Location Analytics for Proactive Complaint Management

Azri Syahmi Azhar1, a), Choo-Yee Ting1, 2, b), Hui-Ngo Goh1, 2, c), Albert Quek1, 2, d)

1Faculty of Computing and Informatics, Multimedia University, 63100 Cyberjaya, Selangor, Malaysia.

2Centre for Big Data and Blockchain Technology, CoE for Advanced Cloud, Multimedia University, Multimedia University, 63100 Cyberjaya, Selangor, Malaysia.

b) Corresponding author: cyting@mmu.edu.my

a) 1211103115@student.mmu.edu.my  
c) hngoh@mmu.edu.my

d) quek.albert@mmu.edu.my

**Abstract.** Complaint management is crucial for the prioritizing public services and infrastructure. Existing methods typically require manual categorization of complaints and fall short in dealing with large numbers of complaints or utilizing data for predicting insights. In this study, an advanced framework is proposed that combines location analytics and machine learning to prioritize local council complaint management. The framework consists of two core features. The first component; a complaint classifier was developed using three embeddings — Term Frequency-Inverse Document Frequency (TF-IDF), CountVectorizer, and transformer-based Large Language Model (LLM) embeddings — tested across eight machine learning models: Logistic Regression and Support Vector Machine and Random Forest and Decision Tree and Extra Trees Classifier and Gaussian Naive Bayes and K-Nearest Neighbors and AdaBoost. The TF-IDF with SVM combination produced the highest F1-score of 83.7%. The second component involves a complaint forecasting system by converting the dataset data into weekly time series information to apply six regression models including CatBoost, Extra Trees Regressor, LightGBM, HistGradientBoosting, Random Forest and XGBoost for future complaint prediction. The CatBoost Regressor exhibited superior performance by achieving RMSE = 5.137, MAE = 3.056 and R² = 0.7173. In this study, this system is developed and evaluated using a dataset provided by a telecommunication company in. It is expected that the outcome of this study can assist organisation to proactively manage complaint and show the potential to transform complaint management to prioritize service delivery, operational efficiency and citizen satisfaction.

# Introduction

A complaint is a negative expression of dissatisfied customer or consumer, about the product, services and organization’s action [1]. Effective complaint management improves service delivery, resolves underlying issues proactively, and builds long-term trust among stakeholders [2]. However, traditional complaint handling systems mostly use a manual paradigm and reaction-based approaches to address difficulties when they occur, which creates several problems in handling numerous complaints effectively [3]. With data analytics and machine learning, organisations can analyze past data, current trends and future complaints. Such approaches include effective and efficient utilization of resources and improvement of the quality of decision making and more effective complaint handling techniques [3][4]. Location analytics involves the analysis of spatial data to determine the complaint areas, alignment of resources and best delivery of services.

## Problem Statement

Currently, the increasing complexity and volume of complaints has posted a challenge to traditional complaint management systems that rely on manual processes. These systems include static workflow in which human factors play a significant role in the classification of complaints and as a result, are ineffective, frustrating, and wastage of time especially in classifying large data [3]. To classify complaints based on spatial, temporal and other factors, integration of location analytics and machine learning can predict service demand and operation more efficiently.

To date, systems that utilize data analytics for complaint management remains scarce in Malaysia [5]. Councils are limited in how they can effectively use spatial data in decision making because there is no system of a location-based complaint prediction system. Consequently, such a gap not only interferes with operational efficiency but also affects citizen satisfaction. Therefore, immediate development and evaluation of such systems to prioritize service delivery and instill confidence in the community is required.

This study develops a predictive complaint management framework using location analytics with machine learning to resolve the observed gaps. The system performs automated complaint classification while utilizing historical trends to anticipate future complaint increases. This research evaluates various embedding methods combined with machine learning models to detect their superior performance on classification and forecasting operations. The research provides an evaluated system prototype which helps local councils predict and handle complaint patterns to prioritize operational efficiency and resident satisfaction. The objectives of this research are:

* To design and develop a predictive framework for complaint management that integrates location analytics and machine learning to classify and forecast complaint patterns.
* To compare and identify machine learning models and embedding methods for both complaint classification and forecasting tasks.
* To implement and evaluate a system prototype that allows proactive monitoring and early warning of potential complaint surges across different locations and complaint categories, based on historical trends.

