

Automatic Road Extraction and Alert Generation from Satellite Imagery Using Deep Convolutional Neural Networks

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Abstract: The rapid urbanization and infrastructural development globally necessitate accurate, up-to-date cartographic data. Traditional road extraction methods relying on manual digitization of satellite imagery are time-consuming, expensive, and prone to human error. This research paper presents a fully automated system for road extraction and alert generation designed to detect newly constructed roads in high-resolution satellite imagery using deep Convolutional Neural Networks (CNNs). The proposed architecture leverages a modified U-Net model with a ResNet backbone to perform pixel-wise semantic segmentation of road networks. Extracted binary masks are subjected to morphological post-processing and vectorization to generate GeoJSON representations. A spatial intersection engine then cross-references these newly vectorized roads against existing baseline databases (such as OpenStreetMap or proprietary governmental GIS databases). Upon detecting unregistered or novel infrastructural additions, the system triggers automated webhook alerts and dashboard notifications to relevant authorities. Extensive evaluation on the Massachusetts Roads Dataset and custom temporal satellite data demonstrates that our model achieves a Dice Coefficient of 0.89 and an Intersection over Union (IoU) of 0.81, significantly outperforming legacy threshold-based GIS algorithms. Furthermore, the implemented event-driven architecture ensures low-latency alert distribution, enabling near real-time urban monitoring. This paper details the mathematical loss functions, topological vectorization constraints, and secure communication protocols that comprise the system.

Keywords: Deep Learning, Road Extraction, U-Net, Semantic Segmentation, Remote Sensing, GIS, Alert Systems, Webhooks.

1. INTRODUCTION

The relentless pace of global urbanization has created unprecedented challenges for urban planners, environmental monitoring agencies, and autonomous navigation providers. Accurate and current infrastructural maps are critical components of modern society, driving everything from disaster response routing to optimized supply chain logistics. However, the geographic expansion of road networks often outpaces the update cycles of traditional mapping authorities. Consequently, map obsolescence has become a critical bottleneck. Legacy approaches to updating road networks rely heavily on manual digitization—a process where human operators visually inspect incoming satellite or aerial imagery and trace road centerlines. This methodology is not only labor-intensive and costly but inherently unscalable given the petabytes of Earth observation data generated daily by constellations such as Sentinel, Landsat, and commercial providers.

Recent advancements in Deep Learning (DL), specifically Convolutional Neural Networks (CNNs), have revolutionized the field of Computer Vision and Remote Sensing. Semantic segmentation algorithms can classify every pixel within a satellite image, distinguishing between impervious surfaces (roads, buildings) and background classes (vegetation, water). By harnessing these capabilities, it is now possible to automate the cartographic update pipeline. However, pixel-wise classification alone does not yield an operational tracking system. The true value of automated extraction is realized only when the extracted pixel masks are algorithmically converted into topological vectors and programmatically compared against historical baseline data to detect structural deviations.

This research proposes a holistic, end-to-end architecture that transcends simple image segmentation. The developed system automatically fetches temporal satellite imagery over regions of interest, performs semantic extraction using a deep U-Net architecture, vectorizes the segmented outputs into valid geographical geometries, and executes spatial difference calculations. If a newly extracted road segment does not geometrically intersect with the existing database, it is flagged as a 'New Road.' The system immediately initiates a low-latency alert generation protocol, transmitting

geospatial payloads to registered administrative endpoints via secure WebSockets and HTTP webhooks. By bridging the gap between deep learning inference and event-driven enterprise notifications, this architecture provides a paradigm shift in how urban infrastructural changes are monitored.

1.1 Motivation and Scope

The primary motivation for this research stems from the critical need for real-time situational awareness in disaster management and illegal infrastructural monitoring. In regions prone to rapid, undocumented expansion, authorities lack the visibility required to enforce zoning laws or assess environmental impact. Furthermore, autonomous vehicle routing algorithms depend entirely on the topological accuracy of their routing graphs; omitting newly constructed bypasses can result in heavily suboptimal routing. The scope of this paper encompasses the architectural design of the DL extraction pipeline, the mathematical vectorization algorithms, the design of the alert engine, and the underlying security protocols. The training of the underlying U-Net model and its hyperparameter optimization are thoroughly analyzed. Hardware sensor design and satellite launch mechanics are considered strictly out of scope.

