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Optimizing Humanitarian Logistic: Securing Aid Corridors in Afghanistan Using Predictive Analytics

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Abstract

Operating in conflict zones, humanitarian organizations are exposed to insecurity, broken supply chains, and unpredictable political environments. These complexities are seen in Afghanistan, which needs new, data-driven logistics approaches. This study proposes a predictive analytics framework based on ensemble machine learning models, Bagging, Boosting, and Stacking to predict fatalities, demonstration events, and high-risk areas to support humanitarian logistics, supply chain optimization, and corridor management in Afghanistan. As a method, it applies conflict data to geospatial and temporal variables to predict security risks well. Predictive outcomes revealed peak risk times and places, which were useful in making logical decisions, optimizing resources, and increasing the safety of humanitarian corridors. The framework's reliability was validated using evaluation metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and classification accuracy. This research is significant because it applies predictive analytics theory to real logistical scenarios with a scalable model that can be used by other humanitarian organizations. The main limitations of the study include the small area of analysis, the absence of socio-economic variables in the analysis, and the lack of integration of real-time data. Future work should include the integration of real-time data streams, extension of the geographical coverage, and the integration of dynamic socio-economic and political variables to improve the accuracy of the prediction model. This study effectively enables peak risk periods and locations to be pinpointed, which in turn enables better targeted interventions to improve the safety of humanitarian workers and reach vulnerable populations on time.

Keywords: Predictive Analytics, Humanitarian Logistics, Conflict Forecasting, Secure Supply Chains

INTRODUCTION

Humanitarian operations in conflict zones are inhibited by chronic constraints of insecure environments, broken supply chains, and politically fragile contexts (Bollettino et al., 2023). To provide humanitarian assistance safely and efficiently in such conditions, it is vital to have proper logistic planning and decision-making strategies. Afghanistan is one of the most challenging environments for humanitarian logistics because of the long-standing and protracted conflict in the country. The conflict has eroded the infrastructure (Stanski, 2023), made the supply lines tortuous, and introduced elements of unpredictability in terms of security, which are a threat to humanitarian workers (Malhouni & Mabrouki, 2023) and the beneficiaries they aim to assist.

The conventional planning practices in humanitarian operations are mostly stochastic in nature and are based on historical data and qualitative analysis (Acar & Kaya, 2021; Grass et al., 2023). However, such approaches may be inadequate for the flexible management of rapidly changing risks in dynamic and unpredictable environments (Ershadi & Shemirani, 2021; Wang et al., 2021; Zhang & Cui, 2021). This paper is an attempt to fill this gap by proposing a framework for predictive analytics that uses conflict, spatial, and temporal data to pinpoint and predict the time and space of risk (Grass et al., 2023).

The main objective of this research is to improve the performance of humanitarian logistics by using predictive analytics (Ershadi & Shemirani, 2021; Jamali et al., 2021; Ji & Fu, 2023) to ensure the supply chain and the humanitarian corridors in Afghanistan, especially between the strategic hubs of *Kabul*, *Herat*, *Kandahar*, and *Mazar-e-Sharif*. Security incidents, fatalities, and demonstrations are forecasted by using ensemble machine learning techniques such as Bagging, Boosting, and Stacking to support early planning, rationalization of convoy scheduling, and optimum use of resources. This research directly links predictive outcomes to practical logistical actions and thus greatly contributes to improving the safety, efficiency, and timeliness of humanitarian operations in Afghanistan and similar conflict-affected environments (Boostani et al., 2020; Chang et al., 2021).

The remaining parts of this article slowly and systematically build the literature review, explain the methodology used, present the main findings and predictive results, and offer recommendations, thereby leading the reader through a step-by-step analysis of the role of predictive analytics in the security of humanitarian logistics. Readers are therefore encouraged to find out how cutting-edge modeling strategies can actually improve the safety and performance of humanitarian assistance.

RESEARCH METHODS

This study adopts a systematic approach to predict security incidents and recommend optimal security corridors based on five datasets: political fatalities, civilian fatalities, protest events, data news monitoring, and humanitarian incidents. The process starts with data preprocessing, including cleaning, normalization, and feature engineering to improve the performance of the model. Important variables, including *temporal* and geographical indicators, fatalities, and event types, are extracted and prepared for modeling.

To help humanitarian organizations design secure and efficient logistics operations such as route planning and the optimal scheduling of movements across corridors, including, in the case of this study, between *Kabul*, *Herat*, *Kandahar*, and *Mazar-e-Sharif*, we used ensemble predictive modeling approaches to anticipate conflict-related risks.

Data Overview

To increase the quality of inputs, consistency checks are performed on datasets from the *Humanitarian Data Exchange* (HDX), and feature engineering is applied. Lagged and binary variables are developed to capture *temporal* dependencies and event categorizations to enhance predictive accuracy.