# RELATED WORK

Complaint management systems are increasingly vital for organizations seeking to prioritize service quality and operational efficiency. Machine learning combined with natural language processing technology now enables automated complaint classification together with forecasting thus enabling organizations to create data-driven proactive responses. The literature review unifies recent academic findings regarding the methods and models incorporated in the proposed two-part framework. A complaint classification system operates together with a complaint warning (forecasting) system. The review follows a thematic approach which starts with analyzing text-based complaint classification and proceeds to time series-based complaint forecasting.

Researchers have extensively studied complaint classification from textual descriptions in domains that handle large unstructured feedback. For the complaint classification system, traditional text representation methods such as Term Frequency–Inverse Document Frequency (TF-IDF) and CountVectorizer continue to demonstrate robustness, especially in low-resource language contexts like Malay. [6] demonstrated that a Support Vector Machine (SVM) model with TF-IDF features reached an F1-score of 89% for classifying e-commerce complaints in Indonesian while surpassing neural embedding methods when working with restricted labeled data. The practical nature of complaint classification scenarios benefits from classical vectorization methods when working with small, annotated datasets [6]. The field of complaint classification has experienced advancement through recent developments in language modeling which utilize domain-specific transformer models. The implementation of IndoBERT and Thai-BERT along with their fine-tuning for ASEAN languages improved complaint dataset classification accuracy by 12–15% compared to generic multilingual BERT [7]. The study demonstrates that contextual embeddings which understand language subtleties along with domain-specific semantics matter for Malaysia complaint data and justify using Malay-BERT or related models in the proposed system [7].

Studies on related domains supports the selection of multiple machine learning classifiers that includes Logistic Regression, SVM, Random Forest, Decision Trees, Extra Trees, Gaussian Naive Bayes, K-Nearest Neighbors, and AdaBoost. [4] conducted a study of various classifiers applied to telecom complaint datasets which demonstrated that SVM and Random Forest exceeded deep learning models particularly when the dataset contained moderate sample sizes. The study revealed that SVM reached 94% precision for high-priority complaints while AdaBoost demonstrated superior performance in managing class imbalance which is prevalent in complaint classification [4]. The systematic evaluation methodology enables teams to select the best suitable classifier that suits their deployment environment.

As for the complaint warning system, the prediction of complaint volumes helps organizations both schedule resources strategically and prioritize their services effectively. Time series forecasting research supports the implementation of both lagged variables with complaint counting history and rolling statistics' mean, standard deviation, maximum calculations. The implementation of XGBoost with [8] displayed comparable features including lagged and rolling information to predict healthcare complaints weekly which resulted in a 7-day-ahead RMSE of 2.8. [8] spotlighted the value of collecting short-term volatility and seasonal information within complaint data for implementation in the suggested framework.

Several tree-based ensemble models including Random Forest, Extra Trees, XGBoost, LightGBM, CatBoost, and HistGradientBoosting lead the field in terms of demand and complaint forecasting accuracy. [9] analyzed how CatBoost, LightGBM, and XGBoost handle retail sales forecasting over multiple periods and showed these models effectively identify market trends. They found LightGBM kept steady results while XGBoost led in short-term forecasts. The research proves that adding lagged data and category information makes prediction models more accurate at estimating complaint levels [9].

In summary, the methodological choices for both the complaint classification and warning systems in this framework are well supported by recent empirical research. Classical and contextual embeddings, combined with a diverse set of machine learning classifiers, provide a robust foundation for accurate complaint categorization. Meanwhile, ensemble tree-based models, advanced time series feature engineering, and dynamic thresholding ensure reliable and actionable complaint forecasting. These approaches are validated by contemporary studies in complaint management, healthcare, retail, and public utilities, confirming their relevance and effectiveness for modern complaint management systems.

# Method

The framework proposed for this project is two parts: a complaint classification system and a complaint warning system. The complaint type as well as the prediction of the complaint volume are addressed using the complaint dataset that is shared between both the components, but via two different analytical pipelines. The overall framework is illustrated in Figure 1.

A black and white rectangular object with red dots

AI-generated content may be incorrect.

**Figure 1.** Overall research framework

## Data Collection and Preprocessing

The Base Dataset is a set of 26,671 complaints from January to October 2024, sourced from a Malaysian telecommunication company. This is complemented by the Location-Based Dataset, which merges OpenStreetMap and TindakMalaysia data to standardize location names, geospatial coordinates and electoral district boundaries to enrich complaint records. These datasets are combined to serve as a base for preprocessing, feature engineering, and a location-aware complaint management system. Data cleaning involved dropping non-critical columns with high missing rate, carefully imputing critical fields (e.g. inferring missing Dun from fuzzy string matching on Lokasi Aduan), and standardizing text features by lowercasing, removing special characters, and trimming spaces. Furthermore, time based features like day, month, year and quarter were engineered from complaint date, and a demographic attribute (Kaum) was inferred from rule-based name pattern and prompting using Llama 3.2 3B. This preprocessing ensured the dataset was complete, consistent, and enriched with additional analytical dimensions.

