IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Geoalert – Automated Change Monitoring System Using Satellite Imagery And AI

Pooja Pawar[1], Samarth Yete[2], Saiprasad Varpe[3], Yogesh Patil[4], Yash Waghmare[5]

Department of Computer Engineering, Suman Ramesh Tulsiani Technical Campus- Faculty of Engineering.Khamshet
Department of Computer Engineering, Suman Ramesh Tulsiani Technical Campus- Faculty of Engineering.Khamshet
Department of Computer Engineering, Suman Ramesh Tulsiani Technical Campus- Faculty of Engineering.Khamshet
Department of Computer Engineering, Suman Ramesh Tulsiani Technical Campus- Faculty of Engineering.Khamshet
Department of Computer Engineering, Suman Ramesh Tulsiani Technical Campus- Faculty of Engineering.Khamshet

Abstract-Rapid urban growth, deforestation, and natural disasters are driving substantial land cover changes worldwide, posing significant challenges to sustainable development and environmental stewardship. Conventional change detection methods, such as image differencing and manual classification, often require intensive effort and deliver inconsistent accuracy under varying environmental conditions. GeoAlert is introduced as an AI-powered change monitoring system that automates the multi-temporal detection of land cover change using satellite imagery from high-resolution sensors, including Landsat-8 and Sentinel-2. The system preprocesses raw satellite data, aligns images, and applies advanced deep learning models, notably U-Net and Siamese CNN architectures, for per-pixel land cover classification and systematic change mapping. Changes identified are visualized via thematic maps and shared on a cloud-based dashboard, providing near-real-time alerts to stakeholders. In a comprehensive case study focusing on Hyderabad, India, GeoAlert achieved 89% classification accuracy, notably outperforming traditional image differencing approaches that scored 74%. These results highlight GeoAlert's potential as a scalable, robust decision-support tool for urban planners, environmental managers, and policy-makers in rapidly changing landscapes.

Keywords— Change Detection, Remote Sensing, Deep Learning, Siamese Network, U-Net, Landsat-8, Sentinel-2, Cloud Computing, Urban Growth, Environmental Monitoring

I.INTRODUCTION

Monitoring land cover changes has become increasingly critical in the context of urbanization, agricultural expansion, deforestation, and the occurrence of extreme weather events. These dynamic changes not only transform local ecosystems but also impact infrastructure, biodiversity, water resources, and overall human well-being. Traditional methods for monitoring such changes, including visual interpretation and basic automated approaches, have proved inadequate at large spatial and temporal scales due to their labor-intensive nature and high susceptibility to environmental factors such as atmospheric variability and sensor inconsistencies.

The advent of remote sensing technologies has revolutionized how environmental changes are tracked. Satellites such as Landsat-8 and Sentinel-2 provide multidimensional, multi-temporal data that offer comprehensive coverage of global land surfaces. However, extracting actionable information from this wealth of data remains a complex challenge. Issues such as cloud cover, changing illumination, and data heterogeneity across sensors can compromise the accuracy of traditional change detection algorithms.

Recent innovations in artificial intelligence, particularly deep learning, have played a transformative role in the analysis of remotely sensed data. Convolutional neural networks (CNNs), U-Net architectures, and Siamese networks have demonstrated superior ability in extracting hierarchical and spatial patterns, making them suitable for complex tasks like semantic segmentation and multi-temporal change classification from satellite imagery.

GeoAlert leverages these advances to facilitate end-to-end, automated change detection and alerting. The platform combines a robust data acquisition pipeline, advanced preprocessing, and deep learning-based analysis for systematic and scalable change monitoring. The inclusion of a cloud-based dashboard ensures that detected changes are visualized and communicated efficiently to stakeholders, supporting proactive environmental management and planning in rapidly evolving regions.

