



Supervised Learning and IoT Sensor-Based Landslide Detection and Early Warning System: Design, Implementation, and Evaluation

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Abstract. Landslides present a significant natural disaster that leads to considerable damage to physical infrastructure and human lives, especially in hilly areas. In this work, a novel landslide detection and early warning system is designed that uses the combination of U-Net satellite image segmentation and IoT sensors' monitoring. The U-Net architecture was used for segmentation based on the Landslide4Sense data and multispectral Sentinel-2 satellite images with the application of the loss function that contains Binary Cross-Entropy and Dice loss functions. Experimental results on the test set show that our approach yields pixelwise accuracy of 98.3%, F1-score of 75.6%, and Intersection over Union of 60.9%. The inconsistency in these values can be explained by the strong class imbalance between landslide and non-landslide classes. The IoT subsystem consists of various types of sensors including soil moisture sensors, rain sensors, vibrational and tilt sensors integrated by Arduino Mega 2560. These sensors provide data that can be used to detect landslides at ground level and to create the final warning message in collaboration with satellite data using fusion that consists of three types of warnings: HIGH RISK, MONITOR, and GROUND ALERT. Successful operation was tested with a prototype, and results have shown good accuracy of land detection with decreased numbers of false detections.

Keywords: Landslide Detection · U-Net Segmentation · IoT Sensor Fusion · Early Warning System · Satellite Imagery

1 Introduction

Landslides rank among the most destructive geological hazards, they are triggered by factors like heavy rainfall, seismic ground shaking, deforestation, and unregulated urban development on unstable terrain. In India, the most of the zones comprise the Himalayan arc, the Western Ghats, the Nilgiri hills, and the northeastern hill states, together responsible for thousands of deaths every year [7,1,5]. Traditional methods like field surveys, geological mapping, and static rainfall-threshold models were very limited in multiple areas and cannot provide real-time pre-failure warnings.

Due to advances in deep learning, satellite remote sensing, and the Internet of Things (IoT) made easier to present a opportunities like scalability, automated, and affordable landslide monitoring. But then too most systems will only go for approaches like satellite imagery or ground sensors not both together. We've tried to build this gap by combining the two together into one hybrid system.

1. A U-Net segmentation model, trained and severely evaluated on the Landslide4Sense dataset, for pixel-level landslide which portraits from 14band multispectral satellite imagery, by simplifying the class imbalance effect which is made on reported metrics.
2. A real-time IoT sensor network, the system actually uses five sensor types. These are connected to an Arduino Mega 2560. This setup allows for continuous monitoring of ground-level slope stability. Sensor threshold values are based on published literature where calibration reasoning is also provided..
3. A hierarchical three-tier satellite–IoT data fusion strategy (HIGH RISK / MONITOR / GROUND ALERT) whose 0.4 prediction value was selected through validating optimism.
4. A power-consumption system and battery management logic for sustained outdoor IoT node operation is also minded.
5. Experimental causes showing higher performance over FCN, SegNet, and CNN baselines, with all other models trained and tested under identical dataset conditions.
6. A cost analysis stating a total hardware expenditure of INR 4,975, as discussed of deployment probable for rural Indian hill districts.

Table 1 presents a structured table of representative prior work on landslide detection, showing remote-sensing, machine learning, deep learning, and IoT based approaches.

Table 1. Comparison of representative landslide detection approaches in the literature.