## Complaint Classification System

The complaint classifier is a task of automatically predicting the main complaint category (Kategori\_Utama) based only on the complaint description (Keterangan Aduan). The data was cleaned and split into 80/20 train-test split, target labels were encoded using a label encoder to prepare them for model training. To represent the text data effectively, three types of embedding were generated for comparison; Term Frequency–Inverse Document Frequency (TF-IDF, CountVectorizer and Malay-BERT, a fine-tuned large language model embedding for the Malaysian context (mesolitica/llama2-embedding-1b-8k), obtained from Hugging Face. For model construction and evaluation, eight machine learning models were developed for the complaint classification task on each embedding, including Logistic Regression (LR), Support Vector Machine (SVM), Random Forest, Decision Trees, Extra Trees Classifier, Gaussian Naive Bayes (GNB), K-Nearest Neighbors (KNN), and AdaBoost. For the prediction, Classification metrics like accuracy, precision, recall and F1 score were used to determine the predictive performance of the models. This comprehensive evaluation ensures that the most effective classifier is saved and selected for the complaint classification task in the final system, contributing to the project's overall goal of prioritizing complaint management.

## Complaint Warning System

The complaint warning system is developed as a time series forecasting framework to predict the number of complaints per week for each Kategori\_Utama and Dun pair. The cleaned dataset was transformed into a weekly time series format with aggregated complaint counts complemented with lag variables (complaint counts from previous 1–3 weeks), rolling window statistics (mean, standard deviation, maximum), and time-based indicators (month, week of year, quarter). The data was split chronologically and the first 80% of weeks were used for model training and the remaining 20% was used for testing. All categorical columns were label encoded, and six regression models were trained on these columns (Random Forest, Extra Trees, XGBoost, LightGBM, CatBoost, HistGradientBoosting). To evaluate predictive performance on unseen weeks, the models were evaluated using regression metrics; root mean square error (RMSE), mean absolute error (MAE), and R². The best-performing models were saved along with their encoders and feature definitions for downstream forecasting tasks. The historical mean and standard deviation of the complaint counts were calculated for each Kategori Utama and Dun pair. If the predicted complaint count for the next week was above the dynamic thresholding formula in Mean Standard Deviation (MSD) method as in Equation (1),

(1)

where is the historical mean, σ is the standard deviation, and k determines the sensitivity of detection, then a warning was triggered as described in [10]. The choice of k=2 aligns with warning limits that flag potential deviations before they reach the traditional 3σ action limits. This approach balances sensitivity and specificity. A 2σ threshold captures 95.45% of normally distributed data, leaving 4.55% of observations as potential anomalies. It reduces false positives compared to narrower thresholds (e.g.,1σ) while providing earlier warnings than 3σ limits. The use of this dynamic thresholding approach is grounded in recent research, which demonstrates that adaptive thresholds based on the local mean and standard deviation are effective for anomaly detection in time series data. For example, the MSD method has been validated for public health surveillance systems to set activity thresholds, effectively distinguishing abnormal surges from normal fluctuations in event counts [10]. Similarly, adaptive thresholding heuristics have been shown to dynamically adjust detection limits based on the statistical properties of the data, minimizing false positives and enabling timely identification of significant anomalies in business and operational contexts [11]. This method ensures that alerts are sensitive to both local patterns and recent variability, flagging abnormal complaint surges that merit management’s attention.

# findings

This paper reports the key findings from the experiments on the complaint classifier, complaint warning system and the integrated dashboard. It discusses the models’ performance, compares embedding strategies, presents the forecasting results, and summarizes the integrated insights offered to aid proactive complaint management.

## Complaint Classifier

Table 1 summarizes the accuracy, macro average and weighted average results of the classification performance for each model. These averages give a holistic view of model performance taking class balance and precision, recall and F1 scores into consideration.