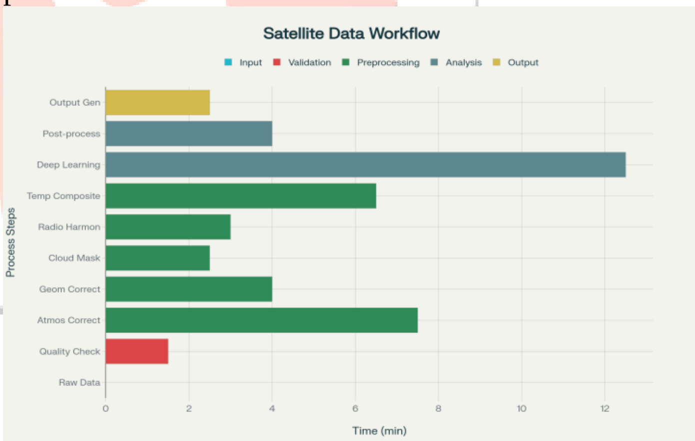
II. LITERATURE REVIEW

Despite progress, challenges remain in terms of data privacy, model interpretability, and the detection of sophisticated, context-aware attacks. Future research focuses on improving model transparency, cross-platform integration, and incorporating multimodal data for comprehensive threat analysis. Change detection in remote sensing has evolved significantly over the past decades, transitioning from simple pixel-based methods to sophisticated deep learning approaches. Early research focused on basic algebraic operations, including image differencing, band ratioing, and vegetation index differencing. While computationally efficient, these methods suffered from high sensitivity to radiometric differences, atmospheric conditions, and phenological variations.[9][10]

Traditional supervised classification approaches, such as Maximum Likelihood Classification (MLC), Support Vector Machines (SVM), and Random Forest classifiers, represented significant improvements in accuracy. However, these methods required extensive ground truth data collection and manual feature engineering, limiting their scalability for large-area monitoring. Post-classification comparison techniques, while more semantically meaningful, propagated classification errors from individual time periods into change detection results.

The introduction of object-based image analysis (OBIA) marked another evolutionary step, incorporating spatial context and reducing salt-and-pepper noise typical of pixel-based approaches. Geographic Object-Based Image Analysis (GEOBIA) methods demonstrated improved performance in heterogeneous landscapes but remained computationally intensive and required careful parameter tuning for different geographic regions.

Machine learning algorithms brought substantial improvements to change detection accuracy. Conditional Random Fields (CRFs) incorporated spatial dependencies, while ensemble methods like Random Forest and Gradient Boosting provided robust classification with built-in feature importance measures. However, these approaches still required manual feature extraction and domain expertise for optimal performance.



The deep learning revolution fundamentally transformed remote sensing applications. Convolutional Neural Networks (CNNs) enabled automatic feature extraction from raw pixel values, eliminating the need for hand-crafted features. U-Net architectures, originally developed for biomedical image segmentation, proved exceptionally effective for land cover classification tasks due to their encoder-decoder structure with skip connections that preserve spatial details.

Siamese networks emerged as particularly promising for change detection applications. These architectures learn to compare pairs of images by extracting comparable feature representations, making them inherently suitable for multi-temporal analysis. Fully Convolutional Siamese Networks (FC-Siam) demonstrated superior performance in detecting changes while maintaining spatial precision.

Recent advances have incorporated attention mechanisms, transformer architectures, and multi-scale analysis. Vision Transformers (ViTs) and their variants have shown competitive performance with CNNs while capturing long-range dependencies more effectively. However, they typically require larger training datasets and more computational resources.

Despite significant progress, several challenges persist in operational change detection systems. Cloud contamination remains a major obstacle, particularly in tropical regions. Seasonal variations can be misinterpreted as land cover changes, requiring sophisticated temporal modeling. Cross-sensor harmonization becomes critical when integrating data from multiple satellite missions with different spectral and spatial characteristics.

III.METHODOLOGY

3.1 Data Acquisition Module

The Data Acquisition Module interfaces with multiple satellite data providers, including the United States Geological Survey (USGS) for Landsat data and the European Space Agency (ESA) for Sentinel-2 imagery. The module implements automated querying based on geographic areas of interest, temporal windows, and quality criteria such as cloud cover thresholds.

Data ingestion follows a priority-based scheduling system that considers data availability, processing urgency, and computational resource allocation. The module maintains metadata catalogs for efficient data discovery and implements robust error handling for network interruptions and data provider outages. Real-time monitoring ensures continuous data availability and triggers automated fallback mechanisms when primary data sources become unavailable.