Modeling Approaches

A systematic pipeline is used for modeling. First, raw data is cleaned, and relevant attributes are identified for prediction. The data is then randomly divided into a training set (70%) and a testing set (30%) to check how well the model performs on new data. Three ensemble models—*Random Forest*, *Gradient Boosting*, and *XGBoost*—are applied to the training data for prediction. A meta-model, specifically *Linear Regression*, is used to combine the outputs of these base models to improve the overall accuracy and robustness of the model. The performance of these models is measured by means of evaluation metrics such as *Mean Absolute Error* (MAE), *Mean Squared Error* (MSE), and *Root Mean Squared Error* (RMSE) to ensure that the models are highly accurate and precise in their predictions.

The intention is to classify the risk as low, medium, or high for classification. The same base algorithms of *Random Forest*, *Gradient Boosting*, and *XGBoost* are used for ensemble classification but with a voting ensemble mechanism to combine predictions. Metrics such as *Accuracy*, *Precision*, *Recall*, and *F1-Score* ensure balanced and reliable classification.

Evaluation and Validation

The MAE, performance MSE, and RMSE measure the accuracy and error magnitude. For classification tasks, *Accuracy*, *Precision*, *Recall*, and *F1-Score* measure how effectively regions are categorized into risk levels. Cross-validation and overfitting checks (although not explicitly presented) were conducted to ensure that the models are reliable and do not suffer from bias.

Outputs

Study outcomes include empirical predictions of fatalities, protests, and dangerous areas, and region-level classifications. These insights help in the planning of secure humanitarian corridors and provide precise, reliable, and actionable recommendations for conflict-affected environments. The integration of spatio-temporal data and ensemble techniques provides robust decision-making in dynamic environments.

Study Limitations

While this methodology offers valuable insights for managing humanitarian corridors, there are several limitations that call for further research to modify and develop the framework. More variables should be considered, real-time changes taken into account, and the geographical scope should be widened to increase the accuracy and applicability of the predictive models in the context of dynamic conflict situations.

This study focuses on five points: *Kabul*, *Herat*, *Kandahar*, and *Mazar-e-Sharif*, and excludes other areas that may also have significant conflict dynamics. Socioeconomic variables like poverty rate and local economic activity are not included in the models. This lack may lead to low prediction accuracy as these factors are usually vital in the conflict and aid distribution processes. The models do not include changes in the conflict actors, regimes, or leadership, which can greatly alter the conflict and the predictions to be made.

Additionally, the effect of new players or stakeholders in the conflict has not been considered, which may affect the generality of the findings. The use of historical data may not be able to capture the real picture or trends of change, and therefore, the model may not be sensitive to changes in the environment. Factors like the state-of-the-art infrastructure, climate, and traffic congestion are not considered, which may limit the practicality of and movement accuracy recommendations.

Lastly, the quality of predictions depends heavily on the accuracy and completeness of input data. Any gaps or biases in the datasets could impact the validity of results. These limitations can be addressed in future studies to develop more sensitive and realistic predictive models to be applied in the context of humanitarian crises that are dynamic and complex.

RESULT AND DISCUSSIONS

The analysis made empirical predictions of fatalities, protests and dangerous areas and region level classifications. The predictive results revealed time periods and spatial patterns of highest risk and therefore can help to improve planning decisions, to improve the effectiveness of logistical decisions and to allocate resources most effectively to secure humanitarian corridors effectively.

Fatality Dataset overview

A highly skewed distribution, where most events report zero fatalities, as indicated by a median of 0.0. However, the mean fatalities (5.46) are disproportionately influenced by a few catastrophic outliers, with a maximum range of 916 fatalities. This highlights the dataset's variability, dominated by a small number of high-fatality events that significantly distort the average.

The histogram illustrates the predominance of low-fatality events, while the boxplot emphasizes the impact of extreme outliers on the dataset. The summary statistics further demonstrate the disparity, with the range highlighting the magnitude of rare but severe incidents. These insights underscore the importance of handling outliers carefully in predictive modeling and focusing on metrics like the median to better represent the central tendencies of the data.

And with a total of 37,015 records, the Civilian dataset provides a granular view of civilian-targeted violence. A sample of ten records illustrates the dataset's structure and highlights its depth and relevance for analysis.

From the analysis of political fatalities it is seen that the distribution is highly uneven, with most events having zero fatalities as revealed by the median of 0.0. However, the mean of fatalities (5.46) is skewed by a small number of extreme outliers, which includes a maximum of fatalities of 916 This disparity tells the story of the dataset's variability since it is dominated by rare but severe incidents that strongly influence the average value.

From the histogram it is clear that most of the events are of low fatality, while from the boxplot it is clear that there is a significant effect of outliers. Other summary statistics also reveal this inequality in a way that illustrates the need to pay particular attention to outliers when doing predictive modeling. For instance, the median is a better representation of central tendencies than the mean because it is less sensitive to extreme values.

