Texture Based Explainable Machine Learning for Automated Glacial Crevasse Detection in GPR Radargrams

***Ripul Ghosh*[1,2]**, *Ashish Lawaniya*[1], *Anuj Kumar Mishra*[1,2], *Sergey Popov*[3,4], *Marina Kashkevich*[3], *Margarita Stepanova*[5], *Satish Kumar*[1,2]

[1]Centre of Excellence for Intelligent Sensors and Systems (iSenS), CSIR-Central Scientific Instruments Organisation, Chandigarh 160030, India
[2]Academy of Scientific and Innovative Research (AcSIR), Ghaziabad 201002, India
[3]Institute of Earth Sciences, Saint Petersburg State University, Saint Petersburg 199178, Russia
[4]Gramberg All-Russian Scientific Research Institute for Geology and Mineral Resources of the World Ocean (VNIIOkeangeologia), Saint Petersburg, Russia
[5]The Faculty of Physics, Saint Petersburg State University, Saint Petersburg 199178, Russia

The 10th International Conference in Deep Learning in Computational Physics (DLCP 2026)

Introduction

- Glacial crevasses are hidden fractures concealed beneath snow bridges, posing serious risk to vehicles, aircraft, robotic systems and field personnel in Antarctica.

- Ground Penetrating Radar (GPR) enables non-destructive subsurface imaging for the identification of hidden crevasse formations.

- Crevasse structures in radargram are typically represented through hyperbolic diffraction signatures embedded within noisy subsurface reflections.

- Traditional interpretation of radargram requires extensive manual inspection and expert-driven analysis, limiting operational scalability.

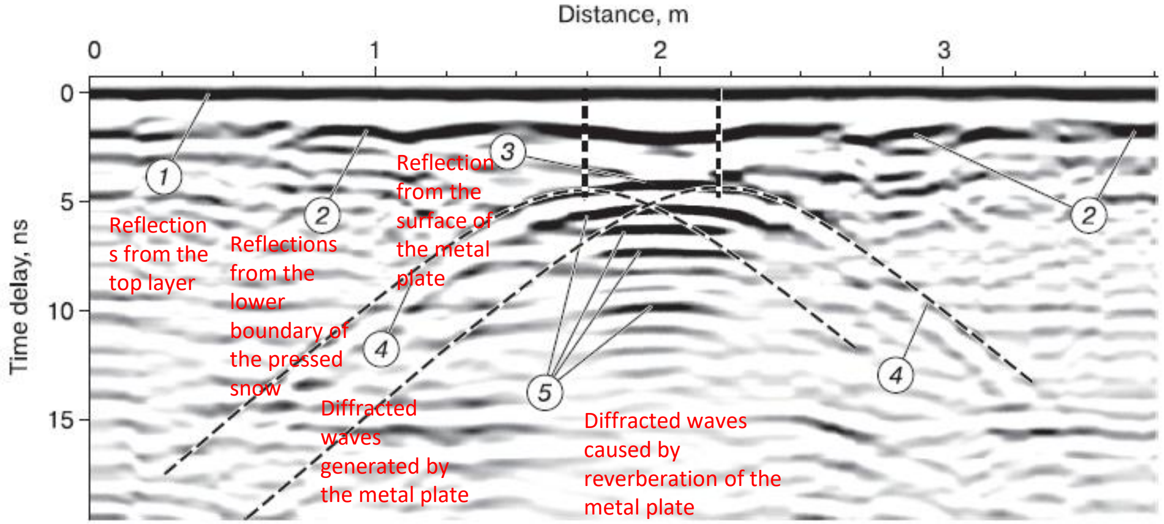
Popov, S. V., and S. P. Polyakov. "Ground Penetrating Radar Sounding Of Ice Crevasses In The Area Of The Russian Progress And Mirny Stations (East Antarctica) During The Field Season of 2014/15." (2016).

Objectives

- Automated feature extraction and classification frameworks for robust identification of crevasse patterns using GPR data.