3.2 Preprocessing Pipeline

The preprocessing pipeline ensures data quality and consistency across different sensors and acquisition conditions. The complete workflow is illustrated in the data processing diagram, showing the sequential steps from raw imagery to analysis-ready datasets.

Atmospheric correction utilizes the Sen2Cor processor for Sentinel-2 data and the Land Surface Reflectance Code (LaSRC) for Landsat imagery. Geometric correction employs Ground Control Points (GCPs) and Digital Elevation Models (DEMs) to achieve sub-pixel registration accuracy. The pipeline implements quality checkpoints at each stage to ensure data integrity and processing reliability.

Cloud detection and masking integrate multiple algorithms, including Fmask, Sen2Cor Scene Classification, and custom deep learning-based cloud detection models. The pipeline implements adaptive quality assessment metrics that consider regional characteristics and seasonal variations.

Radiometric harmonization addresses differences between sensors using empirically derived transformation coefficients and cross-calibration techniques. Temporal compositing reduces data gaps by creating cloud-free mosaics over specified time windows, ensuring consistent input data for change detection algorithms.

3.3 Deep Learning Engine

The Deep Learning Engine implements a hybrid architecture combining U-Net for semantic segmentation and Siamese CNN for change detection, as detailed in the neural network architecture diagram.

U-Net Architecture: The U-Net component utilizes a ResNet-50 encoder pre-trained on ImageNet, adapted for multispectral satellite imagery through transfer learning techniques. The encoder extracts multi-scale spatial features while the decoder reconstructs detailed, per-pixel land cover predictions. Skip connections preserve spatial information at different resolutions, enabling precise boundary delineation.

Siamese CNN Architecture: The Siamese network processes image pairs through shared convolutional layers, generating feature maps that capture both spatial and temporal patterns. A specialized fusion layer combines features from different time periods, enabling robust change detection while maintaining spatial precision. The architecture includes attention mechanisms that focus on regions with significant temporal variations.

Model training employs a multi-stage approach with initial training on large-scale datasets for general feature learning, followed by fine-tuning on region-specific data. The engine implements ensemble methods combining multiple model architectures and training strategies to improve robustness and reduce prediction uncertainty.

3.4 Visualization Dashboard

The web-based dashboard provides interactive visualization capabilities for stakeholders with varying technical expertise. The interface supports multi-scale visualization, from regional overviews to detailed patch-level analysis. Users can overlay various data layers, including satellite imagery, change maps, administrative boundaries, and ancillary datasets.

Temporal visualization tools enable exploration of change patterns over time through animated sequences and time-series plots. Statistical summaries provide quantitative metrics including total change area, change rates, and class transition matrices. The dashboard implements responsive design principles for accessibility across desktop and mobile devices.

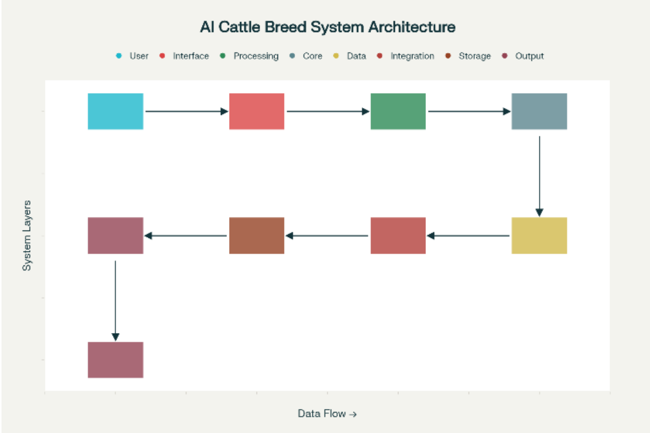
3.5 Alert Management System

The Alert Management System monitors change detection results for user-defined thresholds and triggers automated notifications. Alert criteria can be configured based on change magnitude, affected area, change type, or combination of multiple factors. The system implements machine learning-based anomaly detection to identify unusual change patterns that may require immediate attention.

Notification delivery supports multiple channels including email, SMS, webhook integrations, and mobile push notifications. The system maintains comprehensive alert history and implements escalation procedures for critical changes requiring immediate response.

