



Machine Learning–Based Terrorism Forecasting Using XGBoost on Large-Scale Global Data

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Abstract: This study offers a Global Terrorism Prediction System that uses the Global Terrorism Database (GTD) to identify trends in terrorist activity using XGBoost, a sophisticated ensemble machine learning method. In order to determine terrorist risk levels based on past characteristics including attack type, geography, target category, weapon type, and temporal trends, the system combines data processing, predictive modeling, and interactive visualization. For spatial querying, data is stored in PostgreSQL with PostGIS, and a FastAPI backend offers prediction endpoints that produce GeoJSON for a dashboard that uses Streamlit. The feature significance and partial graphs are used by the model to provide probabilistic insights particularly for academic and research purposes. The model limits and reporting biases are incorporated on ethical issues. XGBoost Model is superior than baseline models like Random Forest and regular Gradient Boosting, which shows 0.49–51 R^2 in severity prediction. This study also outlines the significance of machine learning and geospatial analytics in global security studies.

Keywords: Global Terrorism Prediction, XGBoost, Machine Learning, Geospatial Analysis, FastAPI, PostgreSQL, PostGIS, Interactive Dashboard, Severity Estimation

1. Introduction

In today's date terrorism is not only a domestic problem but a global challenge in all aspects. There are several factors like geopolitical, socioeconomic etc. which are

making a very complex situation. The analysis process is no more a conventional analysis which relies on some statistical and rule-based methods [1, 2, 3]. The complex nature of terrorism often leads to model non-linear relationship and also requires to find evolving trends from a huge dataset [4].

According to the National Consortium for the Study of Terrorism and Responses to Terrorism (START) (University of Maryland), the Global Terrorism Database (GTD) holds in-depth data of more than 200,000 cases of violent incidents in the world since the year 1970 [5, 6]. It is an excellent multidimensional data that makes it easy to train modern predictive models.

This study aims to present an end-to-end and practical machine learning framework for terrorism severity prediction using the Global Terrorism Database. The main contribution of the paper is not a new algorithm, but a deployable workflow that combines XGBoost, rolling temporal features, PostgreSQL/ PostGIS storage, FastAPI services, and an interactive Streamlit dashboard for analysis and visualization.

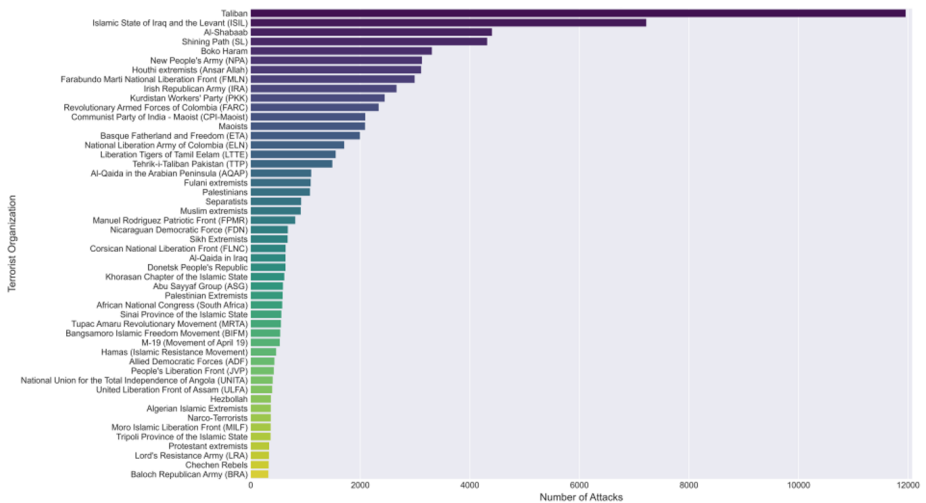


Fig. 1.Top 50 Most Active Terrorist Organizations

This study constructs and analyzes a machine-learning pipeline based on XGBoost (Extreme Gradient Boosting) -A highly efficient gradient boosting algorithm, quite renowned for its performance on tabular and heterogeneous data [7, 8]. The proposed system learns patterns through expected causalities from historical attributes to determine the attack severity. The model generates probability-based estimates for future-like situations rather than modelling terrorism as a self-exciting temporal point process (TPP) [9, 10, 11].

