Explainable Machine Learning for Alarm Prediction

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Keywords: Alarms, Machine Learning, Clustering, Classification, Explainable Model.

Abstract: This paper evaluates machine learning models for the prediction of alarms using geographical clustering, exploring data from an Italian company. The models encompass a spectrum of algorithms, including Naive Bayes (NB), XGBoost (XGB), and Multilayer Perceptron (MLP), coupled with encoding techniques, and clustering methodologies, namely COOP (Coopservice) and KPP (K-Means++). The XGB models emerge as the most effective, yielding the highest AP (Average Precision) values across models based on MLP and NB. Hyperparameter tuning for XGB models reveals default values perform well. Our model explainability analyses reveal the significant impact of geographical location (cluster) and the time interval when the predictions are made. Challenges arise in handling dataset imbalances, impacting minority alarm class predictions. the insights gained from this study lay the groundwork for future investigations in the field of geographical alarm prediction. The identified challenges, such as imbalanced datasets, offer opportunities for refining methodologies. As we move forward, a deeper exploration of one-class algorithms holds promise for addressing these challenges and enhancing the robustness of predictive models in similar contexts.

1 INTRODUCTION

Alarm systems are crucial for safeguarding individuals, properties, and assets, acting as deterrents to potential criminals and enabling prompt responses from security teams or police upon activation (Rutgers University, 2009). Predicting alarms aids patrol management, reducing intervention time by assigning guards to high-risk areas. Machine learning models have been applied in various scenarios, enhancing accuracy and efficiency in alarm prediction (Au-Yeung et al., 2019; Meng and Kwok, 2012; Quinn, 2020; Zhuang et al., 2020). These efforts optimize resource allocation and improve security measures in network systems (Lateano et al., 2023; Zhang and Wang, 2019) and industries (Zhu et al., 2016).

While previous studies focus on alarm prediction, they often overlook geographic locations and lack model explainability. This work addresses these gaps by emphasizing the geographic aspect of alarms and prioritizing model explainability. The study uses real data from Coopservice, an Italian service provider offering logistics, transportation, cleaning, maintenance, and security services, particularly car patrolling in various provinces. Coopservice utilizes a cluster system to optimize its routes and enhance patrol efficiency (Zucchi et al., 2022). When alarms occur, patrols are dispatched, impacting defined routes. To minimize this impact, alarm prediction within each cluster is crucial for considering the probability of alarm incidents when generating routes. Leveraging robust machine learning algorithms, this work explores the use of such tools for alarm prediction.

Thus, the main objective of this paper is to conduct an analysis using real data to achieve effective alarm prediction. The study aims to explore Machine Learning algorithms that can accurately predict alarms within a one-hour time interval to assist companies in their efforts to manage and respond to alarms effectively. Furthermore, the research compares models based on patrols, where each patrol corresponds to a cluster, defined in two ways: (i) the current clusters defined by the company and (ii) those determined through the k-means clustering algorithm. To facilitate the end user's interaction with the proposed approach, we explore aspects of explainability. This allows for a clearer understanding of the model's decision-making process and enhances the system's

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Abreu, K., Reis, J., Santos, A. and Zucchi, G.
Explainable Machine Learning for Alarm Prediction.
DOI: 10.5220/0012625000003690

In *Proceedings of the 26th International Conference on Enterprise Information Systems (ICEIS 2024) - Volume 1*, pages 690-697
ISBN: 978-989-758-692-7; ISSN: 2184-4992

usability. We expect that the strategies presented in this work will provide valuable assistance to companies in optimizing their patrol services.

In addressing the aforementioned objectives, it is essential to highlight that the existing literature lacks comprehensive coverage of scenarios wherein determining not only the occurrence of alarms but also their geographical location is crucial. This gap becomes particularly significant in our context, where understanding the impact of alarms on predefined car patrolling routes is paramount. Notably, the literature also falls short in exploring the explainability of models within this specific domain. In contrast to prior efforts, this study seeks to identify machine learning algorithms capable of predicting alarms within clusters, considering their geographic aspects.

The rest of the paper is organized as follows. In Section 2, we present relevant related work. Section 3 provides a formal problem definition and introduces the dataset used in the study. In Section 4, we present the proposed models, tuning of hyperparameters, and analysis of the best-performing models. Last, Section 5 presents our conclusions.

