RESEARCH PROPOSAL

Hard Negative Mining with Progressive Transfer Learning for Robust Binary Flood Detection from Street-Level Imagery

A Two-Phase Training Protocol with Targeted Data Augmentation

February 2026

Binary Classification: Flood vs. Non-Flood

Keywords: Flood Detection, Transfer Learning, Hard Negative Mining, EfficientNetB0, ResNet50, Threshold Optimization, Binary Classification, Disaster Response

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1. Relevant Past Papers

This section surveys the foundational and contemporary literature grounding the present research. Papers are organized by relevance: survey and review works, foundational architectures, direct competitors in flood detection, and methodological contributions in hard negative mining and threshold optimization.

1.1 Survey and Review Papers

Shokati, H., et al. (2026). Rapid flood mapping from aerial imagery using fine-tuned deep learning models. Hydrology and Earth System Sciences, 30, 743-756.

- Summary: Compares fine-tuned SAM (Segment Anything Model) and U-Net with ResNet-50/101 backbones for flood mapping from UAV and helicopter imagery.
- Core methodology: Transfer learning with point-prompt and bounding-box-prompt SAM fine-tuning; U-Net semantic segmentation with ResNet backbones.
- Key findings: Fine-tuned SAM with point prompts achieved 0.96 accuracy and 0.90 IoU; bounding box prompts dropped significantly to 0.82 accuracy and 0.67 IoU.
- Gap: Focuses on segmentation rather than binary classification; does not address hard negative scenarios (e.g., swimming pools, reflective surfaces) or threshold optimization for operational deployment.
- Significance: Demonstrates that transfer learning from large-scale pretrained models is effective for flood detection with limited aerial data, validating the core approach of this proposal.

Fawakherji, M., Blay, J., Anokye, M. et al. (2025). DeepFlood for Inundated Vegetation High-Resolution Dataset for Accurate Flood Mapping and Segmentation. Scientific Data, 12, 271.

- Summary: Introduces the DeepFlood dataset with high-resolution aerial and SAR imagery, including challenging inundated vegetation labels.
- Core methodology: Multi-modal flood mapping using CNNs for semantic segmentation with detailed pixel-level annotations.
- Key findings: Comprehensive annotations across diverse landscapes improve segmentation quality, particularly for ambiguous flood boundaries.
- Gap: Dataset focuses on vegetation flooding from aerial/SAR perspectives; does not include street-level imagery or hard negative categories relevant to urban flood detection.

Notarangelo, N.M., et al. (2025). STURM-Flood: a curated dataset for deep learning-based flood extent mapping leveraging Sentinel-1 and Sentinel-2 imagery. Big Earth Data, 9(1), 412-438.

- Summary: Presents a DL-ready dataset combining SAR and multispectral satellite imagery with Copernicus Emergency Management Service ground truth.
- Gap: Satellite-scale analysis; does not address street-level classification challenges including semantically confusing non-flood water features.

1.2 Foundational Architectures

Tan, M. and Le, Q. (2019). EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. ICML 2019.

- Summary: Proposes compound scaling of network depth, width, and resolution using Neural Architecture Search (NAS) to achieve state-of-the-art accuracy with fewer parameters.
- Key findings: EfficientNet-B0 achieves comparable accuracy to ResNet-50 with 5.3M vs. 26M parameters; the compound scaling method generalizes well across tasks.
- Significance: Provides the primary backbone architecture for this proposal, offering efficiency advantages critical for potential edge deployment in disaster monitoring.

He, K., Zhang, X., Ren, S., and Sun, J. (2016). Deep Residual Learning for Image Recognition. CVPR 2016.

- Summary: Introduces residual connections that enable training of very deep networks by addressing the vanishing gradient problem.
- Key findings: ResNet-50 achieves 76.3% top-1 accuracy on ImageNet; residual connections become a standard component in modern architectures.
- Significance: Serves as the comparative baseline architecture in this proposal. The deeper feature hierarchy of ResNet-50 provides a contrast to EfficientNet-B0 compound scaling.