This work aspires to have the following:

- ETL pipeline and spatial storage using PostgreSQL + PostGIS
- Feature engineering and XGBoost model training/tuning
- FastAPI-based REST service delivering GeoJSON predictions
- Streamlit-based interactive dashboard with dynamic world map visualization

The platform focuses on interpretability through SHAP (SHapley Additive exPlanations), reproducibility, and ethical transparency. It is primarily for academic, research and analytical use and can be extended further for security decision-making. The aim of this study is to focus on a modular approach of transforming terrorism data analysis through machine learning and web technologies resulting into interactive and insight driven approach rather than static analysis.

2. Problem Objectives and Motivation

2.1 Objectives

- To create an XGBoost regression model for assessing the severity of the terrorist attack using GTD.
- To produce risk scores like region or grid-based for geospatial visualization.
- To generate prediction artifacts (GeoJSON, CSV) with interpretable risk bins.
- To enable temporal and spatial comparison of risk patterns.
- To provide real-time analytics (timelines, regional summaries).
- To deliver an interactive dashboard with a suitable backend.

2.2 Motivation

As the complexity of the global terrorism is increasing by leaps and bounds hence dynamic analytical methods are the foremost required to replace traditional descriptive approaches. Hence, static thresholds and manual rule sets need to be replaced to capture the non-linear feature interactions in the data [12].

The proposed approach (XGBoost) handles these shortcomings through:

- Excellent handling of missing values and categorical features
- Strong generalization on structured data
- Built-in regularization and parallel tree construction
- Native support for interpretability tools (gain, cover, SHAP)

Automating the full pipeline starting from raw GTD ingestion to interactive risk mapping reduces manual effort, improves consistency and make advanced analytics accessible for researchers, students, and policy analysts.

3. System Architecture and Design

3.1 Viability Analysis

- **Technical Viability**-Built using open-source technologies such as Python, XGBoost, FastAPI, PostgreSQL/PostGIS and Streamlit.
- **Operational Viability**-User Friendly and intuitive dashboard for non-technical users.
- **Economic Viability**-No licensing costs and platform independence.
- **Schedule Viability** - Modular approach providing incremental development and testing.

3.2 Architecture Overview

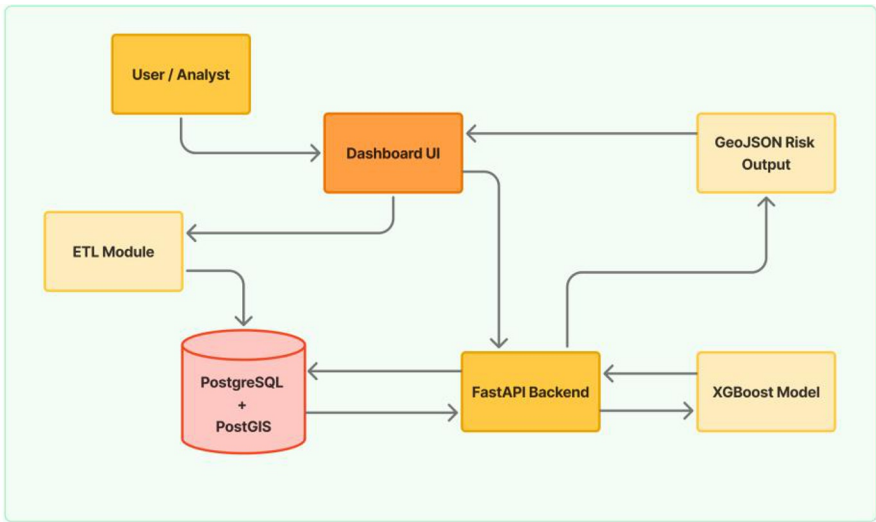


Fig. 2.System Architecture Diagram

Figure2 reflects the different components of the proposed model like an interactive dashboard with data ingestion, integrated with geospatial and machine learning visualizations.