The Support Vector Classifier turned out to be the best performing model using the TF-IDF embedding with an accuracy of around 84.0% and a weighted F1-score of approximately 83.7%. Macro averaged metrics were also performed strongly by ensemble models such as Random Forest and Extra Trees Classifier, but slightly behind weighted F1-score. SVM performed better than LR, and it was stable. The results show that margin-based classifiers such as SVM effectively make use of the high dimensional sparse features from TF-IDF, and the model can learn complex class boundaries and overall classification performance is improved.

With an accuracy of around 82.3% and a weighted F1-score of about 80.5%, the Extra Trees Classifier performed the best when using CountVectorizer. This confirmed the strength of ensemble-based approaches in dealing with frequency-based term counts, as Random Forest closely followed. SVM and LR both managed to be quite competitive, but were unable to catch up too much, indicating that affected term counts can be handled by linear models, but they are outperformed by tree-based models as they are able to capture the underlying structure and interactions of these features. This means that CountVectorizer embeddings work particularly well with ensemble learners.

The Support Vector Classifier achieved the highest scores in the Malay-BERT transformer-based embedding task with 80.4% accuracy and 81.5% weighted F1-score. The rich semantic representations from Transformer embeddings significantly improved SVM's performance. The performance of LR was strong yet simpler models including Decision Trees and AdaBoost struggled because they did not take advantage of the deep contextual features available through the transformer model.

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **TABLE 1.** Overall classification performance | | | | | | | | | | | |
|  |  |  | | **Macro Avg** | | | | | **Weighted Avg** | | |
| **Model** | **Embedding** | | **Accuracy (%)** | | **Precision (%)** | **Recall (%)** | **F1-Score (%)** | **Precision (%)** | | **Recall (%)** | **F1-Score (%)** | |
| AdaBoost | TF-IDF | | 77.15 | | 74.05 | 62.77 | 63.20 | 76.82 | | 77.15 | 74.83 | |
| CountVectorizer | | 76.49 | | 73.21 | 62.40 | 63.21 | 75.95 | | 76.49 | 74.36 | |
| Malay-BERT | | 74.33 | | 63.02 | 61.14 | 60.66 | 71.96 | | 74.33 | 72.59 | |
| Decision Tree | TF-IDF | | 73.55 | | 63.99 | 65.05 | 64.47 | 74.20 | | 73.55 | 73.84 | |
| CountVectorizer | | 74.88 | | 64.89 | 66.65 | 65.66 | 75.85 | | 74.88 | 75.30 | |
| Malay-BERT | | 62.88 | | 53.58 | 53.72 | 53.65 | 62.95 | | 62.88 | 62.91 | |
| Extra Trees Classifier | TF-IDF | | 82.17 | | **78.49** | 67.07 | 69.46 | 81.21 | | 82.17 | 80.32 | |
| CountVectorizer | | 82.28 | | 78.07 | 67.72 | 69.94 | 81.16 | | 82.28 | 80.53 | |
| Malay-BERT | | 77.88 | | 72.99 | 60.28 | 61.93 | 76.34 | | 77.88 | 75.13 | |
| KNN | TF-IDF | | 74.41 | | 76.10 | 60.35 | 63.94 | 77.07 | | 74.41 | 72.77 | |
| CountVectorizer | | 74.13 | | 65.03 | 61.46 | 61.80 | 72.45 | | 74.13 | 72.67 | |
| Malay-BERT | | 80.50 | | 72.73 | 68.22 | 69.79 | 79.27 | | 80.50 | 79.60 | |
| Logistic Regression | TF-IDF | | 81.25 | | 73.05 | 76.67 | 74.30 | **83.59** | | 81.25 | 82.16 | |
| CountVectorizer | | 81.48 | | 72.5 | 74.75 | 73.52 | 82.44 | | 81.48 | 81.89 | |
| Malay-BERT | | 79.25 | | 70.00 | 73.04 | 71.15 | 81.27 | | 79.25 | 80.08 | |
| GNB | TF-IDF | | 43.34 | | 43.32 | 45.60 | 39.26 | 58.98 | | 43.34 | 47.10 | |
| CountVectorizer | | 43.12 | | 43.86 | 46.23 | 39.38 | 59.79 | | 43.12 | 46.94 | |
| Malay-BERT | | 67.59 | | 60.57 | 66.40 | 61.16 | 74.96 | | 67.59 | 69.90 | |
| Random Forest | TF-IDF | | 81.91 | | **78.49** | 66.83 | 69.02 | 80.95 | | 81.91 | 79.95 | |
| CountVectorizer | | 82.00 | | 77.50 | 67.21 | 68.97 | 80.80 | | 82.00 | 80.06 | |
| Malay-BERT | | 78.42 | | 74.06 | 61.36 | 63.19 | 77.13 | | 78.42 | 75.90 | |
| SVM | TF-IDF | | **84.05** | | 76.46 | 74.70 | **75.45** | 83.51 | | **84.05** | **83.72** | |
| CountVectorizer | | 79.94 | | 71.05 | 71.85 | 71.36 | 80.75 | | 79.94 | 80.27 | |
| Malay-BERT | | 80.43 | | 72.16 | **76.84** | 73.70 | 83.43 | | 80.43 | 81.53 | |

