IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 13, Issue 11, November 2026

DOI: 10.17148/IARJSET.2026.131147

Satellite Image Classification to Detect Deforestation Using ResNet50 Transfer Learning and Spatial Risk Forecasting

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Abstract: Deforestation threatens biodiversity, regional climate regulation and carbon sequestration, yet conventional monitoring based on ground surveys or NDVI thresholding suffers from misclassifications caused by cloud shadows, terrain variation and dry soil. This paper presents an end-to- end deep learning framework that combines ResNet50 transfer learning with geospatial boundary clipping and spatial risk forecasting to detect deforestation and canopy intrusion in the ecologically sensitive Tamil Nadu hill stations of Ooty (Udhagamandalam) and Kodaikanal. A ResNet50 network pretrained on ImageNet is adapted to the Sentinel-2 based EuroSAT benchmark (10 land use and land cover classes) and reaches an overall accuracy of 91% with a precision of 0.93 for the Forest class. OpenStreetMap boundary polygons are retrieved with OSMnx and used to clip rasters with Rasterio, after which patch unfolding produces spatial prediction grids. A neighbor convolution risk model then scores each forest patch by the fraction of cleared neighbors and, for the Kodaikanal study region, flags 81.92 hectares of forest as highly vulnerable to near-term encroachment. The work is a proof of concept for automated satellite monitoring and a basis for nationwide cloud integration and application deployment.

Keywords: deforestation detection, satellite imagery, ResNet50, transfer learning, EuroSAT, geospatial clipping, risk forecasting

I. INTRODUCTION

Forest ecosystems cover roughly 31% of the global land area, serving as carbon sinks, stabilizing regional climate and supporting critical biodiversity. Agricultural expansion, urban encroachment, resort construction and illegal logging have accelerated their loss. In ecologically sensitive mountain biomes such as the Western Ghats of Tamil Nadu, including Ooty (the Nilgiris) and Kodaikanal, rapid land cover change threatens endemic flora and fauna and triggers soil erosion and landslides.

Traditional forest monitoring relies on manual field inspection or index-based satellite image processing such as the Normalized Difference Vegetation Index (NDVI) [1]. NDVI is a quick measure of photosynthetic activity, but it yields many false positives because of shadows cast by mountainous terrain, atmospheric interference, clouds and dry soil. Deep learning, and convolutional neural networks (CNNs) in particular, can instead analyze spatial texture, canopy density and context rather than pixel-level color ratios.

Existing monitoring methods cannot automatically separate seasonal foliage variation and cloud shadow from genuine forest intrusion, and conventional indices give no predictive assessment of which adjacent forest patches are likely to be cleared next. This paper addresses these gaps with an automated pipeline that ingests satellite imagery, classifies forest patches, clips administrative boundaries and forecasts localized deforestation risk. The main contributions are:

- A scalable preprocessing and training pipeline on the Sentinel-2 based EuroSAT benchmark, using a ResNet50 classifier for land use and land cover (LULC) with emphasis on the Forest versus Non- Forest decision.
- Geospatial boundary processing that fetches the Ooty and Kodaikanal polygons with OSMnx and clips raster tiles with Rasterio and Geo Pandas.
- Apatch-basedinferenceengineanda3×3neighborconvolution risk model that converts flagged patches into hectares.
- An evaluation with precision, recall, F1-score and confusion matrix, compared against index-based and scratch-trained CNN approaches.

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The scope is regional forested hill stations of Tamil Nadu, giving forest department officials and environmental researchers a tool to spot canopy intrusion early. The architecture is a proof of concept intended to scale to forested regions across India. The rest of the paper reviews related work (Section II), describes the methodology (III), system design (IV) and implementation (V), discusses results (VI) and concludes (VII).

II. RELATEDWORK

A. Existing Approaches

Remote sensing for deforestation detection has evolved through three paradigms. *Index thresholding* uses NDVI = (NIR − Red)/(NIR + Red) [1] and the Normalized Difference Built-Up Index (NDBI) for urban structures; fixed cutoffs struggle with atmospheric degradation and terrain illumination, and reported accuracy is roughly 70–74%. *Classical machine learning*, such as Random Forests (RF) and Support Vector Machines applied to Landsat pixels on Google Earth Engine [2], reaches roughly 80–83% but relies on hand-crafted pixel features and ignores spatial context in complex canopies.
Deep CNNs learn spatial textures, edge boundaries and canopy structure directly. Helber et al. [3] released the EuroSAT dataset from Sentinel-2 imagery and showed that deep architectures such as ResNet and DenseNet significantly outperform classical classifiers on LULC recognition. A CNN trained from scratch on limited regional data, however, tends to overfit severely (roughly 78–82%).