With 37,015 total records provides a comprehensive perspective on violence against civilians. A sample of ten records shows what the dataset is like, and how it can be useful for analysis.

Table 1. Civilian Fatalities Dataset

Country	Admin1	Admin2	ISO3	Admin2 Pcode	Admin1 Pcode	Month	Year	Events	Fatalities
Afghanistan	Parwan	Jabulussaraj	AFG	AF0305	AF03	January	2017	0	0
Afghanistan	Paktika	Giyan	AFG	AF1215	AF12	January	2017	0	0

Country	Admin1	Admin2	ISO3	Admin2 Pcode	Admin1 Pcode	Month	Year	Events	Fatalities
Afghanistan	Nimruz	Kang	AFG	AF3402	AF34	January	2017	0	0
Afghanistan	Nuristan	Paroon	AFG	AF1601	AF16	January	2017	0	0
Afghanistan	Bamyan	Saighan	AFG	AF1003	AF10	January	2017	0	0
Afghanistan	Farah	Bala Buluk	AFG	AF3306	AF33	January	2017	2	2
Afghanistan	Herat	Shindand	AFG	AF3214	AF32	January	2017	1	1
Afghanistan	Kunduz	Qala-e-Zal	AFG	AF1907	AF19	January	2017	0	0
Afghanistan	Wardak	Jaghatu	AFG	AF0408	AF04	January	2017	0	0
Afghanistan	Parwan	Jabulussaraj	AFG	AF0305	AF03	January	2017	0	0

Reveals a sharp tail, as seen from the median value of 0.0, which means most events have zero fatalities. The mean number of fatalities per event is slightly higher (0.29), influenced by small high fatalities incidents. The boxplot underlined dataset's variability with most of the fatalities concentrated around zero and with rare outliers extending up to 118 fatalities. These infrequent but highly influential outliers make a big difference in the overall characteristics of the dataset.

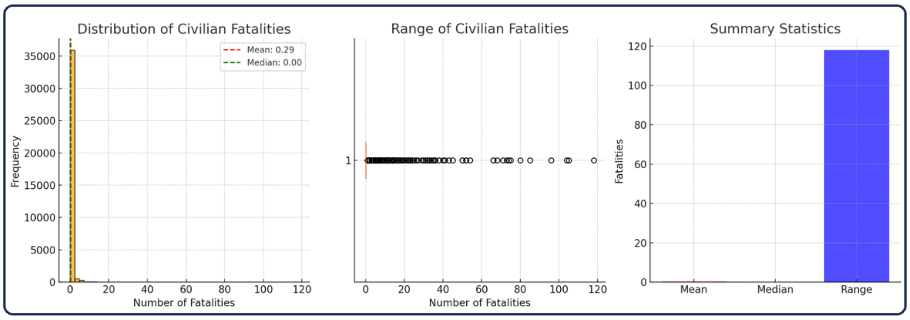

Figure 1. Characteristic of Civilian Fatalities Dataset

This disparity is further illustrated below (**Table 2**) that the low average per event reflected by the mean, while predominance non-lethal event confirmed by the median. The range, on the other side, highlights the significance of the rare high-fatality incidents. These findings underlining the need to carefully manage the outliers and focus on robust metric like the median to better represent the characteristic of civilian-targeting events in the modeling.

Table 2. Comparison of Dataset Distribution

Aspect	Political Fatalities	Civilian Fatalities
Median Fatalities	0	0
Mean Fatalities	5.46	0.29
Range of Fatalities	916	118
Severity of Outliers	High severity and frequent	Moderate severity and less frequent
Distribution Pattern	Highly skewed with extreme outliers	Skewed with fewer extreme outliers

Key differences on dataset distribution and characteristics (Table 2) were revealed as outcome of political and civilian dataset comparison. Both datasets are significantly skewed with most of the events resulting in zero fatalities as reflected by median of 0.0. However, the political fatalities mean is having higher magnitude (5.46) influenced by high-fatality events, where on the civilian fatality side valued as 0.29, reflecting less severe impact per incident.

This is reflected by the presence of rare but devastating political violence significantly broaden the in fatality political range events (916) than in civilian (118). The outlier is pronounced more in the political dataset, which leads to higher peaks and variability, since the civilian fatalities are concentrated at lower values with fewer and less severe outliers.

These differences underscore the importance of tailored modeling strategies. Political fatalities necessitate robust approach to manage the extreme variability and outlier effectively. In the other side, civilian fatalities modelling requires to focus on sensing smaller variations while continue sensitive in detecting rare but significant events. The distinctive strategies emphasize to accurately reflect and predict according to unique characteristics of each dataset through customized approach.

The politically motivated fatalities have a significant surge in May, June, and July 2021 when the conflict was at its peak. In contrast, the civilian fatalities have relatively small and steady trends but always tend to rise when the political fatalities are at their peak, reflecting the spillover effect of political violence on the civilian population during critical periods.