- Explainable AI based feature selection

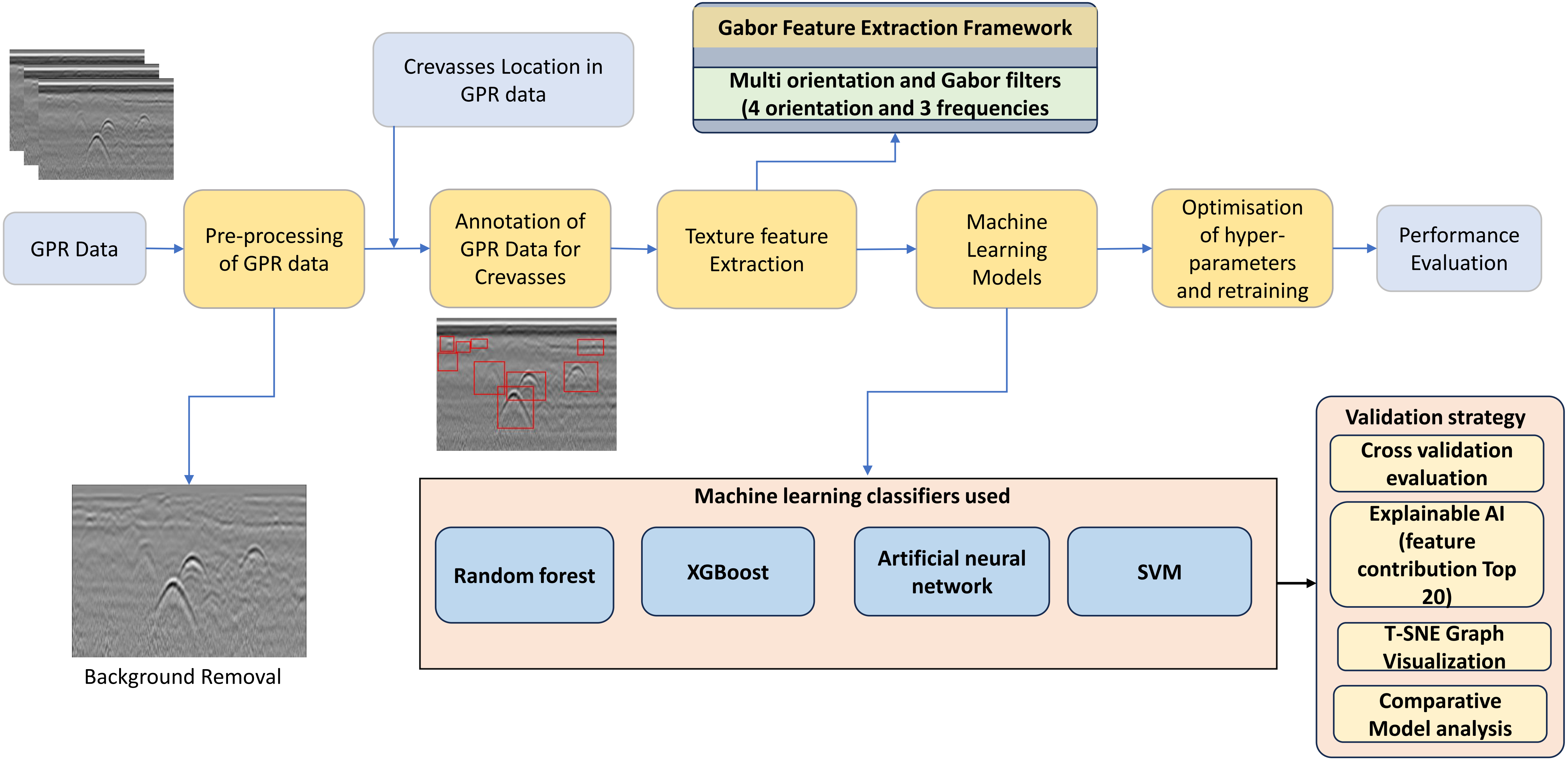
- Evaluation of texture based machine learning models for automated detection of crevasse with background radargram signatures.



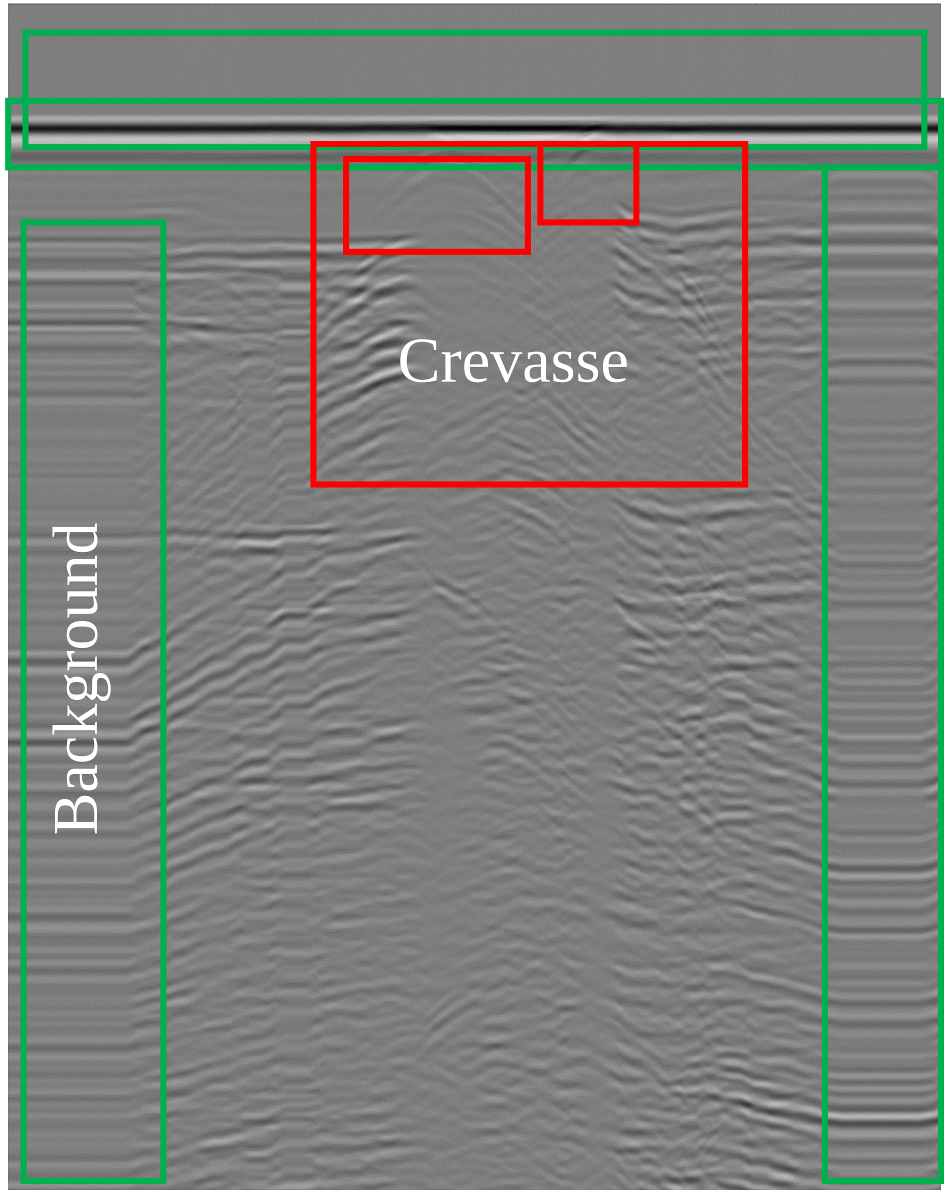
A GPR time-section over the model crevasse with a metal plate on the bottom in the area of the planned runway of the Progress Station.

