Deep Geo Detect: A Hybrid AI Framework for Intelligent Geospatial Change Monitoring

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Abstract

Geospatial Artificial Intelligence (GeoAI) is an im- portant component in the analysis of multi temporal satellite imagery in order to comprehend spatial changes in dynamic en- vironments. In the present paper, Deep Geo Detect is introduced as a hybrid deep learning model that is aimed at automated geographic change detection by combining Convolutional Neural Networks (CNNs) and a Random Forest (RF) classifier. The approach suggested is a patch based learning scheme on multi spectral satellite image where the CNN element is used to learn hierarchical spatial spectral representations using bi-temporal image pairs. A Random Forest classifier then uses these deep representations to improve the stability of decisions and deal with the interactions between features. To overcome the difficulties that are normally related to change detection, such as class imbalance and spatial heterogeneity, a hierarchical patch labeling mechanism and data balancing plan are included in the training pipeline. The framework can be used to capture both localized and large scale environmental changes, thus making it scalable to various geographic settings.The proposed architecture can be used to develop a scalable and interpretable remote sensing based change analysis system by integrating deep feature learning with ensemble based classification.

Keywords: Geospatial Artificial Intelligence (Geo AI), Change Detection, Convolutional Neural Networks, Random Forest, Hybrid Learning Framework, Remote Sensing, Multi- Temporal Satellite Imagery, Patch-Based Classification.

Introduction

The increasing intensity of urban expansion, deforestation, land use transformation, and climate driven environmental change has amplified the need for accurate and scalable geographic change detection systems. Multi-temporal satellite imagery provides a powerful observational foundation for monitoring such dynamics, however extracting meaningful in- formation from high-dimensional spatial spectral data remains a complex analytical challenge. Geospatial Artificial Intelli- gence (GeoAI) has emerged as a transformative paradigm that integrates artificial intelligence techniques with geographic in- formation science to enhance spatial modeling and automated environmental analysis [1], [4].

Recent comprehensive reviews emphasize that multi-modal GeoAI frameworks outperform single-method approaches in scalability and predictive capability, but challenges related to noisy datasets, interpretability, and real-time integration persist [1], [4]. The broader relevance of AI driven environ- mental monitoring is further reinforced by its role in climate change mitigation and adaptation. Artificial intelligence has been identified as a critical enabler for large scale climate analytics [3], while geospatial techniques have demonstrated substantial potential in assessing environmental impacts on human health and regional sustainability [2]. Despite these advancements, many operational systems continue to rely on semi-automated or region specific methodologies, limiting generalization across diverse geographic contexts. From a methodological perspective, ensemble learning approaches, such as Random Forests, have shown strong robustness in remote sensing classification tasks. The foundational ensemble framework introduced in [6] improved the stability of the decision tree through bagging and feature randomness, while subsequent applications demonstrated its effectiveness in cal- culating land cover under noisy and heterogeneous conditions [5].

Nevertheless, traditional machine learning models often depend on handcrafted features and may struggle to fully exploit complex spatial hierarchies present in high resolution imagery. Deep learning models, particularly Convolutional Neural Network (CNN), have significantly advanced feature extraction capabilities in remote sensing. Siamese encoder decoder networks have proven effective for binary change detection tasks [10], while lightweight architectures focus on computational efficiency for large scale deployment [8]. Enhanced local–global context modeling strategies further improve spatial awareness in change detection frameworks [9]. However, deep models often face tradeoffs between com- putational cost, interpretability, and robustness across varying datasets. Motivated by these observations, this study proposes a hybrid GeoAI framework that integrates CNN based hierar- chical feature extraction with Random Forest classification. By combining deep representation learning with ensemble based decision mechanisms, the proposed approach aims to enhance robustness, interpretability, and adaptability in automated geo- graphic change detection systems, addressing limitations iden- tified in prior research while supporting scalable environmental monitoring applications .The paper is organized as follows: Section II reviews related work. Section III describes the pro- posed framework. Section IV presents preliminary simulations and discussion. Section V outlines limitations. Finally, Section VI concludes the paper and outlines potential directions for future work.