2 RELATED WORK

Several stakeholders are interested in alarm-related works (Au-Yeung et al., 2019; Lateano et al., 2023; Zhang and Wang, 2019) to minimize the time between the alarm and remedial action or implement preventive measures. We can group the machine learning research lines applied to alarms into two sets: (i) filtering and (ii) prediction. Within the (i) filtering research works, we observe studies developed to identify false alarms. The work of (Meng and Kwok, 2012), for instance, highlight the issue of the high number of false alarms generated in intrusion detection systems (IDSs) and finds relevant results by applying machine learning models. On the other hand, Au-Yeung et al. (2019) deal with alert alarms in intensive care units (ICUs) responsible for reporting changes in patient's psychological signals. In many situations, interventions are unnecessary, and the alarms become a burden. Additionally, excessive alarms in these environments can cause noise disturbances.

The efforts that follow the (ii) prediction line mainly serve the industry and network systems. In the industrial scenario, we have (Zhu et al., 2016) who apply a probabilistic model to calculate the probability of critical alarm occurrence. Quinn (2020) found excellent results by applying artificial neural networks to predict pressure alarms in natural gas pipelines. On the other hand, Pezze et al. (2022) develop a Deep Learning-based approach for predicting alarms in industrial equipment, representing a low-cost alternative to sensor-based preventive maintenance strategies. In the context of networks, Zhang and Wang (2019) propose an alarm analysis scheme for predicting faults in optical transport networks using support vector machines (SVM) and long short-term memory (LSTM). Zhuang et al. (2020) address the same problem, who use a self-optimizing data augmentation method based on generative adversarial networks (GANs); the results in commercial tests achieve high accuracy. Finally, Lateano et al. (2023) address the prediction of failures in networks through the analysis of real alarm data from microwave network equipment.

However, the works in both groups (i) and (ii) do not address scenarios where it is important to determine not only the occurrence of the alarm but also its geographic location. Unlike previous studies, these scenarios are extremely relevant to our problem, given that it is crucial in determining the impact of alarms on the routes practiced in car patrolling. For example, a car moves according to the defined route to patrol the area, but an alarm is triggered during the displacement. Since alarms represent a possibility of security vulnerability, the patrol must respond to the call, deviating from the planned route. The impact of these trajectory alterations over the year can mean a considerable increase in the operation cost. Moreover, to the best of our knowledge, there is a lack of research exploring the explainability of models within this context. Thus, different from previous efforts, this work seeks to determine machine learning algorithms that can assist in predicting these alarms within clusters while investigating their explainability, which would be a significant contribution to the field of alarm prediction.

3 PROBLEM DEFINITION AND DATASET

This section introduces the alarm detection problem using Coopservice's patrol data. In Section 3.1, we formally define the problem as developing a model for detecting alarms and assigning likelihood scores within specific clusters and time intervals. Section 3.2 presents the dataset, focusing on the studied province and key alarm-related information. The distribution of alarms is analyzed based on variations in month and hour. Section 3.3 outlines the process of clustering alarms, using the K-Means++ algorithm (Arthur and Vassilvitskii, 2007) for theoretical comparison. Last, we discuss creating negative instances, generating features based on date and time, and describe the encoding method for each feature, providing a comprehensive overview for subsequent analysis and model development.

3.1 Definition

Formally, we can define the problem of alarm detection considering geographical location as follows:

Definition 3.1. **(Alarms Detection)** Given a cluster $c \in C$, and a time interval $t \in T$, a model for alarm detection assigns a score $S(c,t) \in [0,1]$ indicating the extent to which the pair c,t is believed to have an alarm. A threshold τ can be defined such that the prediction function $F : C,T \rightarrow \{\text{alarm, not alarm}\}$ is:

$$F(c,t) = \begin{cases} \text{alarm}, & \text{if } S(c,t) > \tau \\ \text{not alarm}, & \text{otherwise.} \end{cases}$$

Our cluster definition assigns a specific geographic region for a car patrol to operate.

3.2 Overview of Dataset

The car patrol dataset from Coopservice in Italy provides rich information, featuring data from 150 patrols across 30+ cities. With over 150,000 alarms recorded between January 1, 2020, and November 6, 2022, the dataset includes essential fields like date, geographic location (i.e., latitude and longitude), activity type, and the associated car patrol. This dataset offers a detailed and comprehensive perspective on Coopservice's car patrol activities.

