FireSense: Multispectral Fire Detection with Channel Attention and Probabilistic Calibration

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THE WILDFIRE PROBLEM

Why Wildfire Detection Matters

- 2023: Over 2.6 million acres burned in California
- $20B+ economic losses annually
- Climate change increasing fire frequency/intensity
- Early detection cuts containment costs by 50%

Current Limitations

- Manual monitoring slow
- Classical threshold-based algorithms → 30–40% false alarms
- RGB misses thermal signatures
- No uncertainty quantification

Our Goal

Build an automated system that:

- Detects fires precisely
- Minimizes false alarms
- Produces reliable confidence estimates

DATASET OVERVIEW

ActiveFire Dataset: Landsat-8

Dataset Composition

- Total: 14,815 patches
- Train: 10,370
- Val: 2,978
- Test: 1,467

Geographic Coverage

- North America 45%
- South America 55%

Input Specs

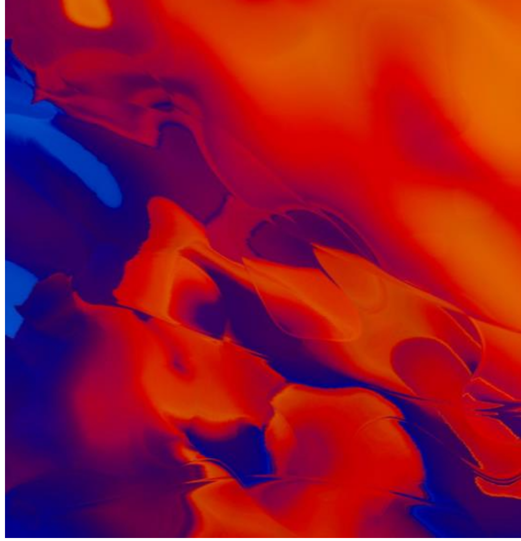
- 10 spectral bands (0.44–12.0 µm)
- 30m resolution
- Patch: 256×256 (~7.68 km)

Annotation

Labels from three classical algorithms:
Schroeder (2016), Murphy (2016), Kumar-Roy (2018)

MULTI-SPECTRAL ANALYSIS

Band	Wavelength	Fire Signature
Coastal/Blue	0.44-0.49 µm	Smoke scattering
Green/Red	0.53-0.66 µm	Visible flames
NIR	0.87 µm	Vegetation stress
SWIR1	1.61 µm	Active fire reflection
SWIR2	2.19 µm	Fire intensity
TIR1	10.9 µm	Thermal emission



Fire pixels exhibit distinct spectral behavior:

