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Towards Predictive Tunnel Safety over Machine Learning Risk Assessment

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Abstract

A complete predictive safety system for tunnels is based on a wireless sensor network and cloud-based machine learning. Unlike traditional reactive maintenance approaches, the proposed system enables real-time risk assessment by continuously collecting data from sensors installed in tunnel linings, drainage systems, and ventilation equipment. Data is transmitted wirelessly to the cloud, where machine learning models detect anomalies, predict future failures, and recommend preventive actions.
The system integrates three specialised modules. SANTUB predicts tunnel lining wear using a random forest regression model trained on vibration, humidity, and age data, and estimates rehabilitation costs to enable time-optimised financial planning. TIPS (Tunnel Integrated Predictive System) combines thermographic imaging, drainage flow monitoring, and ventilation performance logs with a convolutional neural network to detect fan fouling, drainage clogging, and seepage water paths behind the lining.
The primary focus is ROCKSPECTOR, the newest module currently in active development. ROCKSPECTOR addresses water breakthroughs in both TBM and conventional tunnels. Using a gradient boosting classifier trained on historical water ingress events, it predicts the probability and location of imminent water ingress up to three days in advance. When ingress is predicted, ROCKSPECTOR recommends either controlled drainage or crack crystallisation – the latter being a permanent sealing method where crystallisation agents react with water to form insoluble crystals inside cracks.
A key characteristic is that no explicit risk analysis methodology (such as fault trees or event trees) is coded into any module. Instead, all risk patterns are learned directly from historical examples through machine learning. Risk analysis thus emerges implicitly from the data.

Keywords

Wireless sensor network, Machine learning, Predictive maintenance, Tunnel safety, Water ingress.

1 Introduction

Tunnel infrastructure is continuously exposed to degradation processes such as mechanical wear, water ingress, ventilation contamination, and drainage clogging. Traditional inspection methods remain largely periodic, manual, and reactive. Problems are typically detected only after they have already caused damage or created safety hazards.

Wireless sensor networks combined with cloud-based machine learning enable real-time predictive maintenance. Sensors measure temperature, humidity, vibrations, water pressure, and drainage flow. Data is transmitted wirelessly to the cloud, where ML models analyse patterns, detect anomalies, and predict failures before they occur.

A critical characteristic of this system is that it does not apply any explicit, pre-defined risk analysis methodology, such as fault trees or event trees. Instead, all risk patterns are learned directly from historical examples using machine learning. Risk analysis is therefore implicitly embedded within the trained ML models.

This paper presents three integrated modules. SANTUB predicts lining wear and rehabilitation costs. TIPS (Tunnel Integrated Predictive System) integrate thermography, drainage monitoring, and ventilation data. ROCKSPECTOR, currently in active development, focuses on water ingress detection and remediation through drainage or crack crystallisation.

2 System Architecture

The architecture follows an IoT pipeline optimised for tunnels. Sensors include humidity sensors, water pressure sensors behind the lining, drainage flow sensors, vibration sensors on lining segments, and thermographic cameras at ventilation fans, drains, and joints. All sensors communicate wirelessly via LoRaWAN, 4G, or 5G to local gateways.

Data is transmitted to the cloud with latency under five seconds. Cloud storage is structured by tunnel identifier, sensor type, location, and timestamp. Historical data is retained for periodic model retraining.

The machine learning layer performs three analyses: real-time anomaly detection generating immediate alerts, short-term prediction of wear or ingress from one to seven days ahead, and long-term trend analysis for annual degradation and cost projections.

Although the author has developed an explicit risk assessment method called FAUST as part of ongoing doctoral research, the present system deliberately avoids explicit risk formulas. Tunnel degradation patterns are too complex for hand-crafted models. ML learns risk directly from sensor data and historical outcomes – risk analysis emerges from the data.

Tunnel operators receive predictions through a dashboard with real-time sensor maps and risk heatmaps. Critical alerts are also sent via email or SMS with recommended actions.

3 SANTUB – Wear Estimation and Cost Prediction

SANTUB uses a random forest regression model trained on sensor data collected by wireless monitoring (Figure 1), tunnel age, and operational loads. The model predicts current wear levels for each segment as a percentage, forecasts future wear at one, three, five, and ten years, and estimates the probability of segment failure.

