Prediction of Casualty Rate in Emergency Situations Using the XGBoost Method and SHAP Interpretation (Case Study: Upt. Basarnas Medan)

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Abstract
This study aims to predict the level of casualties in emergency situations using the XGBoost method and interpret the model results using SHAP (Shapley Additive Explanations). The data used comes from the SAR operation of Basarnas Medan with variables of incident type, response time, number of personnel, and distance of the incident. The XGBoost model is used to classify the level of casualties into three categories, namely low, medium, and high. The test results show that the model achieved an accuracy level of 87,77%, which indicates a fairly good model ability in classifying. Evaluation using a confusion matrix shows that the model has the best performance in categories with a larger amount of data, especially the low category, while in the medium and high categories there are still some classification errors due to similarity of characteristics between classes and data imbalance. The SHAP interpretation analysis shows that the type of incident is the most dominant factor influencing the model prediction with the highest contribution value of 1,55 , followed by the number of personnel (0,71), the distance of the incident (0,68), and the response time (0,62). This finding is also supported by the SHAP Summary Plot visualization which shows that the type of incident has the broadest influence on the prediction results. Overall, this study shows that the XGBoost method is not only capable of producing accurate predictions, but can also be well interpreted through the SHAP approach, thus potentially supporting more effective decision-making in handling emergency conditions to minimize the level of casualties.

Keywords: *Basarnas Medan , XGBoost, SHAP, Prediksi, Machine Learning*

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Introduction

The National Search and Rescue Agency, better known as BASARNAS, is an institution established to implement the state's responsibility to protect the entire nation and its entire homeland, as well as to fulfill human rights, namely the right to life. This institution is a non-ministerial government agency that handles government affairs in the field of Search and Rescue and is responsible for coordinating the implementation of SAR.[1],one of the main problems facing humanity, and resulting in economic losses for people working in the informal sector, such as damage to agricultural land and loss of livelihood.[2], a disaster is basically an event that occurs suddenly and causes an impact on physical and mental health that can last for years[3]The threat of disasters is so great that all parties, both the government and the community, need to increase their vigilance and preparedness, as the safety of the community can be threatened by the disaster process[4].

Emergency situations such as natural disasters, accidents, and search and rescue operations often result in varying degrees of casualties. The ability to predict the level of casualties in emergency situations is crucial for supporting decision-making, resource allocation, and response strategies. Accurate predictions can help rescue teams determine the urgency of an incident, optimize personnel deployment, and minimize potential loss of life.

Therefore, a systematic, data-driven approach is needed to analyze the factors that influence the severity of casualties in emergency situations, as a preventative and mitigation effort implemented with the primary goal of preparing for and handling emergency situations.[5], with the rapid development of information technology, the application of machine learning has become an effective solution in analyzing complex data and building predictive models. Machine learning allows the extraction of patterns and relationships from historical data to support more accurate and objective decision making, research shows that machine learning-based approaches are able to improve prediction accuracy compared to conventional methods that rely on experience, organize and prepare the personnel and equipment needed to carry out emergency response operations and ensure that human safety[6].

Indonesia itself has geographical, geological, hydrological and demographic conditions that make it possible for disasters to occur, whether caused by natural factors, non-natural factors or human factors that result in human casualties.[7], in handling emergency conditions, various factors such as response time, distance from the incident location, number of personnel, and type of incident have an important role in determining the level of casualties, that delays in response time and limited resources can increase the risk of higher casualties, while effective coordination and responsive response are very much needed in disaster conditions[8], integrating disaster risk reduction initiatives into defense policies is crucial to enhancing preparedness and response capabilities.[9], can significantly reduce the impact of emergency conditions, this emphasizes the importance of utilizing operational data to build predictive models that can support the decision-making process in SAR operations.Among various machine learning algorithms, XGBoost is one of the most widely used methods due to its high performance and ability to effectively handle structured data. XGBoost is a gradient boosting-based ensemble method that can improve prediction accuracy through the combination of multiple decision trees. This algorithm is well-suited for classification tasks involving complex relationships between variables and has been widely applied in various fields, including disaster management and risk prediction.However, one of the main challenges in applying machine learning is the lack of model interpretability.