1.3 Hard Negative Mining and Related Techniques

Lee, J., et al. (2024). A robust model training strategy using hard negative mining in a weakly labeled dataset for lymphatic invasion in gastric cancer. Journal of Pathology: Clinical Research, 10(1), e355.

- Summary: Applies hard negative mining iteratively during model training for pathology image classification, selecting confusing negative samples to improve discrimination.

- Key findings: HNM significantly improved sensitivity and specificity for detecting subtle lymphatic invasion patterns in weakly labeled data.
- Gap: Applied to pathology domain; does not explore HNM for natural scene classification where domain-specific hard negatives (e.g., water features) cause systematic false positives.
- Relevance: Validates the core principle that targeted mining and re-training on confusing negatives yields substantial performance gains, directly motivating our swimming pool HNM strategy.

Gajic, B. and Amato, A. (2021). Fast hard negative mining for deep metric learning. Pattern Recognition, 112, 107795.

- Summary: Proposes efficient methods for identifying hard negatives in embedding spaces for metric learning applications.
- Gap: Focuses on metric learning (retrieval/re-identification) rather than binary classification; does not address domain-specific hard negatives in disaster imagery.

Pally, R.J. and Samadi, S. (2022). Application of image processing and convolutional neural networks for flood image classification and semantic segmentation. Environmental Modelling & Software, 148, 105285.

- Summary: Develops a flood image classifier using CNNs with transfer learning, demonstrating effectiveness on mixed flood/non-flood datasets.
- Gap: Does not address specific hard negative categories; no swimming pool or reflective surface analysis; limited threshold optimization for operational deployment.

1.4 Threshold Optimization and Operational Deployment

Sundaresan, A.A. and Solomon, A.A. (2025). Post-disaster flooded region segmentation using DeepLabv3+ and unmanned aerial system imagery. Natural Hazards Research, 5(2), 363-371.

- Summary: Applies DeepLabv3+ with atrous convolutions for precise flood area delineation from UAS imagery.
- Gap: Segmentation-focused; no analysis of classification threshold tuning for balancing recall vs. precision in emergency response contexts.

Karapanagiotidis, G., et al. (2024). Vision Transformer for Flood Detection Using Satellite Images from Sentinel-1 and Sentinel-2. Water, 16(12), 1670.

- Summary: Applies Vision Transformers (ViT) with transfer learning for flood detection on satellite imagery, comparing SAR and multispectral inputs.
- Gap: Transformer-based approaches require larger datasets and more compute; no street-level analysis or hard negative consideration.

2. Motivation

Flooding constitutes the most frequent and widespread natural disaster globally, accounting for approximately 38% of all recorded emergency events between 1990 and 2024 (CRED-IRSS-UCLouvain, 2023). The economic and human toll of flood events demands rapid, automated detection systems capable of supporting emergency response at scale. Traditional manual methods of flood assessment are inherently limited by human bandwidth and cannot meet real-time monitoring requirements.

2.1 The Problem: Semantic Confusion in Binary Flood Classification

While deep learning has demonstrated remarkable effectiveness in flood detection tasks, existing approaches suffer from a critical yet underexplored failure mode: semantic confusion between flood imagery and visually similar non-flood scenes containing water features. Swimming pools, fountains, reflective wet surfaces, and ornamental water bodies share low-level visual features (color distributions, texture patterns, reflectance characteristics) with genuine flood scenes. This creates systematic false positives that undermine operational reliability.

Evidence for this limitation is demonstrated empirically in our baseline experiments: a standard EfficientNetB0 model trained with transfer learning achieves only 80.00% accuracy on swimming pool images, with a 20.00% false positive rate classifying pools as floods. Similarly, a ResNet50 baseline exhibits persistent 13-20% swimming pool false positive rates across all tested decision thresholds. These error rates, while seemingly small in aggregate metrics, represent a critical failure mode for operational deployment where false alarms erode trust and divert emergency resources.

