Real-Time Vibration Anomaly Detection in Operational Metropolitan Optical Networks Using Machine Learning

Gulmina Malik
DET, Politecnico di Torino, Italy
gulmina.malik@polito.it

Muhammad Umar Masood
DET, Politecnico di Torino, Italy
muhammad.masood@polito.it

Renato Ambrosone
DET, Politecnico di Torino, Italy
renato.ambrosone@polito.it

Ahtisham Ali
DET, Politecnico di Torino, Italy
ahtisham.ali@polito.it

Mashboob Cheruvakkadu Mohamed
DET, Politecnico di Torino, Italy
mashboob.cheruvakkadu@polito.it

Stefano Straullu
Links Foundation, Italy
stefano.straullu@linksfoundation.com

Sai Kishore Bhyri
Nokia
sai.bhyri@nokia.com

Gabriele Maria Galimberti
Nokia
gabriele.galimberti@nokia.com

João Pedro
Nokia
joao.pedro@nokia.com

Antonio Napoli
Nokia
antonio.napoli@nokia.com

Walid Wakim
Nokia
walid.wakim@nokia.com

Vittorio Curri
DET, Politecnico di Torino, Italy
vittorio.curri@polito.it

***Abstract*—This paper presents an experimentally validated machine-learning-based framework for real-time detection and classification of vibration-induced anomalies in a live metropolitan optical transport network. The proposed approach exploits high-frequency state-of-polarization (SOP) fluctuations as an early-warning metric to distinguish critical, potentially harmful vibrations from benign environmental noise. The framework is experimentally validated on a 28.5 km deployed metro fiber link operating under real traffic conditions, where vibrations are intentionally induced to mimic realistic threats such as drilling near buried fibers. A supervised machine-learning pipeline is applied to analyze SOP dynamics and classify vibration events under noisy operational conditions. Multiple classifiers, including Decision Tree, Random Forest, and XGBoost, are evaluated, with XGBoost achieving the best performance, reaching an accuracy of 98.02% and an AUC of 0.987. The results demonstrate reliable discrimination between normal and critical vibration events while maintaining low computational complexity, enabling practical real-time edge deployment. The proposed framework supports proactive fault prevention and enhances the resilience of metropolitan optical networks.**

***Index Terms*—Optical transport networks, SOP monitoring, fiber sensing, fault detection**

I. Introduction

Optical transport networks are the backbone of modern communication, which have evolved beyond their conventional role as data transmission infrastructures. Optical fibers are deployed not just in the backbone, but access networks as well, enabling worldwide connectivity for high-speed, high-capacity data transfers. Recent studies show that fiber-optic cables are highly susceptible to environmental conditions such as temperature, mechanical stress, and vibrations [1, 2], as well as physical threats including fiber breaks, physical tampering, unauthorized eavesdropping, and mechanical vibrations [3, 4]. Such perturbations can compromise optical signal quality, resulting in transmission issues, service outages, and data breaches. By monitoring the high-frequency variations in the state-of-polarization (SOP) [5] or optical phase, the current subsea and terrestrial linkages have been used to detect earthquakes, and provide early warning for tsunamis and other physical fiber tampering that could result in fiber cut [6].

Most metro optical infrastructures rely significantly on subterranean optical fiber links installed decades ago. The aging of this infrastructure poses a risk of performance degradation, which can lead to service disruptions without proper monitoring and control. Hence, early fault detection and preventive mitigation are critical in maintaining network service stability. Traditional monitoring systems are typically based on constantly monitoring some specific indicators of performance and generating an alarm, when there is a breach in a given threshold [7], thus initiating service re-routing. As a result, these solutions are reactive in nature, as they do not make use of early warning indications in the telemetry system that a disruptive event will take place. Given these limits, machine learning (ML) emerges as a powerful approach for proactively