Popov, S. V., and S. P. Polyakov. "Ground Penetrating Radar Sounding Of Ice Crevasses In The Area Of The Russian Progress And Mirny Stations (East Antarctica) During The Field Season of 2014/15." (2016).

Methodology



GPR Labelling Tool



- Developed a custom GPR annotation tool for manual labeling of hyperbola and background regions.
- Supports bounding box annotation, dataset navigation, and label management for efficient dataset preparation.
- Enabled creation of a high-quality labeled dataset for training the proposed machine learning framework.

Dataset Description

Field Survey Sites

Real surveys near Mirny Station (runway siting) and along the Progress–Vostok logistic traverse, East Antarctica.

50%

Sliding-window overlap in both dimensions for spatial localisation and sample diversity

Annotation Format

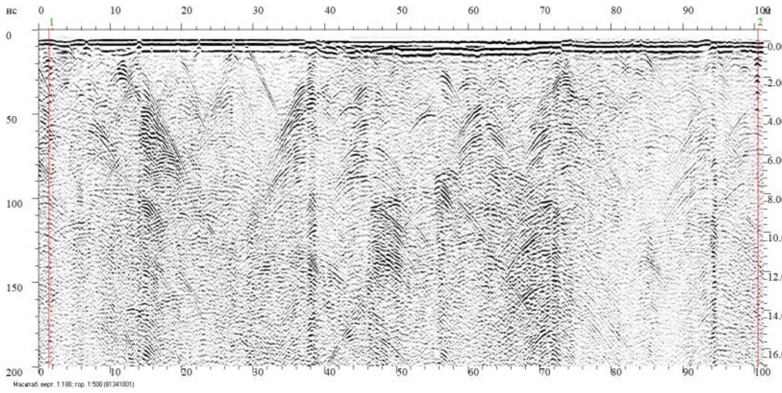
Each patch manually labelled as background or crevasse (hyperbola), stored in COCO format.

503

Labelled radargram image patches, each 512×512 pixels

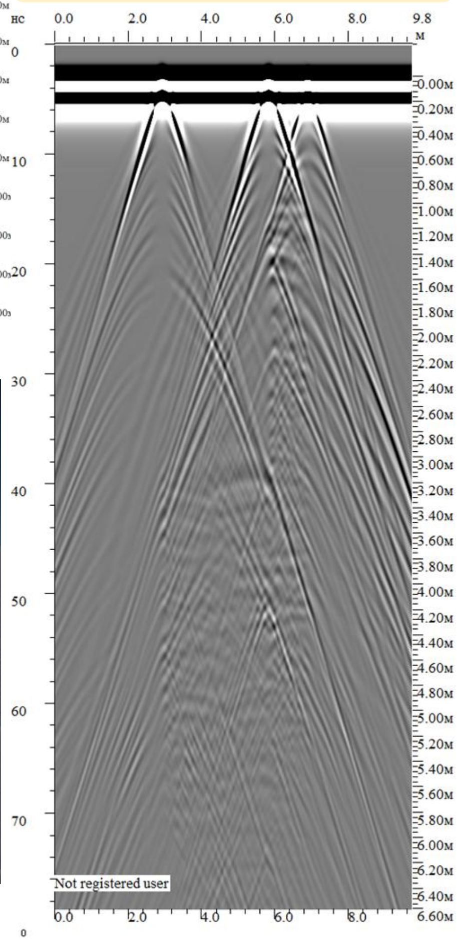
297

Real, field-acquired patches-
OKO-2 GPR, 400 & 150 MHz



206

Synthetic patches from gprMax-150, 400 & 900 MHz



Texture-Based Feature Extraction

Gabor Filtering

Captures **multi-scale texture orientation with frequency responses.** Consistently the **strongest-performing descriptor** in our results.