In order to have efficient spatial querying the ETL module works in the following way:

- extracts the raw data from the Global Terrorism Database (GTD)
- loads into a PostgreSQL database with PostGIS support [13].

If the XGBoost model is trained through proper mechanisms like using historical features then it can measure the severity of terrorism casualties. The FastAPI backend perform the role of fetching data, invoking the model and returning predictions as GeoJSON artifacts. These artifacts are then displayed on an interactive dashboard enabling analysts located around the world to explore spatial risk patterns and severity distributions in a reproducible and explainable manner.

3.3 Core Modules

- Data ETL & Spatial Storage
- XGBoost Prediction Engine
- FastAPI Prediction & Data Service
- Interactive Visualization (Streamlit + Leaflet/Folium)

4. Methodology

4.1 Modeling Approach -XGBoost

The final model is an XGBoost regressor, predicting the expected casualty severity. The Prediction Formula is:

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i) \quad (1)$$

Where:

- K = number of trees
- f_k = the k^{th} learned decision tree.
- Each tree $f_k \in \mathcal{F}$, where $\mathcal{F}$ is the space of regression trees

The General Loss function is:

$$obj(\theta) = \sum_i^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (2)$$

Where:

- $l(y_i, \hat{y}_i)$ is the loss function computing difference between the true value y_i and the predicted value $\hat{y}_i$
- $\Omega(f_k)$ is the regularization term which discourages overly complex trees

The Additive function is:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i) \quad (3)$$

Where:

- $\hat{y}_i^{(t-1)}$ is the prediction from the previous iteration
- $f_t(x_i)$ is the prediction of the t^{th} tree for the i^{th} data point

The Regularization Term is:

$$\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2 \quad (4)$$

Where:

- T is the number of leaves in the tree
- γ is a regularization parameter that controls the complexity of the tree
- λ is a parameter that penalizes the squared weight of the leaves w_j

The Information Gain for a split is:

$$Gain = \frac{1}{2} \left[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda} \right] - \gamma \quad (5)$$

Where:

- G_L, G_R are the sums of gradients in the left and right child nodes
- H_L, H_R are the sums of Hessians in the left and right child nodes

4.2 Feature Engineering

Categories include:

- Attack, target and weapon type (one-hot / target encoding)
- Temporal features (year, month, season, rolling historical frequency) [14]
- Geospatial grouping (country and region)
- Contextual indicators (extended incident, prior attacks within a time window)
- Historical casualty means: region_mean, attack_mean, country_mean
- Log casualties transform to reduce skewness in data [15]

Rolling Historical Mean: To represent the long-term temporal trends, a five-year rolling mean of casualties was calculated for each country. The regions that experience repeated terrorism events often continue to show elevated levels of violence over time. The use of rolling mean in place of data from a single year helps to smooth short-term fluctuations and reduce the impact of isolated extreme events on the prediction

outcome. As a result, the features capture gradual changes in regional risk and provides the model with a more stable measure of historical severity.

Frequency Encoding: The dataset contains several categorical variables such as country, region, attack type, target type and weapon type each with a large number of unique values. Applying one-hot encoding to these variables would create a high dimensional and sparse feature space. To avoid this issue, frequency encoding was used where each category is replaced by the number of times it appears in the training data. This approach retains useful information about the category frequency while also keeping the feature space compact allowing XGBoost to learn more efficiently.