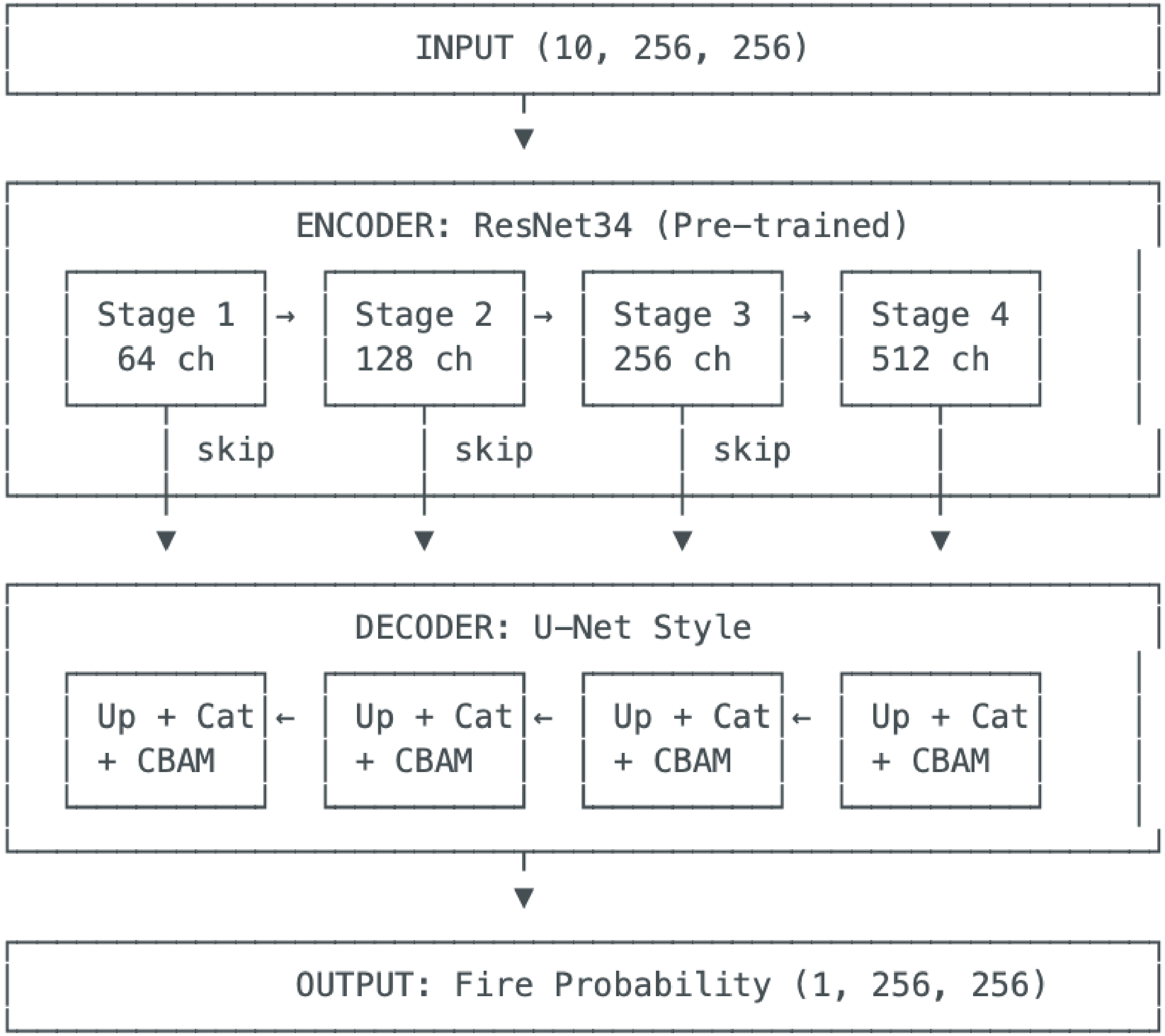
High response in **SWIR** and **TIR** bands → thermal emission

Low response in visible bands → smoke obscures flames

Spectral pattern is unique → confounders cannot replicate this signature

Limitation	Explanation
Cannot detect thermal emission	RGB captures only visible light, missing key heat signatures
Confused by clouds & soil	Bright clouds, bare soil look “fire-like” in RGB
Misses smoldering fires	Fires with no visible flames remain undetected

MODEL ARCHITECTURE



Key Components

- **1. ResNet34 Encoder**
- Transfer lerning (ImageNet)
- Handles 10-band input
- Residual connections prevent gradient loss
- **2. U-Net Decoder**
- Skip connections preserve spatial structure
- Transposed convolutions for upsampling
- **3. CBAM Attention (Added)**
- Highlights important **spectral channels**
- Focuses on meaningful **spatial regions**

Metric	Value
Parameters	24.4M
Model Size	93 MB
Input Shape	10 × 256 × 256
Output Shape	1 × 256 × 256

TECHNICAL NOVELTY 1: SOFT LABELS

The Annotation Problem

Classical algorithms (Schroeder, Murphy, Kumar-Roy) often **disagree** on fire pixels, especially around boundaries and smoke-obscured regions.

Scenario	Schroeder	Murphy	Kumar-Roy	Agreement
Clear fire	1	1	1	100%
Fire edge	1	0	1	67%
Ambiguous	0	1	0	33%

Hard Labels vs Soft Labels

Hard Labels (Traditional)

