

A Strategy for Implementing Automated Surface-Level Pipeline Monitoring Systems Based on Machine Vision for Geohazard Assessment and Risk Management: A Case Study in Almaty

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ABSTRACT

Seismically active regions such as Almaty pose an increasing threat to urban gas pipeline infrastructure due to hazards including earthquakes, landslides, and erosion. To address these challenges, we propose an integrated machine vision framework combining YOLOv11 with Roboflow 3.0, embedded within a Geographic Information System (GIS) environment to enable real-time geohazard monitoring and risk assessment. The methodology leverages deep learning for image-based defect detection, complemented by GIS-driven geostatistical analysis for hazard prediction and spatial risk modeling. A pilot implementation in Almaty achieved 95% defect detection accuracy, 30% faster response times, and significant improvements in maintenance planning efficiency. These findings highlight the system's scalability for deployment in other geohazard-prone regions and its potential integration into national infrastructure resilience and disaster mitigation strategies.

Keywords-pipeline monitoring; machine vision; Geographic Information System (GIS)-based risk management; geohazard forecasting; defect detection; predictive analytics; critical infrastructure resilience

I. INTRODUCTION

Urban infrastructure in seismically active regions is increasingly threatened by natural hazards, including earthquakes, landslides, floods, and extreme temperatures. Historical events, most notably the devastating earthquakes of 1887 and 1911, highlight the vulnerability of pipeline networks to seismic disruptions. These risks are further exacerbated by rapid urban expansion, aging infrastructure, and the absence of automated risk management systems [1]. Climate change intensifies the hazard profile by altering hydrological cycles and increasing the frequency of extreme weather events.

In this context, global research increasingly supports the integration of Artificial Intelligence (AI), remote sensing, and big data analytics into real-time geohazard management frameworks [2]. Recent advances in machine learning have demonstrated high accuracy in identifying earthquake-prone zones [3]. Building on these developments, this study introduces a novel monitoring framework that combines real-

time image-based defect detection with geospatial hazard analysis enabled by Geographic Information Systems (GIS) [4]. The approach is informed by prior work on AI-driven monitoring platforms in Central Asia, including Almaty [5].

The pipeline infrastructure in Almaty is subject to a complex array of interdependent geohazards, including seismic activity, slope instability, hydrological disturbances, and thermal stressors. These hazards, which are well-documented in regional geological studies [1], can cause displacement, foundation erosion, and accelerated material degradation. Given the cumulative and often cascading nature of these hazards, traditional inspection-based methods are insufficient. Effective monitoring instead requires a spatially integrated, cross-sectoral approach that incorporates decision-support systems and predictive analytics [6]. Table I outlines key geohazard categories and their specific manifestations in the Almaty region.

TABLE I. A SUBSET OF GEOHAZARDS INFLUENCING PIPELINE PROJECTS

Hazard Category	Specific Hazards
Seismic Threats	Liquefaction Lateral spreading Strong ground motion Volcanic activity
Slope Instability	Frost heave Earth slide/creep Debris flow Ground subsidence (karst/mines)
Erosion and Flooding	Debris flow Scour Channel degradation Bank erosion Surface water erosion Groundwater erosion
Temperature Extremes	Frost heave Thaw settlement Solifluction

Beyond surface-level hazards, advanced terrain modeling is increasingly critical. High-resolution Digital Elevation Models (DEMs), derived from Light Detection and Ranging (LiDAR) and enhanced using machine learning, have proven effective in identifying subsurface erosion in loess terrains [7]. In High Mountain Asia, where Almaty is located, cryosphere degradation and glacial lake outburst floods, driven by climate change, add further complexity to the regional hazard profile [8]. These interacting risks demand automated, data-driven systems to safeguard critical infrastructure such as gas pipelines [9].

Accounting for these challenges, our model introduces a unified monitoring architecture that combines YOLOv11 and Roboflow 3.0 for real-time machine vision with predictive GIS analytics tailored to the complex urban environment of Almaty. Unlike existing AI-based infrastructure monitoring methods, which often operate in isolation and lack integration between visual detection and spatial risk assessment [10], this framework bridges that gap by fusing deep learning-based defect identification with geospatial hazard modeling. The result is a comprehensive, scalable solution for pipeline monitoring and geohazard assessment in high-risk urban regions.