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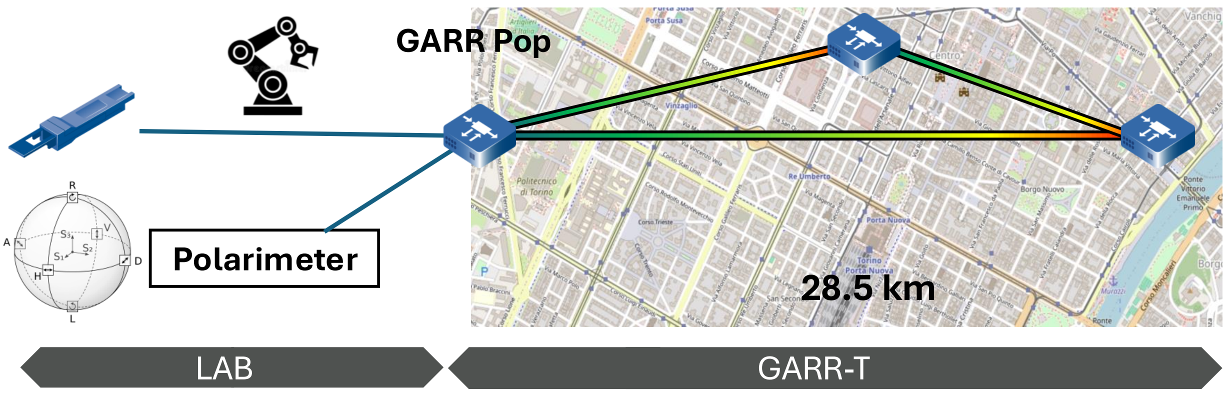

Fig. 1. Experimental setup and vibration-sensing topology over the deployed GARR-T metropolitan fiber network.

integrating these indicators, enabling the development of a more resilient system and reducing the likelihood of service outages. Proactive restoration can increase service or network availability, especially during low traffic demand [8]. This results in fewer network service outages, path relocations, and increased availability, all of which enhance resource efficiency.

In [9], they have used vision-transformer approach for classifying and localizing fiber faults by collecting data from a bidirectional link, highlighting the growing role of Artificial Intelligence (AI) in monitoring faults. ML techniques offer significant potential for addressing the challenges of event detection and localization in optical networks. Although deep learning models can provide high inference performance, they typically require extensive computational resources and large datasets to achieve acceptable accuracy [10]. However, for our investigation, supervised ML algorithms gave efficient and practical solutions due to their low processing costs and reduced demand for a large feature space.

In our early work in [11], we validated an ML-based vibration detection model in a controlled laboratory environment, focusing on harmful detections induced by external activities such as drilling near deployed fibers. Building on this, we have developed a novel framework that uses SOP variations as an early warning metric [12] to classify and detect critical vibrations amid environmental noise in a 28.5 km live metro network. The vision is for a more resilient, self-healing network that enables proactive traffic re-route to a spare optical link to avoid enormous large-scale disruptions.

To the best of our knowledge, this study is the first experimental validation of detecting vibrations and anomalous events in a deployed metro transport network, under real traffic conditions, a practical application that was previously underexplored. In [13], we demonstrated a real-time ML framework for detecting anomalous events, exploiting polarization fingerprints using experimental testbed of our laboratory. To overcome the limitations of controlled laboratory environment, we have applied this framework to the real network, demonstrating the potential for large-scale deployment. We trained and evaluated three distinct lightweight models to ensure a robust evaluation for vibration detection.

II. Vibration Detection in a Live Metro Transport Network

The schematic of vibration sensing topology is presented in Fig. 1. An active continuous wave (CW) laser source sends pulses of light at 1565.496 nm and 3 dBm of power to the fiber loop of GARR-Topology (GARR-T). The setup couples the operational GARR-T metropolitan infrastructure beneath the city of Turin, Italy, with the LINKS Foundation laboratory on campus, linked by an optical access segment to a nearby GARR-T point-of-presence (Pop). A CW laser is injected from the LINKS site into the access fiber and propagated towards the Pop.