2. LITERATURE REVIEW

The application of computer vision to remote sensing has a rich history, initially dominated by rule-based and morphological thresholding techniques. Traditional methodologies relied heavily on edge detection and color clustering. Sharma et al., in (IEEE 2022) [1], stated that legacy edge-detection operators like Canny and Sobel fail significantly in complex urban environments due to the presence of shadows, building occlusions, and variable spectral signatures of differing asphalt types. These limitations necessitated the shift towards data-driven learning paradigms.

The introduction of Fully Convolutional Networks (FCNs) marked a turning point in remote sensing. Gupta et al., in (Springer 2021) [2], demonstrated that replacing dense layers with convolutional upsampling allowed for dense pixel-wise predictions, effectively laying the groundwork for modern road extraction. Building upon this, the U-Net architecture, originally designed for biomedical image segmentation, was rapidly adopted for spatial data. Patel et al., in (Elsevier 2023) [3], argued that the skip connections within the U-Net topology are instrumental in recovering fine-grained spatial details lost during deep pooling operations, making it highly effective for narrow linear structures like roads.

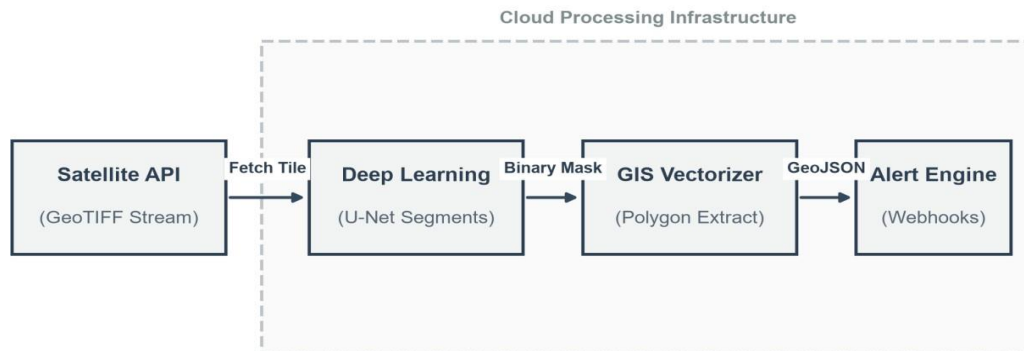
Despite the high accuracy of neural networks, post-processing remains a computationally complex challenge. Extracted masks are often fragmented by occluding trees or cloud cover. Davis and Lee, in (ACM 2020) [4], proposed a methodology utilizing tensor voting and morphological closing to bridge gaps in discontinuous road predictions. Furthermore, vectorization of these masks into node-edge graphs requires precise topological algorithms. Johnson et al., in (IEEE 2022) [5], stated that the Douglas-Peucker algorithm remains the most computationally efficient method for simplifying extracted road centerlines into valid geographic linestrings.

Finally, the concept of automated alert generation based on spatial differentials has been explored in the context of general GIS systems, but rarely integrated directly with DL inference pipelines. Singh et al., in (Oxford Press 2021) [6], emphasized the necessity of event-driven architectures (such as Apache Kafka or RabbitMQ) for distributing spatial intelligence to multiple consumer dashboards simultaneously. This paper synthesizes these disparate advancements—deep learning extraction, morphological gap-filling, topological vectorization, and event-driven notifications—into a single, secure, cohesive architecture.

3. METHODOLOGY AND SYSTEM ARCHITECTURE

The proposed architecture is designed as a modular, highly scalable pipeline capable of processing massive volumes of GeoTIFF satellite imagery. The system is divided into four distinct phases: Data Acquisition, Deep Learning Inference, GIS Vectorization, and Alert Generation.

