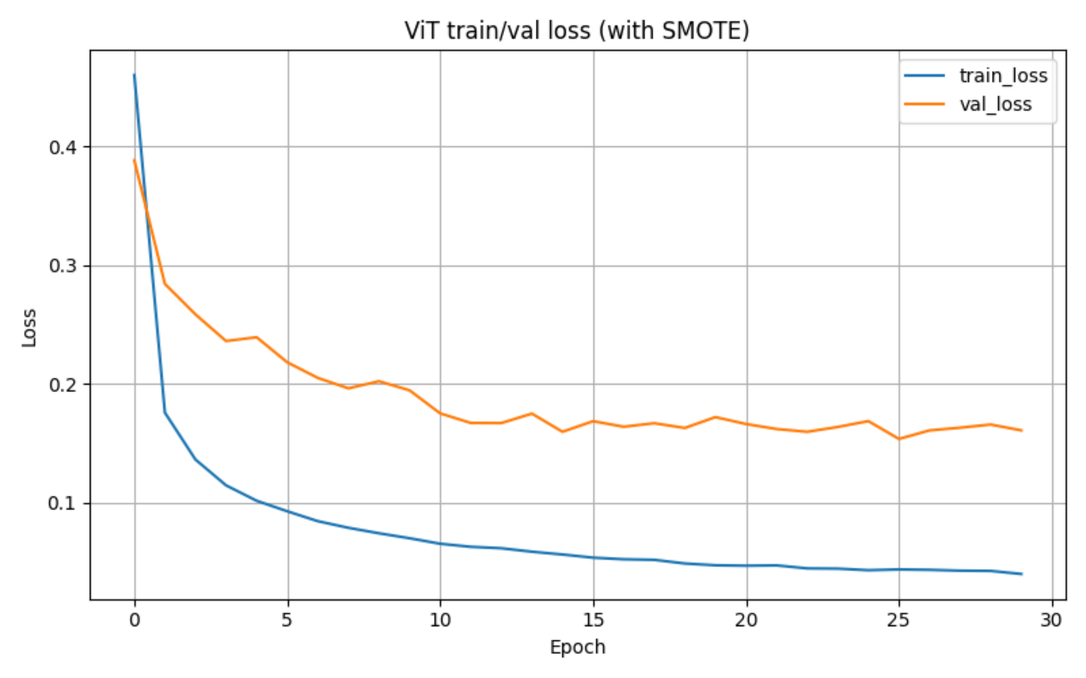
FIGURES (GRAD-CAM)