Based on wear predictions, SANTUB estimates rehabilitation costs. Local crack repairs are calculated per metre of crack length, segment replacement per segment, drainage cleaning as a fixed cost plus a per-metre component, and full lining rehabilitation per square metre. The output is a time-optimised rehabilitation schedule minimising cost while maintaining safety.

When sensors detect sudden changes, SANTUB updates its wear prediction immediately and alerts operators if intervention is needed sooner than planned.



Fig. 1 Tunnel Neumarkt as the part of the project (left), sample of monitoring of salination on the tunnel wall (right).

4 TIPS – Tunnel Integrated Predictive System

TIPS is a modular predictive system that integrates multiple data sources: thermographic cameras for tunnel illumination monitoring, drainage flow sensors, and planned drone-based ventilation inspection. All data is processed by ML models to detect anomalies and predict failures.

4.1 Thermographic imaging for illumination control

Thermographic cameras are used along the tunnel to monitor the illumination level of the tunnel space (Figure 2). Over time, dust accumulation on lighting fixtures, lamp degradation, or reflector contamination can reduce visibility, creating safety hazards for traffic and maintenance personnel. TIPS uses a convolutional neural network trained on thermographic images to classify illumination efficiency as adequate, reduced, or critical. When illumination falls below a safety threshold, the system alerts operators to clean or replace lighting units.

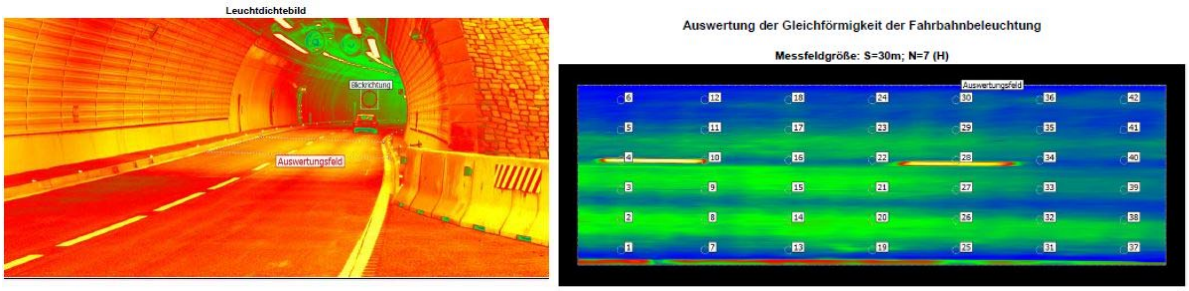


Fig. 2 Luminance image (left) and evaluation of the uniformity of the road lighting (right) in the tunnel Neumarkt.

4.2 Drainage clogging detection

Drainage flow sensors and occasional thermographic inspection of drainage channels help detect clogging caused by sediment or mineral deposits. TIPS classifies drainage status as free, partially clogged, or fully clogged, triggering cleaning alerts when necessary.

4.3 Ventilation monitoring – planned drone inspection

The current plan for ventilation systems is to use periodic drone inspections equipped with high-resolution cameras and optional thermal sensors (Figure 3). Drones can fly close to ventilation fans, ductwork, and exhaust outlets, capturing detailed visual and thermal data without disrupting tunnel operations.

Flight paths are programmed around each ventilation fan and along the main duct, with the drone following the same route every inspection (e.g., monthly or quarterly). The sensor payload includes an RGB camera for visual fouling detection and a thermal camera to identify overheating motors or blocked airflow. Images are transmitted to the cloud where a dedicated CNN classifies fan blade contamination as a percentage, motor temperature anomalies, and duct obstructions. Results are integrated into TIPS. When fouling exceeds sixty percent – a threshold calibrated from historical failure data – the system issues a cleaning alert, even if regular manual cleaning is scheduled twice per year. This predictive alert enables maintenance teams to intervene between scheduled cycles. For the Neumarkt tunnel, drone inspections every three months would complement the biannual manual cleaning, providing early warning of abnormal fouling.