High-performance models are often "black box" models, making it difficult to understand how a prediction is generated. To overcome this, the SHAP (SHapley Additive Explanations) method is used, which is able to provide transparent and easy-to-understand explanations of the model's prediction results. SHAP is based on game theory and calculates the contribution of each feature to the prediction results, thus enabling a deeper understanding of the factors that influence the level of casualties. The use of machine learning in emergency management continues to grow, research that integrates predictive models with model interpretation in the context of SAR operations is still limited.

Therefore, this study aims to build a model for predicting the level of casualties in emergency situations using XGBoost and analyze the contribution of each variable using SHAP. This study uses Basarnas Medan SAR operation data with variables such as type of incident, response time, number of personnel, and distance from the incident location. The results of this study are expected to provide insights that support data-based decision-making and improve the effectiveness of emergency response.

Literature Review

1. Investigating a model for predicting casualties in terrorist attacks using the RP-GA-XGBoost algorithm that integrates Random Forest and PCA for feature selection. The results show superior performance with an AUC score of 87% and an accuracy of 86.33% on a global dataset, and a sensitivity of 94% on a specific dataset. This study emphasizes the importance of hyperparameter optimization using genetic algorithms to improve the predictive power of XGBoost. These findings demonstrate that machine learning approaches are capable of providing early warning and decision support that are crucial for resource optimization in emergency management and public safety.[10]**.**
2. This study examines the development of a machine learning model to predict casualties due to heavy rainfall disasters in South Korea by comparing the Decision Tree, Random Forest, and XGBoost algorithms. The results show that XGBoost achieved the highest accuracy rate of 97.4%, outperforming other models in handling rainfall characteristics and facility damage data. This study emphasizes that in addition to weather factors, the variable of the amount of facility damage has a significant significance in predicting casualties. The findings also highlight the challenge of data imbalance that affects recall values, but overall proves that the XGBoost approach is very effective in supporting an accurate disaster impact prediction system.[11].
3. This study compared the performance of five machine learning algorithms (Random Forest, SVM, Gradient Boosting, XGBoost, and LightGBM) in predicting tsunami events based on geospatial and seismic data. The results showed that ensemble-based models consistently outperformed SVM, with Gradient Boosting providing the best performance with an accuracy of 96.17% and an ROC-AUC value of 0.967. This study emphasized the superiority of the gradient boosting method in achieving perfect recall, indicating the model's ability to detect all disaster events without misclassification. These findings demonstrate that this approach has high sensitivity to hazard signals, making it highly potential for integration into a more responsive and accurate early warning system.[12].
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5. Investigating the interpretability of machine learning models on spatial phenomena by integrating the XGBoost algorithm and the SHAP (SHapley Additive exPlanations) method. The results show that XGBoost explained through SHAP is able to produce spatial effect estimates that are equivalent to traditional statistical models (SLM and MGWR), but with significantly better performance in handling non-linear relationships and complex variable interactions. This study emphasizes the transition from a black-box approach to eXplainable AI (XAI) that allows flexible modeling and visualization of geographic processes. These

findings demonstrate that machine learning models with local interpretation are a powerful alternative to spatial statistical models in providing predictive accuracy and transparency to real-world data.[14].

Research Methodology

Research is a systematic and structured process carried out to obtain knowledge or solutions to a problem.[15], using a quantitative approach with machine learning-based predictive computational methods to analyze emergency operations data. Machine learning is how to automatically recognize complex patterns and make intelligent decisions based on data.[16]The data analysis process is carried out systematically following the workflow shown in Figure 1.

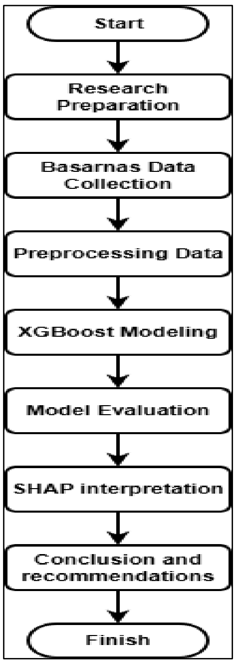

Figure 1. Data Analysis Workflow

The figure illustrates the research stages involved in systematically analyzing SAR (Search and Rescue) operations data. Each stage is explained as follows:

1. Research Preparation Stage

This stage begins with identifying problems related to predicting casualty rates in emergency situations. Researchers conducted a literature review of machine learning methods, specifically XGBoost, and model interpretation methods using SHAP. Furthermore, the research design and determination of the variables used were conducted, namely incident type, response time, number of personnel, and distance from the incident.