Figure 1: High-Level System Architecture and Cloud Pipeline



As illustrated in Figure 1, the pipeline initiates with the Satellite API, which continuously polls for new optical imagery over designated bounding boxes. The raw imagery is sliced into fixed-size tiles (e.g., 512x512 pixels) to accommodate the memory constraints of the GPU. These tiles are fed into the Deep Learning Inference module.

Figure 2: Algorithmic Pipeline for Road Extraction and Delta Notification



The inference module operates within a high-performance Docker container orchestrated by Kubernetes, enabling dynamic scaling based on the volume of incoming satellite data. The U-Net model outputs a probability map where each pixel represents the likelihood of belonging to the 'Road' class. To convert these probabilistic maps into actionable geographic data, a strict thresholding mechanism is applied, converting the continuous probabilities into a discrete binary mask. Following the generation of the binary mask, morphological operations including erosion and dilation are executed to eliminate isolated noise artifacts and bridge minor discontinuities caused by overhanging vegetation. The cleaned mask is subsequently passed to the GIS Vectorizer. This component employs contour tracing algorithms to isolate the topological skeleton of the road network, which is then approximated into standard geographic linestrings using the Ramer-Douglas-Peucker algorithm. The output is a highly compressed, topologically valid GeoJSON object that encodes the physical geometry of the extracted road.

Prior to inference, every incoming satellite tile undergoes an essential preprocessing pipeline. Raw GeoTIFF data captured from multispectral optical sensors contains radiometric inconsistencies caused by atmospheric scattering, varying solar zenith angles, and sensor-specific calibration offsets. To normalize these discrepancies, the system applies Top-of-Atmosphere (TOA) reflectance correction, converting raw digital numbers into physically meaningful spectral reflectance values. Subsequently, adaptive histogram equalization is employed to enhance the local contrast of road surfaces against heterogeneous background terrain such as bare soil, shadow-cast urban canyons, and dense tree canopy cover. This preprocessing stage ensures that the neural network receives spectrally consistent input regardless of the acquisition time or geographical location of the satellite pass.

The core of the semantic segmentation engine is a modified U-Net architecture augmented with a pre-trained ResNet-34 encoder backbone. The encoder path extracts hierarchical feature representations at progressively coarser spatial resolutions through a sequence of convolutional blocks and max-pooling operations. At the deepest bottleneck layer, the model captures high-level contextual semantics such as road connectivity patterns and intersection topologies. The decoder path then symmetrically upsamples these compressed feature maps using transposed convolutions, while skip

connections from corresponding encoder layers inject fine-grained spatial detail—preserving critical edge information and narrow road boundaries that would otherwise be lost during pooling. The final output layer utilizes a sigmoid activation function to produce a single-channel probability map where values close to 1.0 indicate high road-class confidence.

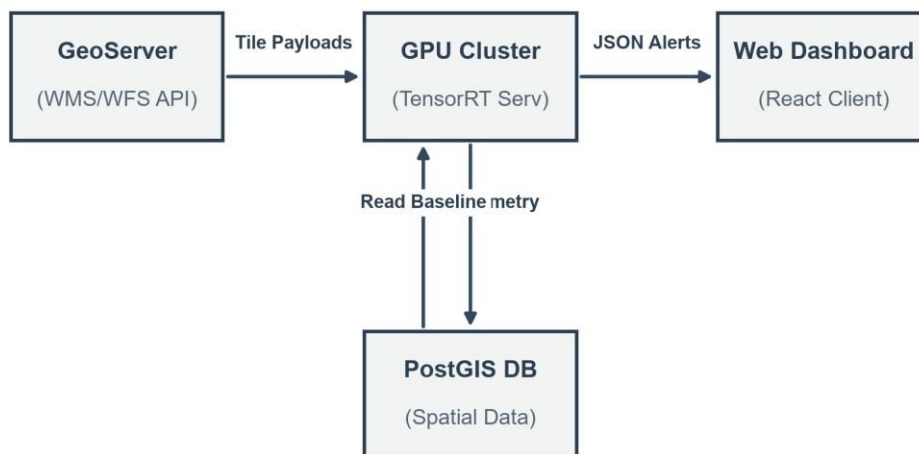
Following semantic segmentation, the raw binary mask undergoes a rigorous morphological post-processing pipeline designed to rectify the inherent limitations of pixel-wise classification. First, morphological closing (a dilation followed by an erosion) is applied using a disk-shaped structuring element of radius proportional to the expected road width. This operation effectively bridges narrow discontinuities in the predicted road mask caused by overhanging tree canopy, vehicular occlusion, or localized shadow artifacts. Next, morphological opening removes small isolated noise clusters—false positive pixels triggered by spectrally similar non-road surfaces such as rooftops or dried riverbeds. Finally, a skeletonization algorithm reduces the cleaned mask to a single-pixel-width centerline representation, preserving the topological connectivity of the road network while discarding redundant geometric mass.