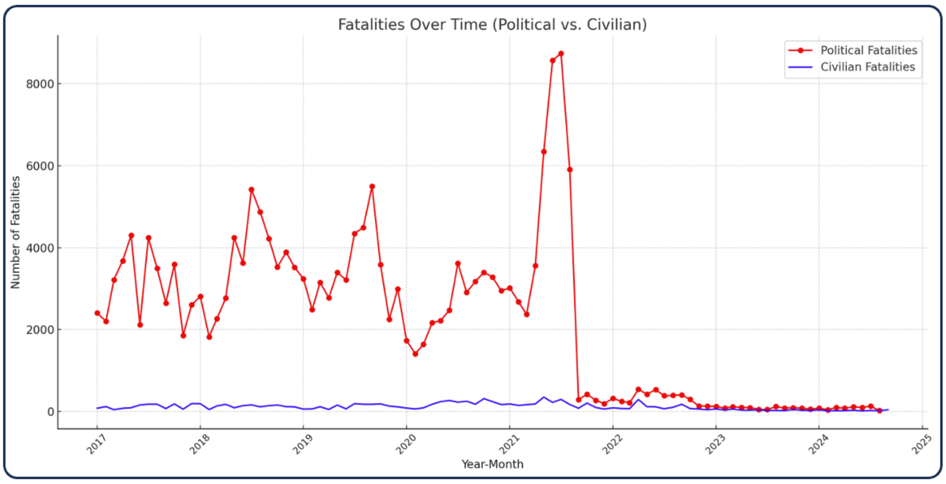

Figure 2. Fatalities Trends Over the Time

Geographical perspective (Figure 3.) indicates that a high level of political violence concentrated in provinces of Nangarhar, Kandahar, and Helmand, areas with high level of conflict. Civilian fatalities, while lower in magnitude, are similarly clustered in these regions, highlighting the overlap between areas that heavily impacted by political violence and civilian-targeting events.

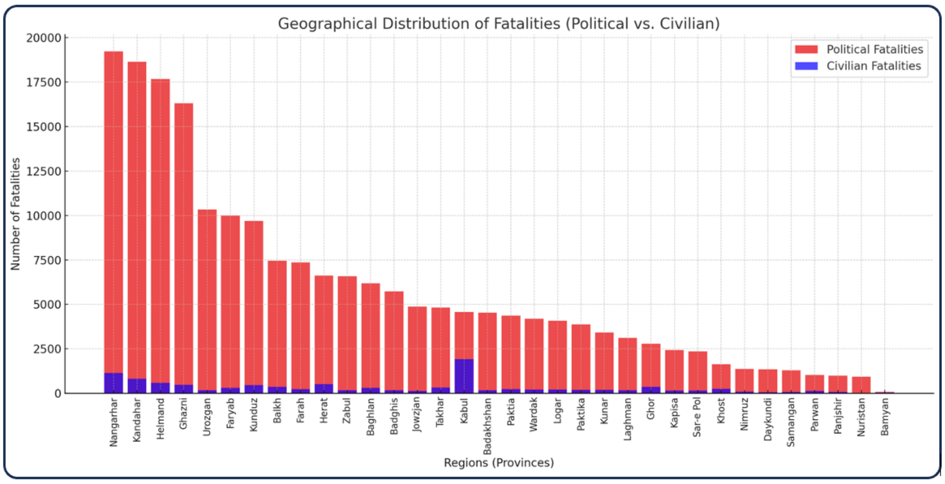

Figure 3. Geographical Spreads of Fatalities

This concludes that there is the dual temporal and geographic effect of conflict, and therefore the focus should be on the development of the strategies for the solution of the violence in the peak periods and in the most affected regions. The interventions that are targeted at these high-risk areas may help to reduce fatalities and to lessen the consequences of politics and violence on civilians.

Demonstration Dataset

It offers a source of important information on the patterns of civil unrest. It includes key variables such as regional information, event dates and the frequency of occurrences. With 37,015 records, the dataset gives a comprehensive overview of the demonstration activities across different regions. The data has a sample of ten records to illustrate its (structure and) depth of information available for analysis.

The histogram highlights a significant skewed pattern, with most regions experiencing few or no demonstrations. This rarity is reflected in the dataset's low mean of 0.04 of and a median of 0, indicating that demonstrations are uncommon practices but, in a few regions, occur at significantly higher frequencies, as the presence of outliers.