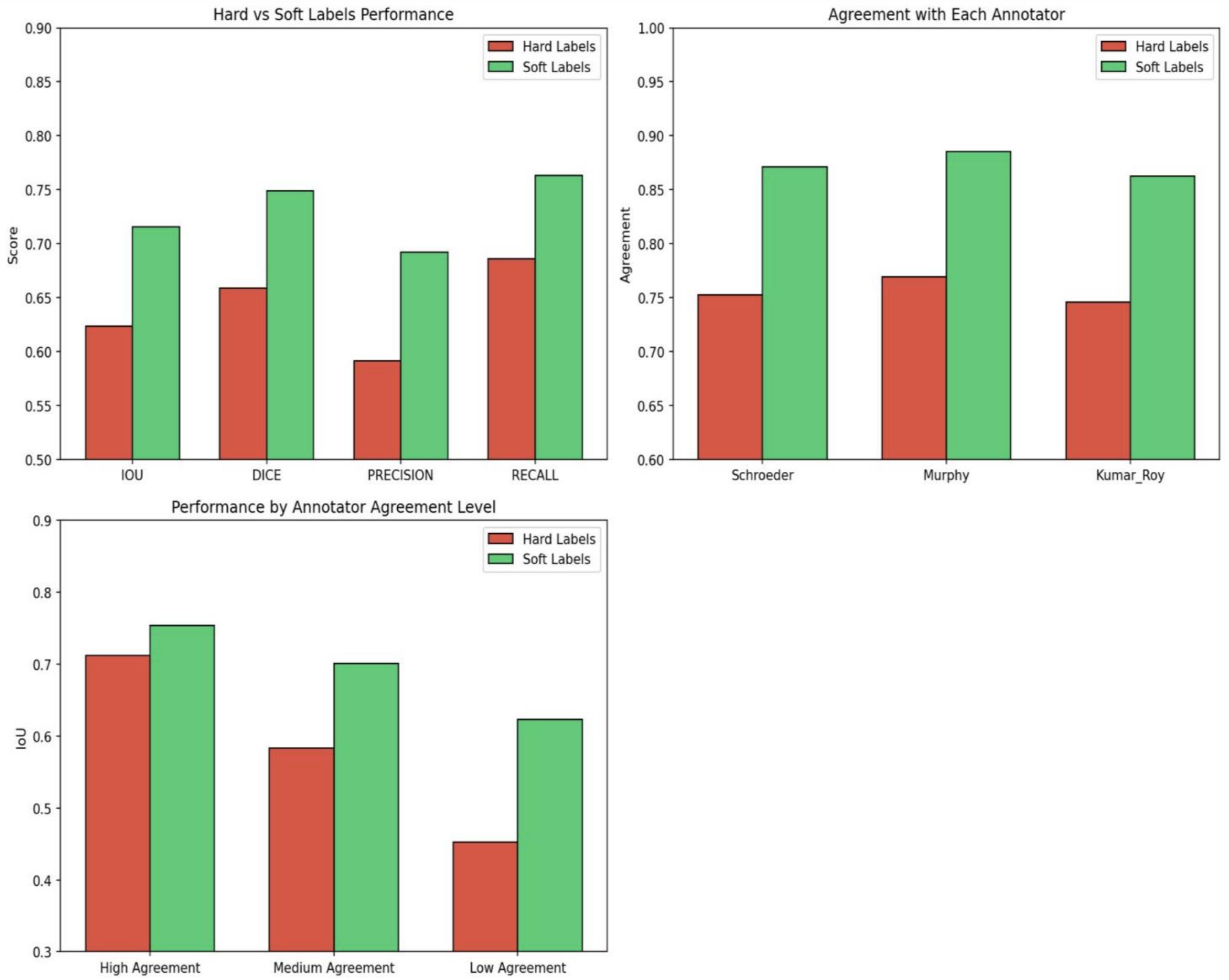
- Binary: **0 or 1**
- Treat uncertain pixels as certain
- Leads to **noisy boundaries** and overfitting

Soft Labels (Our Approach)

- Soft label = **average of 3 annotators**
- Produces values like **0, 0.33, 0.66, 1.0**
- Captures uncertainty at edges
- Encourages smoother predictions
- **Loss Function: Generalized Cross Entropy (GCE)**
- More robust to noisy labels than standard cross-entropy
- Uses **q = 0.7** to control noise tolerance

Results

- Soft labels significantly improve model performance:
- **IoU:** 0.592 → **0.680**
- Clearer boundaries around fire regions
- Better handling of ambiguous / smoky pixels



TECHNICAL NOVELTY-2: SPECTRAL ATTENTION

- **Why Spectral Attention?**
- Different spectral bands carry different fire-related information.
  CBAM helps the model **learn which bands matter most** and **focus on important spatial region**
- CBAM adds **attention** to help the model:
- Identify **important spectral bands** (channel attention)
- Focus on **relevant spatial regions** (spatial attention)
- **Channel Attention:** Learns importance weights for each band
  Spatial Attention: Highlights fire-relevant regions in the image

Learned Band Importance

The model automatically learns which bands are most informative:

Rank	Band	Wavelength	Learned Weight	Physical Meaning
1	SWIR1	1.61 μm	0.18	Fire reflection
2	NIR	0.87 μm	0.15	Vegetation response
3	SWIR2	2.19 μm	0.14	Fire intensity
4	TIR1	10.9 μm	0.12	Thermal emission
5	Red	0.66 μm	0.12	Visible fire/smoke

Key Insight: The model correctly prioritizes thermal and SWIR bands without explicit guidance.