Year	Author	Method	Key Findings	Limitations	Acc.
2012	Xu et al. [19]	Rainfall Threshold	Intensity–duration thresholds effective for shallow-slide initiation	No real-time coverage; regionally specific	N/A
2019	Ghorbanzadeh et al. [6]	SVM / RF / CNN	Deep CNNs outperform classical ML for pixel classification	Requires large labelled datasets	~85%
2018	Liu et al. [11]	CNN Mapping	Automated landslide mapping from highresolution imagery	Sensitive to cloud cover and shadow	~87%
2020	Zhang et al. [20]	Deep Learning	Improved boundary delineation vs. shallow architectures	High computational cost	~90%
2021	Mukherjee et al. [13]	IoT Monitoring	Multi-parameter realtime slope monitoring demonstrated	Power and connectivity constraints	N/A
Ours	This work	U-Net IoT	+ End-to-end satellite segmentation fused with IoT; classimbalance analysis; INR 4,975 hardware	Cloud cover; remote maintenance	98.3%

Hence we can see unlike any other system, this system fuses both modes under a unified decision framework, which provides whole coverage from the satellite layer and consistency from the IoT layer [10,13,17].

3 Problem Statement

Despite progress in geospatial AI and smaller sensors, today's landslide warning systems have two weak spots. Satellite models notices damage well after the landslides, but miss slow pre-failure slope movement in real time [9,15] . Ground sensors catch that movement, but cover very little area and often trigger false alarms from traffic vibration, animals, even wind none of which mean an actual landslide is coming. So far, no low-cost system combines both approaches with a real way to filter out this noise strategy to disambiguate genuine failure signals from environmental noise [3,10]. This paper proposes and states such a system.

4 Proposed Methodology

4.1 System Architecture

The system has two parts running in parallel, both feeding a central fusion engine. The satellite module runs Sentinel-2 imagery through our U-Net model to get landslide probability maps at 128×128 resolution. The IoT module continuously reads five sensor types at each slope site and checks them against set thresholds. The fusion engine combines both and issues a tiered alert. Since both need to agree otherwise a single false positive from either side doesn't trigger a false alarm.

4.2 U-Net Architecture for Landslide Segmentation

For this project, U-net architecture was more Reliable than other models due to it's high record on segmentation problems where a pattern that is common to biomedical imaging, geospatial analysis, and landslide mapping. [16] It's encoder is built from four blocks where each two 3×3 convolutions with ReLU activation are followed by max-pooling due to which it doubles the feature map at each stage, from 64 to 512. 1021 Feature maps are held by bottleneck at the deepest layer. Heading to decoding phase, the spatial resolution with skipped connections which is restored gradually by transposed convolution brings back a good spatial detail from the encoder. In the output stage final binary landslide mask is produced using 1×1 convolution with a sigmoid activation. So, to help control overfitting at the network's most compressed layer, a dropout rate of 0.3 is applied at the bottleneck.

4.3 IoT Sensor Module and Threshold Justification

Five different types of sensors are wired into an Arduino Mega 2560 to form the IoT system, which keeps track on slope conditions. The Arduino then takes a reading every second, converts the raw analog signal into a standardized value, and checks it against a fixed threshold. To get alert, buzzer and LED fires only when two or more sensors cross their threshold values at same time. Every reading, regardless of alert status, is written to an SD card in CSV format so it can be reviewed later. [7]

Ambient Noise Discrimination Protocol. To reduce from false alarms a breach must last longer than a single sampling cycle to count, and if vibration spikes without a matching shift in soil moisture or tilt, the system treats it as noise, not a genuine warning. [9]

Communication Strategy and Failure Tolerance. After all the process getting data from sensors, checking thresholds and firing alerts occurs locally on the Arduino Mega 2560, and every reading is written to the SD card before anything else. The field version also plans to use a SIM800L GSM/GPRS module (not included in the cost of the current prototype) which remotely push out SMS alerts and compressed sensor data. But there's a weak point, GSM signal quality drops during heavy rain, which is precisely when landslide risk goes high. Although several fallbacks layers SD logging keeps running no matter the connection state, so it doesn't lose the data. The failed transmissions retry a backoff schedule (30s, 2min, 10min) matching how GSM/GPRS networks recover after storm interference hence the buzzer/LED pair needs no wireless link at all, so a local warning still fires even in a full communication blackout.