Fig. 3 The ventilation system is one of the main components of the tunnel that is subject to damage and frequent repairs, fans in the tunnel Neumarkt.

4.4 Predictive alerts from TIPS

When any subsystem – illumination, drainage, or ventilation – exceeds predefined thresholds, TIPS issues alerts. Illumination below safety level triggers cleaning or replacement of lighting. Full drainage clogging triggers an immediate cleaning alert. Ventilation fan fouling above sixty percent triggers a scheduled cleaning before the next biannual cycle. Seepage water patterns from thermography or drainage data automatically trigger the ROCKSPECTOR module for water ingress analysis.

5 ROCKSPECTOR – Water Ingress Detection and Remediation

ROCKSPECTOR is the newest module, currently in active development. It focuses on water breakthroughs in TBM with or with no segmental linings and conventional tunnels with shotcrete or cast concrete (Figure 4).

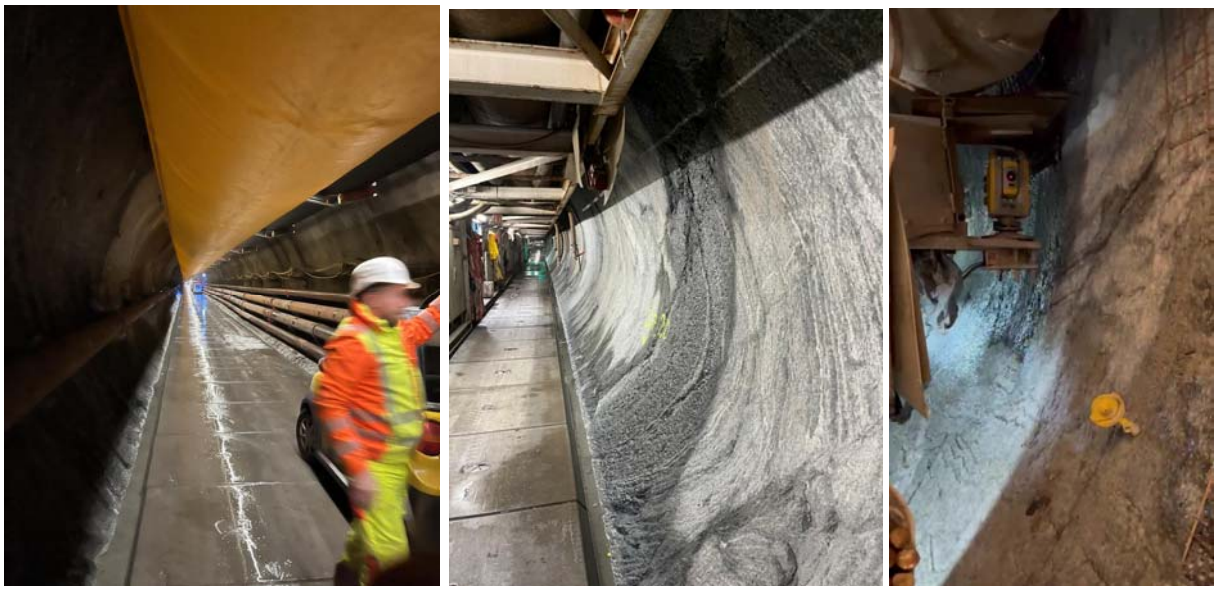


Fig. 4 The views to the rear part of the excavated tunnel in construction with smaller and medium water ingress samples.

Features include weather results, drainage flow trend over seven days, water pressure trend, thermal anomaly score, lining age and wear, and joint opening width. ROCKSPECTOR uses existing sensor data: drainage flow rate (sudden drops indicate clogging), water pressure behind the lining, thermographic anomalies from TIPS, and wear data from SANTUB identifying weak zones. A gradient boosting classifier (XGBoost) and other ML models are trained on historical water ingress events (Figure 5).