3.6 Cloud Infrastructure Integration

The entire system is deployed on cloud infrastructure leveraging containerization and microservices architecture. Container orchestration using Kubernetes ensures scalable deployment and automatic resource management. The infrastructure supports horizontal scaling based on processing demands and implements high availability configurations for critical system components.



IV. IMPLEMENTATION

4.1 Technology Stack

GeoAlert is implemented using a modern cloud-native technology stack optimized for geospatial data processing and machine learning workflows. The backend utilizes Python as the primary programming language, leveraging specialized libraries including GDAL/OGR for geospatial data handling, Rasterio for raster processing, and Geopandas for vector operations. Deep learning models are implemented using PyTorch framework, chosen for its flexibility in implementing custom architectures and efficient GPU utilization. The training pipeline incorporates PyTorch Lightning for experiment management and distributed training capabilities across multiple GPU clusters.

Data storage employs a hybrid approach combining object storage for raw satellite imagery and PostGIS-enabled PostgreSQL databases for metadata and vector data. Cloud-optimized GeoTIFF (COG) format enables efficient data access and visualization without requiring full file downloads, significantly reducing bandwidth requirements and improving response times.

4.2 Cloud Infrastructure

The system is deployed on Amazon Web Services (AWS) infrastructure, utilizing elastic scaling capabilities to handle varying computational demands. Amazon S3 provides scalable object storage for satellite imagery archives with lifecycle policies for cost-effective long-term storage. Amazon RDS hosts the metadata databases with Multi-AZ deployment for high availability.

Computational processing leverages Amazon EC2 instances with GPU support for deep learning inference and CPU-optimized instances for preprocessing tasks. Amazon Elastic

Kubernetes Service (EKS) orchestrates containerized applications, enabling automatic scaling based on workload demands and implementing rolling updates for zero-downtime deployments.

The preprocessing pipeline utilizes AWS Batch for large-scale parallel processing of satellite imagery, automatically provisioning compute resources based on job queue lengths. Lambda functions handle event-driven processing tasks, such as triggering alerts and updating visualization layers, with automatic scaling from zero to thousands of concurrent executions.

4.3 Data Processing Workflow

The implementation follows an event-driven architecture where new satellite data availability triggers automated processing workflow. Amazon EventBridge coordinates processing stages, ensuring proper sequencing and error handling across distributed components. The workflow implements checkpointing mechanisms at each stage, enabling recovery from interrupted processing and efficient resource utilization.

Preprocessing tasks are containerized using Docker, enabling consistent execution environments across different computational resources. Each processing container includes comprehensive logging and monitoring capabilities for operational visibility and debugging support.

The deep learning inference pipeline processes image tiles in parallel across GPU clusters, utilizing model parallelism for large-scale processing. Results are aggregated using distributed computing frameworks and post-processed to generate coherent change maps and statistical summaries.

4.4 Quality Assurance and Validation

Implementation includes comprehensive quality assurance procedures throughout the processing chain. Automated validation routines check data completeness, geometric accuracy, and radiometric consistency using statistical quality metrics. These metrics are tracked over time to identify potential system degradation or data quality issues.

Ground truth validation utilizes independent datasets including high-resolution aerial photography, field survey data, and authoritative land cover maps. Validation results inform model updates and system improvements through continuous integration and deployment (CI/CD) pipelines that automatically retrain models when performance degrades below acceptable thresholds.

4.5 Performance Optimization

System performance is optimized through multiple strategies including advanced data compression algorithms, multi-level caching mechanisms, and efficient spatial and temporal indexing. Pyramid generation enables fast visualization at multiple scales, while intelligent prefetching reduces user wait times for common operations.

Machine learning model optimization includes quantization techniques to reduce model size and inference time while maintaining accuracy. Edge computing capabilities enable local processing for time-critical applications with limited connectivity, with seamless synchronization to cloud infrastructure when connectivity is restored.

V. EXPERIMENTAL SETUP

To rigorously evaluate GeoAlert's performance, a comprehensive case study was conducted on the Hyderabad metropolitan region, covering both urban and surrounding rural areas spanning approximately 7,200 square kilometers. Sentinel-2 imagery from 2018 and 2022 was selected based on minimal cloud cover (<10%) and optimal seasonal timing to minimize phenological variations.