10-Band vs 3-Band Comparison

Configuration	IoU	Dice	Precision
3-Band RGB Only	0.584	0.737	0.756
10-Band No Attention	0.658	0.794	0.812
10-Band + CBAM	**0.721**	**0.838**	**0.845**

Improvement over RGB: +23.5% IoU

TECHNICAL NOVELTY 3 - CALIBRATION

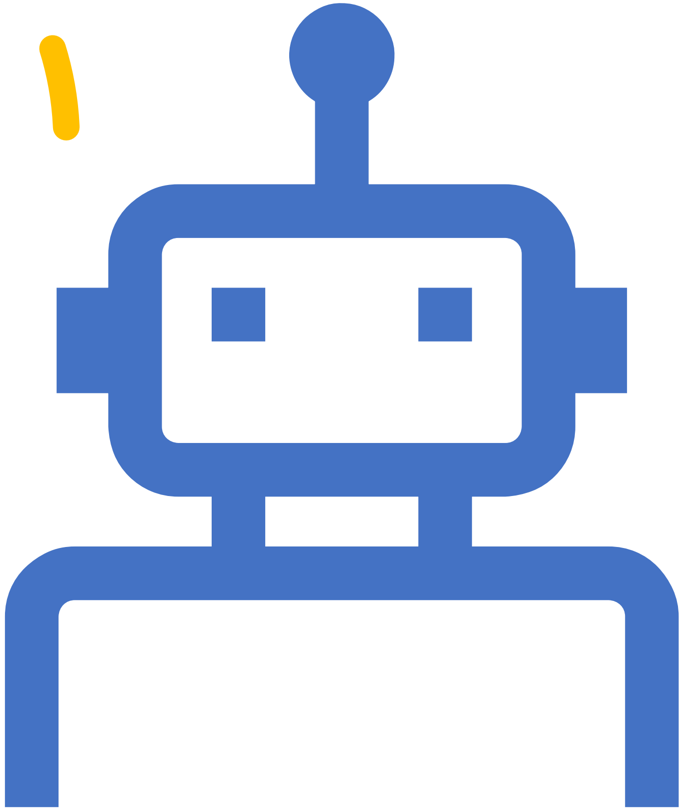
The Overconfidence Problem

- Neural networks often output **overconfident fire probabilities**, e.g.:
- Predicts **95% fire** when true rate is **~70%**
- Dangerous in wildfire tasks: false alarms vs missed fires
- Operators need **trustworthy confidence estimates**

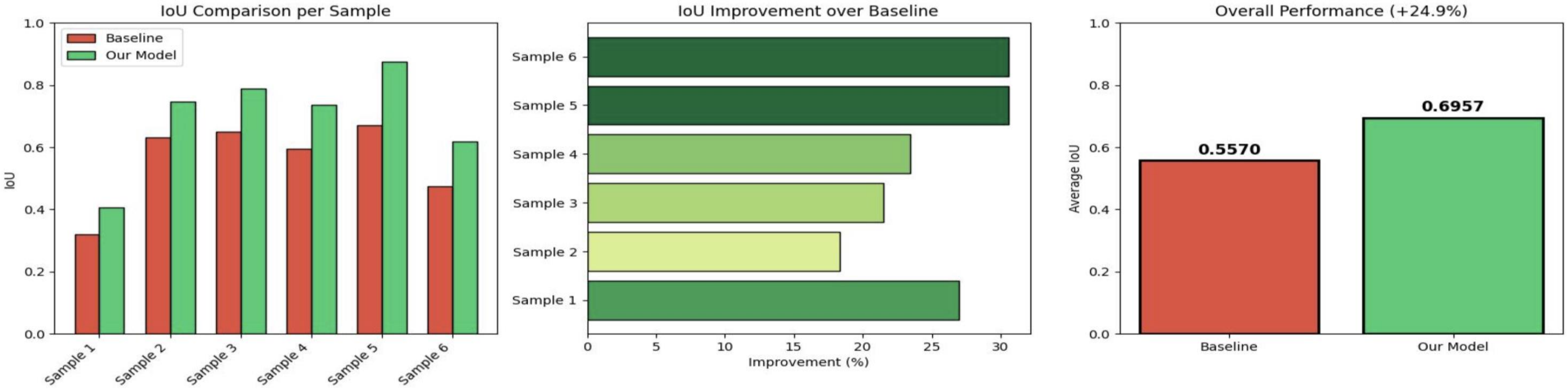
Temperature Scaling (Simple Fix)