B. Research Gap

Although deep models achieve high accuracy on static benchmarks, three gaps remain in the literature:
Lack of geospatial polygon integration: most implementations work on standalone cropped images rather than clipping rasters with administrative from boundary polygons such as those OpenStreetMap.
Absence of risk forecasting: current systems classify what has already been cleared without projecting which adjacent forest patches are vulnerable to expansion.
Lack of scalable inference frameworks: existing scripts do not combine patch unfolding, deep inference and report generation in one deployable workflow.

III. METHODOLOGY

A. Data Collection

To train the model without overfitting, the standard
EuroSAT Sentinel-2 benchmark [3] was used. It contains 27,000 labeled 64 × 64 pixel patches in 10 LULC classes: Annual Crop, Forest, Herbaceous Vegetation, Highway, Industrial, Pasture, Permanent Crop, Residential, River and Sea Lake. For regional testing, the boundary polygons of Ooty (Udhagamandalam) and Kodaikanal were fetched from OpenStreetMap using OSMnx [4] and used to clip a GeoTIFF raster with the same band structure as the training patches using Rasterio [5].

B. Data Preprocessing

Patches are converted to tensors and normalized with the ImageNet channel mean $\mu = [0.485, 0.456, 0.406]$ and standard deviation $\sigma = [0.229, 0.224, 0.225]$, and resized by bilinear interpolation to 224 × 224 pixels to match the ResNet50 input. For regional inference, the clipped raster (3 × 500 × 500) is sliced into non-overlapping 64 × 64 patches with PyTorch tensor unfolding [6], giving a 7 × 7 grid of 49 patches.

C. Model Selectionand Training

ResNet50 [7] was selected because its residual skip connections mitigate the vanishing gradient problem and make deep networks trainable on limited data. The final fully connected layer was replaced, changing the 1000 ImageNet outputs to 10 EuroSAT classes. The network was initialized with pretrained ImageNet weights, the earlier layers were frozen for quick transfer learning, and the new classification head was trained with the Adam optimizer (learning rate 0.001), cross-entropy loss and a batch size of 64. Training ran for 3 epochs on a Google Colab Tesla T4 GPU with an 80/20 split, leaving 5,400 samples for validation. For the regional grid, the predicted class is reduced to a binary decision: Forest (1) versus Non-Forest or Deforested (0).

Convolutional layers extract hierarchical features without hand-crafted spectral indices: low-level layers respond to edges, road cuts and water-land boundaries; mid-level layers capture repetitive canopy textures, field grids and building groups; and high-level layers encode the semantic context that separates dense continuous canopy from cleared land or resort intrusions.

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D. Geospatial Clipping and Patch Inference

The administrative boundary is retrieved with osmnx.geocode_to_gdf() and handled as a GeoDataFrame with GeoPandas [8]. The raster is then cropped to the polygon with rasterio.mask.mask(), unfolded into patches, normalized and passed through the trained network. The predictions are reshaped into a 7 × 7 binary forest grid.

E. NeighborRiskForecasting

To forecast near-term deforestation, the binary grid (0 = nonforest or cleared, 1 = healthy forest) is convolved with a 3 × 3 kernel K whose entries are all 1 except the center, which is 0. For every healthy forest cell, the risk score is the fraction of its 8 surrounding cells that are already cleared:

$$R(i,j)=N_c(i,j)/8 \quad (1)$$

where $N_c(i,j)$ is the number of cleared neighbors of cell (i,j). Cells with $R \geq 0.5$, meaning at least half of the surroundings are cleared, are flagged as high risk (vulnerable). Each 64 × 64 patch at the 10 m Sentinel-2 pixel size covers 640 m × 640 m, so the projected vulnerable area for n_{hr} flagged patches is

$$A=n_{hr}\times(64\times10\text{m})^2/10^4 \quad (2)$$

in hectares, which equals 40.96 ha per patch.

IV. SYSTEM DESIGN

The end-to-end pipeline has four interconnected modules: data acquisition and boundary clipping, deep learning classification, spatial grid reconstruction, and risk forecasting (Fig. 1). Its outputs are a grid map, a risk forecast map and a metrics file, deforestation_metrics.csv.

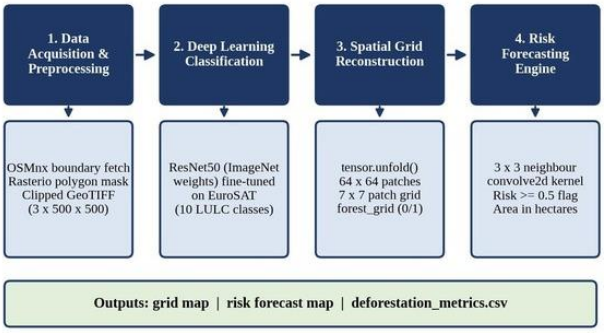


Fig. 1. Project pipeline architecture.