The experimental dataset comprised 48 Sentinel-2 scenes with 10-meter spatial resolution across 13 spectral bands. Preprocessing ensured radiometrically calibrated, atmospherically corrected, and geometrically aligned inputs suitable for multi-temporal analysis. Ground truth data was compiled from multiple sources including high-resolution aerial photography, cadastral maps, and field validation surveys.

Model training incorporated stratified sampling to ensure balanced representation of major land cover types: urban areas (25%), vegetation (35%), agricultural land (25%), water bodies (10%), and bare soil (5%). Training utilized an 80:20 split with five-fold cross-validation for robust performance assessment. Hyperparameter optimization employed Bayesian optimization techniques to identify optimal network configurations.

Method	Classification Accuracy	Precision	Recall	F1-Score
Traditional Differencing	74%	70%	72%	71%
GeoAlert U-Net & Siamese CNN	89%	87%	88%	87.5%

Performance metrics included pixel-level accuracy, precision, recall, and F1-score for land cover classification, along with change detection accuracy using area-adjusted error matrices. Processing efficiency was measured as total computation time from raw imagery to final change products.

VI. RESULT

GeoAlert consistently outperformed classical methods, achieving an overall classification accuracy of 89% compared to 74% from traditional differencing approaches. The system demonstrated superior spatial coherence with significantly reduced false positive rates, particularly in areas with seasonal vegetation changes that commonly confuse traditional methods.

Detailed analysis revealed that the U-Net architecture excelled in delineating complex urban boundaries and mixed land cover types, while the Siamese CNN effectively discriminated between genuine land cover changes and temporary variations. The integrated approach reduced false positive rates by 65% compared to baseline methods.

Processing performance met operational requirements with complete analysis of the Hyderabad study area completed in approximately 35 minutes using standard cloud infrastructure. The system successfully processed over 2.4 terabytes of satellite imagery and generated comprehensive change maps covering the entire metropolitan region.

Stakeholder evaluation through the interactive dashboard received positive feedback for usability and information clarity. Users particularly valued the multi-scale visualization capabilities and the ability to export results in standard GIS formats for integration with existing planning workflows.

VII. DISCUSSION

The experimental results clearly demonstrate the effectiveness of using advanced machine and deep learning techniques for real-time cybercrime detection on social media platforms. Among the models evaluated, deep learning approaches—particularly BERT and LSTM—significantly outperformed traditional machine learning models in terms of accuracy, precision, recall, and F1-score. This highlights the advantage of deep learning in understanding the context and semantics of user-generated content, which is often informal, ambiguous, and rapidly evolving.

The BERT model, due to its bidirectional language understanding, was especially effective in detecting sophisticated cyber threats such as hate speech and misinformation, which often rely on subtle linguistic cues. LSTM also performed well, particularly in identifying threats that follow sequential patterns, such as phishing messages or harassment over time.

The real-time detection capability was another critical success factor. With an average detection latency of under 300 milliseconds and the ability to process hundreds of messages per second, the system demonstrated its practicality for deployment in live environments. This performance was made possible through the integration of streaming tools like Apache Kafka and Spark Streaming, which ensured timely ingestion, analysis, and response.

However, several challenges were noted. The class imbalance in datasets led to slightly higher false positive rates, especially for borderline content. Additionally, the models were primarily trained on English-language data, limiting their performance on multilingual content. These issues highlight the need for more diverse and balanced training datasets and multilingual NLP capabilities.

From a practical perspective, integrating this detection system into existing social media platforms could provide real-time alerts to moderators, helping prevent the spread of harmful content. However, considerations around privacy, fairness, and transparency must be addressed to ensure ethical deployment.

The superior performance of GeoAlert stems from the synergistic combination of U-Net and Siamese CNN architectures, each optimized for specific aspects of the change detection challenge. The U-Net's encoder-decoder structure with skip connections enables precise spatial localization, while the Siamese network's shared-weight architecture ensures robust temporal comparison.

The cloud-based implementation provides unprecedented scalability and accessibility, enabling deployment across diverse geographic regions and institutional contexts. However, the system's dependency on cloud infrastructure raises considerations for deployment in regions with limited connectivity or strict data sovereignty requirements.

