APPLICATION OF ARTIFICIAL INTELLIGENCE FOR DEFORMATION PREDICTION IN GEODETIC MONITORING

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Received:22.06.2026
Revised: 23.06.2026
Accepted:24.06.2026

KALIT SO’ZLAR:

artificial intelligence; machine learning; deep learning; deformation monitoring; geodetic monitoring; GNSS; InSAR; remote sensing; structural health monitoring; landslide early warning.

ANNOTATSIYA:

Geodetic monitoring of engineering structures and natural slopes increasingly relies on continuous, multi-sensor data streams produced by GNSS reference networks, satellite radar interferometry, and terrestrial laser scanning. The volume and heterogeneity of these data exceed the practical capacity of classical deterministic and statistical deformation models, motivating the adoption of artificial intelligence (AI) and machine learning (ML) techniques. This paper reviews how AI methods — ranging from gradient boosting and support vector regression to recurrent neural networks, attention mechanisms, and ensemble stacking — are applied to forecast deformation in dams, bridges, buildings, open-pit mines, and landslide-prone terrain. Particular attention is given to hybrid architectures that combine signal decomposition with deep learning, and to the integration of GNSS time series with InSAR-derived displacement fields. The discussion highlights demonstrated gains in prediction accuracy and early-warning lead time, alongside persistent constraints related to model interpretability, transferability between monitoring sites, and the scarcity of labeled failure events. The paper concludes by outlining prospects for physics-informed networks, multimodal sensor fusion, and pretrained foundation models for deformation time series, arguing that AI is becoming a structural *component of modern geodetic monitoring rather than an auxiliary analytical tool.*

1. Introduction

Geodetic monitoring exists to answer a deceptively simple question: is a structure or a slope moving, and if so, how fast and toward what consequence. For decades the answer came from periodic campaigns — precise levelling, triangulation, pendulum readings inside dam galleries, repeated total-station rounds on bridge piers. These methods are accurate, but they are also discrete in time, labour-intensive, and structurally blind between two consecutive epochs. A crack that opens and partially closes between two levelling campaigns leaves no trace in the record.

Over the past fifteen years this picture has changed substantially. Continuously operating GNSS reference stations now deliver millimetre-level coordinate time series at sub-daily or even sub-second rates; the Sentinel-1 constellation and the Copernicus European Ground Motion Service provide wide-area InSAR-derived displacement fields on a regular repeat cycle; terrestrial laser scanners and UAV photogrammetry add dense three-dimensional snapshots of structural surfaces. The outcome is not a shortage of deformation data but, somewhat paradoxically, an excess of it — multi-source, multi-rate, partly noisy, and too voluminous for an engineer to inspect epoch by epoch.

Artificial intelligence entered geodetic monitoring largely in response to this data abundance rather than to data scarcity. Classical deformation analysis — regression against hydrostatic, seasonal, and time components for dams, or simple kinematic extrapolation for slopes — remains theoretically sound but struggles with nonlinear interactions, several superimposed periodicities, and the abrupt regime changes that often precede failure. Machine learning and, more recently, deep learning offer a complementary toolset: they do not replace the physical understanding of why a structure deforms, but they extend the ability to recognise, close to real time, that the pattern of deformation itself is changing.

This paper examines how AI-based methods are currently used to predict deformation in geodetic monitoring, drawing on recent studies covering dams, bridges, open-pit mines, and landslide terrain. Section 2 reviews the relevant literature; Section 3 describes the principal AI methods employed; Section 4 discusses concrete applications across structure types; Section 5 weighs advantages against limitations; Section 6 outlines near-term prospects; Section 7 concludes.

2. Literature Review

The methodological literature on AI-assisted deformation prediction has converged, over the past three to four years, on a fairly consistent pattern: raw signals are decomposed, structured features are engineered or learned, and a sequence model produces the forecast. Gao et al. compared gradient boosting decision trees, support vector regression, and LSTM networks across ten continuously operating GNSS stations and found that no single algorithm dominated uniformly — performance depended on the noise characteristics and periodic content of each station's coordinate series, which argues against treating GNSS prediction as a one-model problem [1].