Logarithmic Transformation: The casualty distribution in the Global Terrorism Database is highly right skewed. Most incidents involve only a few casualties, whereas a small number result in extremely high casualties. To reduce the influence of these extreme values, the target variable was transformed using the logarithmic function:

$$y = \log(1 + \textit{Casualties})$$

This compression resulted in smaller values, reduced variance, and produced a distribution that was better suited for regression. It also improves training by preventing a small number of severe incidents from dominating the learning process.

Interaction Features: The impact of a terrorist attack depends on the combination of several factors rather than on any single characteristic. To capture these relationships, interaction features were created by combining region and attack type. For example, the same attack method can lead to different casualty levels across regions because of differences in conflict conditions, infrastructure, emergency response, and security measures. These interaction terms allow the model to learn such location-specific patterns more effectively than treating each feature independently.

4.3 Implementation & Tuning

- Grid/random search over learning_rate, max_depth, n_estimators, subsample, colsample_bytree
- Rolling 5-year training windows to capture temporal drift
- GPU acceleration where available
- Persisted pipelines (scikit-learn Pipeline + joblib)

5. Exploratory Data Analysis

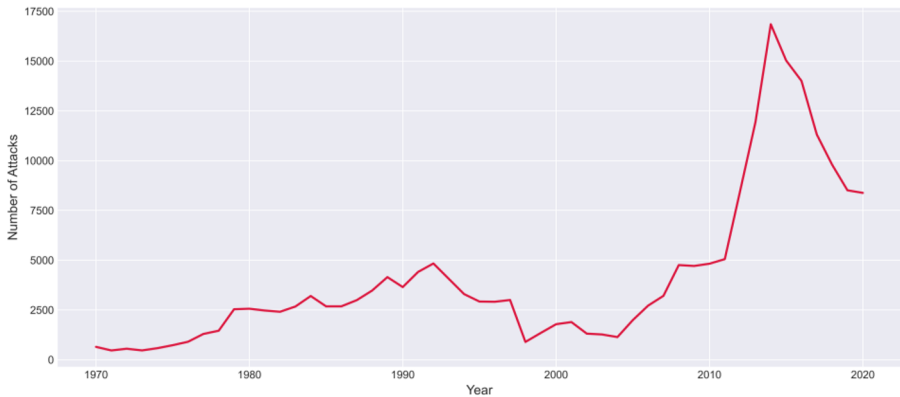


Fig. 3. Attacks per Year (1970–2020)

The line-graph above is depicting the cumulative number of assaults found in the Global Terrorism Database (GTD). Such graphs are helpful in finding out and analyzing the global trends over a timeline. It provides insights on when there was an increase or decrease of terrorism. Such graphs obtained from GTD give a detail insight about the trends of terrorism over decades.

The significance of these is:

- Understanding of historical context
- Years with high geopolitical significance identification
- Feature engineering for the prediction model(e.g., temporal frequency patterns)
- Helping users understand changes in the global security context

This evaluation is the initial phase in data preparation to execute forecasting based on machine learning, where annual changes are used to build relevant features for prediction.