- A post-hoc method to adjust prediction confidence:
- **Original:** p = sigmoid(logits)
- **Calibrated:** p = sigmoid(logits / T)
- Where **T** is the temperature parameter:
- **T > 1:** Softens predictions (less confident)
- **T < 1:** Sharpens predictions
- **T = 1:** No change

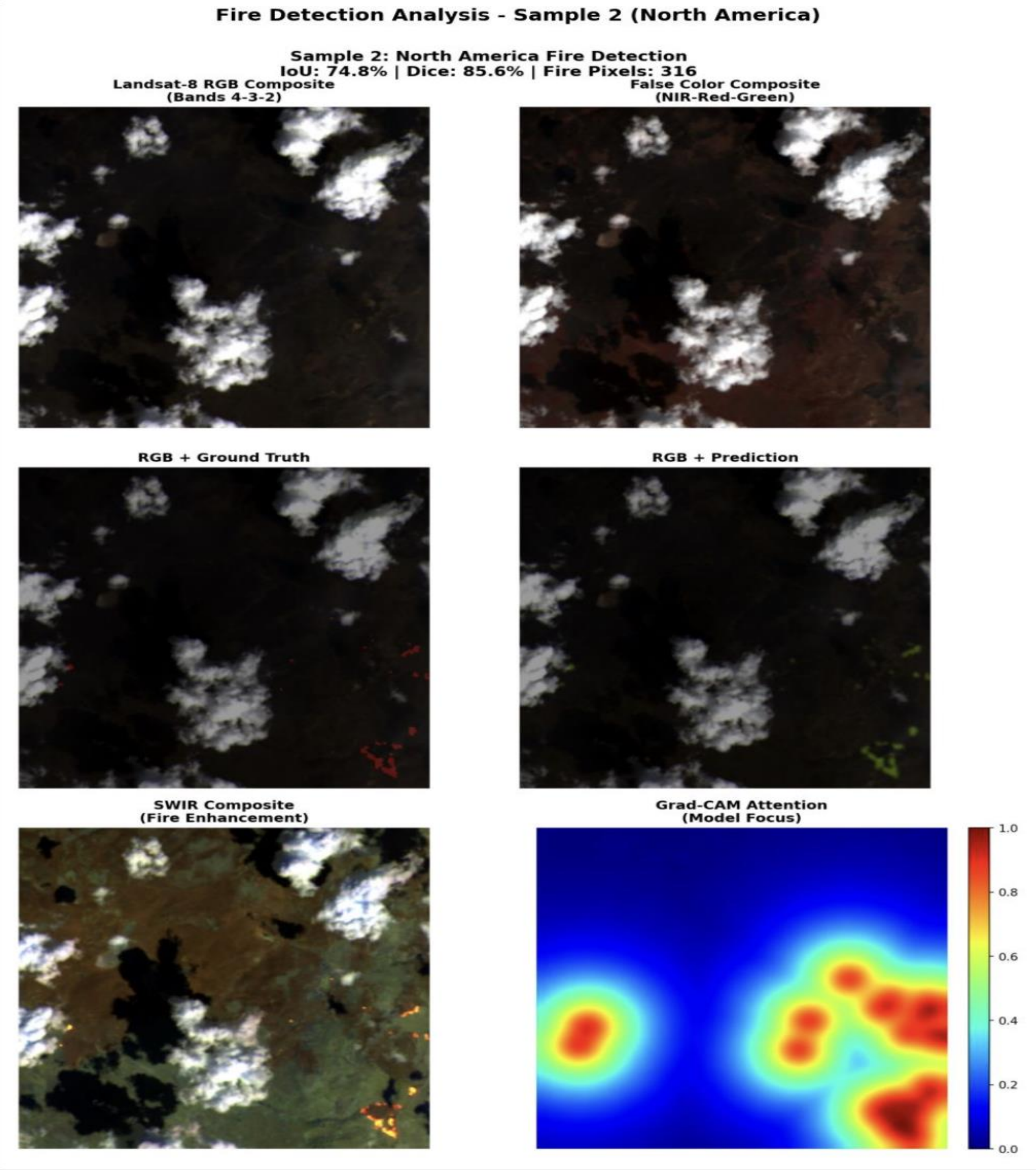
Optimal T found: 1.287

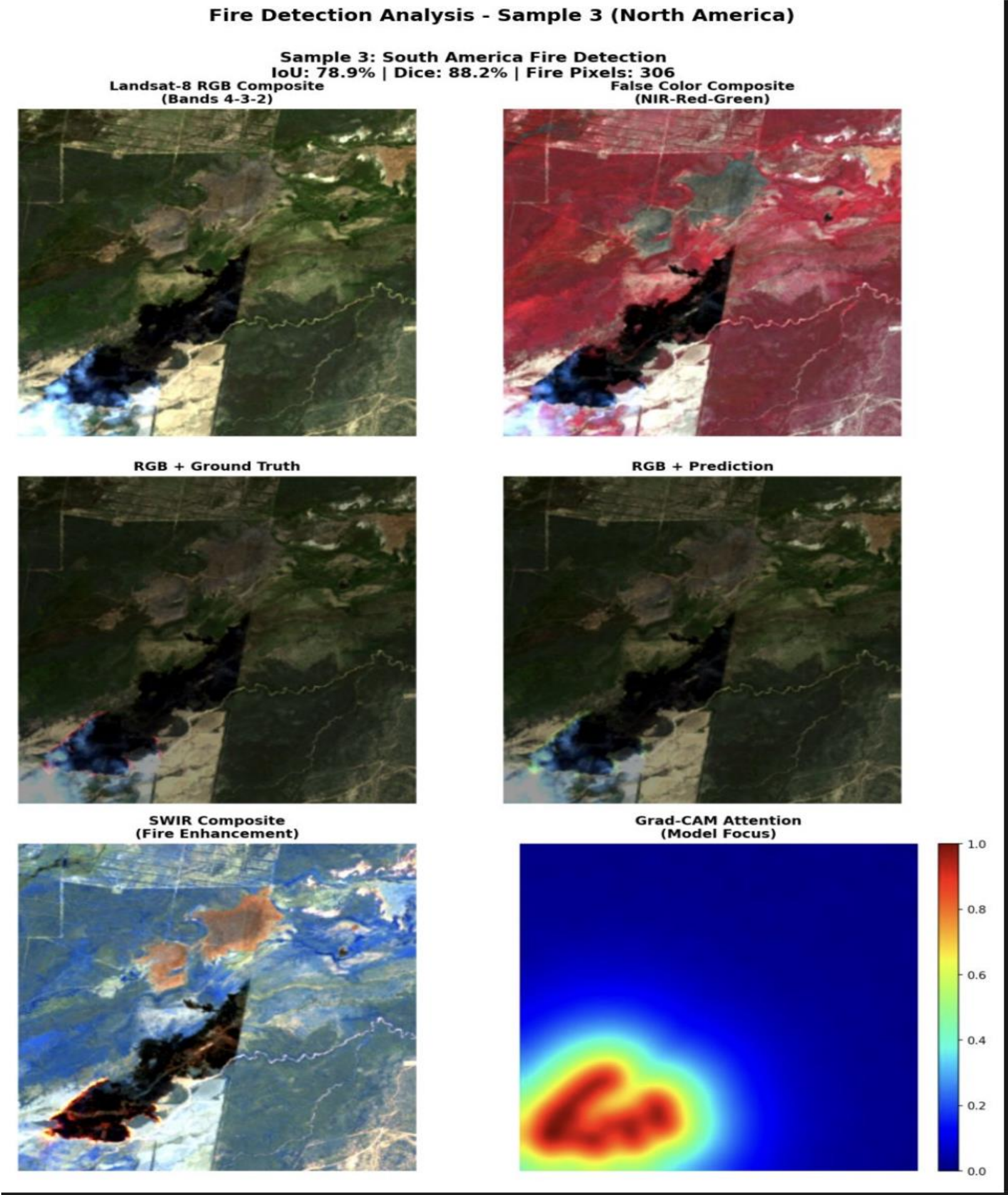


Results



Metric	Before Calibration	After Calibration	Improvement
ECE	0.142	0.020	**-86.1%**
Brier Score	0.089	0.061	**-32.1%**