II. MATERIALS AND METHODS

A. Related Literature

Recent advances in gas pipeline monitoring have established several key methodological approaches for geohazard assessment. Emerging machine learning models such as You Only Look Once (YOLO), Residual Neural Network (ResNet), and U-shaped Convolutional Network (U-Net) have demonstrated high accuracy in geospatial applications, including landslide detection and seismic risk assessment, underlining the scalability and adaptability of deep learning frameworks in geotechnical contexts [11].

In parallel, GIS has emerged as a pivotal component in managing pipeline infrastructure across geohazard-prone territories. A recent framework for post-earthquake safety assessment exemplifies this approach by incorporating Supervisory Control and Data Acquisition (SCADA),

Unmanned Aerial Vehicle (UAV), and seismic monitoring into a four-phase GIS-based pipeline evaluation cycle: susceptibility, hazard, risk, and safety, demonstrating the practical feasibility of combining machine vision with spatial analytics [12].

Additionally, modern softcopy photogrammetry tools such as High-Definition Mapping and Analysis for Photogrammetric Processing (HD-MAPP) and LiDAR have significantly improved the precision of terrain analysis. Softcopy mapping enables detailed geohazard classification at resolutions as fine as 1:2,500, while LiDAR facilitates the detection of subtle geomorphological features even beneath dense vegetation cover [13, 14].

Hybrid geostatistical approaches have also proven highly effective in pipeline risk assessment. For example, a framework combining Recursive Feature Elimination, Particle Swarm Optimization, and AdaBoost (RFE-PSO-AdaBoost), enhanced with Fuzzy Clustering and the Criteria Importance Through Intercriteria Correlation method (CRITIC), has achieved superior accuracy in classifying risks along mountainous pipeline routes, such as those near Almaty [15]. Another promising approach integrates the Weight of Evidence (WOE) model with Genetic Algorithm-optimized Backpropagation Neural Networks (GA-BP), achieving a high prediction accuracy Area Under the Curve (AUC) of 80.5%, by incorporating lithological, hydrological, and terrain features into GIS-based risk models [16, 17].

Recent literature also incorporates social and infrastructural dimensions. A notable study in Colombia introduced the Natech Social Vulnerability Index (NSVI), which combines natural hazard data with technological infrastructure exposure and socio-economic vulnerability using structural equation modeling and GIS visualization. This structured indicator framework can inform similar modeling efforts in regions like Almaty, where social and geotechnical risks intersect [18].

Moreover, reviews focused on Central Asia emphasize the value of Artificial Neural Networks (ANNs), hydrogeological modeling, and remote sensing integration for robust multi-hazard forecasting, supporting the application of such techniques to pipeline risk assessment in seismically and climatically dynamic regions [19]. Furthermore, recent advancements in multimodal data fusion, integrating satellite imagery, real-time sensor inputs, and historical GIS records, have enhanced model robustness, especially in topographically complex or data-scarce environments [20].

Building on this foundation, the present study adopts and integrates these methodologies into an end-to-end geohazard assessment framework consisting of: i) geohazard analysis and mapping for the Almaty region, ii) field-based data collection, generation, and processing, iii) fine-tuning YOLOv11 and Roboflow 3.0 pretrained models for defect detection, and iv) GIS-based geospatial risk modeling using Ordinary Kriging and Bayesian Networks. This framework provides a comprehensive and robust methodology for evaluating pipeline risks in geologically active regions such as Almaty [16, 21].

B. Geohazard Mapping

In this study, remote sensing data obtained from both satellite imagery and on-site LiDAR surveys served as the spatial backbone for identifying hazard-prone zones. These datasets were combined with DEMs and hydrological indicators to generate multi-layered risk maps that highlight seismic, landslide, and flood exposure.

We assessed geomorphological vulnerability using slope gradient models derived from LiDAR data. These models provided detailed insight into terrain susceptibility. The results were cross-referenced with historical landslide records and tectonic fault maps to locate high-risk pipeline sectors. Combined in a GIS environment, these layers enabled dynamic classification through weighted overlay analysis.