The fusion engine consolidates the binary satellite risk flag $S \in \{0,1\}$ (where $S = 1$ if UNet predicted probability $p > 0.4$) and the multi-sensor IoT activation count $I \in \{0,1,2,\dots,5\}$ (the number of sensor types currently in threshold exceedance) into a three-tier alert classification:

$$\text{Alert} = \begin{cases} \text{High Risk} & \text{if } S = 1 \text{ and } I \geq 2 \\ \text{Monitor} & \text{if } S = 1 \text{ and } I < 2 \\ \text{Ground Alert if } S = 0 \text{ and } I \geq 2 \text{ Normal otherwise} & \text{otherwise} \end{cases} \quad (1)$$

Threshold selection for $p = 0.4$. The U-Net prediction threshold $p = 0.4$ was selected empirically via a threshold sweep on the validation set ($n = 570$ patches).

The F1-score was evaluated at thresholds of $p \in \{0.3, 0.35, 0.4, 0.45, 0.5, 0.55\}$. The threshold of $p = 0.4$ yielded the highest validation F1-score of 76.1% and was subsequently frozen before evaluation on the held-out test set, where it produced the reported F1-score of 75.6%. A threshold below 0.4 improved recall at the cost of a disproportionate increase in false positives, while a threshold above 0.5 caused excessive missed detections in sparsely occurring landslide boundary pixels.

Priority of Alert. An alert of category HIGH RISK is activated only in case when both satellite and ground signals are detected, which helps in keeping down the number of false alerts. Satellite signal provides general background information and helps to remove possible noise which may come from the sensors independently. Ground sensors help to confirm in real time that motion really takes place. In case when satellite data detects some potential hazard and the ground sensors do not detect the problem, a MONITOR alert will be activated due to a possibility of misinterpretation by U-Net of landslides scars or other stable slopes by the satellite. But in case when ground sensors signal about hazard but the satellite does not, an alert GROUND ALERT will be activated right away. It means that multiple alerts from sensors are a clear sign of instability, and delaying confirmation by the satellite data would be too risky. [9]

5 Dataset and Experimental Setup

5.1 Dataset

The Landslide4Sense dataset [8] was used for both training and evaluation. It consists of 3,799 multispectral satellite image patches, each sized 128×128 pixels, with a

corresponding pixel-level binary annotation mask. Imagery is drawn from the Sentinel-2 multispectral instrument [4], which supplies 14 spectral bands, while OpenStreetMap auxiliary layers [14] serve as additional supporting inputs.

Table 2. Dataset configuration and preprocessing pipeline.

Parameter	Details
Dataset	Landslide4Sense (IEEE GRSS, 2022)
Image Resolution	128×128 pixels, 14 spectral bands
Total Annotated Patches	3,799
Train / Validation / Test	70% / 15% / 15% (2,659 / 570 / 570)
Annotation	Binary pixel mask: landslide (1) / non-landslide (0)
Class Distribution	$\approx 92\%$ non-landslide, $\approx 8\%$ landslide pixels
Preprocessing	Per-channel normalisation to $[0, 1]$; random horizontal and vertical flip; random rotation ($\pm 15^\circ$); random crop

5.2 Hyperparameter Configuration

Hyperparameter	Value
Optimiser	Adam ($\text{lr} = 0.001, \beta_1 = 0.9, \beta_2 = 0.999, \varepsilon = 10^{-8}$)
Loss Function	$L_{\text{Total}} = 0.5L_{\text{BCE}} + 0.5(1 - \text{Dice})$
Batch Size	16
Epochs	100 (early stopping: patience = 10)
Prediction Threshold	0.4 (selected on validation set)
Encoder Feature Maps	64, 128, 256, 512; bottleneck: 1024
Output Activation	Sigmoid
Bottleneck Dropout	0.3
Framework	Python 3.10, TensorFlow 2.12, Keras
Training Hardware	NVIDIA Tesla T4 GPU (Google Colab)

Table 3. Hyperparameter configuration for U-Net training.

