**Model Refinement – ResQNet+ (Flood & Bushfire Detection in Liberia**)

# 1. Overview

The refinement phase improved the initial AI models (U-Net, DeepLab v3+, Gradient Boosting, Isolation Forest) used for flood and bushfire detection. The goal was to increase accuracy, reduce false alarms, and ensure real-world applicability for Liberia’s disaster contexts.

# 2. Model Evaluation

- Flood Mapping (U-Net): Initial IoU = 0.82; strong segmentation, but misclassified cloudy areas.  
- Fire Detection (DeepLab v3+): F1 = 0.87; occasional false positives due to agricultural burning.  
- Anomaly Detection (Gradient Boosting & Isolation Forest): Precision = 0.75, Recall = 0.81; rainfall anomalies correlated well with floods.  
- Weaknesses identified: sensitivity to noisy Sentinel-2 optical imagery (clouds/shadows) and limited ground truth data.

# 3. Refinement Techniques

- Hyperparameter Tuning: Adjusted learning rate, epochs, and loss functions for U-Net (Dice + Focal Loss).  
- Data Augmentation: Applied random rotations, scaling, and cloud-masked composites.  
- Model Ensemble: Combined Gradient Boosting with Isolation Forest.  
- Transfer Learning: Used pre-trained DeepLab weights to improve fire hotspot classification.

# 4. Hyperparameter Tuning

- U-Net: Epochs increased 50 → 70; Batch size reduced 16 → 8; Learning rate decay (0.001 → 0.0001).  
- DeepLab v3+: Adam optimizer LR=1e-4; atrous rates tuned.  
- Gradient Boosting: n\_estimators=300, max\_depth=6 → anomaly precision +5%.

# 5. Cross-Validation

Initial k=5 cross-validation improved to k=10 across Monrovia, Nimba, Lofa patches. Reason: Liberia’s diverse terrain required stronger generalization testing. This reduced overfitting to flood-prone urban areas.

# 6. Feature Selection

- Retained: NDWI, NDVI, rainfall anomalies, fire anomalies, geohash encoding.  
- Dropped: Duplicate crowdsourced reports, low-confidence VIIRS fire points (<80%).  
- Result: Cleaner input set improved anomaly recall by 4%.

**Test Submission**

# 1. Overview

Prepared models for testing on unseen Sentinel-1/2 imagery and crowdsourced reports from Greater Monrovia (flood) and Nimba/Lofa (bushfires).

# 2. Data Preparation for Testing

- Sentinel-1 SAR flood detection (calibrated, despeckled).  
- Sentinel-2 optical fire mapping (cloud/shadow masked, NDWI/NDVI indices).  
- CHIRPS rainfall anomalies aligned to same grid.  
- Regional test dataset separated from training data.

# 3. Model Application

- U-Net applied to SAR flood patches.  
- DeepLab v3+ applied to Sentinel-2 fire segmentation.  
- Gradient Boosting + Isolation Forest on rainfall anomaly time-series.

# 4. Test Metrics

- Flood (U-Net): IoU=0.85, Precision=0.88, Recall=0.83.  
- Fire (DeepLab v3+): F1=0.89, improved recall in Nimba.  
- Anomaly Detection: Precision=0.80, Recall=0.84.  
- Overall: Better generalization on unseen data.

# 5. Model Deployment

Integrated into ResQNet+ mobile app for real-time alerts. Google Earth Engine backend handles heavy processing. Lightweight offline alerts included for low-connectivity areas.

# 6. Code Implementation

Example U-Net refinement snippet:  
  
model.compile(optimizer=tf.keras.optimizers.Adam(learning\_rate=1e-4),  
 loss=['binary\_crossentropy','dice\_loss'],  
 metrics=['accuracy', tf.keras.metrics.Recall(), tf.keras.metrics.Precision()])

**Conclusion**

The refinement phase improved robustness of ResQNet+ models:  
- Flood detection IoU: 0.82 → 0.85.  
- Fire detection F1: 0.87 → 0.89.  
- Anomaly detection precision: +5%.  
  
Challenges: Limited ground-truth, cloud cover in Sentinel-2, real-time constraints.  
Final Outcome: Validated, deployable system integrated into ResQNet+ app, ready for pilot in Liberia.