After the handoff at Pop, the optical carrier propagates through the GARR-T metro plant under the city, traversing three standard single-mode fiber (SSMF) spans of approximately 7 km, 14 km, and 3.5 km, interconnected by two reconfigurable optical add–drop multiplexers (ROADMs). The 2 km fiber segment is deployed on campus, connecting the LINKS facility to the university Pop. The wavelength is then routed back to the LINKS facility, which is emulated as a datacenter. At the laboratory, the returning carrier is directed to a polarimeter (Novoptel PM1000) that records SOP and optical power time series for subsequent analysis. The resulting SOP fluctuations are primarily driven by environmental disturbances, including traffic and construction activity, due to the underground deployment of the fiber within the metropolitan area.

In the LINKS facility, an Arduino-controlled robotic arm is used to induce vibrations in the testbed just before the GARR Pop. Any mechanical perturbation transmitted through the robotic arm is detected at the polarimeter (Rx) in terms of SOP, which depicts the orientation of the electric field of a light wave as it traverses through fiber.

While the transceiver (Tx) also exposes SOP, it limits the capacity to find the best potential upper bound for SOP. However, polarimeter reduces hardware dependence and offers flexibility in the sampling rates, which helps accommodate variations in network conditions, whereas Tx typically has a fixed sampling rate. These vibrations intend to mimic drilling at a nearby construction site, which could result in a fiber cut.

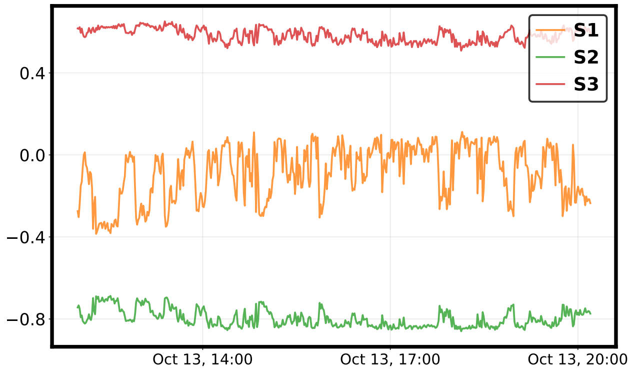

Fig. 2. Evolution in SOP induced by traffic and transportation variations in a live metro transport network.

And in case of critical vibrations (high-risk event leading to fiber cut), it generates an alarm to the optical controller, which then reroutes the traffic to a spare optical path. The sampling frequency is set to 1500 Hz, and averaging time exponent (ATE=21), to record the SOP trajectory correctly and to allow complex transients in urban environmental noise. At this rate, the sampling block takes polarization state measurements on the Poincaré sphere every 0.6 ms over a 22-minute recording period, resulting in about 2.05 million samples per event. As we know live metro networks are inherently noisy due to traffic, construction activities, railway operations, and other environmental perturbations, thereby making real-world production networks considerably more challenging to monitor, analyze, and maintain reliably. The time series evolution of Stokes parameters $\{S_1,\ S_2,\ S_3\}$, highlighting the impact of external disturbances, the GARR-T, is represented by Fig. 2. These fluctuations in SOP, are recorded over a 12-hour period, and reflect the noisy environment caused by nearby traffic and railway activities, as the fiber-optic cable installed underground in the metropolitan city of Turin, Italy, passes near a railway station. Therefore, optical fibers act as a natural vibration sensors since any physical or mechanical stress on the fiber alters the SOP variations, which can be exploited as a highly sensitive metric or feature for environmental sensing [14].

A. Polarimetric Fingerprints

Each event exhibits a unique polarimetric signature. These signatures are collected over a range of vibration intensities and frequencies to ensure a diversity in the observed patterns. The polarimeter continuously streams real-time SOP data from the GARR-T. The variations in SOP reflect the Stokes parameters S_1, S_2, and S_3, which describe light polarization. This SOP data is then sent to an AI/ML engine that is trained to discriminate between normal fluctuations (environmental variations) and risky events. The robotic arm shakes the fiber up and down at varying frequencies and angles of deviation $90°$. These fingerprints are then processed for noise filtering and normalization before being sent to an ML engine.