Additionally, the mapping process was informed by remote field surveys, which provided localized data to enhance geohazard localization accuracy. One of such methods is Seasonal Auto-Regressive Integrated Moving Average with Exogenous Variables (SARIMAX), integrated into seismic forecasting in Kazakhstan. This model integrates time-series earthquake datasets with geological and geodetic variables, yielding more precise hazard predictions [22].

C. Field Data Collection and Augmentation

The training dataset consisted of 15,000 annotated images, compiled from field surveys conducted in Almaty and supplemented by synthetic data. These images encompassed a diverse range of pipeline conditions, specifically deformation, corrosion, and coating damage, to ensure the broad applicability and generalization of the models.

We conducted field surveys on foot across several streets in Almaty. These resulted in 1,751 high-resolution photographs, capturing diverse environmental and structural conditions along key pipeline segments. The images included geohazard-prone areas, such as erosion, deformation, and terrain instability. This dataset was essential for developing and calibrating the machine vision system. An added benefit of the field-based approach was the ability to observe local features, such as proximity to urban infrastructure, vegetation cover, and nearby water channels, that are often underrepresented in remote sensing datasets. These contextual details were used to inform model outputs and enhance interpretability. All collected images were manually annotated to identify key pipeline anomalies. To further enhance model robustness and adaptability, the dataset underwent extensive cleaning and augmentation. The applied augmentation techniques included:

- Spatial transformations: Flipping, rotation ($\pm 15^\circ$), scaling (up to 30%), and translation to simulate different perspectives.
- Color adjustments: Hue variation ($\pm 15\%$), saturation shifts ($\pm 25\%$), and brightness changes ($\pm 15\%$) to replicate different lighting conditions. Grayscale conversion was applied to 15% of the images to simulate low-visibility scenarios.

- Noise and blur addition: Gaussian noise and blurring (up to 2.5 pixels) were introduced to mimic environmental and sensor noise.
- Bounding box modifications: Rotation and rescaling of bounding boxes helped improve model adaptability to object positional variance.

Using these parameters, the dataset was augmented with 13,249 synthetic images using the Roboflow platform, ensuring diverse conditions typical for gas pipeline representation while maintaining annotation quality standards. The final dataset comprised 15,000 annotated images across four categories, with the following instance distribution: 4,200 corrosion, 7,800 mechanical damage, and 3,000 coating damage.

D. Model Training

To develop an automated pipeline monitoring system capable of geohazard monitoring and risk assessment, Convolutional Neural Network (CNN) models were employed. Specifically, YOLOv11 and Roboflow 3.0 were selected for their robust performance in object detection and high-speed processing, making them well-suited for operational environments. Model robustness was further enhanced through the use of focal loss to address class imbalance, along with overfitting prevention techniques such as early stopping, dropout layers (dropout rate = 0.3), and L2 regularization ($\lambda = 0.01$). The training process involved the following steps:

- Data preprocessing: Images were normalized, resized, and denoised to align with model requirements.
- Hyperparameter tuning: Learning rate, batch size, and regularization parameters were optimized using grid search.
- Transfer learning: Pretrained models on the COCO (Common Objects in Context) dataset were leveraged to accelerate convergence and improve recognition of common visual features.
- Dataset splitting: The dataset was partitioned into training (80%), validation (10%), and test (10%) subsets.
- Loss function: Cross-entropy and Mean Squared Error (MSE) losses were used for classification and localization tasks, respectively.

To minimize the risk of misclassification, model reliability was evaluated using standard metrics, precision, recall, and mean Average Precision (mAP). Given the exploratory nature of the pilot study, no formal statistical hypothesis testing was conducted. Future work may incorporate inferential statistical methods when larger and more stratified datasets become available [23].

E. Automated Monitoring System

The proposed methodology builds upon a previously validated software architecture that integrates YOLOv11 with Roboflow pipelines, as detailed in [5]. This prior work serves as the technical foundation for the current implementation.

