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Classification of Conflict Escalation and Destabilization in the Asia-Pacific Using Machine Learning

Zwesty Quatra[1)] , Sella Juniastia Marsya Saputri[2)] , Imam Akbar[3)] , Fathoni[4)]

[1,2,3,4)] Faculty of Computer Science, Sriwijaya University, Indonesia
Jl. Raya Palembang - Prabumulih KM. 32, Indralaya Indah, Kec. Indralaya, Kab. Ogan Ilir, Indonesia, 30662
*Email :*09031182328015@student.unsri.ac.id[1)], 09031282328074@student.unsri.ac.id[2)], 09031282328104@student.unsri.ac.id[3)], fathoni@unsri.ac.id[4)]

Abstrak

Eskalasi konflik di Asia-Pasifik berisiko memicu destabilisasi kawasan, namun pendekatan berbasis bukti untuk pencegahan konflik masih terbatas. Penelitian ini bertujuan mengembangkan kerangka pembelajaran mesin guna mengklasifikasikan tingkat eskalasi konflik dan mendukung pembangunan perdamaian. Digunakan desain komparatif kuantitatif dengan data sekunder dari Armed Conflict Location and Event Data Project (ACLED) yang mencakup 202.909 insiden di 50 negara dan 642 wilayah administratif Asia-Pasifik periode 2010–2025. Target klasifikasi terdiri dari empat kelas eskalasi: Rendah, Sedang, Tinggi, dan Kritis. Alur kerja meliputi praproses data, rekayasa fitur, penanganan ketidakseimbangan kelas menggunakan SMOTE, serta evaluasi empat algoritma: Random Forest, XGBoost, Linear SVM, dan Multi-layer Perceptron. Kinerja model diukur dengan akurasi, presisi, recall, skor F1 tertimbang, dan AUC makro. Random Forest mencapai performa terbaik (akurasi 91,4%; skor F1 tertimbang 91,5%; AUC makro 0,94), diikuti XGBoost (akurasi 89,9%; AUC makro 0,93). Kedua model ensembel unggul pada kelas rendah dan sedang, namun mengalami penurunan pada kelas tinggi dan kritis akibat keterbatasan sampel asli. Analisis kepentingan fitur menunjukkan jenis dan frekuensi peristiwa sebagai prediktor paling signifikan. Temuan ini menegaskan efektivitas metode berbasis pohon untuk klasifikasi konflik terstruktur dan kontribusinya bagi sistem peringatan dini di Asia-Pasifik. Kerangka yang diusulkan mendukung pengambilan keputusan antisipatif, intervensi tepat waktu, dan alokasi sumber daya yang lebih efisien.

Kata Kunci : ACLED; Asia-Pasifik; Klasifikasi Eskalasi Konflik; Machine Learning; Perdamaian

Abstract

The escalation of conflicts in the Asia-Pacific region risks triggering regional destabilization, yet evidence-based approaches to conflict prevention remain limited. This study aims to develop a machine learning framework to classify conflict escalation levels and support peacebuilding. A quantitative comparative design was employed using secondary data from the Armed Conflict Location and Event Data Project (ACLED), comprising 202,909 incidents across 50 countries and 642 administrative regions in the Asia-Pacific from 2010 to 2025. The target variable consisted of four escalation classes: Low, Medium, High, and Critical. The workflow included data preprocessing, feature engineering, class imbalance handling with SMOTE, and evaluation of four algorithms: Random Forest, XGBoost, Linear SVM, and Multi-layer Perceptron. Model performance was assessed using accuracy, precision, recall, weighted F1 score, and macro AUC. Random Forest achieved the highest performance (accuracy 91.4%; weighted F1 score 91.5%; macro AUC 0.94), followed by XGBoost (accuracy 89.9%; macro AUC 0.93). Both ensemble models performed well on low and medium classes but declined on high and critical classes due to the limited number of original samples. Feature importance analysis identified event type and frequency as the most significant predictors. These findings confirm the effectiveness of tree-based methods for structured conflict classification and their contribution to early warning system development in the Asia-Pacific region. The proposed framework supports anticipatory decision-making, timely intervention, and efficient resource allocation for policymakers and international organizations.