We characterized the collected signatures into five distinct classes as detailed in Table I, each characterized by unique

TABLE I
SIGNATURES COLLECTED FOR ANOMALY DETECTION

Event Class	Vibration Intensity; Risk Level
bl	Baseline; Negligible (Idle)
n-v1	Low; (Ambient Noise)
n-v2	Low-Moderate; (Ambient Noise)
n-v5	Moderate; (Routine Activity)
c-v6	Critical; (Anomalous Event)

polarimetric fingerprints on the Poincaré sphere. As we increase the vibrational intensity, the SOP moves faster across the Poincaré sphere [15]. *bl* (baseline or idle fiber) represents the idle fiber state, capturing the inherent environmental noise of the metropolitan network. The *n-v1*, *n-v2*, and *n-v5* classes correspond to low-to-moderate vibrations, as they don't pose any risk to network integrity, due to routine activities such as adjacent light machinery or vehicular traffic. The *c-v6* class corresponds to high-intensity mechanical perturbations (critical). This class represents the high-energy vibration signatures associated with heavy excavation or nearby construction activities, that have potential to compromise the physical fiber link. By designating this as the 'critical' class, we provide a definitive label for the ML engine to trigger proactive rerouting protocols, bypassing the potential faults before physical signal degradation occurs.

Real-time SOP monitoring, paired with AI/ML analytics, has the potential to transform optical networks into self-healing systems, enhancing resilience and operational efficiency. The approach enables discrimination between safe and potentially critical events while preserving low inference latency and enabling for quick network restoration when needed.

III. MACHINE LEARNING FRAMEWORK FOR ANOMALY DETECTION

The proposed ML framework is broken into few steps. First the polarization signatures of different vibration occurrences through the network, are collected, each representing a unique fingerprint. The acquired raw data is then post-processed to remove ambiguities and suppress environmental noise sources, such as nearby vehicular traffic or railway-induced vibrations, thereby enhancing its quality. We sequentially divided the dataset into 70% training and 30% testing. To enhance model generalization and robustness, a set of feature-engineering techniques were applied. To discover trends and stability, rolling statistics like rolling mean (RM) and standard deviation (SD) are computed over three sliding windows [3, 5, 10]. This allows the model to detect new patterns for each window characteristic. To enhance the model's ability to capture temporal patterns and improve its robustness in noisy real-world conditions, we engineered an extended set of features. This included generating lag features for up to 30 previous time steps [2] and computing the first, second, and third-order derivatives for each of the Stokes parameters. We then conducted a survey to identify the features with the greatest impact and highest importance. Since the vibration detection system