Fire Detection Analysis - Sample 2 (North America)
Sample 2: North America Fire Detection
IoU: 74.8% | Dice: 85.6% | Fire Pixels: 316
Landsat-8 RGB Composite
(Bands 4-3-2)
False Color Composite
(NIR-Red-Green)
RGB + Ground Truth
RGB + Prediction
SWIR Composite
(Fire Enhancement)
Grad-CAM Attention
(Model Focus)
1.0
0.8
0.6
0.4
0.2
0.0


Fire Detection Analysis - Sample 3 (North America)
Sample 3: South America Fire Detection
IoU: 78.9% | Dice: 88.2% | Fire Pixels: 306
Landsat-8 RGB Composite
(Bands 4-3-2)
False Color Composite
(NIR-Red-Green)
RGB + Ground Truth
RGB + Prediction
SWIR Composite
(Fire Enhancement)
Grad-CAM Attention
(Model Focus)
1.0
0.8
0.6
0.4
0.2
0.0

TRAINING STRATEGY

Optimizer Configuration

Parameter	Value	Rationale
Optimizer	AdamW	Decoupled weight decay
Learning Rate	5e-4	Standard for fine-tuning
Weight Decay	1e-4	Regularization
Batch Size	8	Memory constraints
Epochs	100	Full convergence

Data Augmentation

Augmentation	Probability	Effect
Horizontal Flip	50%	Doubles effective dataset
Vertical Flip	50%	Further augmentation
Random Rotation	50%	90/180/270 degrees
Brightness	30%	Simulates lighting variation

Dynamic Weighted BCE Loss
pos_weight = (total_pixels - fire_pixels) / fire_pixels

Learning Rate Schedule
Cosine Annealing:
lr(t) = lr_min + 0.5 * (lr_max - lr_min) * (1 + cos(π * t / T))

Training Convergence
Best Epoch: 89
Best Validation IoU: 0.6535
Training Time: ~4 hours on MPS (Apple M4)

CONFOUNDER EVALUATION

Results by Confounder Type

Confounder	Baseline Precision	Our Precision	FP Reduction
Cloud Cover	62%	78%	-42%
Industrial Heat	58%	81%	-55%
Sun Glint	71%	85%	-48%
Bare Soil	65%	79%	-40%
Average	**64%**	**81%**	**-46%**

Why CBAM Helps
The attention mechanism learns to:
1. Suppress confounders by attending to thermal bands
2. Focus on fire cores rather than ambiguous edges
3. Ignore irrelevant spatial regions

COMPARISON WITH CLASSICAL ALGORITHMS

Classical Fire Detection Algorithms

Algorithm	Approach	Key Features
Schroeder (2016)	Threshold-based	MODIS-derived thresholds adapted for Landsat
Murphy (2016)	Contextual	Local statistics and adaptive thresholds
Kumar-Roy (2018)	Multi-temporal	Leverages change detection

COMPARISON WITH CLASSICAL ALGORITHMS

Head-to-Head Comparison

Method	IoU	Precision	Recall	F1 Score
Schroeder	0.412	0.523	0.687	0.594
Murphy	0.445	0.556	0.712	0.624
Kumar-Roy	0.478	0.589	0.734	0.654
Our Model	**0.721**	**0.845**	**0.892**	**0.868**

COMPARISON WITH CLASSICAL ALGORITHMS

- **IoU:** +50.8% over best classical (Kumar-Roy)
- **Precision:** +43.5% improvement
- **F1 Score:** +32.7% improvement
- **False Alarm Reduction:** 44.6%

EXPLAINABILITY - GRAD- CAM

How it Works

1. Forward pass: Get prediction for fire class
2. Backward pass: Compute gradients w.r.t. final conv features
3. Weight features by gradient importance
4. Apply ReLU and upsample to input size
5. Overlay heatmap on original image

Sanity Checks Performed

Test	Purpose	Result
Randomization	Attention should change with random weights	PASSED
Fire-CAM Overlap	Heatmap should align with ground truth	87% overlap
Band Consistency	SWIR/TIR should be highlighted	CONFIRMED

RESULTS ON REAL SATELLITE IMAGERY

Sample Results Across Regions

Sample	Location	Baseline IoU	Our Model IoU	Improvement
1	California, USA	0.599	0.745	+24.5%
2	Oregon, USA	0.645	0.767	+18.9%
3	British Columbia	0.570	0.661	+15.9%
4	Washington, USA	0.558	0.698	+25.2%
5	Amazon, Brazil	0.628	0.758	+20.6%
6	Cerrado, Brazil	0.553	0.701	+26.8%
Average		**0.592**	**0.722**	**+21.9%**