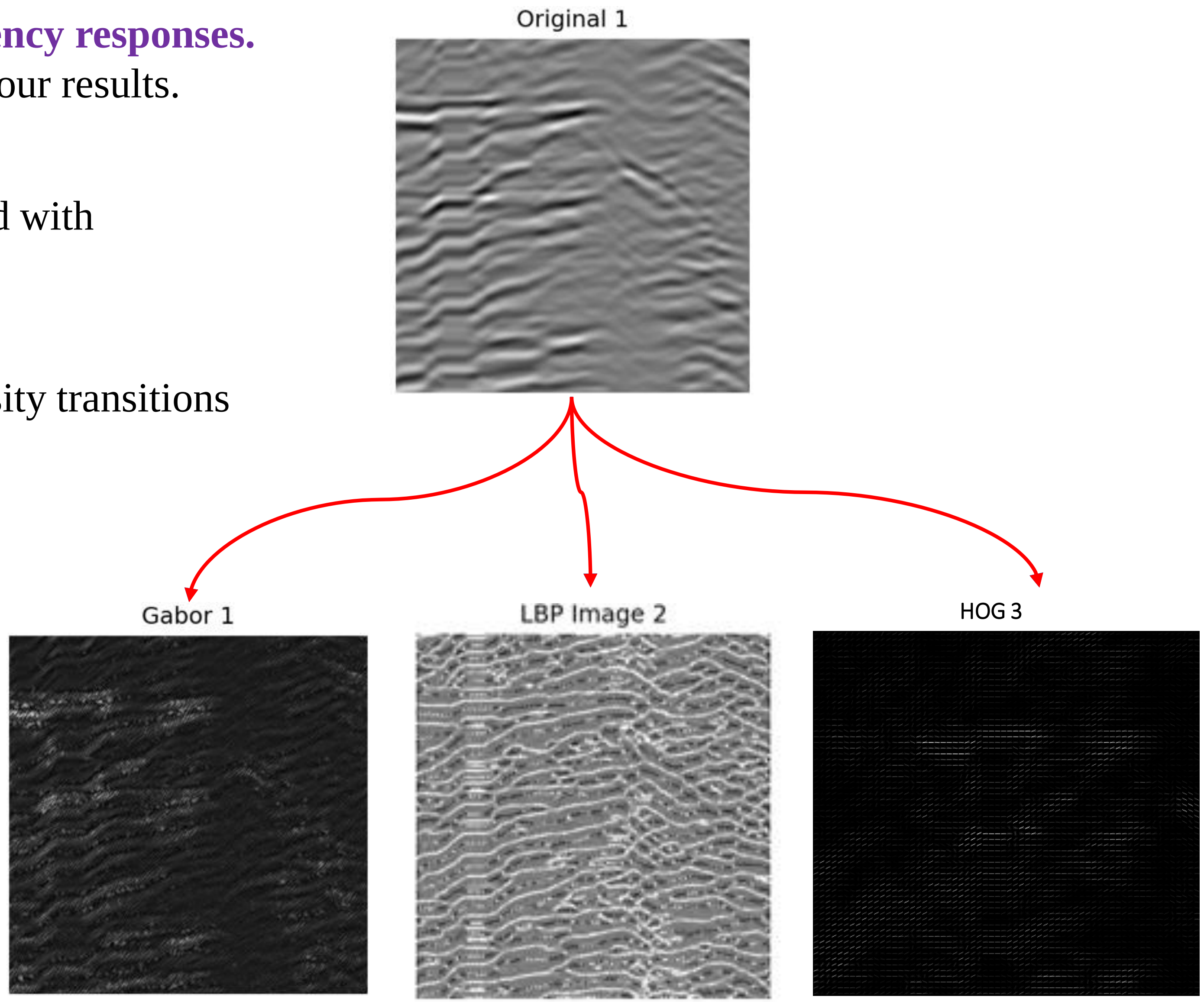
Histogram of Oriented Gradients (HOG)

Represents **local edge-orientation patterns** associated with hyperbolic reflection boundaries.

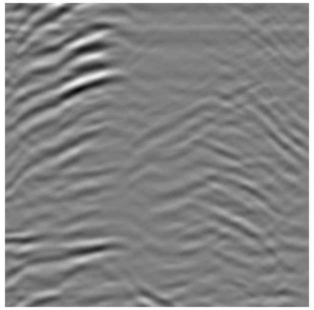
Local Binary Pattern (LBP)

Characterises **local texture micro-patterns** and intensity transitions present in radar reflections.

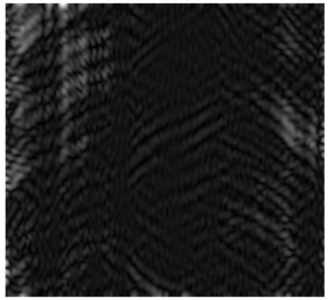
HOG	Orientations	**9**
	Pixels per Cell	**8 × 8**
	Cells per Block	**2 × 2**
	Block Normalization	**L_2-Hys** *(HOG-RF-XGB)*
Gabor Feature	Orientations (θ)	**0°, 45°, 90°, 135°**
	Frequencies	**0.1, 0.3, 0.5**
	Statistics Extracted	**Mean, Variance, Energy**
	Total Features	**36 Features/Image**
LBP Feature	Radius (R)	**3**
	Neighbors (P)	**24**
	Method	**Uniform**
	Histogram Bins	**P + 2 = 26**