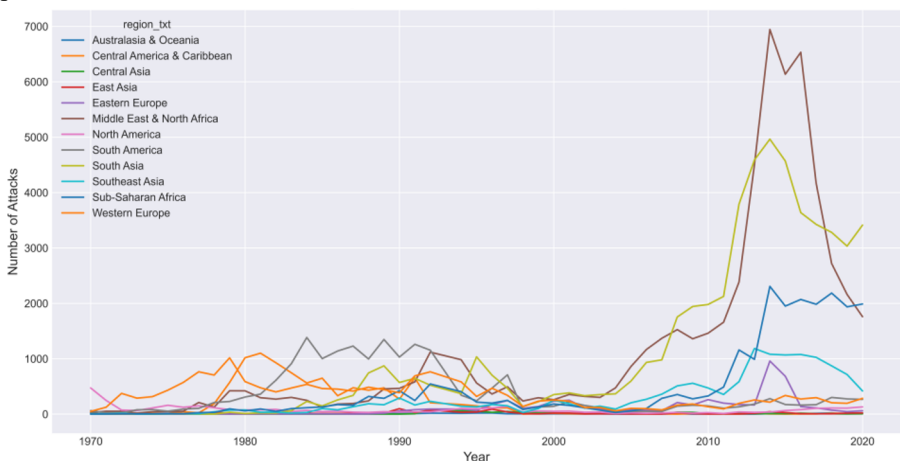


Fig. 4. Regional Terrorism Trends Over Time

This multi-line graph displays the regional trends of terrorist activities across different regions worldwide including the Middle East, South Asia and Africa. The graph also highlights how the focal point of conflicts has shifted over time and that some regions have seen an increment in terrorist activities. This assists in selection of the spatial features for the XGBoost Model.

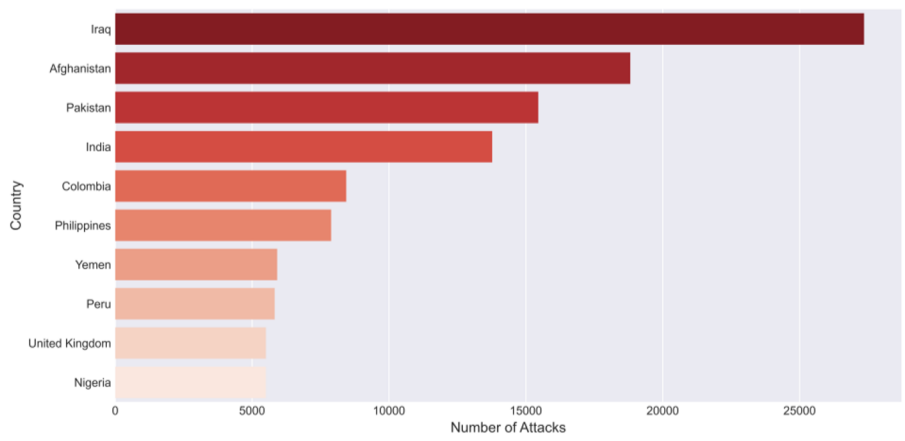


Fig. 5. Top 10 Most Affected Countries

This bar-graph shows the countries that have recorded the maximum number of terrorist incidents. It displays patterns of regional concentration such as a higher density of events in those countries affected by insurgency, internal conflict or geopolitical instability. These hotspots later guide the spatial locations creation for the predictions.

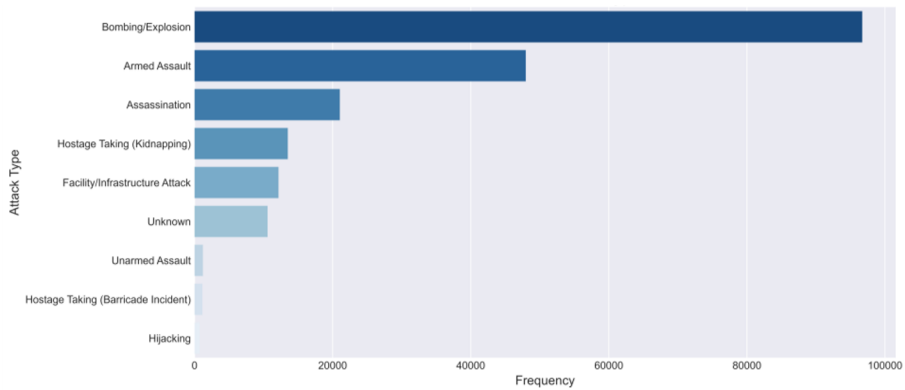


Fig. 6. Distribution of Primary Attack Types

This bar-graph shows the frequency of different types of attacks (such as bombings, armed assaults, kidnappings and many more) happening across the globe. It also helps in determining the most common forms of terrorism worldwide, which is crucial for understanding the actions and behaviour of terrorist organizations and also trends in casualties.