2. Data Collection Stage

The data used in this study is secondary data obtained from Basarnas Medan's SAR operations records. The data is stored in Excel format and contains information related to emergency incidents, including operational data and the number of fatalities. The data is then compiled and prepared for further analysis.

3. Data Preprocessing Stage

At this stage, data cleaning is performed to address missing values, eliminate inconsistencies, and ensure data quality. Next, data transformation is performed, converting categorical variables to numeric variables using encoding techniques. Numerical data is also adjusted to achieve a uniform scale. The dataset is then divided into training and testing data for model training and evaluation purposes.

4. Data Analysis Stage Using Machine Learning

This stage is the core of the research, where the processed data is analyzed using the XGBoost algorithm to build a classification model for fatality levels (low, medium, high). The model is trained using training data and tested using test data. Model performance is evaluated using classification metrics such as accuracy, precision, recall, and F1-score.

5. SHAP Interpretation Stage

To increase model transparency, the SHAP method was used to interpret the prediction results. SHAP is used to analyze the contribution of each variable to the model output, thus identifying the factors most influential on the death toll. This step provides a deeper understanding of the model's prediction results.

6. Evaluation and Conclusion Stage

In the final stage, the model's performance is evaluated based on test results, including confusion matrices and classification metrics. The analysis results are then interpreted to assess the model's effectiveness in predicting casualty rates. Conclusions are then drawn and recommendations are provided to support data-driven decision-making in search and rescue operations.

Research Methodology

The method used in this study is a combination of XGBoost (eXtreme Gradient Boosting) and SHAP (Shapley Additive Explanations). The combination of XGBoost and SHAP creates a regression model with several predictor variables, and then determines the correlation weights of these predictor variables with the response variable[17].

XGBoost Method

XGBoost is one of the advanced Gradient Tree Boosting based methods that can work efficiently in handling large-scale problems with very limited computing resources.[18]This method is used to predict the casualty rate in each emergency based on historical data from Medan's Basarnas operations. Input variables in this study include operational characteristics such as incident type, response time, number of personnel, and distance from the incident. The output variable is the casualty rate, classified into three categories: low, medium, and high.

The XGBoost model forms predictions additively through a number of decision trees as follows:

$$\hat{\boldsymbol{y}}_{\boldsymbol{i}} = \sum_{\boldsymbol{t}=\boldsymbol{1}}^{\boldsymbol{T}} \boldsymbol{f}_{\boldsymbol{t}}\,(\boldsymbol{x}_{\boldsymbol{i}})$$

Where:

$x_i$is the i-th emergency incident data,

$f_t$is the t-th decision tree function, and is the number of trees used in the model.T

The objective function to be minimized in XGBoost is formulated as:

$$Obj = \sum_{i=1}^{n} l(\,y_i, \hat{y}_i) + \sum_{t=1}^{T} \Omega(\,f_t)$$

where is the loss function and is the regularization function.$l\Omega$

In this study, the loss function used for softmax-based multiclass classification is:

$$l(y_i, \hat{y}_i) = -\sum_{k=1}^{K} y_i k log\,(p_{ik})$$

with class probability calculated as:

$$p_{ik} = \frac{e^{\hat{y}_{ik}}}{\sum_{j=1}^{K} e^{\hat{y}_{ik}}}$$

Where:
$K$is the number of classes (low, medium, high), and is the probability that the i-th data is in the k-th class.p_{ik}
The regularization function in XGBoost is stated as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum w_j^2$$

which aims to control model complexity and prevent overfitting, especially in heterogeneous emergency operation data, through a gradual boosting process, the XGBoost model is able to learn the relationship pattern between operational variables such as response time and incident distance to the possibility of increasing the level of casualties in an emergency event.
The model is described additively as follows:

$$f(x) = \phi_0 + \sum_{i=1}^{M} \phi_i$$

Where:
ϕ_0 is the baseline value (expected value), namely the average model output before considering input features.
ϕ_i is the contribution of the i-th variable to the prediction results, and is the output of the XGBoost model for a data.$f(x)$
The SHAP value is calculated based on Shapley's theory as follows:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|\,S\,|\,!\,(M-|\,S\,|\,-1)!}{M!} [f(S \cup \{i\}) - f(S)]$$

