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DATA-DRIVEN NEURAL NETWORK APPROACH TO GEOHAZARD CLASSIFICATION AND RISK EVALUATION

Modern geopolitical conditions and ongoing military conflicts pose a direct threat to the preservation of historical and cultural heritage sites. One of the principal challenges lies in the timely and objective assessment of the technical state of buildings and structures under dynamically changing natural and anthropogenic conditions, as well as in the development of effective management strategies to ensure their structural stability and to prevent the progression of deformation and failure processes.

The aim of this study is to develop, theoretically substantiate, and implement a conceptual model for assessing and predicting the stability of historical natural–technical systems, enabling the identification of destabilization risks over both short- and long-term horizons, and supporting the formulation of data-informed risk management strategies.

The proposed approach introduces a methodological framework for constructing a neural network aimed at classifying exogenous geological processes and assessing hazard levels across different territories using integrated long-term monitoring datasets. The research relies on systematic geomonitoring observations [2] and the adaptation of the existing database, expanded with hydrogeological and geodetic monitoring modules. This extended database integrates multi-temporal and multi-parameter measurements, including groundwater levels, ground deformations, and geodetic displacements, providing a solid foundation for identifying correlations between subsurface conditions and surface deformation indicators. These data serve as the analytical basis for applying artificial intelligence methods to predict geohazard risks and support proactive decision-making in the management of historical sites.

The neural network model classifies events and quantifies hazard levels using input parameters derived from seismic activity and exogenous geological processes such as landslides, collapses, erosion, and ground subsidence. The core objective of the model is to transform heterogeneous, high-dimensional geophysical data into a unified quantitative hazard index, suitable for integration into comprehensive georisk monitoring systems.

The model implementation follows a sequential algorithmic structure (Fig. 1). Initially, a structured feature set is generated, comprising spatial, temporal, and physical characteristics of the observed processes [3]. The dataset is then normalized and partitioned into training, validation, and test subsets to ensure representativeness and minimize overfitting. Subsequently, a Multilayer Perceptron (MLP) neural network is constructed, consisting of an input layer (the number of neurons corresponding to the feature count), several hidden layers with ReLU activation, and a Dropout layer designed to enhance the model's generalization capacity. Training is performed using the categorical cross-entropy loss function and the Adam (Adaptive Moment Estimation) optimizer with an early-stopping criterion to prevent overfitting and ensure stable convergence.

To meet the objectives of the research, the MLP architecture implemented in the TensorFlow Keras framework was selected and further customized to the specific properties of geomonitoring datasets. The model was adapted to handle multichannel time series combining satellite-based observations, hydrogeological parameters, and geodetic data. Additional hidden layers were introduced to capture complex spatiotemporal dependencies between input variables. The optimal training configuration — including the number of epochs, learning rate, and regularization coefficients — was determined experimentally using the categorical accuracy metric. The incorporation of Batch Normalization and Dropout layers improved model robustness, reduced sensitivity to noise, and enhanced generalization performance.

After classification, hazard levels are spatially aggregated into grid cells or administrative boundaries using spatiotemporal integration and geostatistical smoothing. This process enables the transition from discrete, point-based risk assessment to continuous regional-scale hazard mapping [3, 5]. The resulting maps can serve as input layers for decision-support systems, facilitating the prioritization of monitoring zones and the planning of mitigation measures.

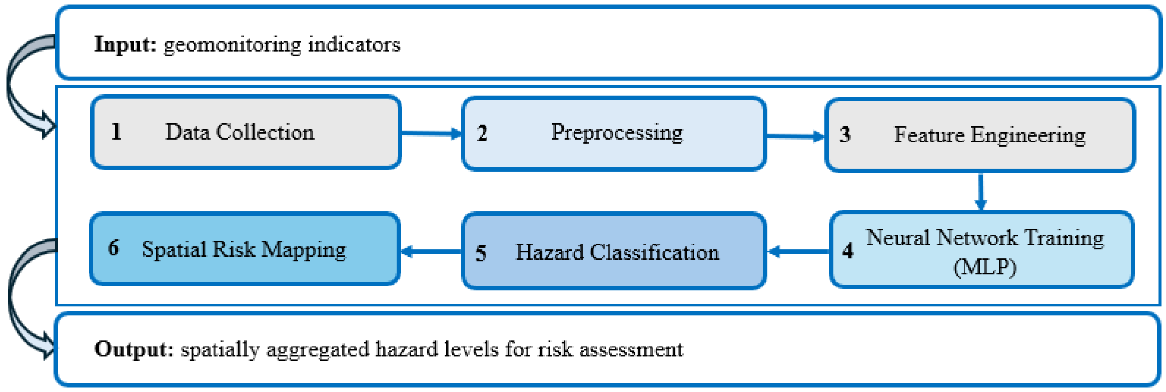

Figure 1 – Neural network workflow for geological hazard classification

The integration of neural network modeling with multisource monitoring data establishes a comprehensive analytical framework for forecasting the evolution of hazardous geological processes in both short- and long-term perspectives. The model allows for the simulation of various scenarios influenced by anthropogenic pressures, climate variability, and external disturbances. Among the predicted processes are flooding, soil overmoistening, ground subsidence, slope movements, collapses of underground structures, and the development of cracks in historical masonry. Each scenario is parameterized through quantitative indicators such as precipitation rates, vibration intensity, groundwater level fluctuations, crack propagation velocities, and terrain morphometry, enabling precise risk quantification and comparative analysis. The developed neural network concept embodies an adaptive, data-driven paradigm for geohazard classification and forecasting in complex urbanized and historical environments. By integrating heterogeneous geomonitoring datasets into a unified analytical system, the proposed approach improves interpretability, spatial resolution, and predictive reliability. It thus provides a methodological foundation for the creation of intelligent decision-support systems in geotechnical monitoring and heritage conservation, contributing to the prevention of deformation-related damage and the long-term preservation of historical structures.

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