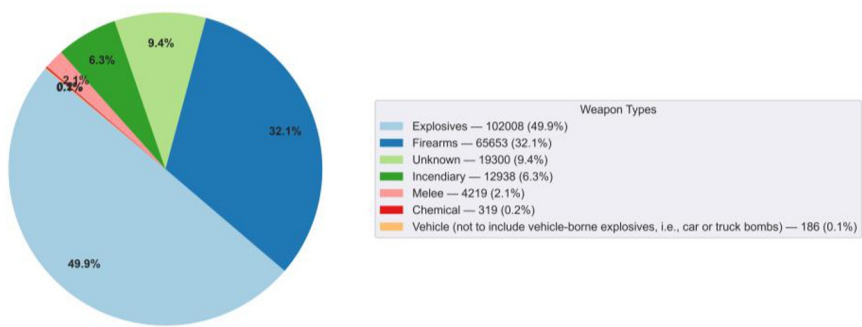


Fig. 7.Weapon Type Distribution

This pie-chart represents the use of different types of weapons during attacks. It indicates the types of weapons used including explosives, firearms and melee weapons as well as the terrorist groups that display a preference for these tactics. This data may help to improve the understanding of attack modalities in particular areas and clarify why areas display a higher predicted probability of attacks by the machine learning algorithm.

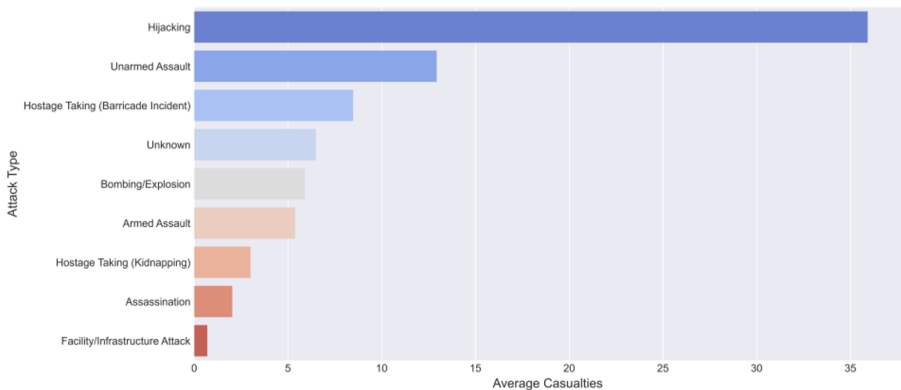


Fig. 8.Average Casualties by Attack Type

This bar-graph indicates the average number of fatalities linked to different types of attack. Additionally, it gives an indication of severity for various types of assaults such as bombings which have a higher death toll while facility attacks having the lowest death toll. These insights help to improve the tuning of the machine learning model and threat evaluation.