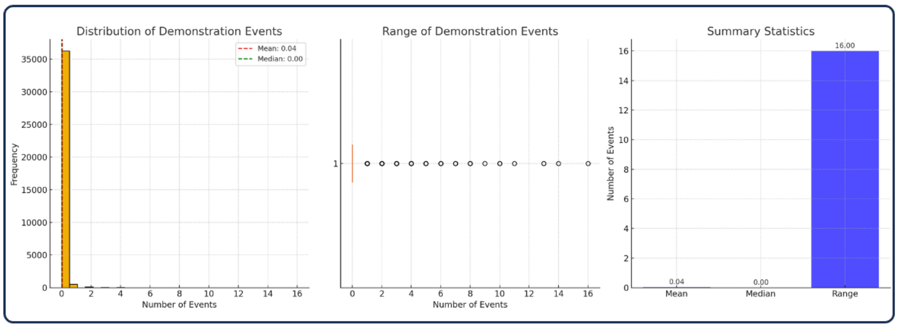

Figure 4. Characteristic of Demonstration Dataset

The boxplot also displays this unevenness of distribution since most of the data points are packed near zero value while a few of them stretch up to as many as 16 events. This also tells us that the data is sparse and a few regions have a high activity.

The summary statistics bar chart is contrasting the low mean and median versus the high range to reinforce the variability in demonstration events. These visualizations that underline the rarity of demonstrations while identifying possible hotspots are useful for resource and attention prioritizing in the unrest prone regions.

The heatmap (**Figure 5**) shows monthly tendencies for several years in more detail, with the highest levels of activity in the middle of 2018 and the beginning of 2022. This detailed visualization of the time and frequency of protests helps in identifying the periodic nature of protests, which is very useful in planning and controlling the protests. Therefore, understanding these temporal and spatial patterns is useful for planning and responding to events.

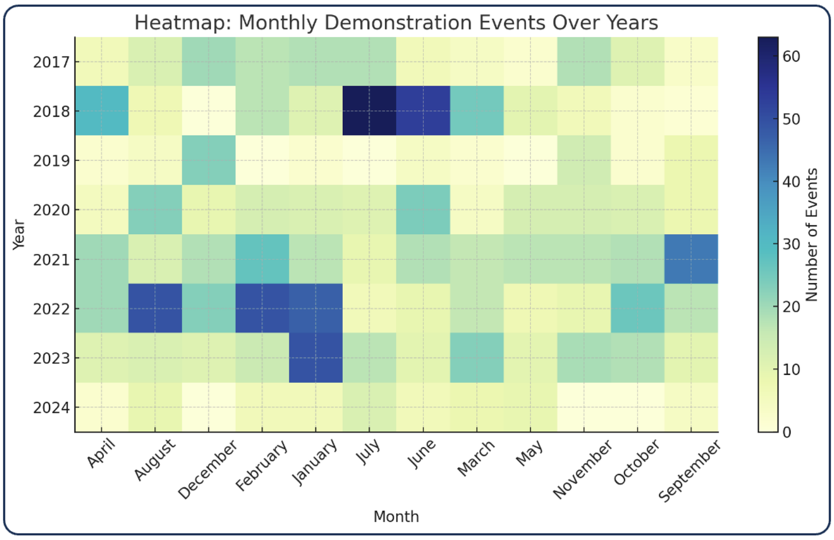

Figure 5. Heatmap of Demonstration Events

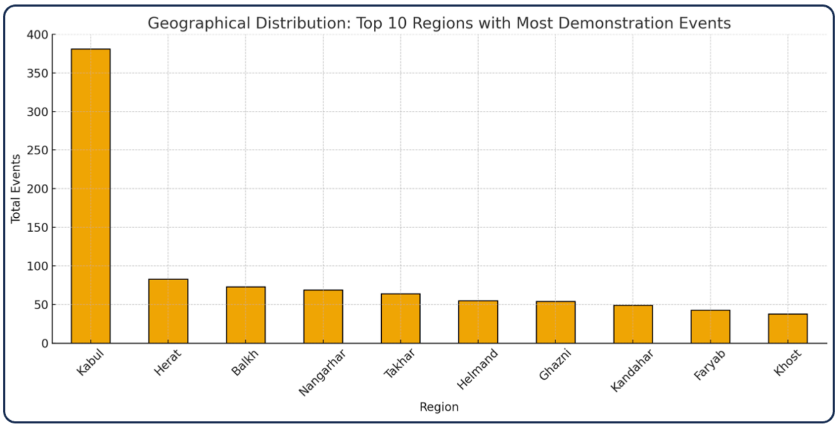

Figure 6. Geographical Spreads of Demonstrations

Incident Dataset

The Reported Incidents dataset (**Figure 5** And **Figure 6**) is containing information about conflict related events like attacks, disruptions and other significant incidents. Major variables are event types, actors and geographical and temporal information. There are 609 records with 30 features in this dataset and it provides a focused, detailed view of reported incidents to help in the analysis of conflict dynamics.