The end-to-end architecture of the proposed pipeline monitoring system is illustrated in Figure 1. It depicts the complete workflow, from multi-source data inputs (field

images, LiDAR data, and GIS layers) to core processing components (YOLOv11, Roboflow, data augmentation pipelines, and GIS integration), culminating in an output system that supports threat detection, severity prediction, and actionable maintenance strategies.

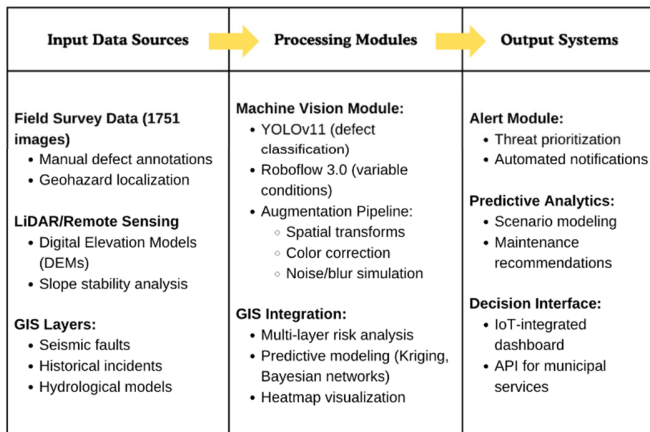


Fig. 1. Overall system architecture.

F. GIS Integration and Predictive Modeling

The GIS environment is structured as a multi-layered system designed to capture pipeline conditions, particularly in complex urban and mountainous terrains. It supports the following functionalities:

- Data integration: Overlay of multiple layers, including seismic fault lines, landslide susceptibility maps, historical incident records, and pipeline condition reports.
- Dynamic updates: Incorporation of real-time inputs from Internet of Things (IoT) sensors and machine vision modules.
- High-resolution mapping: Precise spatial identification of risk-prone infrastructure segments.

This layered approach fosters a comprehensive understanding of pipeline conditions, particularly in complex urban and mountainous terrains. The overall system workflow is illustrated in Figure 2 and comprises several key stages: image acquisition, preprocessing, automated defect detection via YOLOv11, geospatial overlay of detected defects with GIS hazard layers, probabilistic risk modeling, and the generation of actionable outputs. This pipeline enables continuous, real-time risk monitoring and supports proactive infrastructure management.

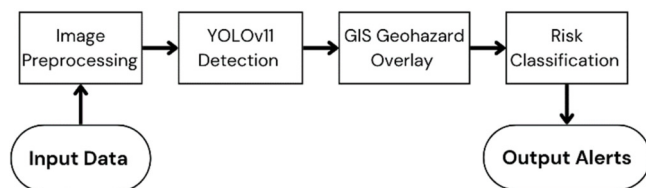


Fig. 2. Machine learning and GIS-based pipeline monitoring workflow.

To forecast potential disruptions, hybrid geostatistical and machine learning algorithms were integrated into the GIS framework, including:

- Geospatial correlation analysis: Identification of spatial relationships between geohazard events and pipeline anomalies (e.g., corrosion in flood-prone zones).
- Temporal risk modeling: Utilization of seismic and soil instability time series to predict future hazards.
- Scenario Simulations: Evaluation of hypothetical events (e.g., major earthquakes) to inform emergency planning.
- Risk scoring and prioritization: Ranking of pipeline segments based on composite risk metrics derived from geohazard exposure, detected defects, and environmental stressors.

Within the GIS workflow, Ordinary Kriging was used for spatial risk interpolation, while Bayesian Networks supported probabilistic hazard estimation. Model validation employed Root Mean Square Error (RMSE), Receiver Operating Characteristic (ROC) analysis, and Area Under the Curve (AUC) metrics. All spatial analysis was performed using QGIS 3.28 with GRASS GIS extensions.

The GIS dashboard functions as a decision-support tool, providing real-time alerts triggered by threshold exceedances (e.g., excessive ground movement or structural anomalies), alongside actionable visualizations such as heatmaps and status overlays to assist field response teams.