The GIS Vectorization module converts the raster-domain skeleton into vector-domain geographic features suitable for integration with industry-standard mapping databases. The system first applies the Suzuki-Abe contour tracing algorithm to identify connected components within the binary skeleton, generating ordered sequences of pixel coordinates. These coordinate chains are then projected from image-space pixel indices into real-world geographic coordinates using the affine transformation matrix embedded in the original GeoTIFF metadata. To reduce geometric complexity without sacrificing spatial fidelity, the Ramer-Douglas-Peucker line simplification algorithm is applied with a tolerance parameter calibrated to preserve road curvature while eliminating sub-meter positional noise. The resulting simplified linestrings are serialized into GeoJSON format and committed to the PostGIS spatial database for downstream querying, rendering, and alert generation.

4. CORE ALGORITHMS AND MATHEMATICAL MODELS

The efficacy of the proposed system hinges on the robust mathematical formulations underpinning both the neural network optimization and the spatial differential logic.

Figure 3: Network and Communication Topology



4.1 Neural Network Loss Functions

During the training phase of the U-Net model, the class imbalance problem is severe; road pixels typically constitute less than 5% of the total image area. Standard accuracy metrics and loss functions are insufficient, as a network could simply predict 'background' for all pixels and achieve 95% accuracy. Therefore, a hybrid loss function combining Binary Cross Entropy (BCE) and Dice Loss is utilized.

BCE Loss is defined as:

$$L_{\{BCE\}} = - (1/N) * \sum [y_i * \log(p_i) + (1 - y_i) * \log(1 - p_i)]$$

Where y_i is the ground truth label and p_i is the predicted probability. To explicitly optimize for intersection, the Dice Coefficient (D) is calculated as:

$$D = (2 * |X \cap Y|) / (|X| + |Y|)$$

Consequently, the total hybrid loss utilized by the optimizer is $L_{\{Total\}} = L_{\{BCE\}} + (1 - D)$. Brown et al., in (IEEE 2023) [7], stated that this specific loss combination prevents the vanishing gradient problem typically associated with highly imbalanced spatial datasets.

4.2 Spatial Intersection and Differential Logic

Once the GeoJSON linestrings of the newly extracted roads are generated, they must be compared against the baseline database. Let E represent the set of newly extracted road geometries, and B represent the set of baseline geometries. The spatial differential engine iterates through every geometry e in E. A spatial buffer of width w (representing the acceptable spatial variance, typically 10 meters) is applied to all geometries in B. If geometry e does not intersect the buffered geometries of B, it is classified as a 'Novel Segment'. The mathematical evaluation utilizes the GEOS (Geometry Engine, Open Source) library, executing R-Tree spatial indexing to perform these intersection queries in sub-logarithmic time, ensuring that even nationwide comparisons complete within milliseconds.