The *geospatial boundary acquisition* module retrieves boundary geometries and crops rasters to the administrative shape. The *patch unfolding and tensor pipeline* converts the raster into a float tensor and slices it into 64 × 64 patches that match the training chip size. The *classification engine* passes normalized patches through the GPU-accelerated ResNet50 to predict Forest versus Non-Forest. The *risk forecasting and area estimation* module applies the kernel with scipy.signal.convolve2d() across the classification grid and converts flagged patches into hectares. Finally, the *reporting* module summarizes the total analyzed area, forest coverage percentage, deforested tile counts and high-risk hectares into a CSV file and Matplotlib maps.

V. IMPLEMENTATION

The system is written in Python 3.10+ and was run on Google Colab with a Tesla T4 GPU. Deep learning uses PyTorch and Torchvision [6]; geospatial processing uses Rasterio, GeoPandas, OSMnx and Shapely; data handling uses NumPy, Pandas [9] and SciPy (signal convolution); and evaluation and plotting use Scikit-Learn, Matplotlib and Seaborn. The software runs on Windows 11 and Linux and needs an Intel Core i5 or an NVIDIA GPU, at least 8 GB of RAM (16 GB recommended) and 10 GB of free storage for rasters and models.

Development followed four stages: (1) installing the geospatial packages in the Colab GPU environment; (2) downloading EuroSAT, building data loaders with ImageNet normalization and training ResNet50 for 3 epochs; (3) fetching the Kodaikanal boundary, clipping the raster, unfolding it into 49 patches (7 × 7 grid) and running batch

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inference; and (4) applying the neighbor convolution, generating color-mapped prediction grids and exporting summary tables.

VI. RESULTS AND DISCUSSION

A. ClassificationPerformance

Training loss fell steadily from 0.8864 (epoch 1) to 0.5099 (epoch 2) and 0.4330 (epoch 3), indicating rapid convergence. On the 5,400 validation samples the model reached an overall accuracy of 0.91 (91%). Table I lists the per-class metrics. The Forest class obtained a precision of 0.93, a recall of 0.90 and an F1-score of 0.91, while River (F1 0.85) was the weakest class and AnnualCrop (F1 0.95) the strongest.

TABLE I. CLAS S IF I CAT IO NREPORT ON 5,400 VALIDATION SAMPLES

Class	Precision	Recall	F1-Score	Support
AnnualCrop	0.95	0.95	0.95	631
Forest	0.93	0.90	0.91	582
HerbaceousVegetation	0.86	0.93	0.89	612
Highway	0.87	0.86	0.87	525
Industrial	0.91	0.94	0.92	484
Pasture	0.90	0.88	0.89	396
PermanentCrop	0.91	0.88	0.90	506
Residential	0.94	0.94	0.94	606
River	0.84	0.87	0.85	497
SeaLake	0.95	0.92	0.94	561
Accuracy			0.91	5400
Macro average	0.91	0.91	0.91	5400
Weighted average	0.91	0.91	0.91	5400

The confusion matrix in Fig. 2 shows that errors concentrate between visually similar classes. The largest Forest error is confusion with Herbaceous Vegetation (31 of 582 forest patches), and 15 herbaceous patches are in turn predicted as Forest. Highway and River are also confused with each other (30 and 28 patches), since both appear as thin linear features.

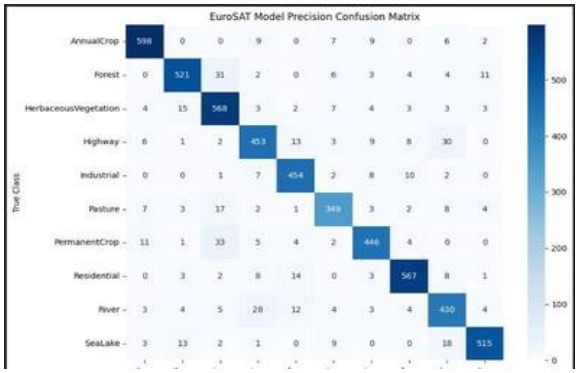


Fig.2. Confusion matrix ofthe fine-tuned ResNet50 on the EuroSAT validation set.

B. Comparison with Baselines

TABLE II. NDVI VERSUS USTOMC CNN VE RS USRES NET 5 0 TRANSFER EARNINGL

Metric	NDVI Index	Custom CNN	ResNet50 (ours)
Overall accuracy	72.4%	78.9%	91.0%
Forest precision	0.68	0.76	0.93
Terrain / shadow resilience	Poor	Moderate	High
Risk forecasting	No	No	Integrated

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[a.] Baseline figures are indicative values.