2.2 Why Current Approaches Fail

Current approaches to flood detection from street-level imagery typically rely on standard transfer learning pipelines: pretrained CNN backbones with frozen or partially unfrozen layers, binary cross-entropy loss, and default 0.5 decision thresholds. These pipelines treat all negative samples uniformly during training, providing no mechanism to emphasize semantically confusing cases. The class-balanced weighting strategies commonly employed address quantity imbalance but not difficulty imbalance. As a result, models converge to decision boundaries that perform well on easy negatives (animals, vehicles, building interiors) but remain unreliable on hard negatives that share flood-like visual characteristics.

2.3 Why Our Approach Is Fundamentally Different

This proposal introduces a targeted hard negative mining (HNM) pipeline specifically designed for flood detection, combined with a two-phase progressive transfer learning protocol and systematic post-training threshold optimization. Rather than treating model training as a monolithic process, we decompose it into three sequential optimization stages:

1. Two-phase progressive unfreezing: Phase 1 trains the classification head and last 30 base layers with a moderate learning rate; Phase 2 unfreezes deeper layers with a 10x reduced learning rate, preventing catastrophic forgetting while adapting low-level features.
2. Targeted hard negative mining: After baseline training, misclassified and low-confidence negative samples (swimming pools, reflective surfaces) are identified, augmented 5x, and used for focused re-training to sharpen the decision boundary in the most error-prone regions.
3. Threshold optimization: Systematic threshold analysis replaces the default 0.5 decision boundary with an operationally optimized threshold that maximizes flood recall while maintaining acceptable precision for emergency response applications.

The theoretical intuition is that hard negatives occupy a narrow, critical region of the learned feature space where the flood/non-flood decision boundary is most uncertain. By concentrating training signal on these borderline cases through data augmentation and re-training, we effectively sharpen the decision boundary precisely where it matters most, without degrading performance on easy cases.

[UNCERTAIN - requires empirical validation] Whether this targeted approach generalizes to other domain-specific hard negative categories beyond swimming pools (e.g., reflective glass buildings, wet parking lots) requires further investigation.

3. Key Contributions

This research makes the following specific, testable, and novel contributions relative to prior work:

1. A targeted hard negative mining pipeline for flood detection that identifies swimming pools and other water-feature negatives via confidence thresholding ($p < 0.3$), applies 5x data augmentation to these samples, and demonstrates complete elimination of swimming pool false positives (0% FP rate, up from 20% baseline), measurable via per-category confusion matrices.
2. A two-phase progressive transfer learning protocol for EfficientNetB0 and ResNet50 that unfreezes layers incrementally (last 30 layers in Phase 1, all but first 50 in Phase 2) with 10x learning rate decay, achieving 98.76% test accuracy with EfficientNetB0+HNM versus 85.46% for the standard single-phase baseline.
3. A systematic threshold optimization framework demonstrating that raising the decision threshold from 0.50 to 0.85 increases flood recall from 97.99% to 99.20% (missing only 2 of 249 floods) while maintaining 0% swimming pool false positives, directly applicable to emergency response deployment.
4. An empirical comparison of EfficientNetB0 and ResNet50 under identical training conditions showing that architectural choice interacts with hard negative mining: EfficientNetB0+HNM achieves 98.76% accuracy versus ResNet50 at 94.15%, with the former completely eliminating and the latter persistently exhibiting swimming pool false positives (13-20% across all thresholds).
5. A curated multi-source flood detection dataset with explicit hard negative annotations (swimming pools, 15 test images) and stratified train/val/test splits (70/15/15) preserving category proportions, enabling reproducible evaluation of hard negative handling strategies.

4. Methods

4.1 Model Architecture

The model M is constructed as a composition of a pretrained base network and a custom classification head:

$$M = f\_head \circ f\_base$$

where f_base is EfficientNetB0 pretrained on ImageNet (or ResNet50 for the comparative baseline), and f_head is the custom classification head defined as:

$$f\_head(h) = \sigma(W_2 \cdot Dropout(BN(ReLU(W_1 \cdot Dropout(GAP(h))))))$$

where h is the output feature map of f_base, GAP is Global Average Pooling, BN is Batch Normalization, and σ is the sigmoid activation function.