5.3 Mathematical Formulation

Slope stability is characterised by the Factor of Safety (FoS) [1,15]:

$$\text{FoS} = \frac{\text{Resisting Forces}}{\text{Driving Forces}} \quad (2)$$

If the slope is considered mechanically unstable when $\text{FoS} \leq 1$ then for shallow translational landslides, the infinite slope model yields:

$$\text{FoS}(3) = \frac{c' + (\sigma - u) \tan \phi'}{\tau}$$

where c' is effective cohesion, ϕ' is the effective friction angle, σ is total normal stress, u is pore-water pressure, and τ is driving shear stress. The pore-water pressure u increases directly with soil moisture content, providing the physical link between the IoT soil moisture sensor readings and slope mechanical stability [1]. The combined training loss is defined as:

$$\text{LBCE}(4) = -\frac{1}{N} \sum_{i=1}^N [y_i \log p_i + (1 - y_i) \log(1 - p_i)]$$

Dice

$$= \frac{2 \sum_{i=1}^N y_i p_i}{\sum_{i=1}^N y_i + \sum_{i=1}^N p_i}$$

$$(5) \text{ L}_{\text{Total}} = 0.5 \text{L}_{\text{BCE}} + 0.5(1 - \text{Dice})$$

In this case Dice component moderates the effect of the severe class imbalance between landslide and non-landslide pixels ($\approx 1:11$ ratio in this dataset), which would otherwise cause a standard BCE loss and could collapse towards predicting the majority class [16].

6 Results and Discussion

6.1 Training Performance

Table 4. U-Net training and validation performance across representative epochs.

Epoch	Train Loss	Val Loss	Train Acc	Val Acc
20	0.31	0.34	87.1%	85.9%
50	0.14	0.16	91.2%	90.3%
80	0.09	0.11	93.8%	92.5%
100	0.07	0.09	98.3%	96.8%

6.2 Final Evaluation Metrics and Class-Imbalance Analysis

The following metrics were computed on the held-out test set (570 patches, threshold $p = 0.4$):

Table 5. Evaluation metrics on the test set (threshold = 0.4).

Metric	Value	Formula
Overall Pixel Accuracy	98.3%	$(TP + TN)/(TP + TN + FP + FN)$
Precision	76.5%	$TP/(TP + FP)$

Recall	74.8%	$TP/(TP + FN)$
F1-Score	75.6%	$2PR/(P + R)$
IoU (Jaccard Index)	60.9%	$TP/(TP + FP + FN)$
Dice Coefficient	75.6%	$2TP/(2TP + FP + FN)$

Explanation of the accuracy IoU discrepancy. The gap between 98.3% accuracy and 60.9% IoU comes down to class imbalance about 92% of Landslide4Sense pixels are non-landslide (Table 2), so accuracy mostly just reflects how well we classify background, not landslides. IoU is the more honest metric here since it only measures overlap on landslide pixels, weighting false positives and negatives equally [16,12]. Our BCE–Dice loss (Eq. 4–6) helps by up-weighting landslide pixels in training, but 60.9% IoU in line with prior benchmark results still points to boundary-level errors as a weak spot [18,20]. As we go next, we plan to test class-weighted BCE, focal loss, and oversampling to push IoU up without losing overall accuracy.