SHAP Interpretation
Interpretative Analysis Using SHAP After the XGBoost model training process is completed, a contribution analysis of the features is performed using SHAP, showing how much each feature individually contributes to the results obtained by the model, referring to Shapley game theory in cooperative games. This analysis is performed at two levels: Global Interpretation to identify which features have the greatest impact on the overall prediction of the model, and Local Interpretation to explain the specific predictions for each input data.[19].
In search and rescue operations, features such as response time, distance from the incident location, type of disaster, and terrain conditions play an important role in determining the level of casualties predicted by the model. Global interpretation is used to identify the most dominant operational factors in influencing the overall level of casualties. This study aims to develop a model using the Extreme Gradient Boosting (XGBoost) algorithm and analyze the interpretability of the model through an Explainable Artificial Intelligence approach based on

Shapley Additive Explanations (SHAP)[20], local interpretation is used to explain the reasoning behind the predictions for each specific event, for example why an event is classified into a low, medium, or high casualty category based on the contribution of each feature to the model's prediction results.

Results

The following is an example of a dataset structure obtained from the Medan Basarnas SAR operational database in Excel file format, namely SAR Operations Data Recap 2018-2024.xlsx. Each row in the dataset represents an emergency incident handled by Medan Basarnas, while each column represents operational attributes such as incident type, response time, number of personnel, and distance of the incident, as well as the casualty category label.

The dataset used in this study reflects real-world conditions in SAR operations, where input variables describe operational characteristics, while output variables represent casualty rates classified into low, medium, and high categories. This dataset served as the basis for developing a predictive model using XGBoost and was further analyzed using SHAP to determine the contribution of each variable to the prediction results. The structure of the Medan Basarnas SAR operational dataset is as follows:

Table 1. Medan Basarnas SAR Operation Dataset

No.	Jenis Kejadian	Waktu Respon (Menit)	Jumlah Korban	Jumlah Personil	Jarak Kejadian (Km)
1	Kondisi Membahayakan Manusia	30	1	18	5
2	Kecelakaan Kapal	75	3	20	195
3	Kondisi Membahayakan Manusia	105	1	30	88
4	Kondisi Membahayakan Manusia	55	1	12	24
5	Kondisi Membahayakan Manusia	90	1	15	65
6	Kecelakaan Kapal	210	5	22	135
7	Bencana Alam	70	4	40	48
8	Kecelakaan Dengan Penanganan Khusus	45	1	15	28
9	Kondisi Membahayakan Manusia	35	1	16	7
10	Kecelakaan Kapal	740	3	24	545
11	Kondisi Membahayakan Manusia	40	1	12	18
12	Kondisi Membahayakan Manusia	40	1	12	28
13	Kecelakaan Kapal	105	1	20	160
14	Kondisi Membahayakan Manusia	190	1	24	115
15	Kecelakaan Kapal	75	2	16	54
16	Kondisi Membahayakan Manusia	150	1	35	92
17	Kondisi Membahayakan Manusia	35	1	14	12
18	Kecelakaan Dengan Penanganan Khusus	175	2	25	162
19	Kecelakaan Kapal	110	1	18	115
20	Kondisi Membahayakan Manusia	25	1	12	4
….	……………………	……	……	……	……
1142	Bencana Alam	110	150	86	120

The dataset used in this study comes from operational data from the Medan Basarnas SAR (Search and Rescue Agency) and is stored in Microsoft Excel format. The dataset consists of a number of emergency incident records with several operational attributes, namely incident type, response time, number of personnel, and distance of incident. Furthermore, the dataset also contains information on the number of victims, which is then used to generate victim category labels. All data has been verified and no missing values were found, so it can be directly used in the modeling stage without requiring data imputation.

1. Determination of Input Variables

The input variables (X) in this study were determined based on operational factors that could potentially influence the casualty rate. The variables used included the type of incident, response time, number of personnel, and distance from the incident. These variables were chosen because they directly relate to the effectiveness of emergency response.

2. Class Label Formation

Class labels (Y) are generated based on the number of casualties in each incident. Casualty levels are classified into three categories: low, medium, and high. This classification simplifies the modeling process and reduces subjectivity in labeling, ensuring that each category objectively reflects the severity of the incident.

3. Data Preparation for Modeling

After the labeling process, the dataset is divided into two main components: input data (X) and target labels (y). The input variables consist of operational attributes, while the target labels are victim categories. Next, categorical variables, such as incident type, are converted into numeric form using label encoding techniques to enable them to be processed by machine learning algorithms.