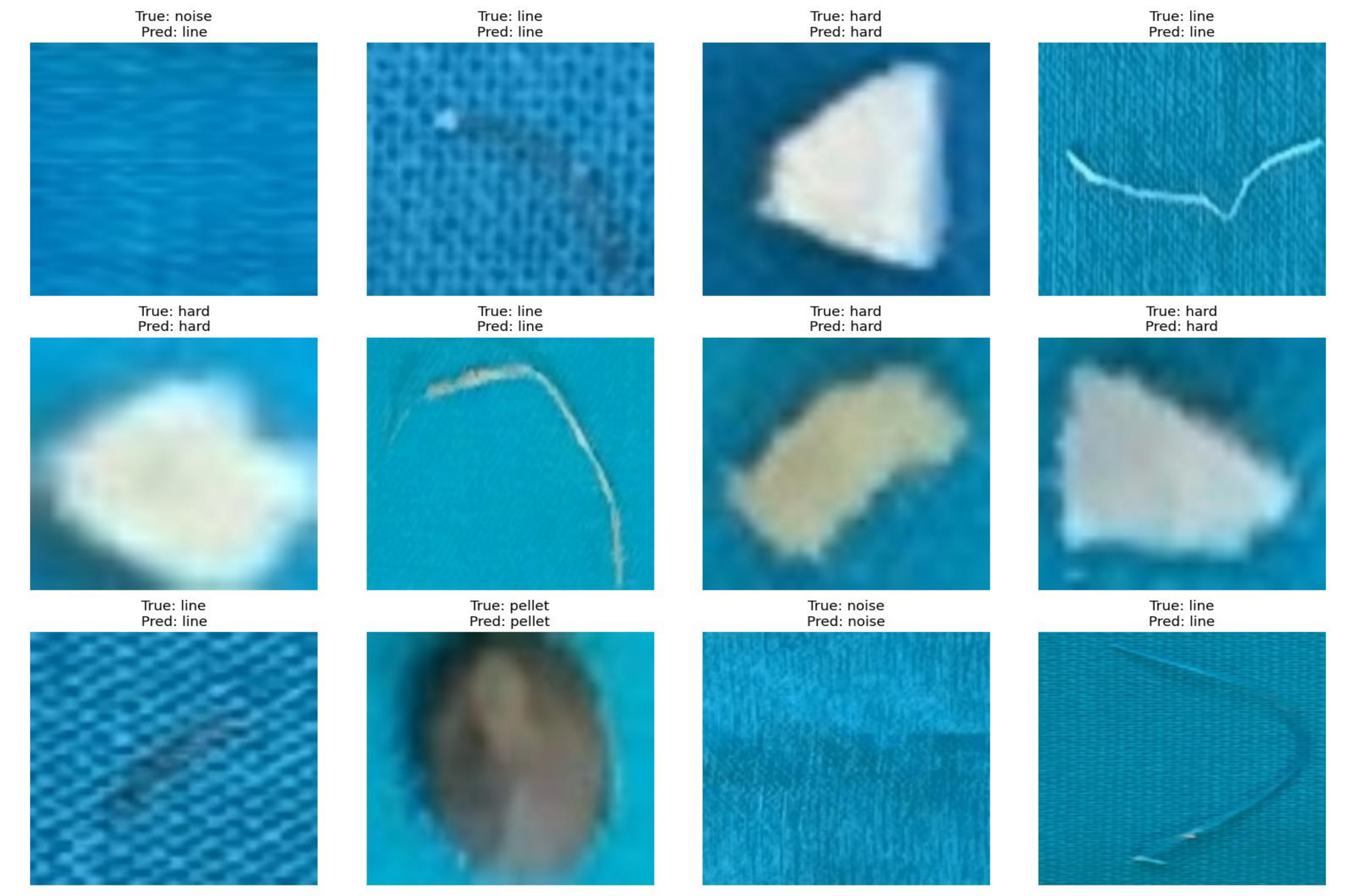


FIGURES (LOSS CURVES)





FIGURES (PREDICTIONS)



STATISTICAL FINDINGS

Classical ML biased toward majority classes → lower IOU for minority categories.

Deep models reduce this gap, especially ViTs.

Only minor overfitting observed (train vs val curves close).

SMOTE helped balance classes but cannot fully simulate texture diversity—may introduce noise.

LESSONS LEARNED

- Fine-tuning pre-trained CNNs drastically improves performance with limited data.
- Explainability tools (Grad-CAM) are crucial for environmental AI applications.
- Balanced datasets are essential for fair evaluation across all classes.
- Data augmentation and transfer learning enhance robustness.

FUTURE WORK

- **Mask R-CNN Segmentation**: Identify particles and extract exact boundaries for size and area measurements.
- **Semi-Supervised Learning**: Reduce labeling effort using pseudo-labels and consistency regularization.
- **Hybrid CNN–ViT Models**: Combine CNN texture features with ViT global attention for improved accuracy.
- **Cross-Domain Validation:** Test models on images from different labs/microscopes to ensure robustness.
- **Real-World Deployment:** Integrate best model into an automated lab/field microplastic analysis pipeline.

CONCLUSION

- Automation of microplastic classification using deep learning on microscopy images.
- Compared classical ML (SVM, Random Forest) with deep models (ViT, ResNet-50,VGG16).
- Fine-tuned Vision Transformer (ViT) achieved 98 % accuracy and macro F1 = 97%.
- Grad-CAM visualizations enhanced interpretability of class regions.

THANK YOU

CODE LINK:

https://github.com/nikkiray309/DeepLearning-for-MicroPlastic-Classification/tree/main