Table 3. Data Monitoring Dataset - A

Country	Region	District	City	UN	INGO	ICRC	NRCS and IFRC	NNGO	Other
Afghanistan	Balkh	Mazar-e Sharif	Mazar-e Sharif (200km W of city on Anchoy-Shibirgan road)	0	0	1	0	0	0
Afghanistan	Nangarhar	Jalalabad	Jalalabad	2	0	0	0	0	0
Afghanistan				1	0	0	0	0	0
Afghanistan				0	0	0	0	0	0
Afghanistan	Herat			1	0	0	0	0	0
Afghanistan				4	1	0	0	0	0
Afghanistan	Samangan	Aybak	Aybak	2	0	0	0	0	0

Table 4. Data News Monitoring Dataset – B

Means of attack	Attack context	Location	Latitude	Longitude	Motive	Actor type	Actor name
Shooting	Combat/Crossfire	Road	36.70904	67.11087	Incidental	Unknown	Unknown
Kidnap-killing	Unknown	Unknown	34.43025	70.44868	Unknown	Unknown	Unknown
Shooting	Combat/Crossfire	Unknown	33.93911	67.70995	Incidental	Non-state armed group: National	Taliban

Aerial bombardment	Unknown	Unknown	33.93911	67.70995	Incidental	State: unknown	Not applicable
Aerial bombardment	Unknown	Unknown	33.93911	67.70995	Incidental	State: unknown	Not applicable
Unknown	Ambush	Road	34.35083	62.2164	Political	Unknown	Unknown
Shooting	Ambush	Unknown	33.93911	67.70995	Unknown	Unknown	Unknown
Unknown	Ambush	Unknown	33.93911	67.70995	Unknown	Unknown	Unknown
Bodily assault	Ambush	Unknown	36.26468	68.01551	Unknown	Unknown	Unknown

The boxplots of incident intensity metrics (**Figure 7**) present the distribution of the severity across variables like *Total killed*, *Total wounded*, *Total kidnapped* and *Total affected*. Most incidents are concentrated near zero, telling that most occurrence are low severity. While outliers are there to showing events of rare but significant with higher impact, for instance that *Total affected* spans from 0 to 48, compared with 0 to 14 for *Total Killed*.

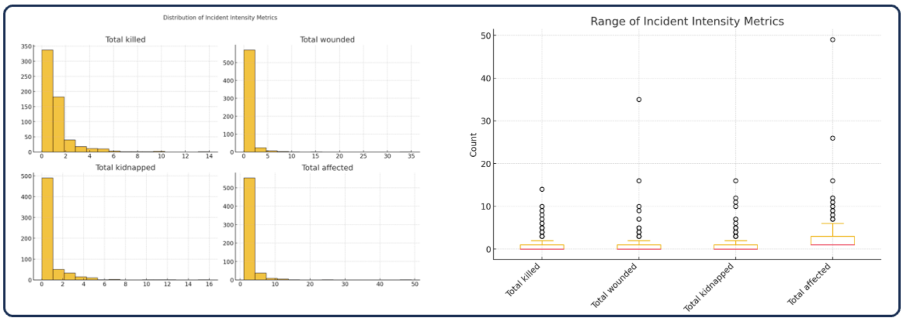

Figure 7. Characteristic of Data News Monitoring Dataset

From the *distribution of incidents by region*, as illustrated on **Figure 8**. we can see which areas have the most frequent incidents. The bar chart highlights which area has more activity that, helping identify areas with strategic concerns or focus for further analysis.

The bar chart shows the *frequency of incident occurrence by region* which underlining obvious differences between locations. Kabul has the most activity, with 65 incidents, while other places have very few. This uneven distribution of incidents highlights the need to focus on hotspots.

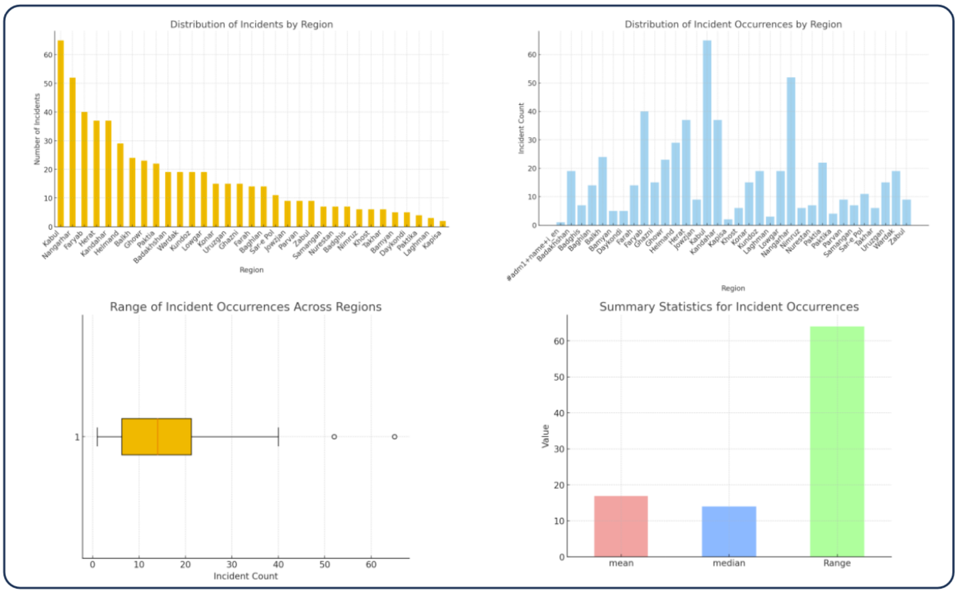

Figure 8. Distribution of Incident by Region

Data News Monitoring Dataset

This dataset, as shown on **Table 5**, adds its records from automated news monitoring and gives real-time events alongside with their context. It is focused on emerging trends, serving major territories and possible conflict triggers. This dataset has 42,021 records and 50 features and is a robust platform for the analysis of the rapidly changing situations in near real time.