4. Division of Training Data and Test Data

The dataset was then divided into training and testing data, with 80% for training and 20% for testing. A stratified splitting method was used to maintain a balanced class distribution across both data subsets, resulting in fairer and more accurate model evaluation.

5. XGBoost Model Training

The model training process was carried out using the XGBoost algorithm to build a casualty classification model. The model was trained using training data to learn the relationship patterns between operational variables and victim categories. XGBoost was chosen for its ability to handle non-linear data and to produce high predictive performance through a boosting-based ensemble technique.

6. Model Interpretation Using SHAP

Once the model was developed, an interpretive analysis was performed using SHAP to determine the contribution of each variable to the predicted results. SHAP was used to identify the dominant factors influencing the casualty rate, both globally and for each specific incident.

```
XGBClassifier

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric='mlogloss',
              feature_types=None, feature_weights=None, gamma=None,
              grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None, num_class=3, ...)
```

Figure 2. XGBoost Model Training Process for Fatality Rate Classification

The model performance in this study was evaluated using several measurement metrics, namely accuracy, classification report, and confusion matrix. Accuracy is used to measure the overall level of accuracy of the model's predictions in classifying the level of casualties. Meanwhile, the classification report provides more detailed information regarding the precision, recall, and F1-score values for each victim category, namely low, medium, and high. The confusion matrix is used to analyze the classification errors that occur in each class, so that it can be seen to what extent the model is able to distinguish between categories of casualties. This evaluation was carried out on the trained XGBoost model, so that the results obtained can illustrate the model's performance in predicting the level of casualties in emergency conditions.

```
=== AKURASI MODEL ===
Akurasi: 87.77%

=== CLASSIFICATION REPORT ===
              precision    recall  f1-score   support

      Rendah       0.95      0.94      0.95       172
      Sedang       0.64      0.75      0.69        28
      Tinggi       0.69      0.62      0.65        29

    accuracy                           0.88       229
   macro avg       0.76      0.77      0.76       229
weighted avg       0.88      0.88      0.88       229


=== CONFUSION MATRIX ===
        Rendah  Sedang  Tinggi
Rendah     162       6       4
Sedang       3      21       4
Tinggi       5       6      18
```

Figure 3. Model Evaluation XGBoost Confusion Matrix

The evaluation results show that the XGBoost model achieved an accuracy rate of **87.77%,** indicating a fairly good classification performance in predicting the level of casualties in emergency situations. The model showed the best performance in the Low category with an **F1-score of 0.95**, indicating excellent predictive ability with a low error rate. In the Medium category, the model produced an F1-score of **0.69**, while in the **High** category it was **0.65**, indicating that the performance was still quite good but not optimal. The confusion matrix analysis showed that most of the data in the **Low** category were successfully classified correctly (162 data). However, in the Medium and High categories there were still classification errors between classes, especially in data predicted as other categories, indicating similar characteristics between classes and an imbalance in the amount of data. Overall, these results indicate that the XGBoost model is effective in classifying the level of casualties, especially in categories with a larger amount of data. However, performance improvements are needed in the Medium and High categories so that the model can provide more optimal prediction results, especially in conditions with a higher level of risk.