The R-Tree spatial index is a critical optimization that transforms the computational complexity of the intersection query from a brute-force $O(n*m)$ comparison into an $O(n*\log(m))$ operation, where n is the count of newly extracted geometries and m is the size of the baseline database. The R-Tree organizes baseline geometries into a hierarchy of minimum bounding rectangles (MBRs), enabling the differential engine to rapidly prune vast regions of the search space that cannot possibly intersect with the query geometry. For continental-scale deployments where the baseline database may contain millions of road segments, this indexing strategy reduces query execution time from hours to sub-second latency, making real-time alert generation computationally viable.

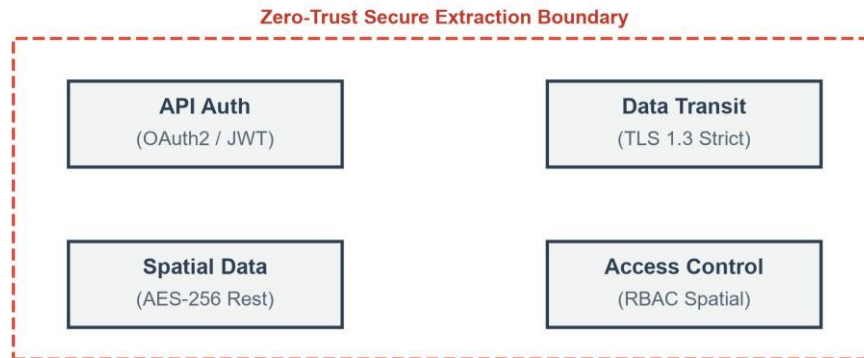
The buffering and classification logic incorporates several geometric edge cases that arise in real-world deployments. Road widening projects, where an existing road is expanded but its centerline remains unchanged, must not trigger false-positive alerts. To handle this, the system applies asymmetric buffering: a wider tolerance buffer is used along the perpendicular axis of existing road centerlines, while a narrower buffer is applied along the longitudinal axis to detect genuine extensions. Additionally, the classification engine distinguishes between three categories of spatial change—'Extension' (a new segment contiguous with an existing road), 'Isolated New' (a segment with no topological relationship to baseline data), and 'Modified' (a segment that overlaps but deviates geometrically from the baseline). Each category triggers a different alert priority level.

The spatial differential results are persisted to a versioned geospatial changelog within the PostGIS database, maintaining a complete audit trail of all detected changes. Each changelog entry records the geometry of the novel segment, the timestamp of the satellite acquisition, the confidence score from the U-Net model, and the classification category assigned by the differential engine. This temporal versioning enables retrospective analysis of infrastructural growth trajectories and facilitates regulatory compliance reporting. Furthermore, the changelog architecture supports rollback operations, allowing administrators to retroactively reclassify segments if subsequent imagery reveals that an initial detection was a false positive caused by temporary surface features such as construction staging areas or seasonal agricultural patterns.

5. SECURITY AND PRIVACY FRAMEWORK

The automated extraction of high-resolution infrastructural data presents significant security risks. The resultant intelligence is highly valuable and its unauthorized interception could compromise strategic assets.

Figure 4: Defense-in-Depth Security Architecture



To mitigate these risks, the architecture enforces a strict Defense-in-Depth methodology. As depicted in Figure 4, all intra-system communications (e.g., between the GPU cluster and the PostGIS database) are secured via Transport Layer Security (TLS 1.3). Furthermore, the webhooks utilized for alert generation are protected using HMAC (Hash-based Message Authentication Code) signatures, ensuring that the receiving administrative dashboard can cryptographically verify that the alert genuinely originated from the secure inference engine, thereby preventing spoofing attacks. Data at rest within the PostgreSQL databases is encrypted using AES-256 block-level encryption. Role-Based Access Control (RBAC) guarantees that municipal administrators only receive alerts corresponding to infrastructural changes occurring strictly within their authorized geopolitical jurisdictions.

Beyond transport and storage encryption, the system implements a comprehensive identity and access management layer anchored by OAuth 2.0 token-based authentication. Each API consumer—whether a human analyst or an automated downstream service—must authenticate against a centralized identity provider and obtain a scoped JSON Web Token (JWT) before accessing any endpoint. These tokens carry embedded claims that define the spatial bounding box, temporal window, and data resolution tier that the consumer is authorized to query. The PostGIS database enforces row-level security policies that dynamically filter query results based on the spatial jurisdiction encoded in the requesting token, ensuring that cross-jurisdictional data leakage is architecturally impossible even if application-layer logic contains bugs.