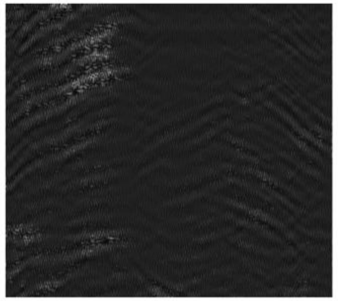
Gabor Filtered GPR Images



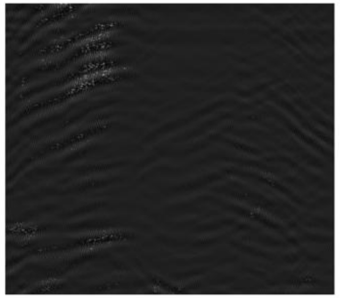
θ=0°
f=0.1



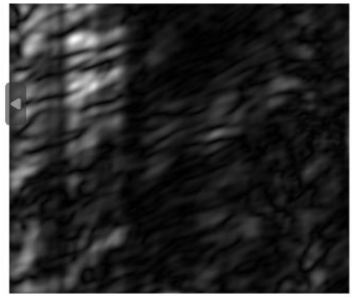
θ=0°
f=0.3



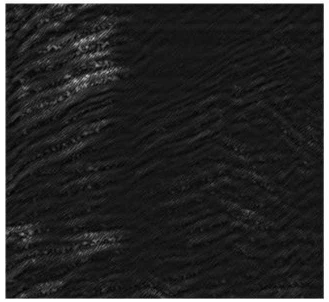
θ=0°
f=0.5



θ=45°
f=0.1

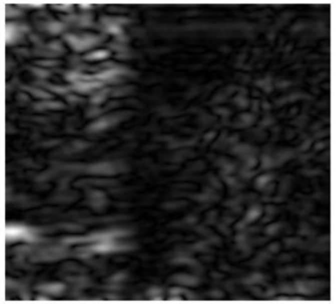


θ=45°
f=0.3



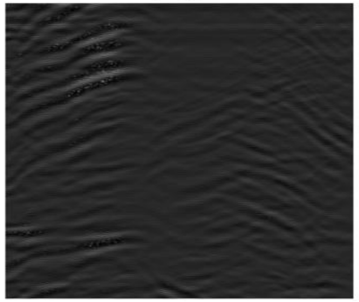
θ=45°
f=0.5

θ=90°
f=0.1

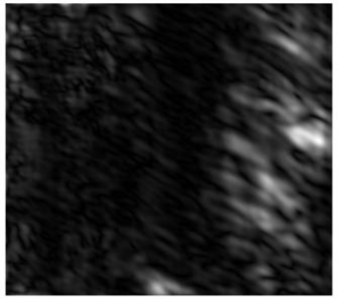


θ=90°
f=0.3

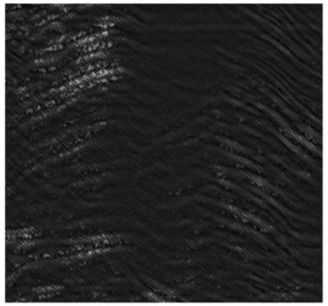
θ=90°
f=0.5



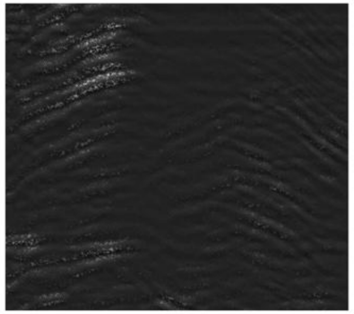
θ=135°
f=0.1



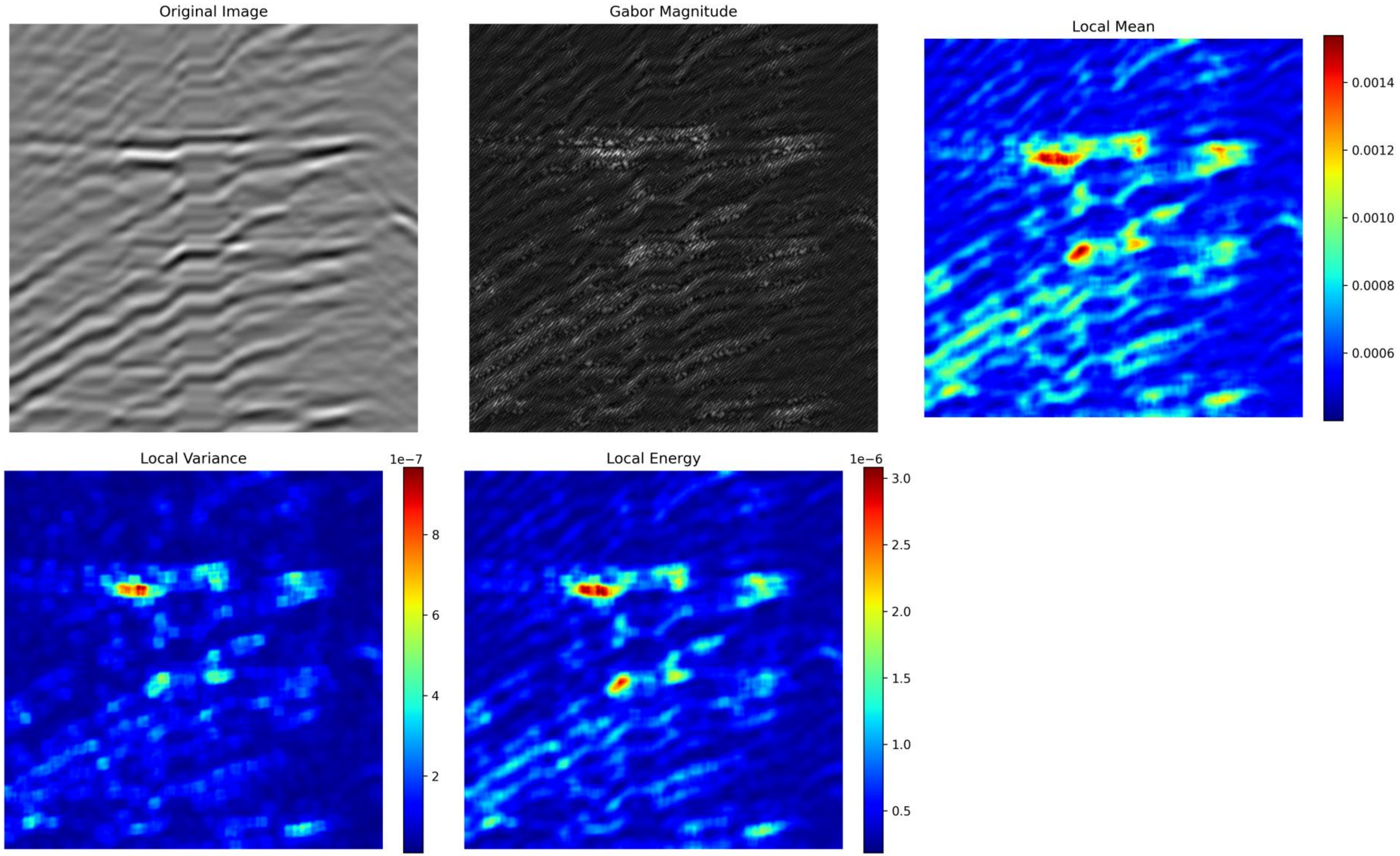
θ=135°
f=0.3



θ=135°
f=0.5



Gabor-features extracted images



Hyper-parameter comparison

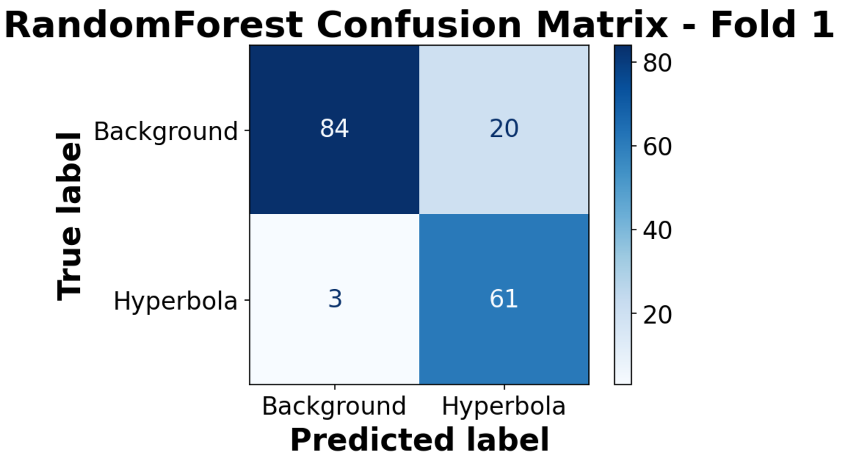
Category	Hyper-parameter	Value Used
General	Random Seed	42
	Cross Validation	3-Fold Stratified
	Validation Split	0.15
	Feature Scaling	StandardScaler (ANN, SVM, RF-XGB models except LBP-RF)
	Threshold Optimization	0.25–0.75
Random Forest	Number of Trees	500
	Maximum Depth	None