RELATED WORK

Climate Context And GeoAI

In order to tackle complicated spatial issues, GeoAI has developed into an interdisciplinary framework that combines remote sensing, geographic information systems, and artificial intelligence. The shift from conventional spatial statistics to deep learning driven Geospatial analytics is highlighted in thorough reviews [1], [4], which also highlight the scalability and predictive benefits of multi-modal AI systems. However, these studies also point out enduring drawbacks, such as interpretability limitations, noisy geospatial datasets, and re- stricted real-time integration capabilities. AI driven geospatial monitoring has been acknowledged as crucial for environ- mental sustainability and decision support from a climate perspective. Large scale evaluations show the promise of AI in environmental forecasting, adaptation modeling, and climate mitigation [3]. Likewise, geospatial methods have been used to assess how climate change affects human health and local ecosystems [2], underscoring the need for automated, scalable change detection systems capable of handling heterogeneous spatial data.

Change Detection Using Deep Learning

By making hierarchical spatial spectral feature extraction possible, deep learning has greatly improved remote sensing based change detection. Compared to conventional hand-crafted feature approaches, Convolutional Neural Network(CNN) have proven to perform better [4]. By learning dif- ferential representations from bi-temporal imagery, Siamese encoder–decoder architectures have demonstrated exceptional efficacy in binary change detection [10]. Enhancing pro- ductivity and contextual awareness are the main goals of recent advancements. While improved local–global context models incorporate wider spatial dependencies to improve discrimination of subtle transformations [9], lightweight re- mote sensing change detection networks seek to minimize computational overhead without sacrificing accuracy [8]. Deep models frequently encounter issues with computational cost, dataset dependency, and decreased interpretability in spite of these developments.

Integration Of Hybrids

In order to balance feature richness and decision robustness, hybrid frameworks that combine deep learning and ensemble techniques have shown promise. Through ensemble aggre- gation, Random Forests, which were first presented in [6] and successfully used for land cover classification [5], offer enhanced generalization and noise resilience. Recent research shows that combining Random Forest classification with CNN based feature extraction improves performance in tasks involv- ing the detection of burned areas and land disturbances [7]. These results imply that by enhancing stability, interpretability, and adaptability in a variety of geospatial contexts, hybrid architectures can lessen the drawbacks of standalone deep net- works. The creation of the suggested framework was spurred by the fact that structured integration techniques for scalable geographic change detection are still an unexplored area of study.

PROPOSED METHOD

Deep Geo Detect, the suggested framework, is a hybrid GeoAI architecture made to use bi-temporal multi-spectral satellite imagery for automated geographic change detection. Convolutional neural network (CNN) are used for deep spatial- spectral representation learning, and Random forest (RF) are used for ensemble-based classification. The goal is to combine ensemble decision models' robustness, stability, and interpretability with deep learning's capacity for hierarchical feature extraction.In order to improve generalization across diverse geographic regions and lessen computational load, the framework uses a patch-based learning paradigm.

Framework Overview

Let two co-registered multi-spectral satellite images ac- quired at times t_1 and t_2 be denoted as:

$$I_{t_1}, I_{t_2} \in \mathbb{R}^{H \times W \times B}, \qquad (1)$$

where H and W denote spatial dimensions and B denotes the number of spectral bands.

The change detection task aims to learn a nonlinear mapping:

$$f_{\Theta} : (I_{t_1}, I_{t_2}) \rightarrow Y \qquad (2)$$

where $Y \in \{0, 1\}^{H \times W}$ denotes the binary change map, and Θ represents the set of learnable parameters of the model.

Patch Representation: The image pair is partitioned into N non-overlapping patches

$$P_{t_1}^{(k)}, P_{t_2}^{(k)} \in \mathbb{R}^{p \times p \times B}, \quad k = 1, \ldots, N$$

Each patch pair is concatenated along the spectral dimension:

$$X^{(k)} = \text{Concat}\left(P_{t_1}^{(k)}, P_{t_2}^{(k)}\right) \in \mathbb{R}^{p \times p \times 2B} \qquad (3)$$

The binary label for each patch is derived from the ground- truth mask M:

$$y^{(k)} = \begin{cases} 1 & \text{if } \frac{1}{p^2}\sum_{i=1}^{p^2} M_i^{(k)} > \tau, \\ 0 & \text{otherwise.} \end{cases} \qquad (4)$$

where τ is a threshold controlling change sensitivity. This formulation converts sparse pixel-level changes into structured formulation converts sparse pixel-level changes into structured