This study concentrates on analyzing alarms in Reggio Emilia, selected due to its notable alarm activity, as illustrated in Figure 1, and its strategic significance to the company. In Figure 2, we observe the distribution of normalized alarm numbers per month and hour. Figure 2a portrays a consistent pattern in alarm distribution over the years, except for August 2022.

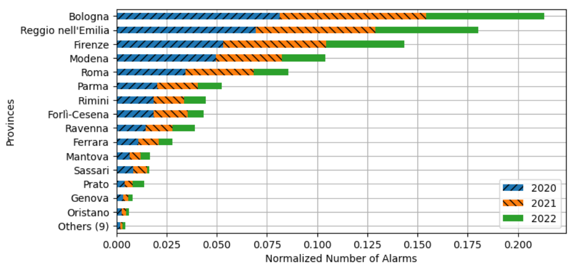
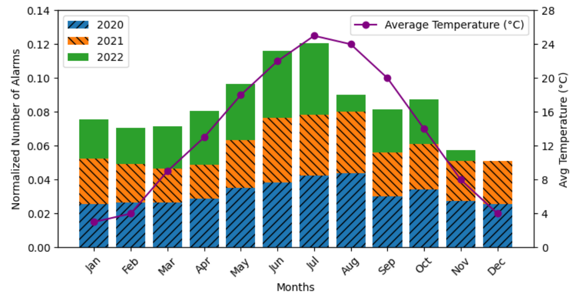
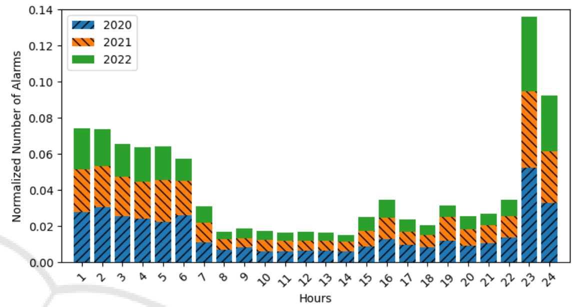


Figure 1: Number of alarms by province. The graphs show the number of alarms per hour and per month, with the y-axis values normalized using the min-max normalization technique. This process ensures that the values are scaled between 0 and 1.



(a) Number of alarms and max temperature by months in Reggio Emilia.



(b) Number of alarms by hours.

Figure 2: The graphs show the number of alarms per month and hour, with the y-axis values normalized using the min-max normalization technique. This process ensures that the values are scaled between 0 and 1.

Data for November 2022 is incomplete, and December 2022 has no available data. The occurrences of alarms tend to increase from April to October, aligning with rising temperatures and a decline in outdoor activities during colder months. Warmer seasons, including Italian summer holidays, witness heightened mobility, especially towards coastal areas. The circulation of people appears to be correlated with the incidence of alarms.

Figure 2b shows higher alarm occurrences during the night, peaking at 23 hours. Data collection during the COVID-19 pandemic impacted alarm distribution, with protective measures influencing the numbers.

3.3 Dataset Preprocessing

To prepare our dataset for predictions, we conduct essential data cleaning steps, addressing missing values and duplicates. Further details on additional steps are provided in the following sections: Dataset Clustering (Section 3.3.1), Non-alarm Instances (Section 3.3.2), Feature Definition and Encoding (Section 3.3.3) and Data Processing Pipeline (Section 3.3.4).

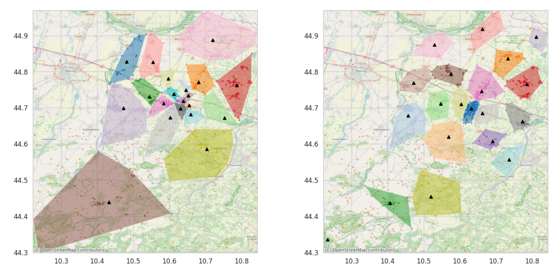
3.3.1 Dataset Clustering

According to Definition 3.1, the problem involves classifying events into alarms or non-alarms within a time interval in a cluster. Understanding information about alarm clusters is crucial for optimizing patrol routes. Currently, Coopservice's alarm response process considers the patrol closest to the event, irrespective of the predefined cluster for that patrol.

In our dataset, we have cluster information for patrols during non-alarm activities. Using the convex hull algorithm, we define the convex region representing each cluster. The convex hull is the smallest convex polygon encompassing all given points, visualized as the outer boundary.