	Class Weight	Balanced
	Parallel Jobs	n_jobs = -1
XGBoost	Number of Trees	500
	Maximum Depth	6
	Learning Rate	0.05
	Subsample Ratio	0.8
	Column Sampling	0.8
	Early Stopping	30 Rounds
	Class Imbalance	scale_pos_weight
	Parallel Jobs	n_jobs = -1

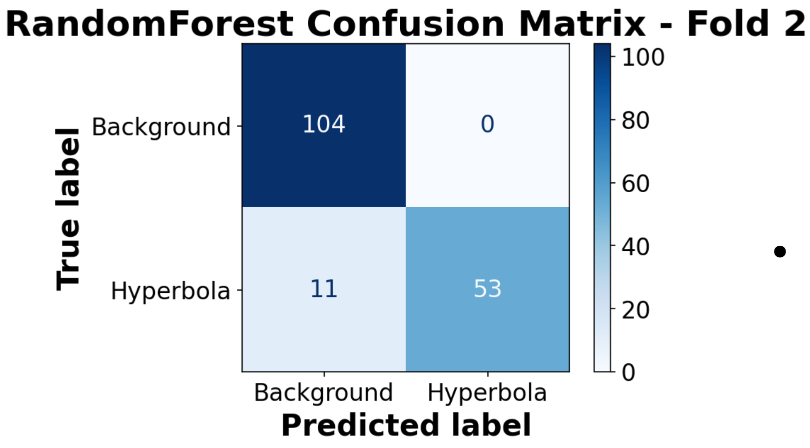
Results: 3-Fold Cross-Validation Performance

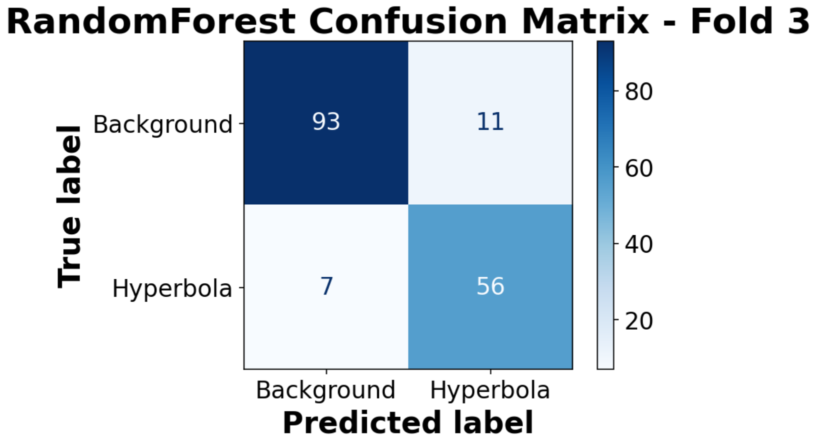
Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Gabor ANN	0.8747	0.8587	0.8326	0.8330	0.9616
Gabor Random Forest	**0.8966**	**0.8629**	**0.8900**	**0.8696**	**0.9712**
Gabor XGBoost	0.8926	0.8727	0.8432	0.8541	0.9637
Gabor SVM	0.8647	0.8097	0.8422	0.8221	0.9425
HOG ANN	0.8827	0.9201	0.7645	0.8314	0.9149
HOG Random Forest	0.8608	0.8233	0.8215	0.8178	0.9469
HOG XGBoost	0.8449	0.7614	0.8637	0.8091	0.9292
LBP Random Forest	0.8847	0.8501	0.8484	0.8482	0.9627

Gabor Random Forest gives the best overall balance of accuracy, F1-score and AUC-ROC. Gabor-based descriptors outperform HOG and LBP across every classifier tested.