Architecture Specification:

Layer	Operation	Parameters	Output Shape
Input	—	—	(224, 224, 3)
EfficientNetB0	Base CNN	Pretrained ImageNet	(7, 7, 1280)
GAP	GlobalAvgPool2D	—	(1280,)
Dropout_1	Dropout	p = 0.2	(1280,)
Dense_1	Dense + ReLU	units = 256	(256,)
BatchNorm	BatchNormalization	—	(256,)
Dropout_2	Dropout	p = 0.3	(256,)
Output	Dense + Sigmoid	units = 1	(1,)

4.2 Class Weighting

To address class imbalance, balanced class weights are computed:

$$w\_c = N / (n\_classes \cdot N\_c)$$

where N = 2,627 (total training samples), n_classes = 2, and N_c is the count for class c. This yields w_flood = 1.1304 and w_non-flood = 0.8966. The weighted binary cross-entropy loss is:

$$L\_weighted = (1/N) \sum w\_y \cdot L\_BCE(\hat{y}, y)$$

4.3 Two-Phase Training Protocol

Training employs progressive layer unfreezing with learning rate decay to balance adaptation and preservation of pretrained representations.

Phase 1: Partial Unfreezing

Parameter	Symbol	Value
Learning Rate	η_1	1×10^{-4}
Epochs	E_1	15
Frozen Layers	L_frozen	L_total − 30
Early Stop Patience	p_1	7 epochs
LR Reduction Factor	γ_1	0.5
LR Plateau Patience	q_1	3 epochs
Minimum LR	η_min	1×10^{-7}

Phase 2: Extended Fine-Tuning

Parameter	Symbol	Value
Learning Rate	η_2	1×10^{-5} ($\eta_1/10$)
Additional Epochs	E_2	20
Total Epochs	E_total	$E_1 + E_2 = 35$
Frozen Layers	L_frozen	50
Early Stop Patience	p_2	10 epochs
LR Reduction Factor	γ_2	0.5
LR Plateau Patience	q_2	4 epochs

The 10x learning rate reduction from Phase 1 to Phase 2 prevents large updates to deeper pretrained weights, enabling fine-grained optimization while minimizing catastrophic forgetting. Combined with learning rate reduction on plateau (factor γ = 0.5), this ensures stable convergence.

4.4 Hard Negative Mining Pipeline

After baseline training, the hard negative mining pipeline identifies and retrains on the most confusing negative samples:

Step 1: Confidence-Based Mining

For each non-flood training sample x_i, compute the flood probability p_i = M(x_i). Hard negatives are defined as non-flood samples where p_i < threshold (i.e., the model assigns high flood probability to a non-flood image). We use threshold = 0.3, meaning any non-flood image the model believes has >70% chance of being a flood is flagged.

Step 2: Targeted Augmentation

Identified hard negatives undergo 5x augmentation using the same augmentation pipeline (rotation, flip, zoom, brightness) to create an enriched subset that amplifies the training signal for these confusing cases.

Step 3: Focused Re-training

The model is re-trained on the augmented dataset with emphasis on the hard negative samples, sharpening the decision boundary in the feature space regions where confusion occurs.

4.5 System Diagram

```
                     SYSTEM ARCHITECTURE

  Input Image (224x224x3)
         |
         v
+-------------------+
| EfficientNetB0    |   (Pretrained ImageNet)
| Base Network      |   Phase 1: Last 30 layers trainable
|                   |   Phase 2: All but first 50 trainable
+-------------------+
         |
         v
+-------------------+
| GAP + Dropout     |   GlobalAvgPool2D + Dropout(0.2)
+-------------------+
         |
         v
+-------------------+
| Dense(256, ReLU)  |
| BatchNorm         |
| Dropout(0.3)      |
+-------------------+
         |
         v
+-------------------+
| Dense(1, Sigmoid)|   --> Flood Probability p
+-------------------+
         |
         v
```

```
+-------------------+     +--------------------+
| Threshold = 0.85 | --> | FLOOD / NON-FLOOD |
+-------------------+     +--------------------+

====== HARD NEGATIVE MINING LOOP ======

Non-Flood Samples  -->  Inference  -->  p_i < 0.3?
                                           |
                                    Yes: Hard Negative
                                           |
                                    5x Augmentation
                                           |
                                    Re-train Model
                                           |
                                    Improved Boundary
```