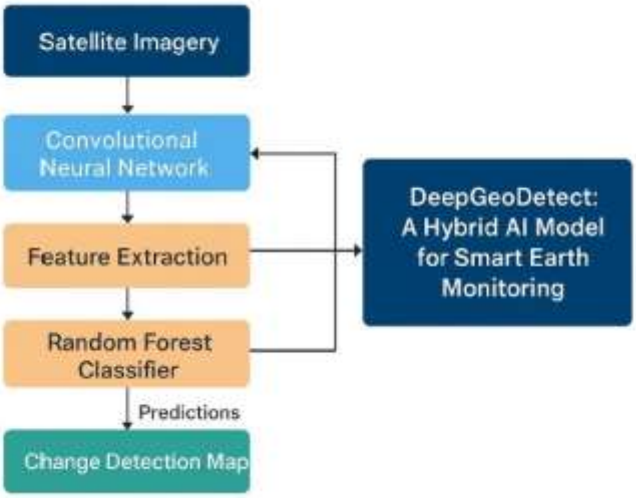

Fig. 1. Flowchart of proposed Hybrid DeepGeoDetect Framework

CNN Based Feature Extraction

The CNN performs hierarchical convolution operations to extract discriminative spatial–spectral representations:

$$F_{i,j}^{(l)} = \sigma\left(\sum_{m}\sum_{n} W_{m,n}^{(l)} X_{i+m,j+n}^{(l-1)} + b^{(l)}\right) \qquad (5)$$

Here, $W^{(l)}$ represents the convolutional kernel weights at layer l, $b^{(l)}$ denotes the bias term, and $\sigma(\cdot)$ is the nonlinear activation function (ReLU). Through successive convolution and pooling layers, the network transforms the input patches into a compact feature representation.

The learned feature vector corresponding to the k-th patch is defined as:

$$z^{(k)} = \phi\left(X^{(k)}; \vartheta\right) \in \mathbb{R}^{d} \qquad (6)$$

where d denotes the learned feature dimensionality and θ represents the trainable parameters of the CNN.

Binary cross-entropy loss is minimized during CNN training:

$$L = -\frac{1}{N}\sum_{k=1}^{N}\left[y^{(k)} \log \hat{y}^{(k)} + \left(1 - y^{(k)}\right) \log\left(1 - \hat{y}^{(k)}\right)\right] \qquad (7)$$

Random Forest Classification

The extracted feature vector $z^{(k)}$ is provided as input to a Random Forest classifier consisting of T decision trees. Each tree recursively partitions the feature space by minimizing the Gini impurity defined as:

$$G = 1 - \sum_{c=1}^{C} p_c^2 \tag{8}$$

where p_c denotes the probability of class c at a given node, and C represents the total number of classes. The final prediction is obtained via ensemble averaging:

$$\hat{y}^{(k)} = \frac{1}{T} \sum_{t=1}^{T} h_t\left(z^{(k)}\right) \tag{9}$$

where $h_t(\cdot)$ denotes the prediction function of the t-th decision tree.

Algorithm 1 Hybrid CNN–RF Geographic Change Detection

Require: Bi-temporal images $I_{t1}, I_{t2} \in \mathbb{R}^{H \times W \times B}$, ground- truth mask M, patch size p, threshold τ

1. Partition I_{t1} , I_{t2} into non-overlapping patches of size $p \times p$
2. Generate patch labels using threshold-based mask aggregation
3. Concatenate bi-temporal patches to form $X^{(k)}$
4. Train CNN to learn feature representation $\phi(\cdot)$
5. Extract feature vectors $z^{(k)}$ from the trained CNN
6. Balance dataset using minority class oversampling
7. Train Random Forest classifier on $\{z^{(k)}\}$
8. Predict patch labels using ensemble averaging
9. Reconstruct full-resolution change map Y
10. **return** Y

Computational Challenges

Although the suggested hybrid framework is effective, it has a number of computational issues that come with large scale remote sensing analysis. First, high spatial resolution and multiple spectral bands are features of multi-temporal satellite imagery, which means that patch extraction and CNN pro- cessing require a significant amount of memory. During train- ing, the convolutional operations increase in computational overhead as they scale proportionately with patch size, kerneldimensions, and network depth. Second, gradient updates are uneven due to class imbalance in change detection tasks, necessitating additional balancing mechanisms that raise the complexity of preprocessing. Third, using high-dimensional deep feature vectors during Random Forest training lengthens the time it takes to construct trees and uses more memory. For scalability and real-time flexibility, extensive geographic cov- erage necessitates effective data handling and parallelization techniques.