Confusion Matrices Across Folds

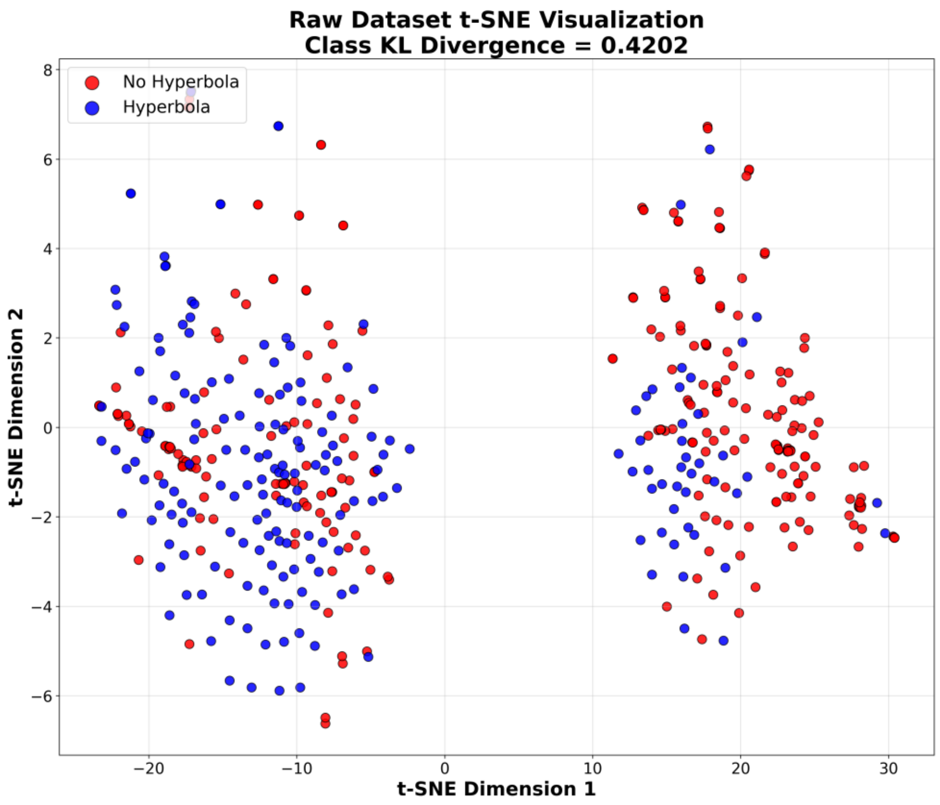


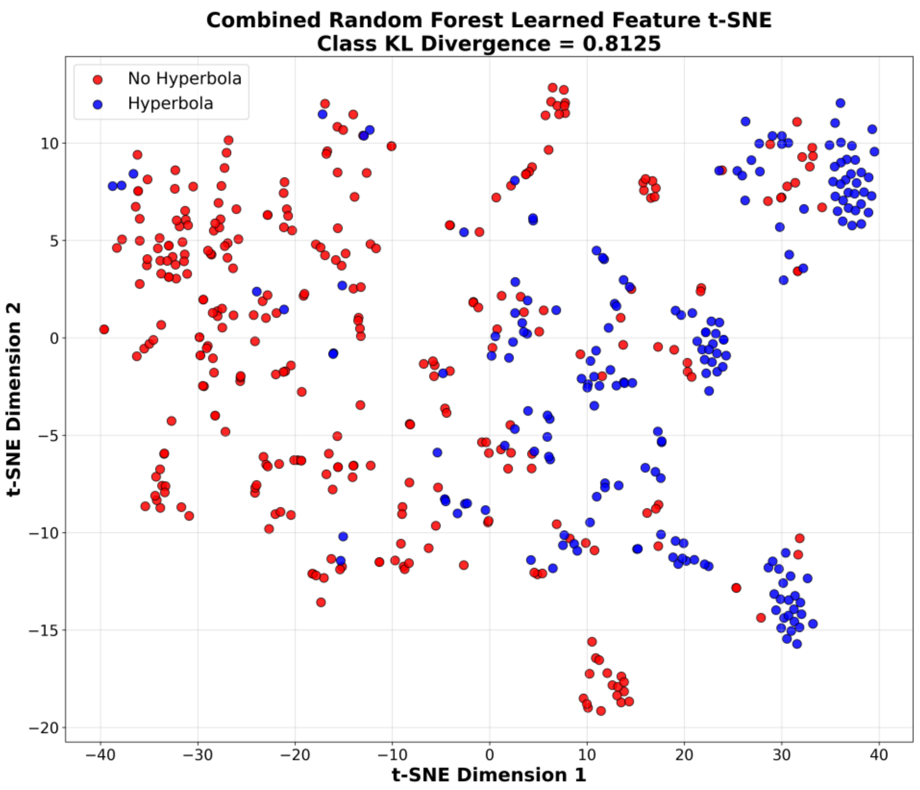




- Confusion matrices from the three-fold cross-validation show consistently high true-positive and true-negative counts, indicating effective discrimination between crevasses and background patches.
- Fold 1 shows the fewest false negatives for crevasse, which is the most operationally important error, since a missed crevasse is a hazard left undetected in the field.

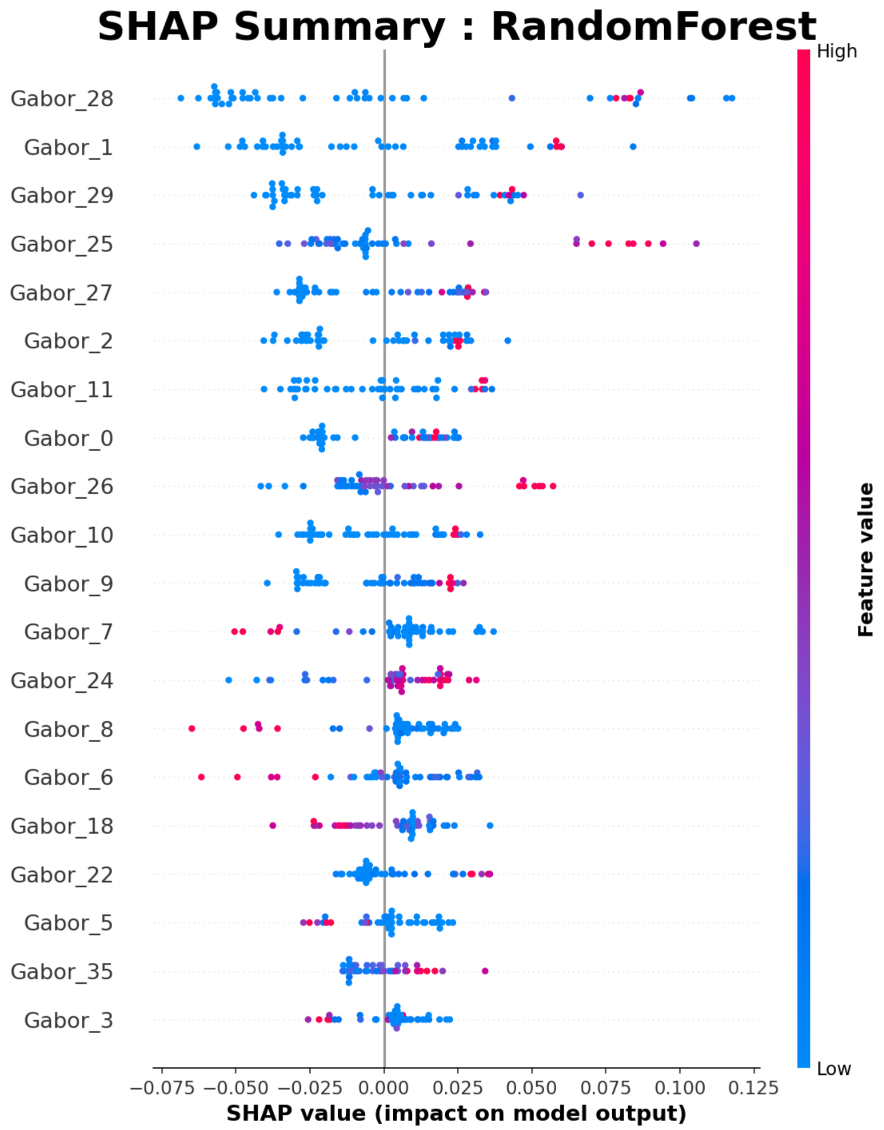
Feature Separability: t-SNE Visualization