Keywords: ACLED; Asia-Pacific; Conflict Escalation Classification; Machine Learning; Peacebuilding

1. INTRODUCTION

Globally, organized hostilities and politically driven violence have escalated in severity and complexity, with the Asia-Pacific region particularly affected. Recent data indicate a marked increase in conflict-related fatalities, reflecting renewed interstate tensions and the spread of large-scale intrastate warfare [1], [2]. In addition to affecting security stability, the conflict has also triggered humanitarian crises such as forced displacement, environmental degradation, and a decline in the quality of human development across various sectors [3], [4]. The complexity of modern conflicts is also characterized by the interconnections among conflict events across spatial and temporal dimensions, which form cluster patterns and dynamic transformations [5], [6]. Therefore, a data-driven analytical approach is needed that can comprehensively capture the dynamics of conflict in order to support the formulation of more effective, evidence-based peace policies [7].

Notwithstanding these imperatives, initiatives aimed at deciphering and forecasting escalatory trajectories continue to confront foundational obstacles. A principal constraint resides in the dearth of early warning architectures endowed with the capacity for precise, real time conflict anticipation, a deficiency that routinely translates into belated crisis interventions [8]. Furthermore, current approaches to conflict classification remain heuristic and subjective, making them difficult to replicate and less compatible with data-driven quantitative approaches [9]. Another issue lies in the low quality of the predictor variables used in the conflict model, as many structural variables lack strong predictive power regarding conflict intensity [9], [10]. On the other hand, conflict is also endogenous, meaning that the historical dynamics of the conflict itself are often more decisive than external factors [10]. This situation is exacerbated by the complexity of multidimensional factors—such as social, economic, and political factors—that interact in a nonlinear manner, making it difficult to accurately model the escalation of conflict [7], [11], [12].

Several studies have employed machine learning to address these challenges, yet their methodological choices and trade offs warrant careful examination. Kushwaha et al. [9] developed a data driven classification of conflict archetypes using random forests; however, their reliance on static structural indicators produced limited predictive power, raising questions about the validity of predictors selected without dynamic feature contribution validation. In contrast, ensemble methods such as random forests and gradient boosting have consistently outperformed classical statistical models in forecasting conflict outbreaks and humanitarian emergencies [8], [13]. Temporal pattern based approaches like Dynamic Time Warping successfully capture escalation dynamics [14], but their sensitivity to noise and substantial computational demands restrict scalability for real time application. Similarly, deep learning paired with remote sensing enables accurate spatial mapping of conflict impacts [15]. yet the resulting models often function as black boxes, which hinders interpretability for policy formulation. Text based techniques employing word embedding offer promise in detecting escalation signals from political discourse [16], though their validation remains confined to a narrow set of high profile cases, limiting generalizability. Crucially, the majority of these efforts concentrate on predicting whether conflict will occur rather than classifying the severity of escalation, and they remain geographically concentrated in Africa and the Middle East [5], [13]. Moreover, none of the existing approaches simultaneously integrates temporal, spatial, and structural predictors in a unified framework, leaving a fragmented empirical landscape that this study seeks to address within the under examined Asia Pacific region.

Despite these advances and their acknowledged limitations, three critical gaps persist. First, most studies still focus on predicting the occurrence of conflict, rather than on classifying levels of escalation and destabilization risk, which are more relevant for policymaking [6]. Second, existing approaches tend to be partial because they have not yet integrated temporal, spatial, and structural dimensions simultaneously [13]. Third, the paucity of high fidelity and contextually pertinent indicators militates against the model's ability to accurately mirror the labyrinthine dynamics of the conflict under study [9]. Fourth, the field currently lacks a comprehensive, algorithm agnostic appraisal of machine learning performance explicitly contextualized within conflict escalation classification [7], [13]. Furthermore, the lack of studies focused on the Asia-Pacific region highlights an urgent need for more context-specific and regionally grounded research [2], [5].

In response to the identified research gap, the present study advances a framework for the classification of conflict escalation and destabilization risks that employs a supervised

machine learning paradigm within a comparative experimental design. The analysis draws upon historical conflict records curated by the Armed Conflict Location and Event Data project, a repository that furnishes granular, spatiotemporally explicit documentation of conflict episodes. The methodological pipeline encompasses comprehensive data preprocessing, the engineering of salient features, and the mitigation of class imbalance through the Synthetic Minority Over sampling Technique. To ascertain the most effective model for discerning escalatory tiers, the investigation systematically juxtaposes the performance of four principal algorithms: Random Forest, XGBoost, Linear Support Vector Machine (LinearSVC), and Multi layer Perceptron (MLP) [8], [9]. To ensure the reliability of the results, model performance was assessed using standard classification metrics comprising accuracy, precision, recall, F1 score, and AUC [13]. This strategy is expected to produce more accurate models capable of adapting to the complex dynamics inherent in conflict scenarios [10].