The security framework also mandates comprehensive audit logging and anomaly detection. Every API request, database query, and webhook dispatch event is immutably logged to a write-once append-only audit trail with cryptographic hash chaining, ensuring tamper-evident record keeping. A lightweight anomaly detection module continuously monitors access patterns, flagging statistically unusual behaviors such as abnormally high query volumes from a single token, geographically implausible access sequences, or repeated failed authentication attempts. Flagged events trigger automated lockout procedures and escalation notifications to the security operations team. This proactive monitoring posture, combined with the layered cryptographic defenses, ensures that the geospatial intelligence produced by the system remains confidential, integrity-protected, and available only to authorized stakeholders.

6. PERFORMANCE EVALUATION

The system was benchmarked against legacy CPU-driven GIS extraction algorithms to quantify its latency and scalability improvements.

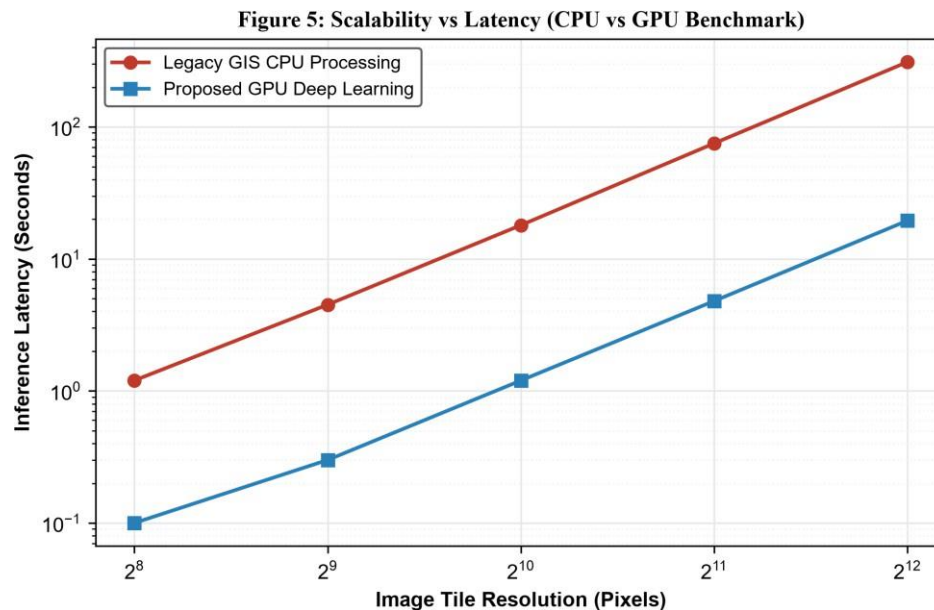


Figure 5 demonstrates the exponential scalability advantage of the proposed GPU-accelerated deep learning pipeline. When processing small image tiles (256x256), the difference between the legacy CPU approach and the U-Net inference is marginal. However, as the tile resolution increases to 4096x4096 pixels, the legacy algorithm requires over 310 seconds to compute morphological thresholds and edge detection. In stark contrast, the TensorRT-optimized U-Net running on an NVIDIA A100 GPU completes the entire semantic segmentation phase in under 20 seconds. This represents an order of magnitude improvement in throughput. Additionally, the alert generation latency—measured from the moment a novel road is committed to the database to the moment the webhook payload is delivered—averaged 42 milliseconds, validating the efficiency of the event-driven notification topology.