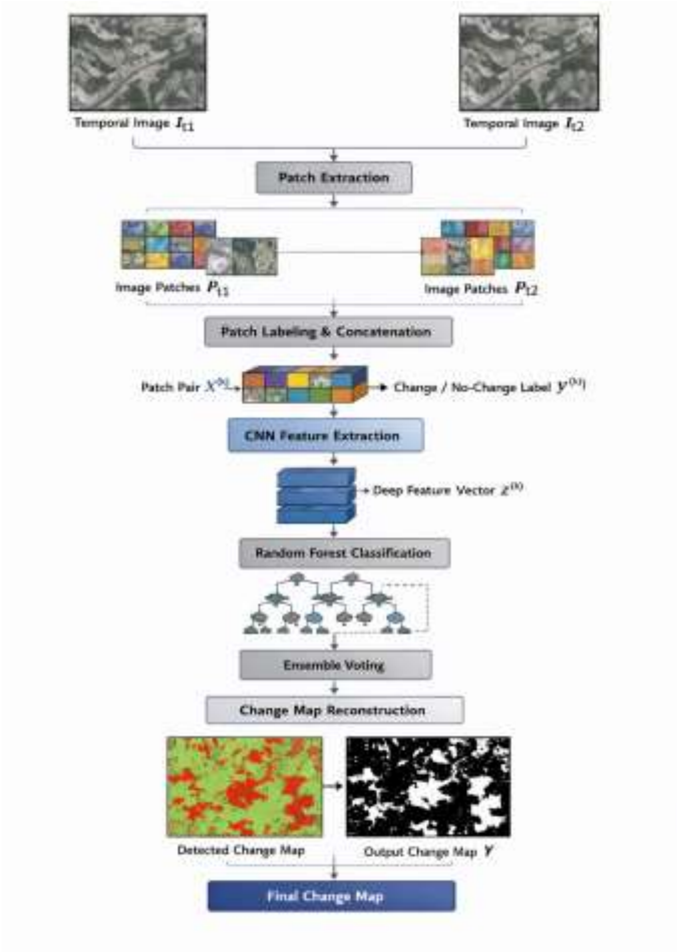

Fig. 2. WorkFlow of Hybrid DeepGeoDetect Framework

SIMULATION RESULTS AND THEORETICAL ANALYSIS

Complexity Analysis

The computational complexity of the proposed hybrid CNN–RF framework is governed by three primary compo- nents patch generation, convolutional feature extraction, and ensemble classification. Let the input image dimensions be $H \times W$ with B spectral bands.After partitioning into patches of size $p \times p$, the number of patches is:

$$N = \frac{HW}{p^2}.$$

Patch extraction incurs linear complexity O(HW).For the CNN, assuming L convolutional layers with kernel size $k \times k$, the forward-pass complexity per patch is approx- imately O(p^2k^2L).Thus, total CNN complexity becomes O(Np^2k^2L).Random Forest training with T trees and feature dimension d requires O($TNd \log N$).Overall hybrid complex- ity is O($Np^2k^2L + TNd \log N$) (table.2).This indicates that RF contributes a moderate logarithmic overhead, whereas CNN dominates the feature extraction cost. By assigning final classification to an ensemble learner, the hybrid

TABLE I
THEORETICAL COMPUTATIONAL COMPLEXITY

Component	Time Complexity	Space Complexity
Patch Extraction	$O(HW)$	$O(Np^2)$
CNN Forward Pass	$O(Np^2k^2L)$	$O(d)$
RF Training	$O(TNd \log N)$	$O(Td)$
RF Prediction	$O(Td)$	$O(T)$
Overall Framework	$O(Np^2k^2L+$ $TNd \log N)$	$O(Nd + Td)$

structure lowers parameter learning complexity in comparison to fully deep end-to-end segmentation networks