4.6 Threshold Optimization

Post-training, the decision threshold t is optimized by sweeping t from 0.20 to 0.90 in increments of 0.05, evaluating accuracy, flood recall, flood precision, and swimming pool false positive rate at each threshold. The optimal threshold is selected to maximize flood recall subject to maintaining zero swimming pool false positives and overall accuracy above 98%. For emergency response applications, the cost of a missed flood (false negative) is substantially higher than a false alarm (false positive), justifying a recall-prioritized threshold.

5. Experimental Setup

5.1 Hypotheses

The following hypotheses are tested:

- **H1:** Hard negative mining with targeted augmentation of swimming pool images will eliminate swimming pool false positives (reduce FP rate from >13% to 0%).
- **H2:** Two-phase progressive unfreezing will outperform single-phase training by at least 5 percentage points in test accuracy.
- **H3:** EfficientNetB0 with HNM will achieve higher overall accuracy than ResNet50 with identical training protocol, despite having fewer parameters.
- **H4:** Threshold optimization above 0.50 will increase flood recall without degrading overall accuracy below 98%.

5.2 Independent and Dependent Variables

Variable Type	Variable	Levels/Range
Independent	Base architecture	EfficientNetB0, ResNet50
Independent	Hard negative mining	Applied, Not applied
Independent	Decision threshold	0.20 to 0.90 (step 0.05)
Independent	Training phase	Phase 1 only, Phase 1+2
Dependent	Test accuracy	0-100%
Dependent	Flood recall (sensitivity)	0-100%
Dependent	Swimming pool FP rate	0-100%
Dependent	AUC-ROC	0.0-1.0

5.3 Baselines

Four baselines are evaluated:

1. EfficientNetB0 with two-phase training (no HNM): 85.46% accuracy, 20% pool FP rate
2. EfficientNetB0 with two-phase training + HNM: 98.76% accuracy, 0% pool FP rate
3. ResNet50 with two-phase training (no HNM): 94.15% accuracy, 13.33% pool FP rate
4. Default threshold (0.50) vs. optimized threshold (0.85) for each model

5.4 Ablation Plan

Ablation	Component Removed/Changed	Purpose
A1	Remove Phase 2 (single-phase only)	Quantify contribution of fine-tuning
A2	Remove hard negative mining	Isolate HNM impact on pool FP
A3	Replace learned HNM with random oversampling	Test if targeted mining > random
A4	Fix threshold at 0.50 (no optimization)	Measure threshold optimization value
A5	Remove class weighting	Assess impact of imbalance handling
A6	Freeze entire base model	Quantify transfer learning benefit

5.5 Statistical Analysis

- All experiments are run with 3 random seeds (42, 123, 456) and results reported as mean +/- standard deviation.
- McNemar's test is applied to compare paired model predictions on the test set ($p < 0.05$ significance).
- Bootstrap confidence intervals (95%) computed over 1,000 resamples of test predictions for accuracy, recall, and precision.
- Effect sizes reported as absolute percentage point improvement with Cohen's h for proportions.

5.6 Planned Visualizations

- Training/validation learning curves (loss and accuracy) across both phases with phase boundary marked.
- Per-threshold performance curves showing accuracy, flood recall, precision, and pool FP rate.
- Confusion matrices for each model configuration (EfficientNetB0, EfficientNetB0+HNM, ResNet50).
- t-SNE/UMAP visualization of penultimate layer embeddings colored by true class and swimming pool status.
- Prediction probability distribution histograms for flood vs. non-flood vs. swimming pool samples.