This sensitivity to signal composition is precisely what motivated hybrid decomposition-plus-learning architectures. Xie et al. combined variational mode decomposition with a convolutional network for feature extraction and an LSTM for temporal forecasting, applying the pipeline to GNSS deformation records from hydraulic structures; their reported improvement of roughly seventy-five per cent over a baseline forecasting accuracy illustrates how much signal conditioning, rather than model choice alone, contributes to predictive performance [2]. A related logic appears in bridge monitoring, where Zhang et al. fused GNSS displacement estimates with speedometer-derived dynamic response on the Jiangyin Bridge, again using VMD to separate the slow structural trend from high-frequency traffic- and wind-induced vibration before further analysis [3].

In landslide research, the InSAR community has moved toward attention-based and multi-task architectures that explicitly target interpretability rather than raw accuracy alone. Zhou et al. proposed a coupled CNN-Attention-BiGRU model for the Xinpu landslide in the Three Gorges Reservoir Area, combining multi-temporal InSAR time series with rainfall and reservoir-level covariates; the attention component was designed to let engineers see which time steps and which input variables drove a given forecast, addressing the long-standing complaint that deep-learning models for landslide early warning behave as black boxes [4]. Strnad et al. pushed this further with a multi-task neural network trained simultaneously on several landslide sites, an explicit attempt to ease the transferability problem that single-site models tend to suffer from when applied elsewhere [5].

Open-pit mining adds another layer of complexity, because deformation there is driven by an evolving excavation geometry rather than a fixed structural footprint. Dong et al. addressed this with a stacking ensemble combining several time-series and machine-learning base models, fed by GNSS RTK observations pre-processed through a cascade of median, Butterworth, and Savitzky–Golay filtering together with an adaptive Kalman filter, and using elastic net regression as the meta-learner that combines the base predictions [6]. Taken together, this body of work suggests that the field has largely settled the question of whether AI helps — it generally does — and has shifted its attention to subtler questions of robustness, transferability, and trust.

3. Artificial Intelligence Methods for Deformation Prediction

Three broad families of methods recur across the literature reviewed above, and in practice they are frequently combined rather than used in isolation.

The first family consists of classical, feature-based machine learning: support vector regression, random forests, and gradient boosting decision trees. These methods require an analyst to define informative input features — displacement rate, acceleration, residuals after removing a deterministic trend, lagged values, environmental covariates such as temperature or reservoir level — but they train quickly, tolerate moderate amounts of missing data, and remain interpretable through feature-importance scores. The comparison by Gao et al. across multiple GNSS stations illustrates where these methods sit: competitive, sometimes superior to deep learning, but inconsistent across sites with different noise profiles [1].

The second family is sequence-oriented deep learning: recurrent architectures such as LSTM and GRU, including bidirectional variants, often preceded by a convolutional layer that extracts local spatial or spectral features before the temporal model takes over. These architectures suit deformation time series precisely because deformation rarely behaves as one clean periodic signal — it typically superimposes a slow secular trend, an annual oscillation tied to temperature or hydrostatic load, and irregular short-term excursions tied to rainfall, traffic, or blasting. Because a raw network struggles to learn all of these scales simultaneously from a few years of daily data, nearly every recent study reviewed above inserts a decomposition step — empirical mode decomposition or, increasingly, variational mode decomposition — ahead of the network, splitting the signal into modes of comparable frequency content. The VMD-CNN-LSTM design used for hydraulic structures and the VMD-based GNSS–speedometer fusion used for the Jiangyin Bridge both follow this logic [2, 3].