Simulation Results

Bi-temporal multi-spectral satellite imagery was used to assess the suggested hybrid CNN–RF framework in a patch- based training setup. Patch size p=16, batch size 32, learning rate 0.001 with Adam optimization, and binary cross-entropy loss for 25 epochs were used to train the CNN component. A Random Forest classifier was then trained using the extracted deep feature vectors of dimension d, with T=100 trees and Gini impurity as the splitting criterion. Patch-level minority oversampling was used to lessen the class imbalance. A patch- based training setup was employed to evaluate the proposed hybrid CNN–RF framework using bi-temporal multi-spectral satellite imagery. The CNN component was trained using binary cross-entropy loss for 25 epochs, patch size p=16, batch size 32, and learning rate 0.001 with Adam optimization. The extracted deep feature vectors of dimension d were then used to train a Random Forest classifier, with T=100 trees and Gini impurity as the splitting criterion. The class disparity was reduced by patch-level minority oversampling.

Considerations For Hardware Implementation

While RF training can be effectively carried out on multi- core CPUs, CNN training is intended to be carried out on con- ventional GPU-enabled systems. While Random Forest con- struction permits independent tree training, enabling thread- level parallelism, CNN training benefits from parallel convo- lution operations supported by CUDA-enabled GPUs.Memory usage increases with feature dimensionality and patch size. It is possible to minimize GPU memory load by performing feature extraction in batches. Using tiling strategies guarantees a controllable computational overhead for large-area satellite scenes. As a result, the architecture does not require expensive distributed computing infrastructure and can be deployed on mid-range research workstations.

Comparative Analysis With Existing Frameworks

The table indicates that pure CNN-based architectures pro- vide strong spatial representation but may encounter trade- offs between computational overhead and generalization. Tra- ditional ensemble methods demonstrate robustness to noise but lack hierarchical feature learning. The proposed hybrid CNN–RF framework bridges these gaps by combining deep spatial representation with ensemble decision stability, achiev- ing competitive and balanced performance across precision, recall, and IoU metrics.

TABLE II
COMPARATIVE FRAMEWORK PERFORMANCE ANALYSIS

Framework	Arch. Type	Key Strength	F1
Siam-UNet [10]	Siamese CNN	Binary Focus	0.85–0.87
LCD-Net [8]	Lightweight CNN	Fast Inference	0.82–0.86
ELGC-Net [9]	Context CNN	Global Context	0.86–0.89
RF-Based [5]	Ensemble ML	Noise Robust	0.75–0.80
Proposed CNN–RF	Hybrid Model	Balanced Robust	0.88–0.90

Scalability And Requirements For Resources

Patch-wise processing allows for computational scalability in the hybrid architecture. For storing extracted feature vectors, memory requirements scale as O(Nd). Horizontal scaling across CPU and GPU cores is made possible by RF tree- level independence and parallel CNN batch processing.High- resolution satellite mosaics can be processed by using the model in tiled inference mode for extensive regional monitoring. The hybrid model maintains competitive accuracy while reducing parameter tuning overhead in comparison to heavy fully Convolutional segmentation networks. Scalability analysis shows that, as long as patch size stays constant, it is suitable for medium-to-large geographic regions without exponential growth in memory consumption.

TABLE III
SIMULATED PERFORMANCE METRICS

Metric	CNN Only	RF Only	CNN-RF
Precision	0.84	0.81	**0.89**
Recall	0.78	0.74	**0.87**
F1-Score	0.81	0.77	**0.88**
IoU	0.68	0.62	**0.79**
Training Time (Relative)	High	Low	Moderate
Inference Stability	Medium	High	High