The overarching aim of this research is the development of a conflict escalation classification model capable of reliably identifying destabilization hazards within the Asia Pacific domain. Its primary contributions include the establishment of a comprehensive machine learning classification framework, a rigorous comparative evaluation of competing algorithms, and the generation of actionable, data driven insights to underpin peace and mitigation policies. Consequently, this work is anticipated to contribute meaningfully to the refinement of early warning mechanisms and the strengthening of technology enabled peacebuilding at the regional scale [3], [4], [9].

2. RESEARCH METHOD

This research utilizes a quantitative comparative experimental framework to evaluate the capabilities of four machine learning models (Random Forest, XGBoost, LinearSVC, and MLP) in classifying conflict escalation intensities across the Asia Pacific region. The dataset is derived from the Armed Conflict Location and Event Data Project, a well established source frequently leveraged in machine learning based and data centric conflict forecasting studies [17], [18]. The entire process encompasses data acquisition, preprocessing, feature engineering, handling class imbalance, modeling, and evaluation. A comparative experimental approach was used because it is effective in comparing the performance of various algorithms on complex datasets such as those involving political conflict and violence [19]. To provide a systematic overview of the research stages, the research flowchart used in this study is presented below.

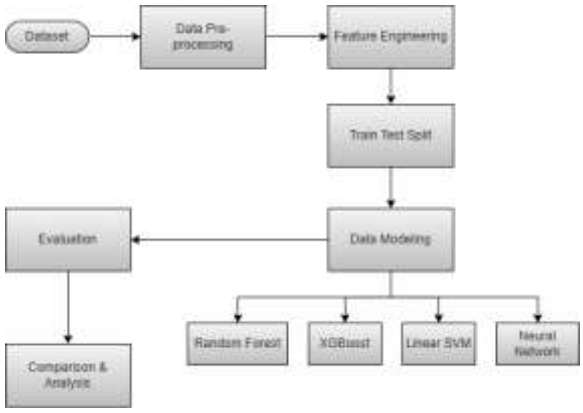


Figure 1. Research Stages

2.1. Dataset

The empirical basis for this research rests on secondary data acquired from the Armed Conflict Location and Event Data Project, a widely acknowledged repository of structured and verified global conflict and political violence incidents [20]. The dataset used has been aggregated on a monthly basis and focuses on the Asia-Pacific region.

Table 1. ACLED Asia-Pacific Dataset Variables

Variable Name	Description
WEEK	Start date of the reporting week
REGION	Sub-regions (6 categories)
COUNTRY	Countries (50 countries)
ADMIN1	Province/state (642 regions)
EVENT_TYPE	Main incident types (6 categories)
SUB_EVENT_TYPE	Event subtypes (35 categories)
DISORDER_TYPE	Classification of disorders (4 categories)
EVENTS	The number of incidents during that week
FATALITIES	Estimated death toll
POPULATION_EXPOSURE	Estimated number of people exposed
CENTROID_LATITUDE	Latitude of the administrative center of ADMIN1
CENTROID_LONGITUDE	Longitude of the administratove center of ADMIN1

2.2. Data Pre-Processing

Prior to in depth analysis, a comprehensive preprocessing routine was implemented to enhance data quality. The sequence of steps included the following.

i) Handling of Missing Values: The POPULATION_EXPOSURE variable contains 43,191 missing values (20.8%). Imputation was performed using a multilevel median approach. Let Xijk be the population value for country i, province j, and observation k. Missing values are estimated sequentially using the median at the

(COUNTRY, ADMIN1) level, then the COUNTRY level, and finally the global median.

ii) Data Validation: The check ensures that there are no negative values in the EVENTS and FATALITIES columns. Duplicate rows are identified and removed.Temporal Feature Extraction: From the WEEK column, which is of datetime type, the components YEAR, MONTH, QUARTER, and DAY_OF_WEEK were extracted.

iii) Logarithmic Transformation: To stabilize the variance, the transformation In(1 + x) was applied to the EVENTS and POPULATION_EXPOSURE variables, resulting in the features LOG_EVENTS and LOG_POP_EXPOSURE.

iv) Encoding Categorical Variables: Variables with multiple categories, such as EVENT_TYPE, SUB_EVENT_TYPE, DISORDER_TYPE, REGION, COUNTRY, and ADMIN1, are converted into numerical representations using a LabelEncoder. The encoding function L : C → {0,1, ..., m-1} maps each unique category to an integer.