The transfer-learning model gains roughly 12 to 19 percentage points in accuracy over the baselines and learns canopy texture, which makes it more robust to terrain shadow. It is also the only approach here that supports risk forecasting through the 3 × 3 convolution kernel. The tradeoff is that patch-grid inference needs a GPU runtime.

C. Regional Deforestation Analysis

For the clipped Kodaikanal raster, 49 tiles covering about 20.07 km² were analyzed. The model labeled 7 tiles (14.3%) as healthy forest and 42 tiles (85.7%) as deforested or nonforest, an estimated 17.20 km² (Fig. 3). The 3 × 3 neighbor convolution risk model then flagged 2 patches as highly vulnerable, a projected high-risk forest area of 81.92 hectares (2 × 40.96 ha, Fig. 4). The resulting grid for Ooty is shown in Fig. 5. Such priority zones can help forest rangers intervene before clearing occurs.

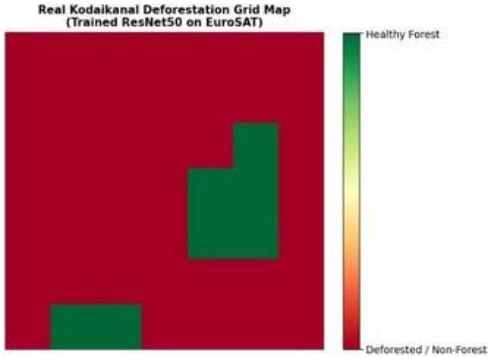


Fig.3. Kodaikanal predicted deforestation grid map (ResNet50trained on EuroSAT).

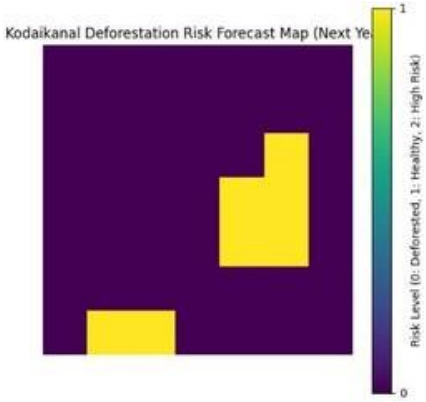


Fig.4. Kodaikanal deforestation risk forecast map for the next year.

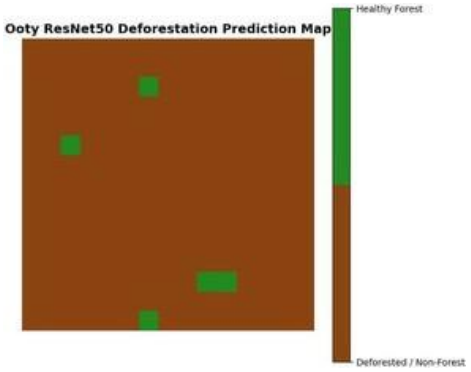


Fig.5. Ooty (Udhagamandalam) ResNet50 deforestation prediction map.

VII. CONCLUSION AND FUTURE WORK

This paper developed and evaluated an end-to-end satellite image classification and deforestation risk forecasting framework. The ResNet50 transfer-learning model achieved 91% overall accuracy and 0.93 forest precision, well above the NDVI and scratch-trained CNN baselines. OSMnx boundary fetching and Rasterio clipping were integrated for the

DOI: 10.17148/IARJSET.2026.131147

Tamil Nadu hill stations, and the 3 × 3 convolution risk engine converted neigh boring cleared- land density into a vulnerable area estimate of 81.92 hectares for Kodaikanal.

The current prototype has limitations. Large raster tile downloads were constrained by local storage, and rapid offline Colab runs relied on simulated or pre-packaged raster tensors, so the regional maps demonstrate the pipeline rather than verified ground conditions. In addition, the model is trained on European EuroSAT patches, and its accuracy on Western Ghats canopy has not been validated with ground truth labels.

Future work will scale the proof of concept in two directions. First, nationwide cloud integration will extend inference from regional hill stations to forested regions across India through Google Earth Engine and Copernicus cloud streaming APIs. Second, a real-time mobile and web dashboard (React Native or Flutter) will push alerts to forest officials and field rangers whenever deforestation intrusion or high risk is detected in their sector. Data augmentation [10] and fine-tuning on locally labeled imagery are natural next steps to address the validation gap.

ACKNOWLEDGMENT

The authors thank Dr. P. Chitra, Professor and Head, Department of Computer Science and Engineering (Emerging Technologies), and the management of SRM Institute of Science and Technology, Vadapalani Campus, for the facilities and support extended for this work.

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