The third family centres on attention mechanisms and ensemble methods, which serve two rather different purposes. Attention layers, embedded inside a CNN-BiGRU or similar architecture, let the network learn which past time steps and which covariates matter most for a given forecast horizon — the property that allowed Zhou et al. to produce a landslide displacement forecast an engineer could partially audit rather than accept on faith [4]. Stacking ensembles, in contrast, are not primarily about interpretability but about robustness: by combining several independently trained base models through a meta-learner, a stacking approach reduces the risk that any single model's blind spot dominates the final prediction, which is the rationale behind the mine-deformation framework proposed by Dong et al. [6]. Multi-task learning, used by Strnad et al. for landslide early warning across several sites simultaneously, addresses yet another weakness: a network trained on one location often fails to generalise, and sharing representations across sites during training is one way to push toward a model that captures common deformation mechanics rather than site-specific noise [5].

4. Application of AI in Geodetic Monitoring

Dams remain the structure type with the longest tradition of instrumented monitoring, and they illustrate the transition from purely statistical models to hybrid AI pipelines especially clearly. The conventional hydrostatic–seasonal–time regression model, still embedded in most dam-safety guidelines, explains displacement as a function of reservoir level, a periodic seasonal term, and a slow time-dependent term. What it explains poorly is anything outside that template — an irregular thermal shock at an outlet structure, or a developing crack whose displacement signature does not match any of the three predefined components. Decomposition-based deep learning, of the kind applied by Xie et al. to GNSS records from hydraulic structures, is essentially an attempt to let the data reveal its own frequency components rather than assuming them in advance, and the substantial accuracy gain reported in that study suggests the assumptions embedded in the classical model are often too restrictive for real concrete or embankment dams [2].

Bridges present a related but distinct challenge: their deformation operates on two very different time scales — the slow settlement or creep of piers and foundations, and the fast, vibration-dominated response to traffic and wind loading. The work of Zhang et al. on the Jiangyin Bridge shows one practical way to separate these scales instrumentally and computationally, combining GNSS, which captures slow absolute displacement well but is noisier at high frequency, with a speedometer-type sensor that captures dynamic response, and using VMD to decompose the fused signal into components dominated by each phenomenon [3]. Similar reasoning extends naturally to tall buildings, where AI-supported fusion of rooftop GNSS monitoring with terrestrial laser scanning of the façade is increasingly used to separate genuine foundation settlement from wind-induced sway, although large-scale, openly published case studies devoted specifically to buildings remain less numerous than those on dams or bridges.

Open-pit mines and quarries are arguably the most demanding application, because the geometry being monitored is not fixed: benches are excavated, slopes steepen, and the spatial relationship between sensors and the moving rock mass changes continuously. The stacking-ensemble framework proposed by Dong et al. for mine deformation reflects this reality — rather than relying on a single physically motivated model, it lets several base learners, trained on cumulative displacement decomposed into trend, seasonal, and residual parts together with rate and acceleration features, vote through a meta-model, an approach better suited to a setting where the “normal” deformation pattern itself keeps shifting as mining advances [6].

Landslide-prone terrain ties the discussion back to remote sensing rather than purely ground-based instrumentation, since InSAR coverage of wide, often inaccessible slopes is frequently the only economically viable observation method. The Xinpu landslide case study by Zhou et al. demonstrates how attention-based deep learning can fuse multi-temporal InSAR displacement with rainfall and reservoir-level records from the Three Gorges Reservoir Area to forecast near-term displacement, while the multi-task framework of Strnad et al. targets the harder problem of building an early-warning model that performs acceptably at sites it was not specifically trained on — a property that matters considerably for regional, rather than single-slope, hazard management [4, 5].