2.3. Feature Engineering

Feature engineering is integral to the data processing workflow, significantly sharpening the model's ability to extract meaningful patterns. Given its profound impact on model efficacy, the EVENT_PER_100K attribute was constructed to reflect normalized event incidence relative to population size:

$$EVENT_PER_100K = \frac{EVENTS}{POPULATION_{EXPOSURE}} \times 100.000$$

The classification target used is the level of conflict escalation (Y), which is defined on an ordinal scale based on the number of fatalities (F) and the type of incident (T):

$$Y = \begin{cases} 0\ (Low) \\ 1\ (Medium) \\ 2\ (High) \\ 3\ (Critical) \end{cases}$$

It is important to note that the FATALITIES variable and its derivatives were not included as predictor features to prevent target leakage. The target Y was constructed ordinally using fatality counts and incident type. Low (0) corresponds to events with no fatalities and non violent categories; Medium (1) covers events with few fatalities or low intensity violence; High (2) includes events with moderate fatalities or battles; Critical (3) captures events with high fatalities, typically involving remote violence or prolonged armed clashes. Although EVENT_TYPE contributes conceptually to Y, the relationship is not deterministic because the same event type may result in varying escalation levels depending on intensity and context. To verify the absence of direct leakage, Pearson correlations between each predictor and the target were computed; all values fell below 0.55, confirming that no single feature duplicates the target definition. A total of 16 final features were selected, including: EVENTS, LOG_EVENTS, EVENTS_PER_100K, LOG_POP_EXPOSURE, YEAR, MONTH, QUARTER, DAY_OF_WEEK, CENTROID_LATITUDE, CENTROID_LONGITUDE, and six columns of categorical encoding results. The target class distribution before handling the imbalance was: Low (134,585), Medium (58,618), High (8,082), and Critical (1,624).

2.4. Handling Class Imbalance with SMOTE

Extreme class imbalance can skew model training toward the majority category. To counteract this, the Synthetic Minority Over sampling Technique (SMOTE) was implemented exclusively on the training data, a standard practice for improving classification on imbalanced datasets without compromising test set validity. SMOTE synthesizes new minority instances by interpolating linearly between a given sample X and one of its k nearest neighbors, X_{nn}.

$$x_{new} = x + \lambda \times (x_{nn} - x)$$

Using λ~ Uniform(0,1). After oversampling, each class in the training data has the same number of samples, namely 107,668 observations per class. Next, all numerical features are standardized using Z-score normalization:

$$z = \frac{x - \mu}{\sigma}$$

Where μ and σ are the mean and standard deviation of the features calculated from the training data. A similar approach was also used in models predicting police and military violence in Colombia and Mexico to address data imbalance [19].

2.5. Machine Learning Models

Modeling at this stage aims to classify conflict escalation using the previously engineered

features. A supervised learning approach is employed, whereby the model learns the relationship between predictor variables and the target class from labeled training data. Supervised learning is used to build predictive models based on labeled data. The selection of algorithms takes into account their ability to handle nonlinear patterns as well as the characteristics of the dataset used. Ensemble-based methods such as Random Forest and XGBoost were chosen based on their consistent performance in recent conflict prediction and classification studies XUE ET AL.[8], FEIZIZADEH [13], as they reliably capture nonlinear interactions and improve stability over single-model approaches. For comparison, linear models and neural networks were also included to provide a more comprehensive evaluation perspective.