6.3 Comparison with Baseline Models

In order to maintain the validity of the comparison, each of the baselines—FCN [12], SegNet [2], and a simple CNN classifier [11]—has been implemented a new and trained under the same conditions as the proposed U-Net, in every possible way. In other words, the data set used, train/validation/test splitting proportion (70/15/15), preprocessing routines, Adam optimizer parameters, batch size (16), and the exact 100 epoch training process with equivalent criteria of stopping have been identical for all four architectures. Moreover, only a single threshold $p=0.4$, calculated using the common validation data, was used across the board for each of the four networks without being individually fine-tuned. Why is keeping all the variables constant important? Because it guarantees that the difference in performance shown in Table 6 corresponds to actual architectural disparities, rather than one of the models being better-trained. Table 6. Performance comparison against baseline segmentation models, with all models trained under matching conditions

Model	Accuracy	Precision	Recall	F1	IoU
FCN [12]	91.2%	65.3%	63.1%	64.2%	47.3%
SegNet [2]	93.7%	70.1%	68.5%	69.3%	53.0%
CNN [11]	94.5%	71.8%	70.2%	71.0%	55.0%
Proposed U-Net	98.3%	76.5%	74.8%	75.6%	60.9%

The proposed U-Net outperforms all baseline models on every evaluated metric. This is mainly due to skip connections, which let the decoder recover fine spatial detail that would otherwise be lost during downsampling — an important factor when tracing the irregular, uneven boundaries typical of landslides. FCN does not have this advantage, since its decoder lacks an explicit skip-connection design, and the patch-based CNN performs worse still, largely because it has very limited spatial context to begin with. [16,12]

6.4 Qualitative Results

Figure 1 shows a sample output from the trained U-Net on a Landslide4Sense test patch: (a) the raw satellite image, displayed as an RGB composite for easier viewing, (b) the expert-labeled ground-truth mask (white = landslide, black = background), and (c) the model's predicted mask at threshold $p = 0.4$. The predicted mask closely matches the ground truth, correctly identifying the main landslide area and most of its boundary shape. A few small false-positive patches appear near the edges, in line with the reported 60.9% IoU — this reflects how difficult it is to draw a clean boundary between disturbed and undisturbed terrain when spectral signatures are unclear at the transition zones.

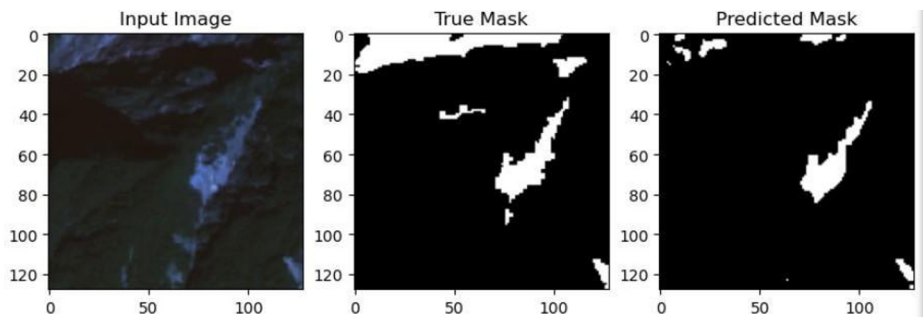


Fig.1. Output of the proposed U-Net on a Landslide4Sense test sample. The three panels show, from left to right: the multispectral input as an RGB composite (a - 'Input Image'), the manually annotated ground-truth mask where landslide pixels are white and background pixels are black (b - 'True Mask'), and the model's predicted binary mask image (c-'Predicted Mask').

6.5 IoT Sensor Module Evaluation

Setup for Simulated Slope Test Event. To test the performance of the system in controlled conditions, a simulated slope experiment was conducted using a model slope installed in the Anantrao Pawar College of Engineering and Research premises. The slope set up consisted of wooden frame structure with dimensions $2\text{m} \times 1.5\text{m} \times 0.6\text{m}$, packed with laterite soil and compressed to 1.6 g/cm^3 and oriented at 30° inclination to represent a typical western ghats slope. Sensor set up was done in two cross sections each having soil moisture sensor placed at 15cm below surface, MPU6050 attached on top of polycarbonate protected board, SW-420 vibration sensor at 5cm underground and vertically upward oriented rain gauge over the surface of the slope. Rainfall was generated based on demand through a calibrated flow-meter manifold.