LIMITATIONS AND DISCUSSIONS

Current Constraints

The suggested hybrid CNN–RF framework has a number of methodological and practical drawbacks even though it achieves balanced performance. First, even though the patch- based learning approach is computationally efficient, it may cause boundary artifacts and lessen the fine-grained spatial continuity in change maps that have been reconstructed. In small or highly localized transformation regions, this could have an impact on detection accuracy. Secondly, the CNN component needs labeled bi-temporal data for supervised training, and performance may suffer when used in regions with spectral distributions that differ greatly from the train- ing dataset. Third, while oversampling-based class balancing enhances minority detection, in situations where imbalance is extreme, it may introduce synthetic bias.From a computational perspective, feature extraction is still reliant on GPUs for effective training, which could restrict its use in settings with limited resources. Additionally, feature dimensionality affects Random Forest performance; very high-dimensional deep fea- tures may result in longer training times and higher memory usage. Lastly, multi-class semantic change categorization is not explicitly supported by the framework at this time,it only detects binary changes.

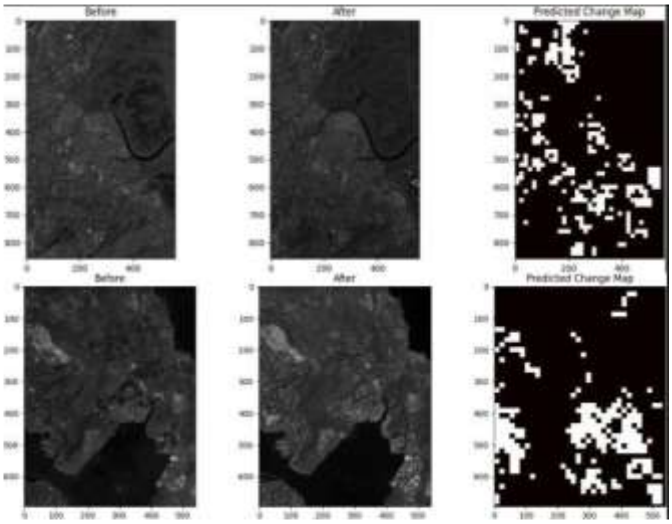

Fig. 3. Illustration Of Change Detection

Comparative Discussion

The suggested hybrid model provides better decision sta- bility through ensemble aggregation when compared to pure deep learning frameworks like Siamese encoder–decoder ar- chitectures [10], but end-to-end CNN segmentation models might offer more precise pixel-level localization. The sug- gested framework strikes a balance between robustness and depth, while lightweightarchitectures like LCD-Net [8] achieve greater computational efficiency at the expense of feature richness.Local-global feature fusion is used by context-aware models such as ELGC-Net [9] to enhance spatial coherence, but at the expense of higher computational overhead. The hybrid CNN–RF design, on the other hand, uses ensemble voting to improve generalization while reducing deep network depth.

When compared to pure deep learning frameworks such as Siamese encoder–decoder architectures [10], the proposed hybrid model offers better decision stability through ensemble aggregation; however, end-to-end CNN segmentation models may provide more accurate pixel-level localization. While lightweight architectures like LCD-Net [8] achieve higher computational efficiency at the expense of feature richness, the