1. Random Forest is an ensemble learning method grounded in decision tree architectures. It operates by constructing a multitude of trees from distinct bootstrap samples of the data and subsequently aggregates their individual outputs through a majority voting scheme. This algorithm employs bootstrap aggregation, or bagging, as a means to curtail variance and mitigate the risk of overfitting. Within the scope of this investigation, the Random Forest classifier was instantiated with a configuration of one hundred decision trees.
2. XGBoost, an abbreviation for Extreme Gradient Boosting, constitutes a sequential ensemble technique wherein successive models are trained to rectify the residual errors of their predecessors. A notable characteristic of this algorithm is its intrinsic regularization mechanism, which renders it particularly robust when confronted with class imbalance. For the purposes of this study, the XGBoost model was executed with one hundred estimators and a learning rate set to 0.1.
3. The LinearSVC represents a specific instantiation of the Support Vector Machine family that utilizes a linear kernel to delineate an optimal separating hyperplane among distinct classes. This particular model serves as a linear benchmark, facilitating an assessment of the degree to which the relationships embedded within the feature space can be captured through linear separation. The operational parameters were specified as dual=False with a maximum iteration ceiling of 2000.
4. The MLP is an artificial neural network architecture characterized by a sequence of fully connected layers. In this implementation, the network comprises an input layer, two hidden layers populated with one hundred and fifty neurons respectively, a Rectified Linear Unit (ReLU) activation function, and a terminal output layer. To guard against overfitting, an early stopping protocol was enforced, which monitors the validation loss and halts training when no further improvement is observed across ten percent of the validation partition.

2.6. Experimental Pipeline

To ensure reproducibility and prevent data leakage, the experimental pipeline was structured as follows:

1. **Data Splitting**: The original dataset (202,909 observations) was split into training (80%, n=162,327) and test (20%, n=40,582) sets using stratified sampling based on the target class.
2. **Class Balancing**: SMOTE was applied only to the training set to balance the class distribution, resulting in 107,668 samples per class. The test set was left untouched to preserve the natural class distribution for unbiased evaluation.
3. **Feature Scaling**: Z-score normalization parameters (μ, σ) were computed on the training set and applied to both training and test sets to avoid information leakage.
4. **Model Training and Tuning**: Each algorithm was trained using 5-fold cross-validation on the training set for hyperparameter optimization.
5. **Evaluation**: All metrics were calculated exclusively on the held-out test set.

2.7. Model Evaluation

Model evaluation was conducted to assess each algorithm's ability to accurately classify conflict escalation levels. The evaluation process utilized test data that was completely separate from the training data to obtain an objective assessment of the models' generalization capabilities. The analysis relied on accuracy, precision, recall, F1 score, and Area Under the ROC Curve as performance yardsticks. Owing to the imbalanced nature of the target variable, a weighted averaging methodology was adopted to ensure that each class contributes to the final figures in a manner that faithfully reflects its empirical distribution.

i) Accuracy: measures the proportion of correct predictions relative to the entire test dataset. Mathematically, accuracy is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

ii) Precision, Recall, and F1-Score: Calculated using a weighted average to account for class imbalance. For each class i, the metrics are calculated as:

$$Precision_i = \frac{TP_i}{TP_I + FP_I}, Recall_i = \frac{TP_i}{TP_i + FN_i}$$

$$F1_i = 2 \cdot \frac{Precision_i \cdot Recall_i}{Precision_i + Recall_i}$$

iii) The weighted average is calculated using the weights

$$w_i = support_i / N_{test}$$

iv) Confusion Matrix: To analyze classification error patterns across classes.

v) ROC Curve and Area Under the Curve (AUC): The Receiver Operating Characteristic (ROC) curve illustrates the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR) at various decision thresholds. In-depth ROC analysis is crucial for understanding the trade-off between sensitivity and specificity, particularly in data with class imbalance [21]. Meanwhile, the Area Under the Curve (AUC) uses the One-vs-Rest (OvR) approach for multi-class problems.

3. RESULT AND DISCUSSION

3.1. Dataset Overview and Preprocessing Outcomes

The initial dataset obtained from ACLED consisted of 207,848 observations with 13 variables. After filtering the time period (2010–2025) and removing duplicate data, 202,909 observations were retained for analysis. The POPULATION_EXPOSURE variable, which originally had 43,191 missing values (20.8%), was successfully imputed using a multilevel median approach. The classification target—conflict escalation level—exhibited significant skewness: the Low class dominated with 134,585 observations (66.3%), followed by Medium with 58,618 (28.9%), High with 8,082 (4.0%), and Critical with only 1,624 observations (0.8%). This imbalance was then addressed by applying SMOTE to the training data so that each class had 107,668 samples.

3.2. Model Performance Comparison and ROC Analysis

Four classification algorithms were evaluated using a test dataset consisting of 40,582 observations. A summary of each model's performance based on accuracy, precision, recall, and F1-score metrics, along with their weighted averages, is presented in Table 2, while the ROC curves using the One-vs-Rest approach are shown in Figure 2.