Among all tested pairings, TF-IDF with SVM achieved the highest F1-score at 83.7 percent. It was closely followed by Malay-BERT with SVM at 81.5 percent and CountVectorizer linked with Extra Trees Classifier at 80.5 percent. Different combinations show distinct patterns based on these results. SVM proves reliable as a classification method whether it uses TF-IDF or Malay-BERT embeddings to process text. Random Forest and Extra Trees classifiers achieve their best results with CountVectorizer because they can identify non-linear trends and relationships in frequency-based word counts. GNB and KNN failed to produce good results with any embedding type because they struggle to process complex complaint text data effectively.

In summary, the integration of advanced embeddings with reliable classifiers produces better results for complaint classification. The findings suggest that pairing transformer-based embeddings or TF-IDF with SVM, or using ensemble models with CountVectorizer, provides the best performance, offering strong candidates for deployment in proactive complaint management solutions.

## Complaint Warning System

Table 2 summarizes the evaluation results of the complaint warning system, which was designed to forecast weekly aggregated complaint counts per (Kategori Utama, DUN) combination. The models were evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R²).

The CatBoost Regressor showed the best results by producing an RMSE of 5.137 with MAE at 3.056 and R² of 0.7173. It demonstrates its capacity to find complex non-linear relationships in complaint data and deliver accurate predictions for new unseen data. The Extra Trees Regressor showed nearly identical results with CatBoost by delivering an RMSE of 5.226 and an R² of 0.7074. LightGBM, HistGradientBoosting, and Random Forest produced similar results as they achieved performance scores between 0.695 and 0.699 while XGBoost performed below these models with an R² of 0.6754.

|  |  |  |  |
| --- | --- | --- | --- |
| **TABLE 2.** Overall regressor performance | | | |
| **Model** | **RMSE** | **MAE** | **R²** |
| Extra Trees | 5.226 | 3.147 | 0.7074 |
| Random Forest | 5.335 | 3.234 | 0.6951 |
| XGBoost | 5.505 | 3.266 | 0.6754 |
| LightGBM | 5.299 | 3.135 | 0.6992 |
| CatBoost | **5.137** | **3.056** | **0.7173** |
| HistGradBoosting | 5.293 | 3.143 | 0.6998 |

Our findings generate multiple important conclusions. The boosting algorithms CatBoost, LightGBM, and HistGradientBoosting achieved better error reduction and variance interpretation than the bagging algorithms Random Forest and Extra Trees. CatBoost beats other models probably because it processes categorical features and automatic adjustments better than other models. XGBoost underperformed relative to other boosting methods, possibly due to its sensitivity to hyperparameters and a higher tendency toward overfitting in this context. Ensemble methods outperformed basic starting points because they detect complex non-linear patterns in customer complaints.

CatBoost Regressor emerges as the top model for complaint warning systems because it shows strong performance across various scenarios. The system uses reliable forecasts to detect upcoming weeks and locations that will generate many complaints. The system helps local councils respond to problems earlier to prevent them from worsening by using their available resources.

## Dashboard Integration

The sample interface is displayed in Figure 2. Local councils now have access to a strong proactive complaint management resource through the integrated dashboard which unifies machine learning predictions and time-series forecasting. The dashboard solution integrates organization, forecasting and visualization functions which helps fulfill the project’s mission of prioritizing service delivery together with operational effectiveness and higher citizen satisfaction.