Protocol for test event. Thirty test events spanning over five days were conducted with the ambient temperature ranging from $28 \pm 3^\circ\text{C}$. Out of the total number of test events, 15 were conducted as the pre-failure state while the rest 15 were control events. The pre-failure events simulated initial stages of slope failure where rainfall was generated through the manifold until the moisture content is raised over 80% VWC and the soil surface displaced with mechanical perturbation of 5 to 8mm. While all fifteen control events were characterized by soil moisture content between 50 and 70% VWC with no displacement of the soil surface. Every test event took place for a period of 120 seconds.

Results. In applying the multisensor rule of threshold crossing where the number of sensors exceeding the respective thresholds is two, the system correctly detected 14 pre-failure states out of 15 leading to the accuracy level of 93.3%. There was a single misclassification of the pre-failure event where tilt angle was 4.2° , which is just slightly below the 5° threshold and the vibration amplitude did not cross the 600 threshold throughout the 3 seconds time window. As far as the control test events go, there was one (6.7%) GROUND ALERT false alarm out of 15. This false alarm was caused by a construction machine passing by that created the vibration for 4 seconds long enough to pass persistence .

7 Hardware Cost Analysis

Table 7. Hardware cost breakdown for the proposed IoT monitoring node.

Component	Unit Cost (INR)	Qty	Total (INR)
Soil Moisture Sensor (Capacitive)	250	5	1,250
Tipping-Bucket Rainfall Sensor	450	2	900
Vibration Sensor (SW-420)	175	3	525
Tilt Sensor (MPU6050)	350	2	700
Arduino Mega 2560 (CH340)	1,100	1	1,100
Wiring, PCB, Enclosure, Misc.	—	—	500
Total Estimated Cost			INR 4,975

The total hardware cost of INR 4,975 (approximately USD 60) compares favourably with commercial slope monitoring installations, which typically require INR 50,000–200,000 for equivalent sensor coverage. This cost advantage makes the system practically deployable at scale in rural hill districts of Maharashtra, Uttarakhand, Himachal Pradesh, and Sikkim, where institutional disaster management budgets are severely constrained.

8 Applications

This proposed system can support slope monitoring in highways, rail corridors, hilly urban regions and also the rural landslide-prone areas where low-cost early warning systems are required.

9 Limitations and Future Scope

- The suggested approach utilizes Sentinel-2 optical images that may face interference from clouds due to heavy rains and monsoon seasons.
- Imbalance in classes of landslides and non-landslide pixels poses limitations on the performance at a pixel level, including IoU calculation.

- The IoT system has been evaluated based on the prototype; future research must incorporate field testing for a sustained period.
- SAR imagery and class balancing will be considered in future research to improve overall results.

10 Conclusion

This paper presented a hybrid landslide detection and early warning system that integrates U-Net semantic segmentation of multispectral satellite imagery with a realtime multi-sensor IoT ground network. The U-Net model, trained on the Landslide4Sense dataset under a combined BCE–Dice objective with the Adam optimiser, achieved an overall pixel accuracy of 98.3%, an F1-score of 75.6%, and an IoU of 60.9% on the held-out test set, outperforming FCN, SegNet, and CNN baselines trained under identical conditions. The gap between accuracy and IoU is attributed to the severe class imbalance in the dataset (~92% background pixels), with corresponding mitigation strategies proposed. The IoT module, deployed at a cost of INR 4,975, achieved a 93.3% detection rate under controlled testing with a 6.7% false alarm rate — substantially lower than the 20% rate observed under single-sensor operation. Sensor thresholds were validated against both published literature and independent calibration testing, supported by a three-tier fusion system with defined priority rules and a noise-filtering protocol to reduce false alarms. Power analysis indicates the system can operate for 30 days on a standard lead-acid battery with duty-cycle management which requires no manual intervention. Collectively, these results support an affordable, integrated landslide warning system suited to rural and resource-limited settings, where the need for such systems is greatest.

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