- Raw feature space (left graph) shows substantial overlap between crevasse and background samples with KL divergence of 0.4202.
- Learned Gabor feature space (right graph) shows distinct, well-separated clusters for each class with higher KL divergence of 0.8125, indicating stronger discriminative structure.

SHAP-Based Feature Importance Analysis

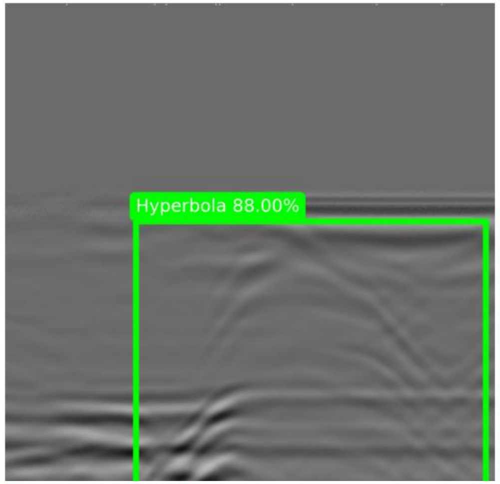


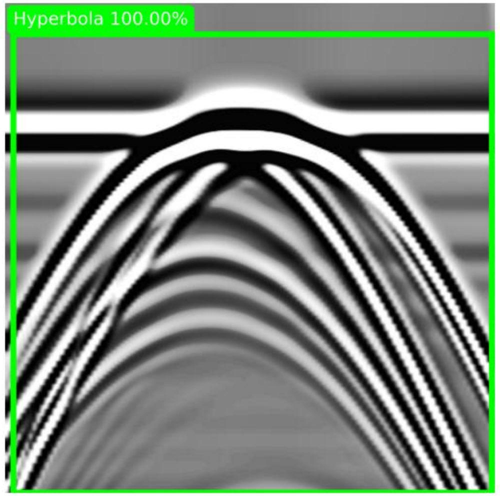
- SHAP (SHapley Additive exPlanations) was used to interpret the decision-making process of the Random Forest classifier.
- The analysis identifies the most influential Gabor texture features contributing to hyperbola detection performance.
- Features such as Gabor_28, Gabor_1, Gabor_29, and Gabor_25 showed the highest impact on classification outcomes.
- Positive SHAP values indicate features pushing predictions toward the Crevasse class, while negative values favor the Background class.

SHAP Explainability	Background Samples	**50** (ANN/SVM), **100** (RF/XGB)
	Explained Samples	**20** (ANN/SVM), **50** (RF/XGB)
	Displayed Features	**Top 20**
	Explainer	**DeepExplainer (ANN)** **KernelExplainer (SVM)** **TreeExplainer (RF/XGB)**

Key Findings

- Gabor Random Forest is the best-performing model attaining Accuracy 0.8966, Precision 0.8629, Recall 0.8900, F1-Score 0.8696, AUC-ROC 0.9712.
- Gabor-based texture descriptors consistently outperform HOG and LBP across all four classifiers, confirming that frequency- and orientation-sensitive analysis best characterises GPR hyperbolic reflections.
- Gabor-Random Forest achieves a 23.6% reduction in False Negative Rate (FNR) compared to HOG XGBoost, directly translating to fewer missed crevasses in the field.
- SHAP explainability confirms which texture features drive each decision, giving field operators a transparent basis for trusting automated detections.
- The framework offers a computationally efficient, interpretable alternative to deep learning, well suited to real-time deployment during Antarctic field operations.





Conclusion & Future Work

- Handcrafted texture descriptors combined with lightweight classical ML classifiers provide a computationally efficient and highly interpretable alternative to deep learning for automated crevasse detection.
- The Gabor + Random Forest combination, supported by SHAP explainability, offers the strongest balance of accuracy, robustness and transparency for safety-critical field use.
- This framework is particularly valuable for real-time field deployment where power, compute and interpretability constraints rule out heavier deep learning pipelines.
- Future work: extending validation to larger and more diverse real-field radargram datasets, and exploring hybrid handcrafted + learned feature pipelines.

Thank You

Acknowledgement:

This research work is supported by CSIR-SPbU collaborative Project Grant No: IST552509