Table 5. Data New Monitoring Dataset

where_coordinates	where_description	adm_1	adm_2	latitude	longitude
Kabul city	Iraqi embassy in Kabul	Kabul province	Kabul district	34.531094	69.162796
Kabul international airport	Kabul airport (Abbey gate entrance)	Kabul province	Kabul district	34.564444	69.217222
Jalalabad town	Police District 7 of Jalalabad city	Nangarhar province	Jalalabad district	34.428844	70.455750
Kabul city	Kabul city (district 15)	Kabul province	Kabul district	34.531094	69.162796
Nangarhar province	Nangarhar province	Nangarhar province	Nangarhar province	34.333330	70.416670
Kunduz province	Kunduz province	Kunduz province	Kunduz province	36.750000	68.750000

where_coordinates	where_description	adm_1	adm_2	latitude	longitude
Salang pass	Salang pass (on the main highway linking Kabul with the Soviet border)	Baghlan province	Khinjan district	35.315833	69.038889
Kabul city	Kabul city	Kabul province	Kabul district	34.531094	69.162796
Salang tunnel	Salang tunnel (near, villages near the main Soviet withdrawal route, Salang tunnel)	Baghlan province	Khinjan district	35.316030	69.038710

Analyzing the location based on clashes, illustrated on **Figure 9**, it is revealed that the distribution is highly skewed; the vast majority of areas have only a few incidents. The mean number of clashes per region is 75,329, but the median is only 8, which explains the existence of a few high-conflict regions that increase the overall average. This contrast situation indicating the outliers that significantly driving the overall average upward.

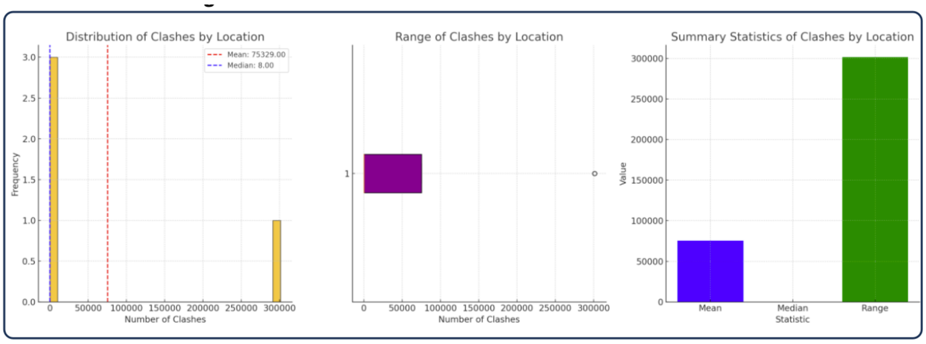

Figure 9. Distribution of Clashes

The box plot, further underscores this disparity clearer that most regions are in a relatively narrow range of clashes, with a few outliers extending far beyond. The range of 301,300 clashes also reveals the enormous difference between the regions that have been most and least affected by conflict over time.

These findings suggest that resources and interventions should have been targeted to the few highly affected areas, rather than the majority of regions. This focused approach can help to bring about the most benefit in the reduction of conflicts where they are most severe.

From the analysis shown on **Figure 10**, some trends in Afghanistan's conflict or clash data are identified, specifically in fatality statistics. There is a noticeable disparity; extreme events inflate the range, whereas the mean (7.44) and median (3.0). Relatively low fatalities resulted from most clashes, while in the other side, outliers indicate high-intensity conflict which drastically influence overall variability. This uneven distribution further emphasizes the importance of considering outliers in conflict analysis to make correct interpretations.