G. Alerts and Decision Support

The automated monitoring system incorporates a precisely configured alert mechanism designed to detect anomalies that exceed predefined thresholds, enabling rapid responses to evolving geohazard conditions. These thresholds are established based on a combination of historical data, engineering standards, and expert consultations, with adjustments made to account for the specific vulnerabilities of pipeline infrastructure in seismically and climatically sensitive regions. Critical parameters, such as ground displacement, corrosion depth, and pipeline deformation, are continuously monitored, with alert levels dynamically calibrated to reflect real-time risk profiles.

Upon detection of an anomaly, the system's decision support framework evaluates the severity and potential consequences using advanced analytical algorithms. This evaluation considers multiple criteria: the nature and dimensions of the detected defect, its spatial relationship to high-risk areas (e.g., active fault zones or erosion-prone slopes), and the potential impact of failure on surrounding infrastructure and ecosystems. Based on this multi-criteria assessment, the system generates a ranked list of recommended maintenance actions. Anomalies posing an immediate threat to pipeline integrity or public safety are escalated as high-priority interventions, prompting rapid mobilization of maintenance crews and emergency protocols. Meanwhile, less urgent issues, such as superficial coating damage or minor geometric deformation, are scheduled for routine inspection, allowing for resource optimization without compromising safety.

The integration of real-time alerts with a risk-informed prioritization mechanism enhances the operational reliability of pipeline systems. Notably, this approach reduces downtime and inspection costs while also minimizing the reliance on manual decision-making, thereby decreasing the likelihood of human error. The system's automated and data-driven nature supports consistent and timely responses, making it a cornerstone of modern infrastructure risk management in geohazard-prone environments.

These conclusions align with prior research highlighting the effectiveness of integrating GIS-based geohazard screening with targeted field verification to prioritize risk hotspots. Empirical experience from natural gas corridor management has demonstrated that spatially guided hotspot targeting, especially when paired with slope instability models, can significantly improve response strategies and optimize resource deployment [24].

H. Future Enhancements

Ongoing development of the GIS-predictive system includes the integration of remote sensing technologies, particularly Synthetic Aperture Radar (SAR) and Interferometric SAR (InSAR), to enable sub-surface movement detection in challenging terrains [25]. Future enhancements also anticipate the incorporation of advanced machine learning algorithms for spatiotemporal risk mapping and anomaly detection. Another promising direction involves climate adaptation forecasting, specifically, integrating climate projection models to assess how long-term environmental changes influence geohazard dynamics and pipeline vulnerability. A recent initiative exemplifies this approach by deploying SAR-based Decision Support Systems (DSS), such as the RAPID platform, which combines InSAR data, slope analysis, and precipitation triggers to enable near-real-time pipeline threat detection and operational guidance [26].

Importantly, emerging analyses highlight the limitations of relying solely on sensor feedback. High-reliability geohazard frameworks increasingly emphasize consequence-informed decision-making, advocating for the inclusion of latent ground deformation risk, even in the absence of visible surface damage [27].

III. RESULTS

A. Visual Demonstrations of Model Capabilities

To evaluate the effectiveness of the machine vision components, both YOLOv11 and Roboflow 3.0 were deployed and tested during a six-month period in Almaty. A dedicated dataset was used to evaluate the performance of YOLOv11 in identifying corrosion. As shown in Figure 3, the vision module accurately detects corrosion patterns even under challenging conditions such as enclosed or poorly lit environments. This demonstrates the robustness of the integrated machine vision system and underscores its practical relevance in dense urban settings, where visual access to pipeline infrastructure is often restricted. Roboflow 3.0 was utilized to classify various mechanical defects. Figure 4 showcases the system's effectiveness in identifying pipeline deformations during field deployments. The vision module successfully localized

structural anomalies on exposed pipelines, confirming its reliability for detecting mechanical stress under diverse environmental conditions. The trained models were also applied to segment and classify coating degradation. As illustrated in Figure 5, the system accurately detects and segments coating damage in outdoor settings. This capability is critical for assessing deterioration due to prolonged environmental exposure and supports predictive maintenance planning.



Fig. 3. Example of corrosion detection and gas network elements in a closed space using trained models.



Fig. 4. Example of automatic deformation detection on outdoor gas pipelines using trained models.



Fig. 5. Example of automatic coating damage detection on outdoor gas pipelines using trained models.