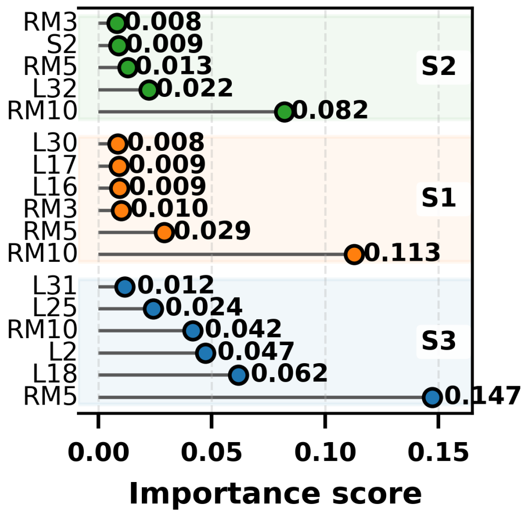

Fig. 3. Feature-importance ranking for the XGBoost classifier

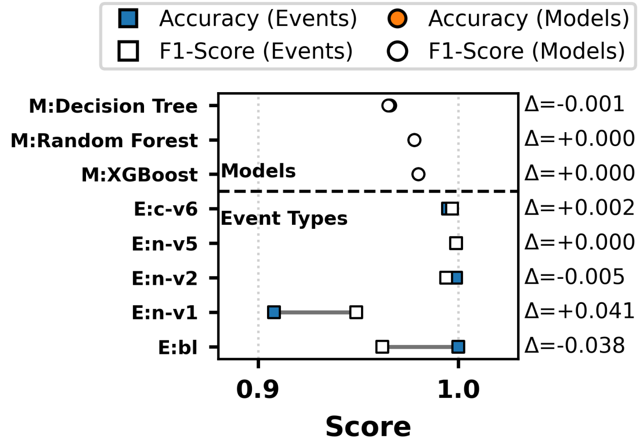

Fig. 4. Comparison of accuracy and F1-score for different classifiers and vibration event classes, with Δ indicating the diff. between precision and recall for each case.

operates in real time, prioritizing these key features allows us to conserve both time and computational resources. This focused approach ensures that only the most significant features are used for model training, testing, and ongoing monitoring. This feature importance analysis is discussed below. Fig. 3 presents the feature importance distribution obtained from the XGBoost [16] classifier. Each shaded region represents one of the three Stokes parameters, S_1 (orange), S_2 (green), and S_3 (blue). Within each region, the marker shows the relative importance of the engineered features in detecting vibration patterns. RM captures local short-term statistical trends of the vibration patterns over the last x [3, 5, 10] data points, whereas Lag (L) feature captures the delayed temporal dependencies (over 30 points) of the vibrations pattern in Stokes parameters. The analysis indicates that short-term RM features, particularly RM5 for S_3 with an importance score of 0.147, are the most impactful. This means that mechanical perturbations predominantly affect the component of circular polarization more. Overall, the second and third highest feature are RM10 for S_1 and S_2. It shows that short-term statistical trends have a greater impact than the other engineered features or the Stokes parameters themselves, as the RM is effectively smoothing out the noise while preserving the vibration signatures by smoothing over a short-term window (up to 10 data points). This suggests that local smoothing of the signal is highly effective for isolating vibration signatures from noise. For real-time edge deployment, this analysis explicitly emphasized the reduction of features, by prioritizing the calculation of high-importance feaures (like RM3, RM5, RM10), which reduces the computational overhead and optimizes the feature extraction pipeline.

IV. Performance Analysis of ML

Subsequently, we evaluated three supervised classification models: XGBoost, Decision Tree (DT) [17] and Random Forest (RF) [18] to classify various fingerprints, with the primary goal of accurately distinguishing them from activity within the network's geographical footprint. Throughout the training process, we employed a validation-based early stopping mechanism to ensure that the models maintained their predictive power without succumbing to overfitting. Fig. 4 compares the accuracy and F1-score of the models and event types, indicating whether each classifier is balanced or biased. The models achieved accuracies of 98.02% (XGBoost), 97.8% (RF), and 96.6% (DT), with XGBoost demonstrating the highest overall classification performance. The Δ values, on the right side of the figure, represent the difference between accuracy and F1-score. When $\Delta \approx 0$, the model predicts all classes proportionally well, as seen for RF, XGBoost, and events like *n-v5* or *c-v6*. Negative Δ values (e.g., *n-v1*, *bl*)

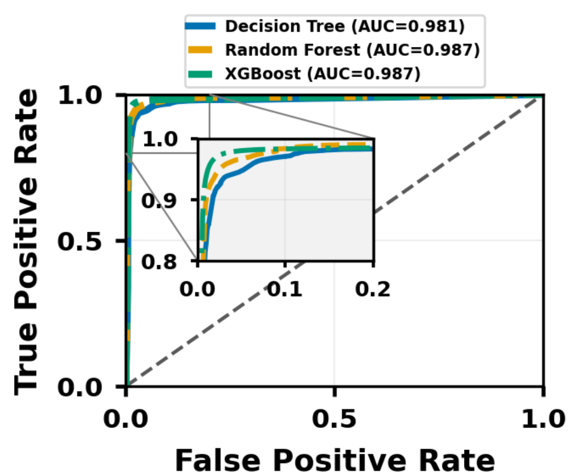

Fig. 5. ROC curves for event classification models, demonstrating reliable identification of vibration events while preserving low false-alarm rates in operational metro networks.