5. Advantages and Limitations

The advantages documented across these studies are reasonably consistent. AI-based pipelines tend to improve forecasting accuracy relative to purely statistical baselines, sometimes substantially, as in the roughly seventy-five per cent gain reported for the VMD-

CNN-LSTM model applied to hydraulic structures [2]. They cope naturally with multi-source, multi-rate data — GNSS, InSAR, accelerometers, and environmental sensors can, in principle, be fed into the same learning pipeline without forcing every stream onto a common physical model first. They also tend to extend monitoring lead time: by detecting subtle shifts in pattern before a threshold-based alarm would trigger, several of the reviewed frameworks aim explicitly at earlier warning rather than only more accurate post-hoc fitting.

The limitations are equally consistent, and they are not merely technical footnotes. Interpretability remains the most cited concern, which is precisely why attention mechanisms have become popular in landslide forecasting rather than being a stylistic preference — an engineer signing off on an evacuation decision needs some account of why the model is concerned, not only a number [4]. Transferability across sites is a second, closely related problem: a model trained on one dam's reservoir-level and temperature regime does not automatically transfer to a structure with different geometry and climate, which is exactly the gap that multi-task learning attempts, only partially, to close [5]. A third limitation concerns the scarcity of true failure events in the training data — deformation leading to actual structural failure is, fortunately, rare, so most models are trained almost entirely on stable or slowly evolving conditions and have limited direct evidence of what precedes collapse. Data quality is a fourth, more mundane but practically dominant constraint: GNSS multipath, atmospheric delay in InSAR, and gaps from sensor outages all propagate into AI predictions unless preprocessing — filtering, decomposition, gap interpolation — is done carefully, as the elaborate filtering cascade in the mine-deformation study illustrates [6]. Finally, computational and organisational cost matters: running ensemble or attention-based deep-learning models continuously at dozens of monitoring points, with the retraining discipline needed to keep them current, is a different operational commitment than reading a pendulum once a month.

6. Future Prospects

Several directions appear likely to shape the next phase of this field. Pretraining on large, heterogeneous deformation archives — most plausibly InSAR products such as the Copernicus European Ground Motion Service, which already covers much of Europe on a regular repeat cycle — followed by fine-tuning on a specific structure's local GNSS or InSAR record, is an approach already being tested experimentally; it directly targets the transferability limitation by giving a model broad exposure to deformation patterns before it ever sees the site it will actually be used to monitor. Physics-informed neural networks, which constrain a data-driven model to remain consistent with known mechanical or hydraulic relationships rather than letting it fit arbitrary patterns, are a natural complement to the purely data-driven decomposition pipelines reviewed above, and may help address both interpretability and the failure-data scarcity problem by encoding what is mechanically plausible even when historical failure examples are absent.

Multimodal fusion is likely to deepen further, with graph-based neural architectures well suited to combining point-wise GNSS time series with spatially distributed InSAR or laser-scanning fields, since a graph naturally represents the irregular, non-gridded geometry of a monitoring network. On the operational side, a move toward edge computing — running lightweight versions of these models directly at monitoring stations rather than only in a centralised data centre — would shorten the latency between an anomalous reading and an alert, which matters disproportionately for fast-moving hazards such as landslide reactivation.

7. Conclusion

Across dams, bridges, open-pit mines, and landslide terrain, the recent literature converges on a similar conclusion: artificial intelligence does not substitute for geodetic measurement, but it substantially extends what can be done with the measurements once they exist. Decomposition-based deep learning, attention mechanisms, and ensemble stacking each address a different weakness of earlier statistical models — respectively, multi-frequency signal content, interpretability, and robustness — and the gains reported across the studies reviewed here are large enough to be operationally meaningful rather than merely statistically significant. At the same time, the limitations are not cosmetic: interpretability, cross-site transferability, and the scarcity of genuine failure data remain open problems rather than solved ones. The most credible near-term trajectory is therefore not a wholesale replacement of physical models by AI, but a closer integration of the two — physics-informed architectures, multimodal sensor fusion, and pretrained models adapted to local conditions — so that AI becomes, as the title of this paper suggests, a structural component of geodetic monitoring rather than an add-on analytical layer.

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