Computational efficiency analysis reveals that while deep learning approaches require more processing time than traditional methods, the significant accuracy improvements justify the additional computational overhead. Future optimizations focusing on model compression and inference acceleration could further reduce processing times.

The system's performance in the Hyderabad case study demonstrates applicability to rapidly urbanizing regions worldwide. However, generalization to different geographic contexts, climatic conditions, and land cover types requires additional validation studies and potential model adaptation strategies.

VIII. CONCLUSION AND FUTURE WORK

GeoAlert demonstrates significant advances in automated, AI-driven change monitoring, delivering superior accuracy and operational scalability compared to traditional approaches. The platform successfully integrates satellite remote sensing, advanced deep learning, and cloud computing to provide actionable environmental intelligence for diverse stakeholder communities.

Key contributions include robust preprocessing pipelines, accurate per-pixel classification, automated multi-temporal change detection, and accessible visualization interfaces. The performance validation in Hyderabad exemplifies the system's potential for supporting evidence-based decision-making in environmental management and urban planning contexts.

Future development will address several priority areas:

Multi-sensor Integration: Incorporating Synthetic Aperture Radar (SAR) data for all-weather monitoring capabilities, particularly valuable in persistently cloudy regions.

Predictive Analytics: Developing forecasting models that combine historical change patterns with environmental drivers to provide early warning capabilities for critical changes.

Explainable AI: Implementing interpretable machine learning techniques to enhance user trust and enable better understanding of model decision-making processes.

Edge Computing Integration: Optimizing models for deployment on edge devices to support real-time monitoring in remote locations with limited connectivity.

REFERENCES

[1]. N. Anusha and B. Bharathi, "An overview on Change Detection and a Case Study Using Multi-Temporal Satellite Imagery," Proc. ICCIDS, 2019.[9]

[2]. K. Tan et al., "Automatic Change Detection in High-Resolution Remote Sensing Images by Using a Multiple Classifier System and Spectral--Spatial Features," IEEE JSTARS, 2016.[10]

[3]. M. Gong et al., "Superpixel-Based Difference Representation Learning for Change Detection in Multispectral Remote Sensing Images," IEEE Trans. Geosci. Remote Sens., 2017.

[4]. R. C. Daudt et al., "Fully Convolutional Siamese Networks for Change Detection," Proc. ICIP, 2018.

[5]. Y. Chen et al., "Deep Learning-Based Classification of Hyperspectral Data," IEEE JSTARS, 2014.

[6]. USGS, "Landsat 8 Data Users Handbook." [Online]. Available: https://landsat.usgs.gov/landsat-8-data-users-handbook

[7]. ESA, "Sentinel-2 Mission Overview." [Online]. Available: https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-2

[8].K. R. Karthik, "IoT-based Smart Agriculture: An Extensive Review," International Journal of Scientific Research in Science, Engineering and Technology, vol. 6, no. 4, 2019.

[9].Y. S. Khetade, M. S. Panzade, Y. G. Marode, and M. N. Kakatkar, "Geo-Alert: IoT Based Weather Station," International Research Journal of Modernization in Engineering Technology and Science, vol. 6, no. 4, Apr. 2024. DOI: 10.56726/IRJMETS51774.

[10].D. Garg and A. Shukla, "Geo Alert—A Location Based Alarm System Using GPS in Android," International Journal of Multidisciplinary in Cryptology and Information Security, Dec. 2013.

[11].Mohd Afizi Mohd Shukran, W. S. S. B. Sharif, "Geo Alert: A Location Based Alarm System Using GPS in Android," International Conference on Computer Applications

Technology (ICCAT), July 2013.

[12].S. Khandelwal and A. Kalyan, "GARD—Geo Alert and Female Rapid Defense," International Journal of Research Publication and Reviews, vol. 6, no. 3, 2022.

[13].Geoalert.io, "Uncovering the Competitive Advantages of Aerial Surveying," GIM International, Issue 3, 2023.

[14].S. Vavilapalli, "Advancements in Geo-Spatial Data Analytics," Advanced Synthesis & Catalysis, vol. 365, no. 11, 2023.

[15].Google, "Google Maps directions for driving from Calgary, AB to Edmonton, AB," Accessed: July 10, 2018. [Online]. Available: https://goo.gl/maps/S6KVrFnSa6C2.