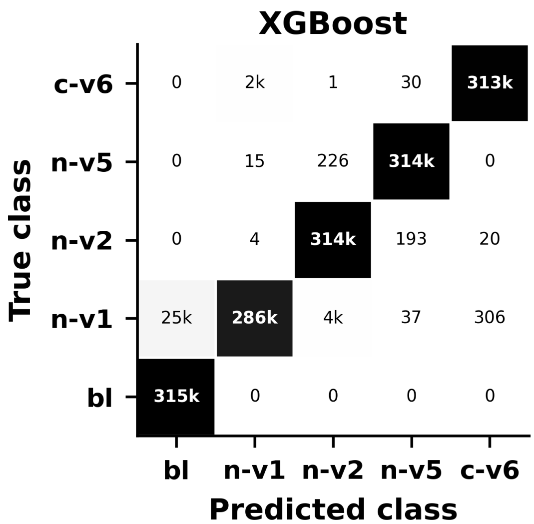

Fig. 6. Confusion matrix for the XGBoost classifier applied to five vibration classes, showing strong discrimination of baseline and critical vibration events in a live metro network.

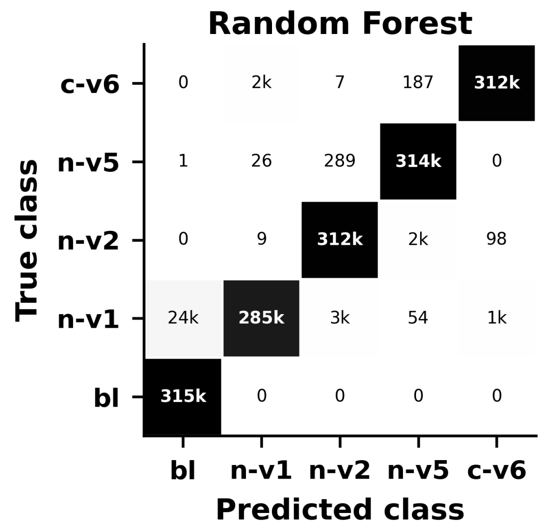

Fig. 7. Confusion matrix for the Random Forest classifier.

indicate that accuracy is higher than F1, which means the model struggles with minority classes, suggesting some class imbalance. A positive Δ (e.g., *n-v2*) indicates that the model prioritizes recall and effectively manages class imbalance, as evidenced by a slightly higher F1 than accuracy.

The Receiver Operating Characteristic (ROC) curve employed for the ML models are shown in Fig. 5. True positive rate (TPR) is compared against false positive rate (FPR) to assess each model's performance, and the trade-offs between sensitivity (recall) and specificity at various thresholds. TPR measures the proportion of correctly identified positive instances, while FPR measures the proportion of negative instances incorrectly classified as positive. The model's ability to distinguish between classes by quantifying the area under receiver operating characteristic (ROC) curve is indicated by the area under the curve (AUC) values; XGBoost and RF both achieved an AUC of 0.987, while DT had a little lower AUC of 0.981. As all the models demonstrate high TPR values at very low FPR levels, which implies that they can correctly identify the majority of positive cases while generating few false alarms. This behavior is evident in the inset that emphasizes the region with the lowest FPR, demonstrating that all models in that range perform similarly. This analysis implies that the ensemble-based models maintain greater sensitivity for a given FPR, especially as the decision threshold is relaxed.

The confusion matrices for each tested model applied to the noisy metro network dataset are shown in Figs. 6, 7, and 8. These matrices illustrate how well each classifier predicted the five distinct event categories (Tab.I). Fig. 6 illustrates the confusion matrix for the XGBoost model, where the true classes are shown on the y-axis and the predicted classes on the x-axis. Overall, XGBoost demonstrates excellent performance, with the *bl* (baseline) class being classified most accurately, followed by the *n-v5* and *c-v6* classes. However, some misclassifications occur among the low-vibration classes, resulting in a small number of false alarms as well as occasional critical events being misclassified as normal events.