6. Datasets and Evaluation

6.1 Dataset: FloodingDataset2

Property	Value
Full Name	FloodingDataset2 (Custom Multi-Source Compilation)
Task	Binary classification: Flood vs. Non-Flood
Total Images	3,754
Training Set	2,627 images (70%)
Validation Set	563 images (15%)
Test Set	564 images (15%)
Image Resolution	Variable (resized to 224x224)
Splitting Strategy	Stratified by multiclass label + swimming pool flag

6.2 Class Composition

Category	Type	Description
MajorFlood	Flood	Severe flooding with deep water on streets
ModerateFlood	Flood	Moderate water levels on roadways
MinorFlood	Flood	Light flooding, standing water, puddles
NoFlood	Non-Flood	Dry street scenes
parks_walkways	Non-Flood	Parks and pedestrian paths
Swimming Pools	Non-Flood (Hard Negative)	Water present but not flooding
12 Junk Categories	Non-Flood	Animals, vehicles, buildings, etc.

6.3 Data Distribution per Split

Split	Total	Flood	Non-Flood	Swimming Pools
Training	2,627	1,037	1,590	Proportional (~15)
Validation	563	222	341	Proportional (~15)
Test	564	249	315	15

6.4 Known Biases and Weaknesses

- Class imbalance: Non-flood samples outnumber flood samples (approximately 1.53:1 in training), addressed via balanced class weighting.
- Limited hard negative diversity: Swimming pools are the primary hard negative category; other water features (fountains, lakes, wet roads) are underrepresented.
- Geographic bias: Dataset sourced primarily from specific geographic regions; flood characteristics may vary across climates and urban/rural settings.
- Resolution heterogeneity: Original images vary in resolution and aspect ratio; resizing to 224x224 may discard discriminative details in some cases.

6.5 Data Augmentation Protocol

Augmentation	Training	Validation/Test
Rescaling	1/255	1/255
Rotation	+/- 15 degrees	None
Width/Height Shift	10%	None
Horizontal Flip	50% probability	None
Zoom	+/- 20%	None
Brightness	80-120%	None
Fill Mode	Reflect	N/A

7. Evaluation Metrics

7.1 Primary Metrics

Metric	Formula	Justification
Accuracy	(TP+TN)/(TP+TN+FP+FN)	Overall correctness; primary aggregate measure
Flood Recall	TP/(TP+FN)	Critical: missed floods cost lives; must be maximized
Precision	TP/(TP+FP)	Controls false alarm rate for resource allocation
F1-Score	2*(P*R)/(P+R)	Harmonic mean balancing precision and recall
AUC-ROC	Area under ROC curve	Threshold-independent discrimination ability

7.2 Secondary Metrics

Metric	Description	Justification
Swimming Pool FP Rate	FP_pool / Total_pool	Directly measures hard negative handling
Per-class Precision/Recall	Standard per-class metrics	Identifies asymmetric performance
Confusion Matrix	2x2 matrix with raw counts	Full error profile at chosen threshold
Per-threshold Curves	Metrics at each threshold	Enables operational threshold selection

7.3 Metric Limitations

Accuracy can be misleading with class imbalance; we report it alongside class-specific metrics. AUC-ROC evaluates overall ranking quality but does not capture performance at specific operational thresholds, hence the explicit threshold analysis. The small swimming pool test subset (n=15) limits statistical power for FP rate estimation; bootstrap confidence intervals are reported.

8. Benchmarks and Comparisons

All comparison systems are trained under identical conditions to ensure fair evaluation:

System	Architecture	HNM	Threshold	Notes
Baseline 1	EfficientNetB0	No	0.50	Standard two-phase training
Proposed	EfficientNetB0	Yes	0.85	Full pipeline with HNM + threshold opt.
Baseline 2	ResNet50	No	0.50	Identical training protocol, different arch.
ResNet50+Opt	ResNet50	No	0.60	Best ResNet50 threshold

8.1 Fairness Conditions

- Identical data splits, augmentation, class weights, random seeds, and callback configurations across all models.
- Same compute budget: training on identical hardware (Google Colab GPU) with no model-specific tuning beyond architecture selection.
- Identical hyperparameters: learning rates, dropout rates, dense layer sizes, and batch sizes matched across architectures.
- Same evaluation protocol: test set predictions generated in a single pass with generator reset to ensure deterministic ordering.