Coopservice operates with 20 patrols in Reggio Emilia province, each represented by a distinct convex region, as shown in Figure 3a. These regions serve as clusters for alarm response. Cluster sizes and the number of locations vary significantly, based on Coopservice's established practices. Some patrols may be overloaded, covering numerous locations or long distances, while others may be less occupied. For comparison, we employ the K-Means++ algorithm, selecting $k = 20$ to match Coopservice's clusters. Distances between alarms and centroids were computed based on latitude and longitude. The results are depicted in Figure 3b.

The convex regions from both methods significantly differ in area, location count, and alarm distribution, as seen in Figure 4. K-Means++ yields smaller patrol coverage areas, potentially reducing travel time. However, it exhibits extremes in location and alarm distribution, with some clusters having high activity and others being more idle compared to Coopservice's established distribution.



(a) Convex regions obtained through Coopservice patrols.

(b) Convex regions obtained through K-Means++.

Figure 3: Convex regions of clusters formed through geographical locations. The centroid of the points in each convex region is represented by a black triangle.

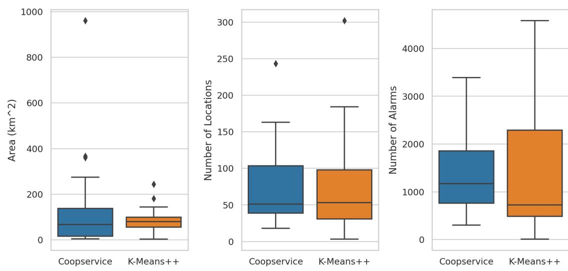


Figure 4: Boxplot comparing covered area, number of locations, and alarm distribution of convex regions generated by Coopservice and K-Means++ methods.

3.3.2 Non-Alarm Instances

In the preceding section, we outlined how we defined clusters, resulting in two datasets: one based on Coopservice's practices (COOP) and another using K-Means++ with k equal to 20 (KPP). Both datasets have two columns: datetime (alarm occurrence timestamp in yyyy-MM-dd hh-mm-ss format) and cluster_code. Our prediction function, per Definition 3.1, classifies outcomes as alarm or not alarm based on a defined threshold. However, our dataset only contains alarm occurrences, lacking negative instances. To address this, we introduce negative occurrences through the three-step process detailed below.

Figure 5 illustrates the steps for generating our binary dataset (BD) with positive and negative occurrences. Focusing on the one-hour interval, our first step involves rounding datetime by hour, creating the rounded dataset (RD). The second step generates hourly datetime entries for each cluster on the first and last day through RD, forming the combinations dataset (CD). For instance, a 10-day interval with five clusters results in 1200 instances (10 days x 24 hours x 5 clusters). Finally, we join RD and CD, retaining all CD entries. We label entries in both datasets as alarm and those only in CD as no alarm, as RD only contains alarm occurrences. The resulting binary dataset (BD) has two classes: alarm and no alarm, with 475,152 non-alarm instances, following the same steps for COOP and KPP.

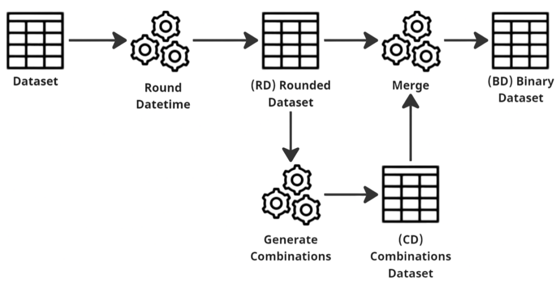


Figure 5: Steps to generate the binary dataset BD that includes both classes: alarm and no alarm.

Table 1: Properties of the features for the datasets.

Feature	Type	Encoding
year	Discrete	Label/Ordinal
month	Discrete	Label/Ordinal
day	Discrete	Label/Ordinal
hour	Discrete	Label/Ordinal
shift	Ordinal	Label/Ordinal
day_of_week	Ordinal	Label/Ordinal
cluster_code	Nominal	One-Hot Label/Ordinal

3.3.3 Feature Definition and Encoding

The final data processing step involves feature definition and encoding. Our datasets contain two columns: datetime and cluster_code. Using the datetime column, we generate temporal features: year, month, day, hour, shift, and day_of_week. These features help us understand the relevance of individual time characteristics for our model or their combined evaluation. Table 1 displays the model features, data types, and encoding methods.