The confusion matrix for the Random Forest model is presented in Fig. 7. Similar to XGBoost, Random Forest classifies the *bl* class with perfect accuracy, but exhibits some challenges in correctly identifying the *n-v1* and *n-v5* classes. Despite this, the model effectively distinguishes between neighboring vibration frequencies, which tend to generate overlapping SOP variations. By constructing multiple decision trees from random bootstrap samples and randomly selected feature subsets and aggregating their predictions, RF reduces model variance and helps mitigate overfitting in this vibration classification task.

The confusion matrix for DT is shown in Fig. 8. As we can observe, it classifies the *bl* class perfectly since the fiber is idle at that time with only environmental variations in the network. However, The DT performs weakly in higher vibration classes like *n-v5* and *c-v6*, due to overlapping feature distributions lead to both false alarms and missed detections. In DT, Each decision rule only uses one attribute at a time and can employ only a subset of the initial attributes, reducing the impact of irrelevant features [19].

In conclusion, XGBoost performs significantly better than DT and RF in terms of accuracy, AUC, and class balance, demonstrating proficiency in categorizing the vibrations, with suitable inference latency of < 10 ms on a standard mid-range CPU, confirming its suitability for real-time edge deployment. It has superior performance – 98.02% accuracy – and balanced training time, due to its powerful regularization features, computing efficiency, low inference and adaptability. Nevertheless, challenges remain in accurately distinguishing the critical events *(c-v6)*, which represents high-intensity disturbances such as drilling, due to partial overlap with moderate vibration

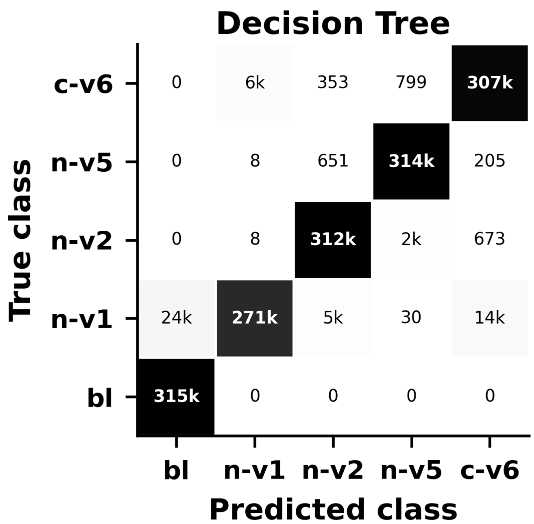

Fig. 8. Confusion matrix for the Decision Tree classifier.

signatures (e.g., *n-v5*), occasionally leading to misclassification. DT offers a faster training time, making it a viable option when training speed is prioritized over accuracy. The identified trade-off allows flexibility depending on the specific requirements of the deployment environment.

V. Conclusion and Future Work

In this work, an ML framework for real-time detection of vibration-induced anomalies in optical transport networks was presented, leveraging SOP variations as an early-warning physical-layer metric. The proposed approach was experimentally validated on a 28.5 km deployed metropolitan fiber link operating under live traffic and realistic environmental noise, demonstrating the feasibility of SOP-based sensing in production networks. The results show that vibration events generate distinct polarimetric signatures that can be reliably classified using supervised learning models when combined with appropriate feature engineering. Among the evaluated classifiers, XGBoost achieved the best performance, reaching 98.02% accuracy and an AUC of 0.987, while maintaining balanced precision and recall. Overall, the study confirms that SOP-based machine-learning analytics provide an effective and deployable solution for early detection of harmful vibrations, enabling proactive fault prevention and enhanced resilience in metropolitan optical transport networks. Moving forward, we plan to augment our data repository with high-magnitude perturbations to test our model's scalability and assure the consistency of its detection capabilities across diverse operational environments.

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