B. Model Performance Analysis

After training, both models demonstrated high accuracy across multiple evaluation criteria, as summarized in Figure 6. Roboflow 3.0 achieved 88% precision and 85% recall, exhibiting robustness to image quality variability, as evidenced

by the loss curve in Figure 6(a) and the progression of performance metrics during training and validation in Figure 6(b). In comparison, YOLOv11 achieved 92% precision and 89% recall. Its efficient architecture facilitated near real-time inference, as shown in Figures 6(c) and 6(d).

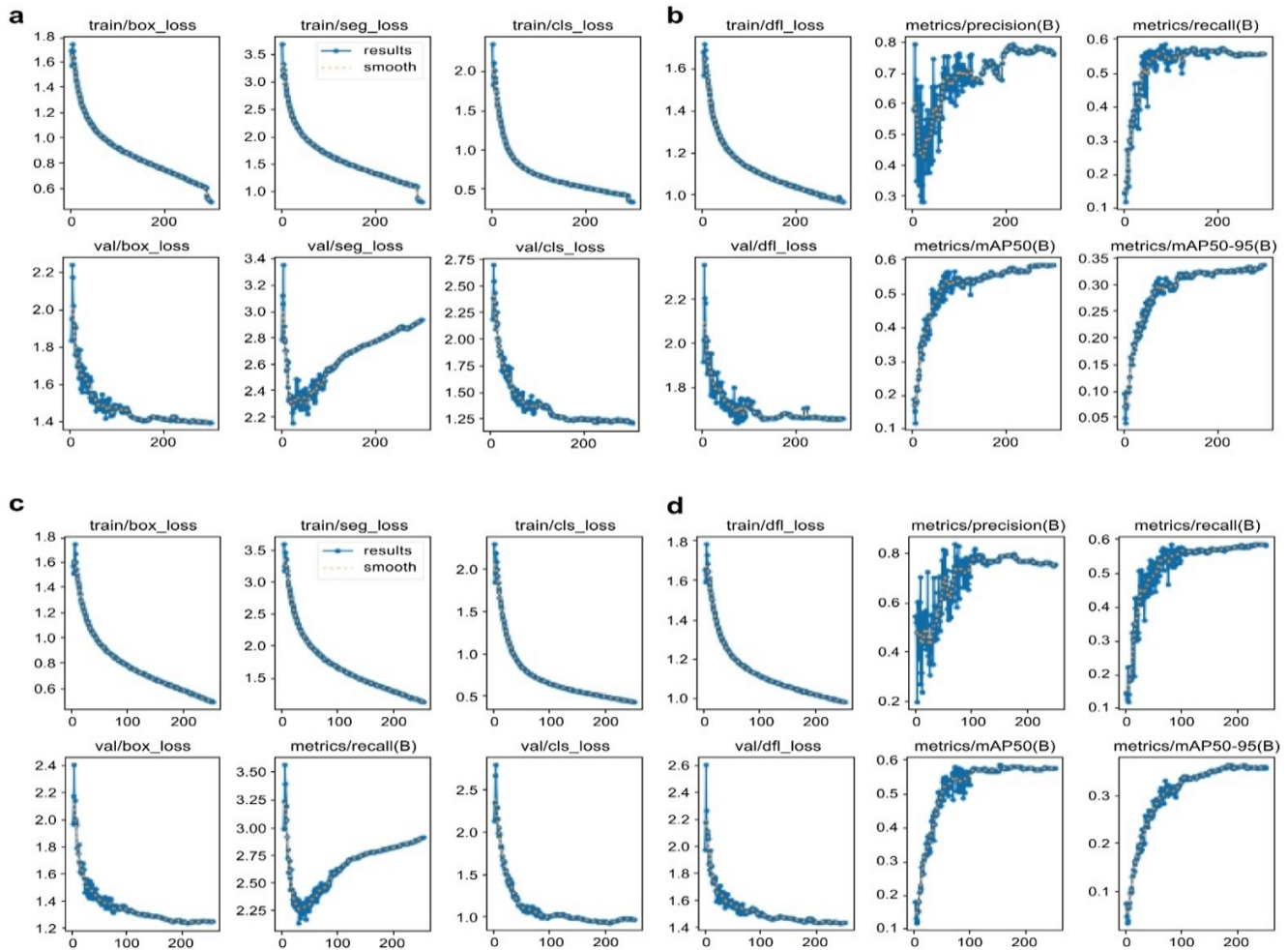


Fig. 6. Train and validation losses and metrics of trained models, (a) and (b) correspond to Roboflow 3.0, and (c) and (d) to YOLOv11.