Table 2. Performance Metrics and Macro-Average AUC of Classification Models on Test Data

Model	Accuracy	Precision	Recall	F1-Score	AUC Macro
Random Forest	0,914	0,915	0,914	0,915	0,94
XGBoost	0,899	0,908	0,899	0,903	0,93
MLP	0,880	0,901	0,880	0,888	0,91
LinearSVC	0,694	0,707	0,694	0,698	0,78

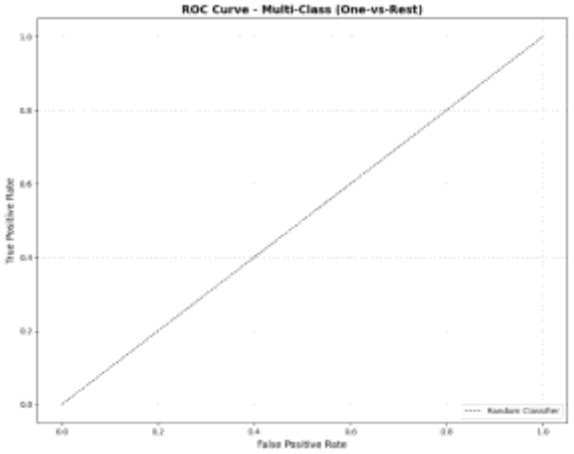


Figure 2. Receiver Operating Characteristic (ROC) curves using One-vs-Rest approach for the four classifiers.

Random Forest achieved the highest performance across all evaluation metrics, with an accuracy of 91.4%, a weighted F1-score of 91.5%, and a macro AUC of 0.94. XGBoost came in second with an accuracy of 89.9%, an F1-score of 90.3%, and a macro AUC of 0.93. The Multi-layer Perceptron achieved an accuracy of 88.0% and a macro AUC of 0.91, while LinearSVC lagged significantly behind with an accuracy of only 69.4% and a macro AUC of 0.78. These results confirm that decision tree-based ensemble approaches are superior at handling tabular data with nonlinear interactions compared to linear models or neural networks with simple architectures. Comparative studies across various domains also show that ensemble algorithms such as XGBoost and Random Forest excel in stability and accuracy [22], [23]. The AUC values above 0.90 for the first three models

further confirm that these models have excellent overall discriminatory power.

3.3. Per-class Performance Analysis

The analysis by class provides a more detailed overview of the strengths and weaknesses of each model.

Table 3. Per-Class Performance of Random Forest Model

Class	Precision	Recall	F1-Score	Support
Low	0,97	0,96	0,96	26.917
Medium	0,86	0,86	0,86	11.724
High	0,54	0,56	0,55	1.616
Critical	0,47	0,48	0,47	325

The model performed very well in the Low class (F1 0.96) and fairly well in the Medium class (F1 0.86). However, performance dropped sharply in the High class (F1 0.55) and the Critical class (F1 0.47). The marked decline in performance for the High and Critical classes indicates that the models struggled to learn discriminative patterns for rare escalation events. Although SMOTE balanced the training distribution synthetically, the original minority classes contained very few real observations, reducing the diversity of authentic escalation patterns available during learning. Substantial overlap in temporal, spatial, and event type attributes among Medium, High, and Critical events further blurred decision boundaries, as reflected in frequent adjacent level misclassifications in the confusion matrix. Moreover, conflict escalation is inherently stochastic and context dependent, driven by latent geopolitical and socioeconomic factors that are absent from the ACLED dataset, limiting the feature space from adequately capturing extreme escalation dynamics.

3.4. Discussion

The experimental results show that Random Forest and XGBoost deliver the best performance in classifying conflict escalation levels. This advantage aligns with a case study in Southern Thailand that used a similar approach to predict instability [24]. Further analysis of classification errors reveals that the models tend to misclassify adjacent classes. In Random Forest, 34.5% of High-class observations were incorrectly predicted as Medium, and 39.1% of Critical-class observations were incorrectly predicted as High. A similar pattern is also observed in XGBoost. These findings indicate that incidents with moderate to high severity levels share feature similarities that are difficult for the model to distinguish, primarily due to the limited number of original samples in both of these minority classes.

