Advancing SAR Target Recognition through Self-supervised Learning A Vision for Enhanced ATR System

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Project Overview

Synthetic Aperture Radar (SAR) Automatic Target Recognition (ATR) is challenged by limited labeled data and significant variability in target signatures. While synthetic data has been used to mitigate this issue, it often fails to capture the complex electromagnetic scattering characteristics present in real measured SAR images. This work introduces a novel self-supervised learning (SSL) framework that eliminates synthetic data dependency while achieving new performance benchmarks with strong data and computational efficiency. In addition, we conduct a systematic layer-wise representation analysis to understand how different network depths impact SAR feature transferability.

Fig. 1. McDonnell Douglas MD-80 aircraft and Airbus A300-600R jetliners [1]

Motivation

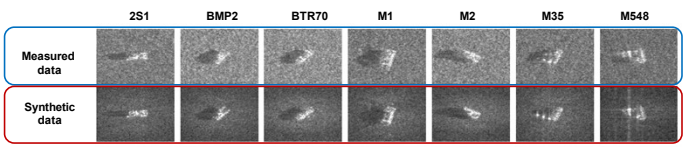


Figure 2. Measured and synthetic data in SAMPLE [2] dataset

Data Scarcity Crisis: SAR ATR systems suffer from severe labeled data limitations due to high collection costs, security constraints, and expert annotation requirements.

Synthetic-Real Domain Gap: Existing synthetic data generation approaches fail to bridge the domain gap between simulated and measured imagery (Figures 2, 4).

Operational Constraints: Real-world SAR systems must handle diverse environmental conditions, sensor configurations, and target orientations while maintaining computational efficiency for deployment scenarios.

Limited Evaluation Frameworks: Current SSL approaches for SAR ATR lack comprehensive evaluation across diverse architectural families and data availability scenarios.

Limited Representation Analysis: Existing SSL approaches in SAR ATR typically extract features from a single fixed layer, with a limited understanding of optimal feature extraction depth.

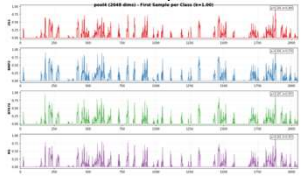
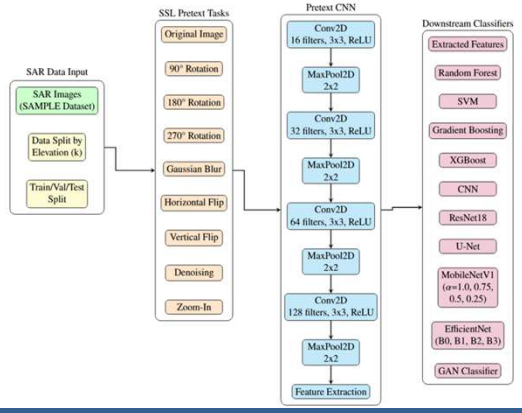


Fig. 3. Extracted signals for different target classes with the fourth pooling layer

Fig. 4. Performance degradation observed when synthetic data exceeds 60% of training data [2]

Proposed Self-supervised Learning Framework



Comparative Performance Analysis

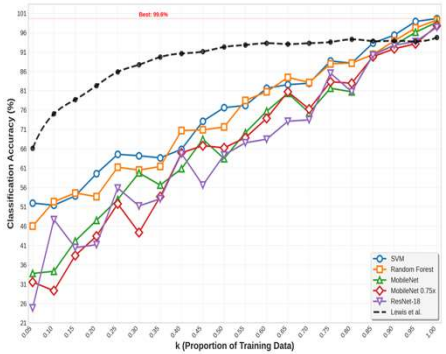


Figure 5. Exclusively measured data trained SSL outperformed Lewis et al.'s [2] approach that utilized synthetic replacements

Publications

[C1] Al Siam, M., Noor, D.F., Ndoye, M. *"Layer-Wise Feature Analysis for Self-Supervised SAR Target Recognition: Identifying Optimal Representations Across Data Regimes."* In IEEE SoutheastCon 2026. Best Paper Finalist (Top 3)

[C2] I Siam, M., Noor, D.F. *"Self-Supervised Learning for SAR Target Recognition with Multi-Task Pretext Training."* IEEE SoutheastCon 2025. Best Paper Finalist (Top 5)

[J1] Siam, M.A.; Noor, D.F.; Ndoye, M.; Khan, J.F. *"Advancing SAR Target Recognition Through Hierarchical Self-Supervised Learning with Multi-Task Pretext Training."* Sensors 2026, 26, 122.

Results

Outstanding Performance: ML approaches achieve exceptional accuracy than DL methods, with SVM achieving SOTA 99.63% accuracy with near-perfect ROC AUC (≥0.9998), and Random Forest achieving 99.26% accuracy (with pool4 features).

Data Efficiency:
Demonstrates remarkable robustness under severe data constraints:

- Traditional ML classifiers significantly outperforms deep learning in low-data scenarios.
- Maintains operational viability even at minimum data levels.

Computational Efficiency:
Real-time deployable capability:

- Pool4 feature extraction time is 15.35 ms from the pretext model, while the inference time ranges between 0.01 and 0.37ms across different downstream classifiers.
- Tolerating 5% FPR, we achieved TPR above 95% across different downstream classifiers even with reducing 25% of the measured data.

Layer-wise Feature Analysis:

- Earlier layers (pool1-pool2) consistently outperform deeper layers in ML methods.
- SVM achieves 100% accuracy using pool1 features at full data.
- Deep models show balanced performance across pool1–pool3.
- All classifiers exhibit severe degradation at the fully connected layers, indicating over-specialization to SSL pretext objectives.

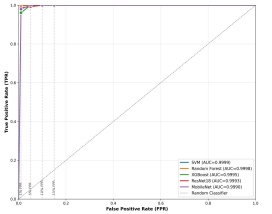


Figure 6. Near perfect ROC curves for top classifiers

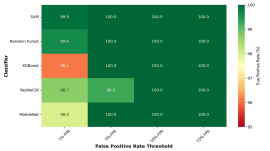


Figure 7. TPRs at FPR thresholds

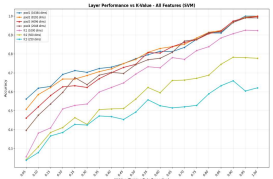


Fig. 8. Layer-wise performance trajectories in data availabilities

Conclusion

Our detailed experimentation of 16 downstream classifiers in 160 data availability scenarios demonstrate that measured-only SSL training eliminates synthetic domain dependency while achieving superior robustness. Early-layer representations preserve discriminative scattering information, and traditional machine learning classifiers effectively exploit these features under label scarcity. Our theoretical contribution advances domain-specific representation learning through radar-specific multi-task pretext training, opening new avenues for remote sensing applications.

References

[1] breakingdefense.com, accessed on 9/5/2025
[2] B. Lewis, T. Scarnati, E. Sudkamp, J. Nehrbass, S. Rosencrantz, and E. Zelnio, "A sar dataset for atr development: the synthetic and measured paired labeled experiment (sample)," in Algorithms for Synthetic Aperture Radar Imagery XXVI, vol. 10987. SPIE, 2019, pp. 39–54.