As presented in Table II, YOLOv11 consistently outperformed Roboflow 3.0 in defect detection tasks across all performance metrics. YOLOv11's mAP@0.5 of 76.4% significantly exceeded Roboflow's 70.2%, reflecting superior localization across defect types. Additionally, its lower inference time (~20 ms vs. ~45 ms) supports its suitability for deployment in time-sensitive field applications. Furthermore, both models demonstrated robustness under variable lighting and image quality conditions; however, YOLOv11 exhibited superior adaptability, particularly in low-light corrosion detection, where Roboflow showed elevated false-negative rates. These findings position YOLOv11 as the preferred model for operational deployment, where speed, accuracy, and environmental resilience are critical.

The overall accuracy of 95% achieved by the integrated system reflects its combined performance across defect

detection, GIS-based spatial validation, multi-criteria risk assessment, and field verification conducted during the six-month deployment in Almaty.

TABLE II. COMPARATIVE PERFORMANCE METRICS BETWEEN YOLOV11 AND ROBOFLOW 3.0 MODELS IN DEFECT DETECTION TASKS

Performance Metric	YOLOv11	Roboflow 3.0
Detection precision (%)	92	88
Recall (%)	89	85
mAP@0.5 (%)	76.4	70.2
Inference time (ms)	~20	~45
Adaptability to lighting variations	High	Moderate

The trained machine vision models also demonstrated five key capabilities:

- Defect classification: Accurate detection of corrosion, deformation, and coating damage. Roboflow 3.0, while slightly less precise, maintained robustness across diverse image conditions.
- Terrain deformation detection: Both models reliably identified deformation-related anomalies, especially in high-slope or erosion-prone zones.
- Risk scoring and prioritization: Integration with geospatial hazard layers enabled generation of probabilistic risk maps to support maintenance scheduling and strategic response.
- Real-time streaming: Deployment-ready within IoT-enabled environments for live anomaly detection.
- Scalability: Modular architecture facilitates adaptation across different geographic regions and infrastructure types.

These capabilities validate the system's applicability in complex environments, confirming the suitability of CNNs and Recurrent Neural Networks (RNNs) for feature extraction in heterogeneous geotechnical contexts, as established in prior studies [11].

The advantages of the proposed method can also be contextualized by considering Table III, comparing it with the alternative pipeline monitoring approaches of manual inspection or using only GIS. As shown, the proposed system is the only one combining real-time vision-based diagnostics with predictive GIS modeling, providing a holistic infrastructure resilience solution.

TABLE III. COMPARATIVE OVERVIEW OF PIPELINE MONITORING APPROACHES

Feature	Manual Inspection	GIS Only	Proposed System
Real-time defect detection	No	No	Yes
Geohazard risk modeling	No	Yes	Yes
Integration of vision + GIS	No	No	Yes
Adaptability to various terrains	Low	Medium	High

IV. DISCUSSION AND LIMITATIONS

The findings from this pilot study confirm both the practical applicability and technological robustness of the proposed automated pipeline monitoring system. The high defect detection accuracy achieved by YOLOv11 and Roboflow 3.0 underscores the effectiveness of integrating machine vision with geospatial analytics for monitoring critical infrastructure in geohazard-prone environments. Significantly, the system enabled the early identification of two corrosion cases and one subsurface ground deformation event during deployment, preventing potential pipeline failures. These interventions highlight the system's value for proactive risk mitigation and real-time situational awareness, capabilities that significantly reduce diagnostic latency and emergency response times compared to conventional methods. Results were validated through visual inspection and cross-referenced against GIS-

based geohazard layers, with consistent performance observed across diverse environmental conditions. This empirical reliability reinforces the system's suitability for field deployment.