3.3.4 Data Processing Pipeline

We generate four datasets using two clustering models (COOP and KPP) and two encoding methods for cluster_code: Label/Ordinal Encoding (LOE) and Label/Ordinal/One-hot Encoding (L2OE). Figure 6 illustrates the sequential steps in our data processing pipeline. Initially, we extract patrol data from the Coopservice database and use the ArcGIS API[1] to obtain address information, transforming latitude and longitude into city, province, and other details. This forms the Base Dataset. Applying Coopservice's clustering methods, K-Means++, and a non-alarm creation function, we create the COOP and KPP datasets. Through encoding techniques, we produce the final datasets for model training.

The datasets comprise 499,680 instances, covering alarm occurrences and non-occurrences. LOE datasets have 7 features, while L2OE datasets boast 26 features due to One-Hot Encoding transforming the cluster_code feature into 20 features, each corresponding to a distinct cluster. The datasets exhibit an imbalance, with only 5% of instances representing alarm occurrences, yielding a ratio of 1 occurrence for every 19 non-occurrences. Notably, the alarm occurrences in this dataset do not represent the total number attended by Coopservice. As a cluster comprises multiple locations, an alarm in any location within a specific cluster defines an instance with an alarm in our problem. Thus, a cluster can have multiple alarms in a time interval without affecting our model, considering an alarm occurrence if the count is greater than 0; otherwise, it is a non-occurrence.

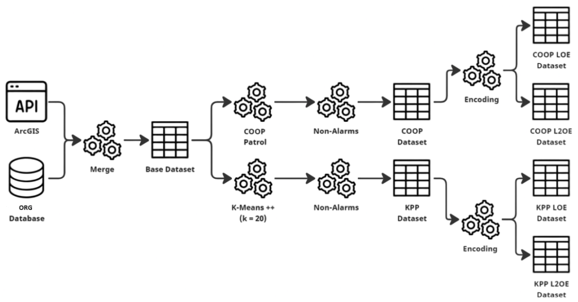


Figure 6: Illustration of the data processing pipeline.

[1] https://developers.arcgis.com/python/

4 MODELING AND ANALYSIS

This section explores model selection, evaluation, and refinement for three machine learning models: Naive Bayes (NB), eXtreme Gradient Boosting (XGB), and Multilayer Perceptron Classifier (MLP). The focus is on the efficiency of these models in predicting alarm occurrences using two clustering methods: ORG-2022 (COOP) and K-Means++ (KPP). Thorough assessments, primarily using the AP metric.

The exploration includes hyperparameter optimization, particularly for the XGB algorithm, aimed at improving model performance. Advanced interpretative techniques like the SHAP framework are also employed to understand feature importance and the influence of various factors on alarm classification. Subsequent sections detail model selection in Section 4.1, hyperparameter optimization in Section 4.2, and the analysis of the best models in Section 4.3.

4.1 Model Selection

The dataset covers 1041 days from January 1, 2020, to November 6, 2022. Models are trained on 720 days, representing 69.09% of the total, with a temporal split ensuring that test data occurs entirely after the training set, minimizing bias. The remaining portion is dedicated solely to model evaluation.

Three machine learning approaches are selected for the study: Naive Bayes (NB) (Hand and Yu, 2001), eXtreme Gradient Boosting (XGB) (Chen and Guestrin, 2016), and Multilayer Perceptron Classifier (MLP) (Murtagh, 1991). These models represent different machine learning families: NB is probabilistic, XGB is an ensemble, and MLP belongs to artificial neural networks. Training is conducted on Google Colab using Python 3, importing NB and MLP from Scikit-Learn and XGB from the xgboost library.

Default configurations are used from the libraries, along with identical training and test sets for a fair comparison. Evaluation utilizes the area under the PR curve (AP) metric, suitable for imbalanced datasets. Our tests showed that the best model was generated through XGB, in all scenarios (LOE, L2OE, KPP, and COOP). Therefore, we decided to proceed with hyperparameter optimization for XGB in order to achieve better performance.

4.2 Hyperparameter Optimization

Our hyperparameter tuning process involves optimizing the settings of the XGB algorithm to enhance its performance in predicting alarm occurrences. To achieve this, we utilize a 10-fold cross-validation approach, splitting the training data into folds with distinct distributions for training, validation, and testing. Each fold represents a 72-day interval, with a training period of 36 days, followed by 18 days for validation and another 18 days for testing.