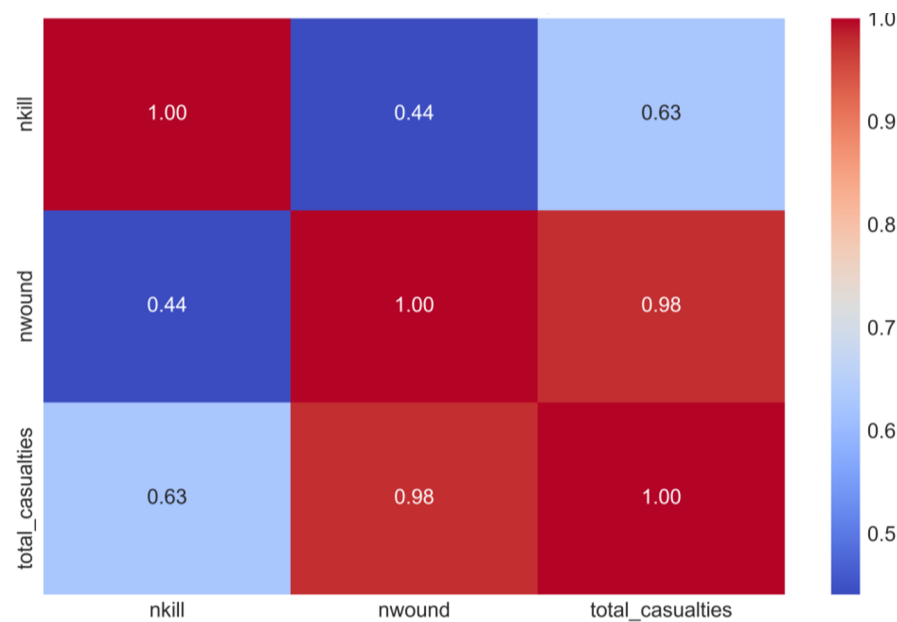


Fig. 9. Correlation Heatmap of Casualty Metrics

This heatmap displays the correlation of attributes like fatalities, injuries and damage. It helps to uncover various relationships in the datalike whether events with high fatalities are linked to a higher number of injuries and vice-versa. These correlations help in validating the internal consistency of the features used for the data analysis process.

6. Model Evaluation & Results

6.1 Performance Summary

Table 1. Key System Performance Metrics

Component	Metric	Result
ETL	Valid records loaded	~100%
Model training	Time (GPU)	~4.8 seconds
Prediction	R ² (severity)	0.49 – 0.51
Prediction	MAE (casualties)	3.41
API	Response time (cached)	~320 ms
Dashboard	Map render latency	< 5 seconds

6.2 Model Comparison

Table 2.Comparative Performance of Regression Models

Model	R ²	MAE	Notes
Decision Tree	0.1103	5.36	Performs poorly, high variance, overfitting.
Random Forest (v1)	0.1502	4.44	Initial baseline, shallow trees
Random Forest (v2)	0.2364	4.02	Improved stability, limited nonlinearity
Gradient Boosting (v1)	0.3154	3.77	Baseline boosting, untuned
Gradient Boosting (v2)	0.3600	4.36	Better pattern capture
XGBoost (Base)	0.3918	4.28	Untuned XGBoost baseline
XGBoost (Rolling Window)	0.4783	3.50	Added 5-year rolling temporal window
XGBoost (Fine-Tuned)	0.4936-0.51	3.41	Best overall performance



Fig. 10. Comparative Analysis of Regression Models

Comparative Performance Analysis: Figure 10 compares the performance of the evaluated regression models using the coefficient of determination (R^2) and Mean Absolute Error (MAE). As the models get advanced the performance improves significantly.

The Weakest performance is of the Decision Tree model with ($R^2 = 0.1103$). This indicates that the model has very limited ability to get the underlying patterns in the data. The Random Forest model has an R^2 value of 0.2364 indicating improved predictability by reducing the prediction error. Gradient Boosting model has an increased R^2 score to 0.3600 also enabling nonlinear pattern learning. The proposed model is the best having R^2 of 0.4936 and the lowest MAE of 3.41 casualties.

This finding supports the importance of combining domain-specific feature engineering with ensemble learning for terrorism severity estimation.