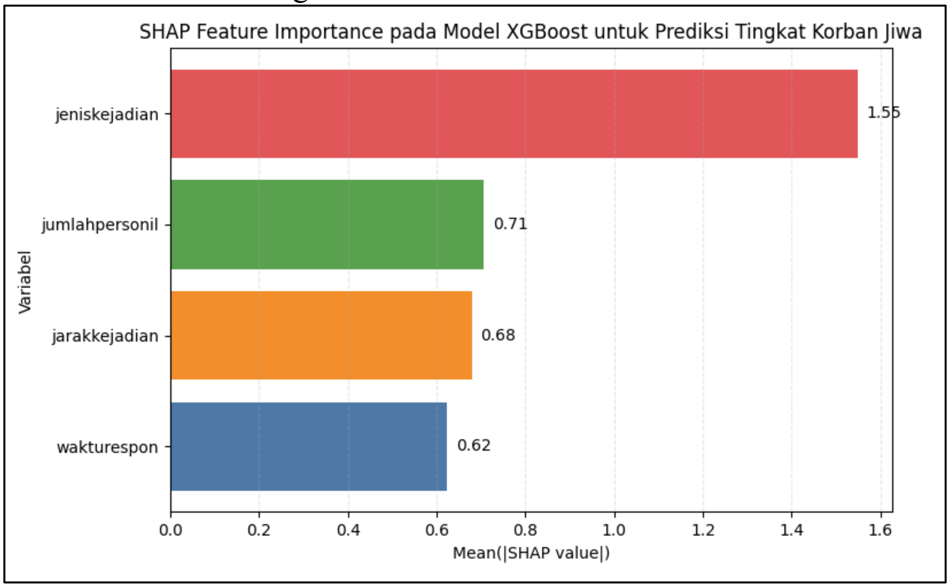

Figure 4. SHAP Feature Importance in the XGBoost Model

The SHAP Feature Importance results show that the incident type variable has the largest contribution in the model with an average SHAP value of **1,55**, making it the most dominant factor in determining the level of casualties. Furthermore, the number of personnel variable has a contribution of **0,71**, followed by the **incident distance (0.68)** and **response time (0.62)**. Although these three variables have a smaller influence than the incident type, their contribution values still show a significant role in supporting the prediction process. Overall, these results indicate that incident characteristics are the main factor, while operational factors such as the number of personnel, distance, and response time play a supporting role in the model.

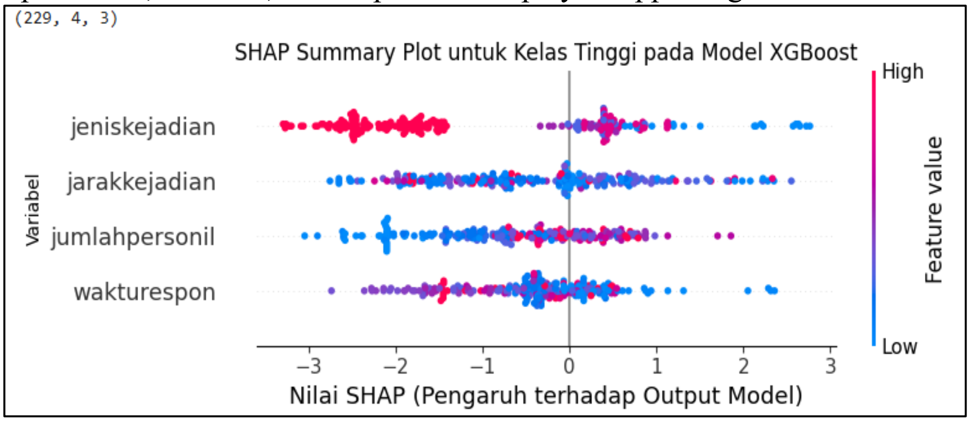

Figure 5. SHAP Summary Plot for High Class in XGBoost Model

The SHAP Summary Plot shows the distribution of each variable's influence on the model prediction. Each point represents a single data point, where the horizontal position indicates the magnitude and direction of the influence (negative values decrease the prediction, while positive values increase the prediction). Color indicates the feature value, namely red (high values) and blue (low values). The incident type variable has the most dominant influence with a SHAP value range of around **-3** to +**1,5**, indicating the largest contribution to the model. Meanwhile, the distance of the incident and the number of personnel have a moderate influence with a range of around **-2** to +**2**, while the response time has the smallest influence with a range of around **-1** to **+1**. Overall, these results confirm that the type of incident is the main factor, while other variables play a supporting role in determining the level of casualties.

Conclusion

Based on the testing and analysis conducted, it can be concluded that the XGBoost model is able to provide good performance in predicting the level of casualties in emergency conditions with an accuracy level of **87,77%**. This value indicates that the model has a fairly effective ability to classify the category of casualties into low, medium, and high classes. The results of the evaluation using a confusion matrix show that the model has a high level of accuracy in categories with a larger amount of data, especially in the low category. However, in the medium and high categories there are still several classification errors, which are influenced by the similarity of characteristics between classes and the imbalance of data distribution.

The interpretation results using the SHAP method show that the type of incident variable is the most dominant factor in influencing model predictions, with the highest contribution value of **1,55**, followed by the number of personnel (**0,71**), distance from the incident (**0,68**), and response time (**0,62**). These results are supported by the SHAP Summary Plot, which shows that the type of incident variable has the widest range of influence compared to other variables.

Overall, this study demonstrates that the XGBoost method is not only capable of providing accurate prediction results but can also be well interpreted using the SHAP approach. Therefore, this model can be recommended as an effective approach to support decision-making related to emergency management, particularly in minimizing the number of casualties.

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