The primary goal of this approach is to ensure that the selected hyperparameters are not overly dependent on specific characteristics of the training data. By using small samples in each fold, we aim to create a model that generalizes well to new information and avoids overfitting issues. This separation into training, validation, and testing sets aids in the robust evaluation of the model's performance.

In our hyperparameter tuning process, we allocate the remaining 321 days for the final evaluation of model AP scores. Due to the time series nature of the problem, we adopt isolated block-wise splits, training models on one portion of the dataset, and evaluating them on subsequent chronological sections. This practice mimics real-world scenarios where only historical data is available for prediction.

Among the considered hyperparameters, we focus on key parameters widely applicable in XGB and other tree-based models (Developers, 2023): max_depth, learning_rate, n_estimators, early_stopping_rounds.

Throughout the 10-fold cross-validation, the configuration with the best average AP across folds is considered the optimal set of hyperparameters. Selection is based on information from the XGB documentation (Developers, 2023) and the *Analytics Vidhya blog's guide on XGB parameter tuning* (Jain, 2016), recommended by *Awesome XGB*[2] (DMLC, 2023).

Table 2 shows a summary of the AP obtained from the models with default hyperparameters and the tuned ones. The table indicates that the models

[2]Awesome XGB is mentioned in the documentation as a source of resources on XGB, available at https://xgboost.readthedocs.io/en/stable/tutorials/index.html.

Table 2: AP comparison for XGB models trained with distinct clustering and encoding methods.

	AP		
Models	**Default**	**Tuned**	**Improvement**
xgb_coop_loe	0.149	0.154	0.5%
xgb_coop_l2oe	0.148	0.155	0.7%
xgb_kpp_loe	0.190	0.197	0.7%
xgb_kpp_l2oe	0.190	0.197	0.7%

did not show significant performance improvements, with only a 0.7% increase in AP for the KPP models in the best case scenario. However, it is important to note that the choice of clustering method has a more substantial impact on the models, resulting in an approximately 4% increase in AP for the KPP models compared to the COOP models.

For XGB models, exclusive use of Label/Ordinal Encoding (LOE) is favored over One-Hot Encoding due to comparable performance and simplicity. LOE's fewer features enhance model evaluation and enable seamless applicability to datasets with consistent feature numbers, fostering adaptability across provinces with varying patrol counts. This choice aligns with a straightforward and efficient approach to data analysis, opening possibilities for transfer learning applications in diverse scenarios.

4.3 Analysis of Optimal Models

When dealing with complex machine learning models, it is important to be able to interpret their predictions. However, achieving both accuracy and interpretability can be challenging. A framework called SHapley Additive exPlanations (SHAP) was developed by Lundberg and Lee (2017) to address this problem. SHAP assigns importance values to features for specific predictions, offering a unified and theoretically supported approach. Widely used for enhancing model interpretability, SHAP is chosen in this work, following precedents in studies like (Li, 2022), (Ekanayake et al., 2022), and (Mangalathu et al., 2020).

For the xgb_coop_loe model, Figure 7 illustrates SHAP information. The feature ranking highlights the crucial impact of hour, cluster_code, and day_of_week, with significantly higher absolute SHAP values compared to other features. The distribution of feature values against SHAP values, reveals how different features impact the classification of alarm occurrences or non-occurrences. The distribution, aligned with SHAP values, highlights that extreme hours (both low and high) and weekends positively influence alarm occurrences, often associated with minimal pedestrian traffic, particularly during sleeping hours.

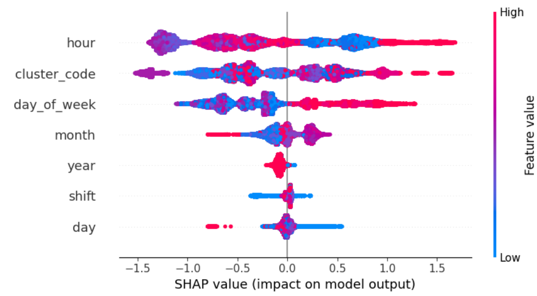


Figure 7: Feature importance and distribution analysis using SHAP scores for the COOP model.

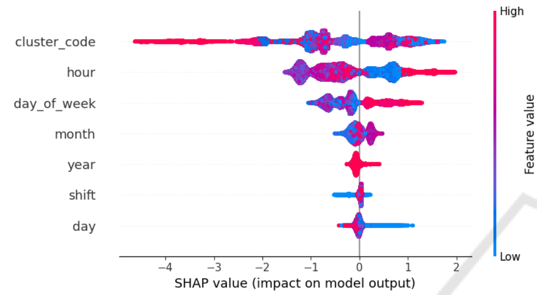


Figure 8: Feature importance and distribution analysis using SHAP scores for the KPP model.