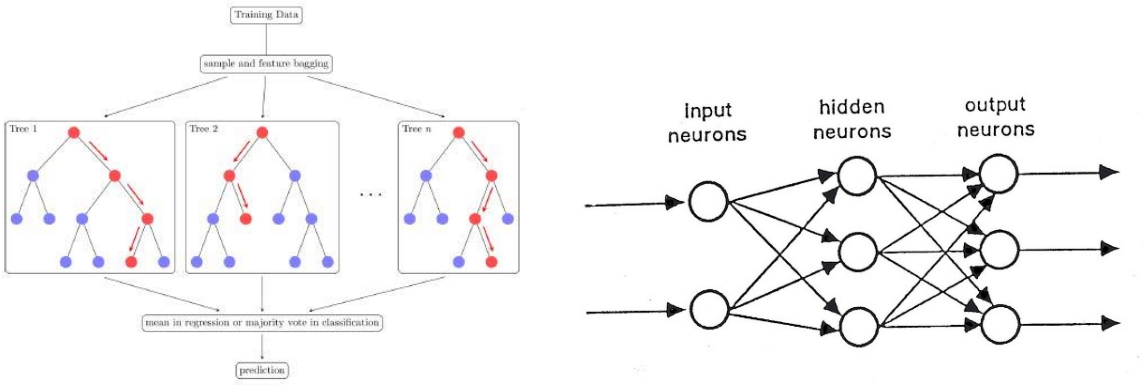


Fig. 5 Flow chart of "Random forest" (decision-tree type) machine learning scheme (left) and the principal sketch of neural network machine learning method for prognostics of monitoring results.

The model outputs the probability of ingress within three days as a percentage, the expected location (specific joint or segment), and a confidence interval. No classical risk analysis method (FMEA, event tree, fault tree) is coded into ROCKSPECTOR. The classifier learns risk patterns by comparing thousands of historical examples – an implicit, data-driven risk model.

When ingress is predicted, ROCKSPECTOR recommends one of two actions. Controlled drainage involves cleaning existing drains or installing temporary channels, suitable for moderate water volumes. Crack crystallisation injects a crystallisation agent into the crack or joint; the agent reacts with water to form insoluble crystals, permanently sealing the ingress path. Crystallisation is preferred for TBM segment joints and radial cracks as it preserves structural flexibility.

ROCKSPECTOR is in prototype phase, trained on over 150 historical water ingress events and undergoing validation on two active tunnels. One of a typical workflows: TIPS detects a thermal anomaly near a joint; ROCKSPECTOR analyses drainage flow which may have dropped forty percent over three days; the ML model predicts eighty-seven percent ingress probability within forty-eight hours and recommends crystallisation of that joint. The maintenance team applies the agent, post-repair thermography confirms sealing, and drainage flow normalises.

6 Integration and Benefits

The three modules work together within the same infrastructure. SANTUB receives vibration and humidity data for wear and cost predictions. TIPS receives thermographic images, drainage flow, and ventilation logs for fouling alerts. ROCKSPECTOR receives drainage flow and water pressure for ingress risk assessment and remediation recommendations.

Operators see a dashboard with a colour-coded tunnel map (green = safe, yellow = monitor, red = intervene), predicted failure probabilities for the next seven days, and recommended actions.

The benefits compared to traditional inspection are: continuous versus periodic monitoring, automated versus manual, predictive versus reactive, with cost optimisation from SANTUB and ingress prediction with crystallisation from ROCKSPECTOR.

7 Conclusions

This paper presented a major predictive safety system elements for tunnels based on wireless sensor networks and methods of machine learning. The three modules are covering basic challenges and are depicted through practice requirements. SANTUB module covers wear extent of structural parts and corresponding maintenance costs, TIPS considers thermography photos of a tunnel showing pollution of visibility, drainage limitations through sedimentation and ventilation damages through continued use and ROCKSPECTOR is estimating danger of possible water ingresses and directs appropriate solutions diversion or crystallisation.

Risk analysis is implemented implicitly through ML, not through explicit probabilistic or structural models. ML models are trained on examples of past failures, near-misses, and normal operation – an approach particularly suitable for rock engineering where explicit models often fail.

SANTUB and TIPS are operational; ROCKSPECTOR is in prototype phase. Future work includes completing validation on over 500 water ingress events, integrating autonomous crystallisation injection materials and developing on-edge ML versions.

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