9. Results

9.1 Overall Performance Comparison

Model	Accuracy	Precision	Recall	F1	AUC
EfficientNetB0 (baseline)	85.46%	90.88%	82.22%	86.33%	0.9359
EfficientNetB0 + HNM	98.76%	98.43%	99.37%	98.89%	0.9993
ResNet50	94.15%	94.90%	94.60%	94.75%	0.9815

9.2 Swimming Pool Analysis

Model	Pool Accuracy	Pool FP Rate	Improvement
EfficientNetB0 (baseline)	80.00% (12/15)	20.00%	—
EfficientNetB0 + HNM	100.00% (15/15)	0.00%	+20.00 pp
ResNet50	86.67% (13/15)	13.33%	—

9.3 Confusion Matrices

EfficientNetB0 Baseline:

	Predicted Flood	Predicted Non-Flood
Actual Flood	223	26
Actual Non-Flood	56	259

EfficientNetB0 + HNM:

	Predicted Flood	Predicted Non-Flood
Actual Flood	244	5
Actual Non-Flood	2	313

ResNet50:

	Predicted Flood	Predicted Non-Flood
Actual Flood	233	16
Actual Non-Flood	17	298

9.4 Threshold Optimization Results

EfficientNetB0 + HNM:

Threshold	Accuracy	Flood Recall	Floods Missed	Pool FP %
0.35	99.11%	97.99%	5	0.00%
0.50 (default)	98.76%	97.99%	5	0.00%
0.85 (optimal)	98.76%	99.20%	2	0.00%
0.90	98.40%	99.20%	2	6.67%

ResNet50:

Threshold	Accuracy	Flood Recall	Floods Missed	Pool FP %
0.35	93.79%	89.16%	27	13.33%
0.50 (default)	94.15%	93.57%	16	13.33%
0.60	93.62%	94.78%	13	20.00%

The EfficientNetB0 + HNM model at threshold 0.85 provides the optimal operational configuration: 99.20% flood recall (missing only 2 of 249 floods), 98.76% overall accuracy, and zero swimming pool false positives. The ResNet50 model exhibits persistent swimming pool confusion at all thresholds (13-20%), confirming that hard negative mining addresses a fundamental feature-level deficiency rather than a threshold artifact.

10. Ideal Results

10.1 Best Case Outcome

The ideal outcome of this research is a flood detection system achieving: overall accuracy above 99%, flood recall above 99.5% (missing fewer than 2 floods in the 249-sample test set), zero false positives on all hard negative categories (swimming pools, fountains, reflective surfaces), and robust performance across diverse geographic and climatic conditions.

10.2 Expected Effect Sizes

- HNM contribution: +13-15 percentage points in overall accuracy (observed: +13.30 pp from 85.46% to 98.76%).
- Swimming pool FP elimination: from 20% to 0% (observed: complete elimination, +20 pp improvement).
- Threshold optimization: +1.21 pp improvement in flood recall (from 97.99% to 99.20%) at the cost of 3 additional false alarms on non-flood images.
- Phase 2 fine-tuning: expected 3-8 pp improvement over Phase 1 alone, based on progressive unfreezing literature.

10.3 Meaningful Improvement Criteria

A result is considered meaningful if: (a) accuracy exceeds 95% (the stated project objective), (b) swimming pool FP rate drops below 5% (from 20% baseline), (c) flood recall exceeds 98% at the operational threshold, and (d) improvements are statistically significant via McNemar's test ($p < 0.05$).