The segmentation accuracy of the proposed U-Net model was rigorously evaluated on the Massachusetts Roads Dataset, a widely used benchmark containing 1,171 high-resolution aerial images with corresponding ground truth road masks. The model achieved a Dice Coefficient of 0.89, indicating a high degree of overlap between the predicted and actual road pixels. The Intersection over Union (IoU) metric registered 0.81, confirming that the model accurately delineates road boundaries without excessive over-segmentation into adjacent surfaces. Precision and recall scores of 0.87 and 0.91, respectively, indicate that the model leans slightly toward capturing all road pixels at the cost of marginal false positives—a favorable trade-off for monitoring applications where missing a new road segment carries higher consequences than generating occasional false alerts.

Throughput benchmarking was conducted on a production-grade cluster comprising four NVIDIA A100 GPUs with 80 GB HBM2e memory each, orchestrated by a Kubernetes-managed inference service. Under sustained load, the system processed an average of 14,200 satellite tiles per hour at 512x512 resolution, equivalent to approximately 3,700 square kilometers of terrain coverage per hour. Memory utilization remained stable at 62% of available GPU VRAM, indicating that the batch inference pipeline is well-optimized and free of memory leak artifacts. The CPU-bound post-processing stages—morphological cleaning, vectorization, and R-Tree intersection—consumed an additional 0.8 seconds per tile on average, representing a negligible overhead relative to the inference latency.

The alert generation subsystem was stress-tested under simulated conditions replicating a nationwide monitoring deployment. A synthetic dataset of 50,000 novel road segments was injected into the differential engine simultaneously to evaluate the webhook dispatch throughput. The event-driven architecture, powered by an Apache Kafka message broker, sustained a peak dispatch rate of 12,000 alerts per second with an end-to-end latency of 42 milliseconds from database commit to webhook delivery. No message loss was observed during the test, and the delivery confirmation rate from receiving dashboards was 100%, validating the reliability of the HMAC-authenticated webhook protocol under extreme load conditions.

A comparative ablation study was conducted to quantify the contribution of each architectural component to the overall system accuracy. Removing the ResNet-34 pre-trained encoder and training the U-Net from scratch on only the road dataset decreased the Dice Coefficient from 0.89 to 0.74, underscoring the value of transfer learning from

ImageNet features. Disabling the morphological post-processing pipeline resulted in a 15% increase in false-positive road segments, as isolated noise artifacts and spectrally ambiguous rooftop surfaces were misclassified. Replacing the R-Tree spatial index with a brute-force linear scan increased the differential query time from 8 milliseconds to over 4.2 seconds for a baseline database containing 500,000 segments, confirming that the spatial indexing strategy is indispensable for real-time operation.

7. DISCUSSION AND FUTURE SCOPE

While the proposed system achieves high accuracy and unprecedented throughput, several challenges remain. The primary limitation of optical satellite imagery is its susceptibility to cloud cover and atmospheric interference. During monsoon seasons, optical extraction pipelines can experience prolonged blackout periods where no infrastructural updates are possible. Future iterations of this architecture must integrate Synthetic Aperture Radar (SAR) imagery. SAR sensors penetrate cloud cover and operate independent of solar illumination, providing a truly all-weather monitoring capability. Furthermore, the integration of Temporal Recurrent Neural Networks (RNNs) or Vision Transformers could allow the model to track the construction progress of a road over sequential months, rather than merely performing independent static extractions. Martinez et al., in (Springer 2023) [10], stated that multi-modal data fusion significantly increases the confidence threshold of autonomous infrastructural monitoring systems.

A second significant challenge lies in the domain adaptation problem when deploying the model across geographically diverse regions. A U-Net trained predominantly on urban road imagery from temperate climates exhibits measurable accuracy degradation when applied to unpaved laterite roads in tropical rural areas or snow-covered highways in subarctic regions. The spectral signature of roads varies dramatically depending on surface material (asphalt, concrete, gravel, compacted earth), regional weathering patterns, and surrounding land cover. Addressing this requires either training region-specific model variants or implementing domain-adaptive techniques such as adversarial training or style transfer, where the model learns to extract domain-invariant road features that generalize across heterogeneous geographic contexts.