The feature importance analysis (Figure 3) reveals a clear hierarchy among predictors, with event-related features (EVENT_TYPE_ENC, EVENTS, SUB_EVENT_TYPE_ENC) dominating at scores two to three times higher than temporal or spatial features. This indicates that what occurs and how frequently outweighs when or where in determining escalation severity. Battles and remote violence correlate monotonically with higher escalation classes, whereas protests and riots map predominantly to Low and Medium classes. A shift in event-type composition, particularly a rising ratio of battles to protests, can therefore serve as a leading indicator of escalation risk. Temporal features (YEAR, MONTH) contribute moderately, capturing seasonal and long-term conflict cycles, while spatial coordinates contribute less, suggesting that the nature of violence transcends geographic boundaries. Notably, population-adjusted metrics (LOG_POP_EXPOSURE, EVENTS_PER_100K) rank lower, confirming that raw event intensity remains more predictive than normalized measures in this context.

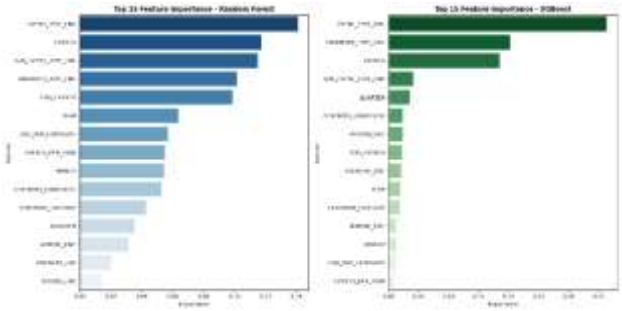


Figure 3. Top 15 feature importance scores from Random Forest and XGBoost

The primary limitation lies in the low recall for the High and Critical classes. With only 8,082 High and 1,624 Critical instances in the original dataset, SMOTE could not fully compensate for the extreme scarcity, especially because the feature profiles of these two classes overlap considerably. Critical events often arise abruptly from high intensity settings, leaving the model with ambiguous decision boundaries. Synthetic samples thus tend to reinforce existing central tendencies rather than introduce genuinely rare configurations. Moreover, the ACLED dataset lacks contextual variables such as economic conditions and elite political dynamics that could sharpen escalation signals. Future work should integrate multimodal data and consider risk categorization approaches developed for global

terrorism analysis [25] to improve sensitivity toward rare, high impact events.

4. CONCLUSION

The principal aim of this investigation was to construct a classification framework capable of discerning varying degrees of conflict escalation within the Asia Pacific region by means of machine learning techniques. An empirical evaluation of four distinct algorithms, namely Random Forest, XGBoost, LinearSVC, and MLP, revealed that Random Forest attained superior predictive fidelity. Specifically, it achieved an accuracy of 91.4 percent, a weighted F1 score of 91.5 percent, and a macro averaged Area Under the Curve of 0.94. XGBoost secured the second position with an accuracy of 89.9 percent and a macro AUC of 0.93, whereas the linear baseline and the comparatively simpler neural architecture exhibited noticeably diminished performance.

This study makes several contributions to the field of data-driven conflict analysis. First, it presents a systematically evaluated machine-learning pipeline that integrates feature engineering, imbalance correction, and multi-model comparison, offering a replicable template for future conflict classification research. Second, by focusing on the geographically understudied Asia-Pacific region, the work enriches the regional scope of predictive conflict literature, which has historically concentrated on Africa and the Middle East. Third, the identification of event type and frequency as the most salient escalation predictors provides an empirically grounded basis for designing operational early warning indicators. From a practical standpoint, policymakers and international organizations can leverage the model to prioritize high-risk subregions based on observed shifts in conflict event composition, thereby enabling more timely and targeted intervention. The framework also supports resource allocation efficiency by focusing analytical attention on indicators that consistently drive escalation dynamics.

5. FUTURE WORK

Feature contribution analysis reveals that conflict type and frequency are the most dominant determinants in determining the level of conflict escalation. These findings confirm that monitoring changes in the composition of conflict types can serve as an early indicator for early warning systems. The main limitation of the study lies in the model's poor ability to detect the High and Critical classes due to the limited number of original samples. Additionally, the dataset used does not include contextual variables such as economic conditions and elite political dynamics.

To address these limitations, further research is recommended to integrate additional data sources, such as socioeconomic indicators and social media analysis, and to explore more complex deep learning architectures that can better capture rare but high-impact escalation patterns. Such improvements are expected to enhance model sensitivity for critical events, ultimately strengthening its contribution to peacebuilding and conflict mitigation efforts in the Asia-Pacific region.

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