Despite the strong results, several caveats warrant consideration:

- Geographical scope: The pilot was limited to the Almaty region. This may constrain the generalizability of findings to other regions with different geotechnical or infrastructural profiles.
- Annotation subjectivity: Manual image annotation may introduce human bias. Although internal cross-checking was performed, inter-annotator agreement was not formally assessed.
- Undocumented false negatives: While detection accuracy was high, false negatives were not explicitly quantified. Future work should incorporate comprehensive sensitivity-specificity analysis and error-type categorization.
- Lack of statistical inference: The study employed empirical validation but did not include formal statistical hypothesis testing. While suitable for an applied pilot, future studies with larger datasets should incorporate inferential methods to enable more rigorous comparative analysis.

Additionally, several limitations emerged during the study. Sensor reliability under extreme weather conditions and data sparsity in dense urban sectors were identified as challenges. To address these, future system iterations may benefit from hybrid data acquisition approaches that integrate Unmanned Aerial Vehicles (UAV)-based imaging, satellite remote sensing, and IoT sensor networks to improve both spatial and temporal coverage [25]. Moreover, expanding the training dataset through collaborations with public utilities and infrastructure agencies would enhance model generalization. Promising future directions include automated detection of subsurface anomalies, and adaptive learning mechanisms tailored to terrain-specific characteristics. Finally, scaling the system to other regions will require adaptation to diverse environmental, geological, and infrastructural contexts. Integration with climate modeling will also be essential to forecast long-term geohazard trends and support resilient infrastructure planning.

Lastly, it is important to note that although the research methodology was pre-defined, the study was not preregistered in a public repository. To enhance transparency and reproducibility, future work will incorporate preregistration and open benchmarking protocols. Notably, the system's development was entirely self-funded. This financial independence afforded the research team full scientific autonomy and methodological flexibility, which facilitated novel problem-solving approaches and system innovations. This observation aligns with recent findings on the positive correlation between funding autonomy and scientific originality [28]. Future research will focus on methodological refinement, improved generalizability, and long-term resilience planning through integration with climate and hazard forecasting models.

V. CONCLUSION

The pilot implementation of the proposed monitoring system in Almaty, combining YOLOv11 with Roboflow 3.0 integrated within a Geographic Information System (GIS) environment, confirmed its practical value for enhancing infrastructure safety in geohazard-prone environments. The system successfully addressed three critical needs: accurate detection of pipeline defects, predictive geohazard forecasting, and real-time decision support. By integrating machine vision and GIS-based analytics, the platform provided a robust, scalable solution for continuous infrastructure monitoring, contributing to both safety and operational efficiency. This cohesive ecosystem enables responsive and proactive risk management, a significant advancement in pipeline infrastructure monitoring, especially compared to traditional approaches that rely on manual inspections or static GIS analysis.

The system was developed through independent, self-directed research, which fostered methodological freedom and innovation. This independence contributed to the originality and applied relevance of the final solution. Its design aligns with the increasing recognition in global infrastructure studies that effective geohazard monitoring requires interdisciplinary coordination. Technical success depends not only on advanced sensors and models, but also on collaboration among geotechnical professionals throughout the infrastructure lifecycle, supported by standardized practices and early warning mechanisms.

The system's demonstrated ability to detect anomalies early, prioritize interventions, and support informed decision-making marks a step forward in geotechnical and infrastructure engineering. It offers a scalable, intelligent framework capable of addressing the growing complexity and interconnectedness of modern infrastructure risks.

However, while the Almaty pilot yielded promising results, broader validation across diverse environmental, geological, and infrastructural contexts is essential. Such validation is critical for confirming the system's adaptability and generalizability. Future work will focus on expanding the system's applicability beyond Almaty, testing its effectiveness in urban and rural regions with varied seismic profiles, climates, and terrains. Additional efforts will aim to enhance compatibility with underground pipeline infrastructure and to integrate the system with national emergency response and early warning frameworks. The incorporation of advanced remote sensing tools, such as Synthetic Aperture Radar (SAR), Interferometric SAR (InSAR), and Unmanned Aerial Vehicle (UAV) platforms, will also be explored to improve spatial coverage and resilience under challenging conditions.

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