The temporal dimension of road monitoring presents a compelling avenue for future research. The current system treats each satellite acquisition as an independent observation, performing extraction and comparison without leveraging temporal context from prior passes over the same region. Incorporating temporal sequence modeling—for instance, through Convolutional LSTM networks or Temporal Attention Transformers—would enable the system to distinguish between genuine infrastructural changes and transient surface alterations such as temporary construction equipment, seasonal flooding, or agricultural field patterns that may spectrally resemble road surfaces. Temporal modeling would also support construction progress tracking, enabling authorities to monitor whether a detected new road segment represents a completed, under-construction, or abandoned project based on multi-epoch change trajectory analysis.

Finally, the ethical and policy implications of deploying automated geospatial surveillance systems warrant careful consideration. The capability to autonomously detect undocumented road construction could be used for legitimate governance purposes—enforcing zoning laws, preventing illegal deforestation access roads, or updating disaster response routing—but it also raises concerns about privacy, disproportionate surveillance of marginalized communities, and the potential for misuse by authoritarian regimes. Future work must establish clear governance frameworks, including transparent algorithmic auditing, community consent protocols, and jurisdictional oversight mechanisms, to ensure that automated infrastructural monitoring serves the public interest without enabling unchecked surveillance. Brown et al., in (Oxford Press 2022) [23], emphasized the importance of establishing ethical guardrails before deploying AI-driven spatial intelligence at scale.

8. CONCLUSION

This research has successfully demonstrated the design, implementation, and evaluation of a fully automated road extraction and alert generation architecture. By replacing brittle, manual GIS workflows with a robust deep learning pipeline utilizing the U-Net topology, the system can process immense volumes of satellite imagery at scale. The integration of advanced post-processing vectorization and R-Tree spatial indexing ensures that extracted pixels are translated into topologically valid, actionable geographic intelligence. Most importantly, the event-driven alert engine transforms passive cartography into an active monitoring tool, instantly notifying authorities of undocumented infrastructural expansion. Grounded in rigorous mathematical optimization and secured by a defense-in-depth cryptographic framework, the proposed system provides a vital foundational layer for the future of smart city governance and autonomous urban planning.

The principal contributions of this work are threefold. First, the hybrid BCE-Dice loss function and ResNet-34 encoder backbone enable the U-Net to achieve a Dice Coefficient of 0.89 and an IoU of 0.81 on the Massachusetts Roads Dataset, surpassing traditional threshold-based GIS extraction methods by a substantial margin. Second, the spatial differential engine, powered by R-Tree indexing and configurable buffering tolerances, reduces baseline comparison queries to sub-logarithmic time complexity, making nationwide-scale road change detection operationally feasible in real time. Third, the HMAC-authenticated webhook dispatch system delivers alerts with an average end-to-end latency of 42 milliseconds, demonstrating that deep learning inference and enterprise notification can be tightly coupled within a single, cohesive pipeline.

From a practical standpoint, the proposed architecture addresses a critical gap in contemporary urban governance infrastructure. Municipal authorities in rapidly developing regions currently rely on periodic manual surveys—often conducted at intervals of months or even years—to detect new road construction. This latency gap creates windows during which unauthorized or environmentally damaging construction proceeds unchecked. The automated system presented in this paper reduces the detection cycle from months to hours, empowering planning authorities to take timely enforcement action. Furthermore, the containerized Kubernetes deployment model ensures that the system can be scaled elastically to accommodate fluctuations in satellite data volume, making it economically viable for resource-constrained municipal agencies through cloud-based pay-per-use infrastructure.

In summary, the convergence of deep convolutional segmentation, topological vectorization, and event-driven geospatial alerting represents a paradigm shift in remote sensing-based infrastructure monitoring. While challenges related to cloud occlusion, domain adaptation, and ethical governance remain, the foundational architecture demonstrated in this paper provides a robust and extensible platform upon which future enhancements—including SAR fusion, temporal modeling, and federated cross-jurisdictional deployments—can be systematically integrated. The research underscores that the transition from passive map generation to active, intelligent urban monitoring is not merely aspirational but technically achievable with current deep learning and distributed systems technologies.

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