# CONCLUSION

This study developed a new proactive complaint management solution that combined a text classification system and a complaint count prediction tool in one dashboard. Through advanced data analysis, our system detected complaint types correctly and told us what will happen to complaints in the future. The TF-IDF and SVM pairing generated better results than alternative model combinations and showed that CatBoost Regressor produced superior complaint count forecasts. When combined, these tools could help local councils better manage resources and services to serve their communities before complaints grow out of control. Our developed Complaint Management System dashboard gave predictions plus a live platform to monitor current issues and make better decisions. This study set a starting point for researchers to study more external elements while making real-time data handle better plus apply this system to other urban control areas. Since the current work explores only one LLM-based embedding approach, future studies could incorporate multiple transformer-based embeddings to further enhance the performance of the model.

|  |
| --- |
| A screenshot of a computer  AI-generated content may be incorrect. |

**Figure 2.** Sample interface of the dashboard

This research recognizes the limitations of the dataset that offers future research opportunities. Our dataset has 26,671 complaints, so it is sufficient to train a traditional machine learning algorithm, but a medium-size corpus to train an optimally fine-tuned transformer, which usually needs 100k+ samples of a specific domain. In future, larger datasets should be used to increase the performance of the transformer, multi-year period to better detect seasonal patterns, and external data such as weather and demographic data should be integrated. Also, the present work investigates only a single approach to embedding based on LLMs, so in the future, several transformer-based embeddings and ensemble techniques might be added to achieve better performance and consider the trade-offs of computational efficiency in a municipal deployment scenario.

# References

1. S. F. Azzahra, Osly Usman, and Suherdi, “Analysis of Customer Complaints Management in The Customer Care Department at PT X,” Isc-Beam **2**(1), 2580–2593 (2024).
2. P. Mosimanegape, O. Jaiyeoba, C. G. Iwu, and C.-M. Cheneso, “Examining the Relationship between Service Quality and Customer Satisfaction in the Public Service. The Case of Botswana,” WSEAS TRANSACTIONS ON BUSINESS AND ECONOMICS **17**, 579–593 (2020).
3. R. Dayyeh, W. AlSawareah, B. Kasasbeh, R. Qaddoura, and S. Kamal, “Comparative Analysis of Decision Trees, Random Forest, and k-Nearest Neighbors in Predictive Analytics for Orange Telecom’s Customer Complaint Data,” in *2023 2nd International Engineering Conference on Electrical, Energy, and Artificial Intelligence (EICEEAI)*, (IEEE, Zarqa, Jordan, 2023), pp. 1–6.
4. M. M. Gewaly, M. S. Saeed, and A. M. Ammar, “Machine Learning Approach for Complaint Prediction in the Telecom Industry,” in *2024 Intelligent Methods, Systems, and Applications (IMSA)*, (IEEE, Giza, Egypt, 2024), pp. 12–17.
5. R. Ali, A. S. Abdul Latiff, and S. Abdul Wahab, “Exploring the Black Box of Knowledge Capture in Public Complaint Management,” MJSSH **9**(9), e002998 (2024).
6. D. Pakpahan, V. Siallagan, and S. Siregar, “Classification of E-Commerce Product Descriptions with The Tf-Idf and Svm Methods,” SinkrOn **8**(4), 2130–2137 (2023).
7. A. N. Azhar, and M. L. Khodra, “Fine-tuning Pretrained Multilingual BERT Model for Indonesian Aspect-based Sentiment Analysis,” in *2020 7th International Conference on Advance Informatics: Concepts, Theory and Applications (ICAICTA)*, (IEEE, Tokoname, Japan, 2020), pp. 1–6.
8. A. Teller, U. Pigorsch, and C. Pigorsch, “Short- to Long-Term Realized Volatility Forecasting using Extreme Gradient Boosting,” SSRN Journal, (2022).
9. A. C.C. Sousa, T. G. Do Rêgo, Y. D. A. M. Barbosa, and T. D. Menezes E Silva Filho, “Comparing Gradient Boosting Algorithms to Forecast Sales in Retail,” in *Anais Do XX Encontro Nacional de Inteligência Artificial e Computacional (ENIAC 2023)*, (Sociedade Brasileira de Computação - SBC, Brasil, 2023), pp. 596–609.
10. M. A. Sinnathamby, T. Bourouphael, J. Boateng, M. Collonnaz, C. Quinot, N.A. Aziz, S. Elgohari, R.E. Green, G. Dabrera, J. Lopez-Bernal, and A. Allen, “Setting thresholds to determine COVID-19 activity levels using the mean standard deviation (MSD) method, England, 2022–2024,” Eurosurveillance **29**(45), (2024).
11. E. R. H. P. Isaac, and A. Sharma, “Adaptive Thresholding Heuristic for KPI Anomaly Detection,” in *2024 16th International Conference on COMmunication Systems & NETworkS (COMSNETS)*, (IEEE, Bengaluru, India, 2024), pp. 737–741.