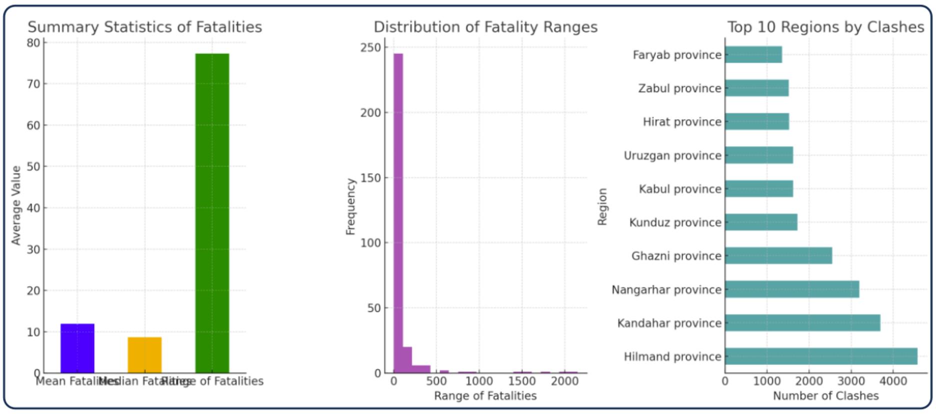

Figure 10. Trends of News Monitored Clashes

Prediction outcomes

The following subsections provide a more precise prediction of the predictive outcomes of the analytics framework developed, and how they can help improve humanitarian logistics and supply chain management. These results show how to use them to develop proactive operational strategies and optimal corridor scheduling and targeted resource allocation by accurately identifying political and civilian fatalities, demonstration patterns, and security incidents. The first subsection is aimed at the political fatalities dataset, which reveals vital temporal and spatial risk insights critical for strategic planning.

Political Fatality Prediction

August is expected to have the most fatalities, over 700, and July, June, and January all over 500. This means that February and September are likely to have the fewest fatalities, which may reveal seasonal patterns or other factors at work at these times.

There is a peak in mid-year and a secondary increase at the end of the year for fatalities, which is likely due to situational or environmental factors.

These findings are useful for allocating resources and designing response strategies, which differ by high-fatality month. Fluctuations in these causes can result in improved prediction and proactive planning.

Civilian Fatality Prediction

With rather monthly fluctuations, the line graph displays the expected year's civilian fatality count. Peak falls in April, June, and October; perhaps due to seasonal influences, operational restrictions, or more violence, while January and May are often peaceful times in comparison.

Demonstration prediction

The line graph displays on **Figure 11** for the year, the monthly trends for protest or demonstration activities. With over 20 events planned in January, protest activities are expected to peak then steadily drop through February, March, and April to a low of around 10 events in April. This implies early in the year low political or social tensions.

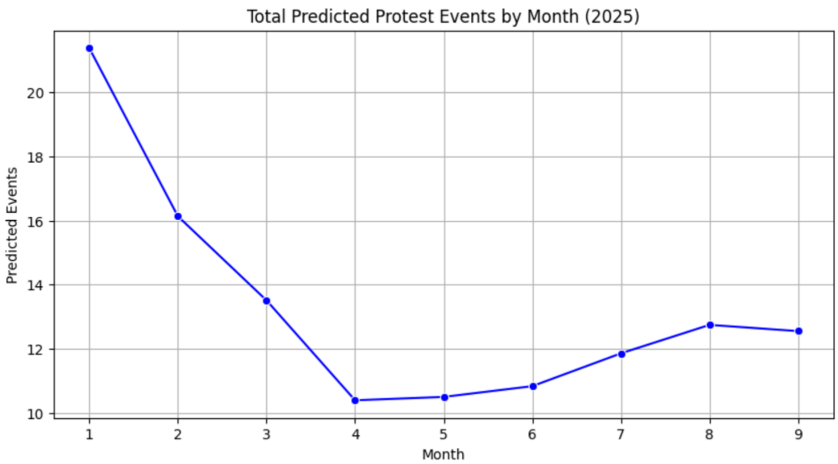

Figure 12. Demonstration or Protest Event Prediction

Protest occurrences steady at low levels with little variation from May to July, suggesting a short relief of problems or efficient dispute resolution. But from August to September, a slow comeback is seen, peaking at about 12 incidents, possibly signifying fresh conflicts or rekindling of tensions.

These trends underline the need of preemptive planning in high-activity months like January in order to stop escalation. The calm of the mid-year also offers a chance for efforts at dispute settlement to keep peace all year long.

CONCLUSION

This study demonstrates how predictive analytics can be effectively used to support the coordination of humanitarian corridors during crises, with

Afghanistan as the case study. The predictive framework developed can pinpoint high-risk times and locations, providing insights for optimizing logistical management, convoy routing, and the strategic deployment of humanitarian assets to enhance the safety and efficiency of aid delivery. The findings highlight the trends in *time* and *space* risks, which can inform decisions on logistics management, convoy scheduling, and the strategic placement of assets to improve supply chain performance. However, the study has limitations, including a narrow study area, the exclusion of *socio-economic* factors, and the lack of real-time data integration. To improve the robustness of the model, future studies should consider a broader geographical scope, incorporate *socio-economic* and environmental factors, and integrate real-time data such as satellite images and live conflict updates to address sudden escalations. Additionally, incorporating dynamic conflict actors and testing the framework in different conflict zones would enhance its generality and practical application. These improvements could refine the predictive framework, enhancing the effectiveness of humanitarian operations, increasing safety, and ensuring timely aid delivery in complex conflict-induced crises.

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