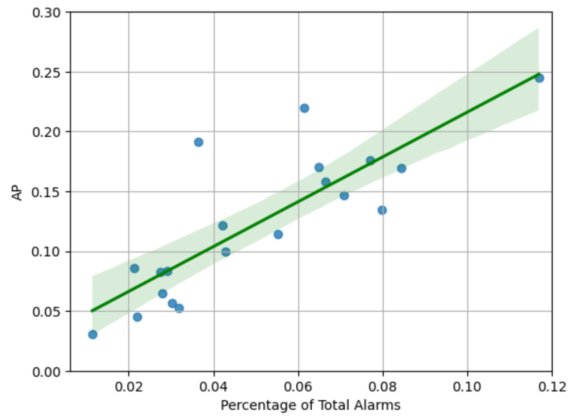
In Figure 8, a parallel analysis is conducted for the xgb_kpp_loe model, mirroring the approach taken with the previous model. The findings reveal a model emphasis on times with low pedestrian traffic and weekends for KPP. A noteworthy difference surfaces as cluster_code emerges as the most crucial feature, underscoring its significance in enhancing the model's performance. Interestingly, the contribution of each feature to the models shows closely aligned values, with cluster_code standing out with notably higher importance.

Analyzing the correlation between the model's AP for each cluster and the percentage of alarms within clusters in Figure 9 reveals intriguing relationships. For COOP in Figure 9a, and KPP in Figure 9b there's a positive correlation of 0.830 and 0.900, respectivaqmente. Clusters with more alarms are more readily assessed by the XGB model.

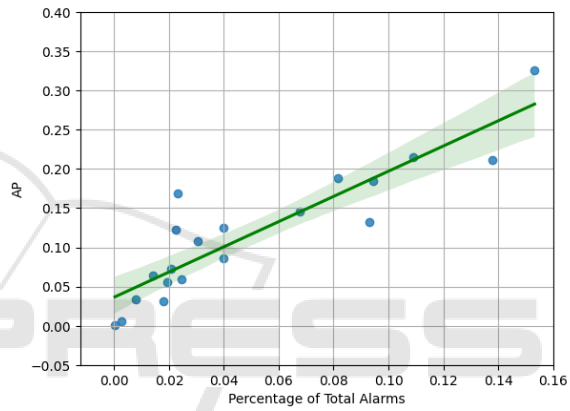
These observations underscore the varied implications of alarm distribution within clusters on model efficacy. Employing k-means for distribution yielded clusters with higher alarm density compared to the strategy employed by Coopservice. Consequently, clusters exhibiting higher alarm density demonstrate superior performance in alarm prediction. This finding sheds light on the crucial role of data distribution strategies in optimizing predictive model outcomes.

As clusters play a crucial role in alarm predictions, enhancing collaboration between the route optimizer and the alarm predictor is relevant. Assigning an AP score to each cluster and time of day is a promising approach. The optimizer can then prioritize alarm predictions for clusters and time slots with higher scores, reducing significance for those with lower accuracy.

This strategy optimizes resource allocation, enhancing the efficiency of the alarm response system. Patrol teams are dispatched more reliably, reducing unnecessary deployments to regions with lower prediction accuracy. Incorporating AP scores into decision-making fine-tunes the system to each cluster's characteristics and variations in alarm occurrence patterns throughout the day.



(a) AP and alarm percentage for COOP clusters.



(b) AP and alarm percentage for KPP clusters.

Figure 9: Comparative analysis of AP-alarm percentage correlations for COOP and KPP clusters.

5 CONCLUSIONS

Our paper evaluated machine learning models across three algorithms, two encoding methods, and two clustering techniques for alarm prediction using data from an Italian company. XGB, particularly with K-Means++ clustering, showed the highest performance. Despite hyperparameter tuning, improvements were marginal. SHAP analysis emphasized key features like cluster identification and alarm time. However, further study is needed as our best scenarios fell below 0.5 AP. As future work, we intend to explore techniques for dealing with highly unbalanced datasets or one-class classification algorithms.

ACKNOWLEDGEMENTS

K. Abreu, J. Reis, and A. Santos are grateful to CAPES and FAPEMIG for funding different parts of this work.

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