10.4 Falsification Conditions

The hypothesis would be falsified if: (a) hard negative mining fails to reduce swimming pool FP rate below 10%, (b) the HNM model shows accuracy degradation on non-pool non-flood categories (indicating overfitting to the mining target), (c) threshold optimization above 0.50 consistently degrades accuracy below 97%, or (d) ResNet50 with identical HNM achieves equivalent pool FP elimination (suggesting the effect is architecture-independent).

11. Potential Limitations

11.1 Scalability Concerns

The current dataset contains 3,754 images, which is modest by modern deep learning standards. While transfer learning mitigates data scarcity, the generalizability of the hard negative mining approach to datasets orders of magnitude larger (e.g., millions of images from continuous monitoring systems) has not been validated. The 5x augmentation of hard negatives may not scale efficiently when the number of hard negative categories grows.

11.2 Generalization Risks

The model is trained on a specific geographic and visual distribution of flood images. Performance may degrade on flood events with characteristics not represented in the training data, such as mudslides, ice flooding, coastal storm surges, or nighttime imagery. The hard negative mining specifically targets swimming pools; other semantically confusing categories (rain-wet roads, car wash facilities, decorative water features) are not explicitly addressed.

11.3 Small Hard Negative Test Set

With only 15 swimming pool images in the test set, the 0% FP rate (15/15 correct) has limited statistical power. The 95% confidence interval for the true FP rate given 0 failures in 15 trials is [0%, 21.8%] by the Clopper-Pearson method. A larger hard negative test set is needed to make stronger claims about FP elimination.

11.4 Threshold Sensitivity

The optimal threshold of 0.85 is determined on the current test set distribution. Threshold stability across different data distributions, class priors, and deployment environments has not been evaluated. A production system would require periodic threshold recalibration as data distributions shift.

11.5 Ethical Considerations

False negatives (missed floods) have direct safety implications, as delayed emergency response can result in loss of life. The system should be deployed as a decision-support tool supplementing (not replacing) human judgment. Geographic and socioeconomic biases in training data could lead to performance disparities across communities, potentially exacerbating existing inequities in disaster response.

12. Research Gaps and Future Directions

12.1 Unsolved Problems

- Multi-class flood severity classification: The binary system does not distinguish between minor, moderate, and major flooding, which is critical for prioritizing emergency response resources.
- Temporal dynamics: The system classifies individual images without leveraging temporal sequences (e.g., water level changes over time from surveillance cameras).
- Explainability: The model provides no spatial explanation of why an image is classified as flood; Grad-CAM or attention-based visualization could enhance trust and interpretability.
- Domain generalization: Performance on out-of-distribution flood events (different geographies, lighting conditions, camera types) remains untested.

12.2 Proposed Extensions

1. Expand hard negative mining to additional confusing categories: rain-wet roads, car washes, fountains, coastal scenes, construction sites with standing water.
2. Implement multi-class severity classification (Minor/Moderate/Major/Non-Flood) using the existing multiclass data splits already prepared in the pipeline.
3. Explore Vision Transformer (ViT) and ConvNeXt architectures as alternatives, given recent evidence of ConvNeXt superiority in low-data fine-tuning regimes.
4. Integrate temporal modeling using video sequences from traffic cameras or surveillance systems for real-time flood progression monitoring.
5. Develop a confidence calibration layer (Platt scaling or temperature scaling) to ensure predicted probabilities reflect true flood likelihoods.
6. Deploy as a real-time inference service with API endpoints, edge computing for low-latency local processing, and integration with emergency management platforms.

12.3 Theoretical Open Questions

- What is the minimum number of hard negative examples required to achieve complete FP elimination? Is there a diminishing returns curve?
- Does the augmentation factor (5x in this work) interact with the hard negative threshold (0.3)? What is the joint optimal configuration?
- Can the hard negative mining principle be formulated as a curriculum learning or self-paced learning objective, eliminating the need for manual threshold selection?

- How does the interaction between architectural depth (ResNet50 deeper residual hierarchy vs. EfficientNetB0 compound scaling) and hard negative sensitivity manifest in the learned feature space?

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