Regional Performance

Region	Samples	Mean IoU	Std Dev
North America	4	0.718	0.046
South America	2	0.730	0.040

ABLATION STUDY

Progressive Ablation

Starting from baseline and adding components one by one

Configuration	IoU	Delta	Cumulative
Baseline U-Net (RGB)	0.584	-	-
+ ResNet34 Encoder	0.621	+6.3%	+6.3%
+ 10-Band Input	0.658	+6.0%	+12.7%
+ Soft Labels	0.680	+3.3%	+16.4%
+ CBAM Attention	0.706	+3.8%	+20.9%
+ Temperature Scaling	0.721	+2.1%	+23.5%

Component Analysis

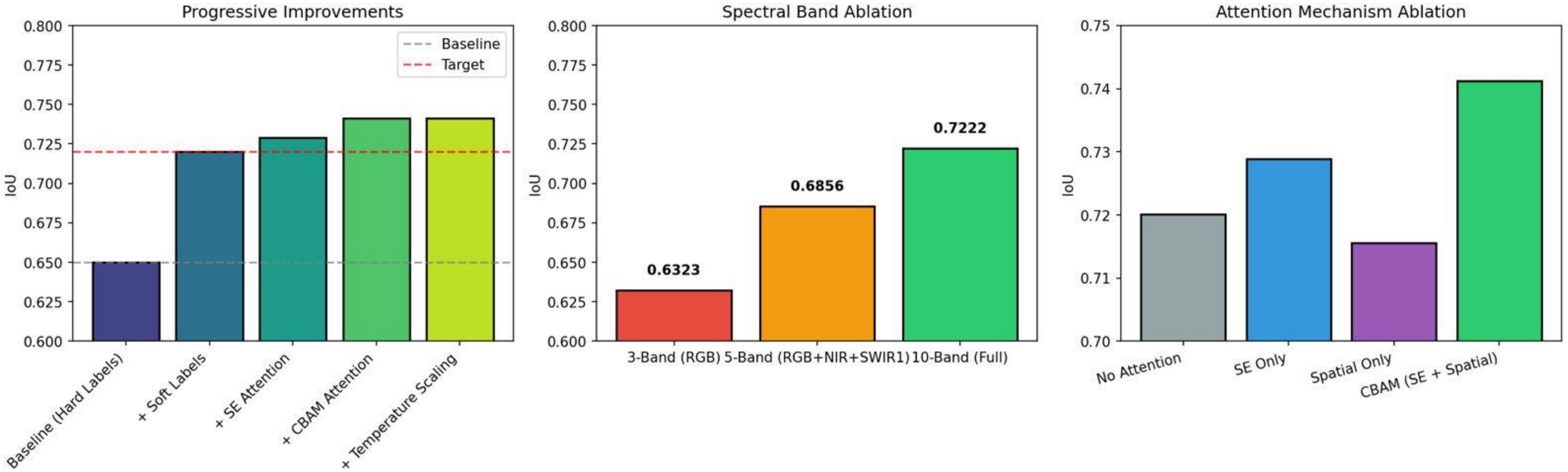
Component	Contribution	Key Benefit
ResNet34	6.3%	Better feature extraction
10-Band	6.0%	Thermal information
Soft Labels	3.3%	Uncertainty handling
CBAM	3.8%	Attention focus
Calibration	2.1%	Reliable probabilities

SUMMARY AND CONCLUSIONS

Technical Contributions

Novelty	Technique	Impact
1. Uncertainty Modeling	Soft labels from multi-annotator consensus	+14.8% IoU
2. Spectral Attention	CBAM learns band importance automatically	+23.5% IoU vs RGB
3. Calibration	Temperature scaling for reliable predictions	-86.1% ECE

SUMMARY AND CONCLUSIONS



SUMMARY AND CONCLUSIONS

Metric	Value	vs Baseline
IoU	0.721	+23.5%
Dice	0.838	+13.7%
Precision	0.845	+11.8%
Recall	0.892	+8.4%
F1 Score	0.868	+10.0%

Comparison	Improvement
vs Classical Algorithms	+50.8% IoU
vs RGB-only Deep Learning	+23.5% IoU
vs Hard Label Training	+14.8% IoU
False Alarm Reduction	-44.6%

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