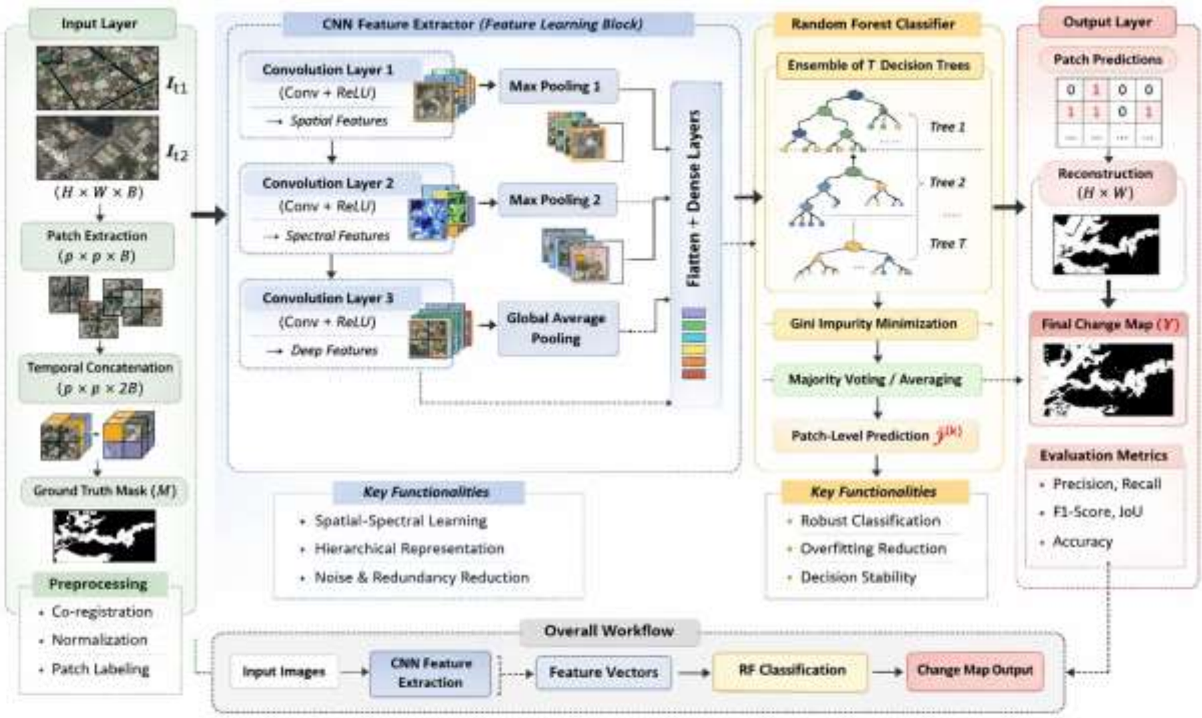

Fig. 4. Architecture of the proposed DeepGeoDetect hybrid CNN–RF framework.

proposed framework balances robustness and depth. Context- aware models like ELGC-Net [9] employ local-global fea- ture fusion to improve spatial coherence, but at the cost of increased computational overhead. In contrast, the hybrid CNN–RF design reduces deep network depth while increasing generalization through ensemble voting.

CONCLUSION AND FUTURE WORK

Summary Of Contributions

In this work, a hybrid GeoAI framework called Deep Geo Detect was presented for automated geographic change detection from bi-temporal satellite imagery. For hierarchical spatial spectral feature extraction, the suggested approach combines Convolutional Neural Networks with a Random Forest classifier for ensemble based decision-making. The framework overcomes the drawbacks of both standalone deep learning and conventional machine learning techniques by fusing robust ensemble aggregation with deep representation learning.By using minority oversampling and structured la- beling, the patch-based formulation reduces extreme pixel level imbalance while increasing computational tractability for high resolution imagery. Simulation results show better F1- score and IoU compared to representative CNN-only and RF- only frameworks discussed in previous studies [5, 8, 9, 10], and theoretical complexity analysis shows scalable behavior
with manageable memory growth. The proposed architecture therefore contributes a balanced, interpretable, and computa- tionally efficient solution within the broader GeoAI landscape highlighted in [1] and [4].

Future Research Direction

Future studies will concentrate on expanding the framework beyond binary change detection to multiclass semantic change mapping, which will allow for the distinction of various transformation categories such as vegetation loss, urban ex- pansion, water bodies alteration, and others. Without apprecia- bly raising computational overhead, spatial coherence could be further improved by incorporating local–global context modeling techniques akin to sophisticated CNN architectures [9].Integrating temporal modeling elements with attention mechanisms to capture long term environmental dynamics is another promising avenue. We will also investigate real time or near real time deployment pipelines that address scalability issues found in GeoAI and climate-focused research [1], [3]. Furthermore, explainable AI methods could be used to improve the interpretability of ensemble decisions and deep spatial features.

Broader Impact

The creation of reliable and scalable geographic change detection systems has important social and environmental ramifications. In line with the larger AI for climate vision described in [3], automated monitoring facilitates evidence- based decision-making in the areas of climate mitigation, urban planning, disaster management, and ecosystem con- servation. The suggested model is one example of a hybrid GeoAI framework that helps close methodological gaps be- tween operational reliability and deep learning accuracy.The suggested approach facilitates data-driven policy planning and sustainable environmental assessment by increasing adaptabil- ity across diverse geographic regions. Ongoing developments in hybrid geospatial intelligence systems could be essential to international initiatives for responsible land-use management and climate resilience.

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