6.3 Model Evaluation Plots

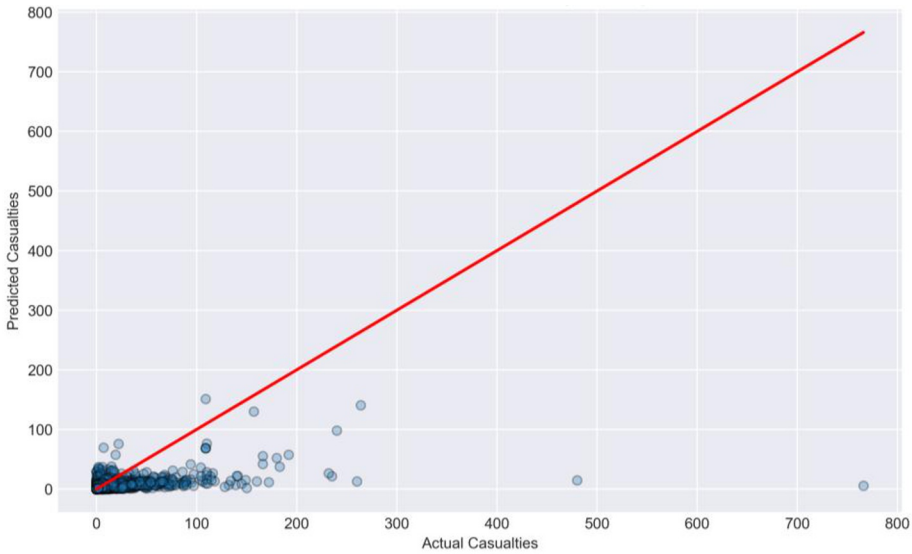


Fig. 11. Actual vs Predicted Plot

Figure 11 demonstrates the correlation between actual numbers of casualties and the predicted numbers using the XGBoost regression model. The majority of observations cluster around the lower range of casualties indicating the highly skewed nature of terrorism severity data. Predictions generally follow the ideal $y = x$ trend for low to moderate severity events, signifying effective learning of dominant historical patterns. For high-casualty incidents the model exhibits increasing underestimation, which is expected due to the rarity and extreme variance of such type of events [16, 17]. This has been known to be challenging in modelling heavy-tailed distributions of casualties.

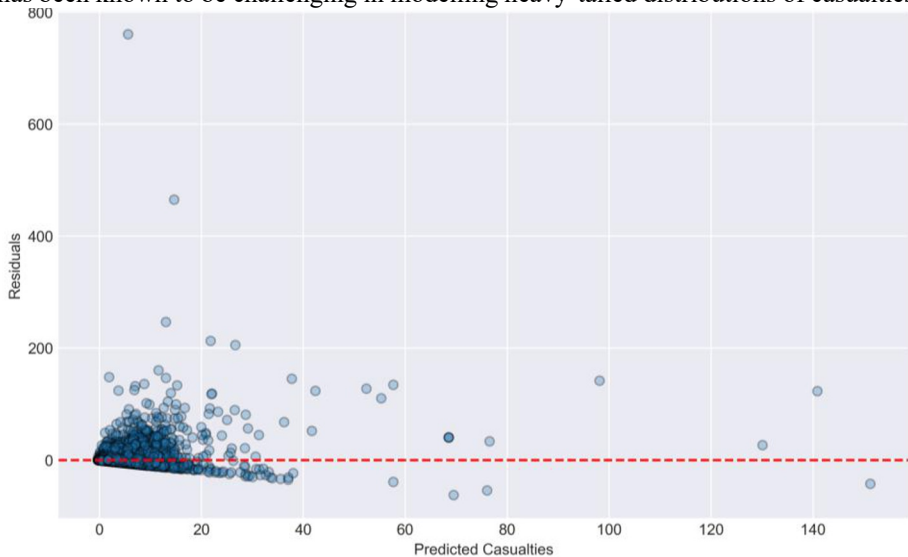


Fig. 12. Residual Analysis

Figure 12 demonstrates the distribution of residuals (actual - predicted casualties) as a function of predicted severity. The lower predicted values are centred around the zero line. This indicates the more frequent events have low systematic bias.

But, for cases like extreme instances of casualties are reflected since the residuals are not constant across all values of the independent variables indicating reduced accuracy of the model. The reason behind this outcome indicates that the model can capture general severity trends very effectively but unable to predict accurately rare and severe attacks which is a major challenge.

6.4 SHAP-Based Explainability Analysis

To improve the transparency and interpretability of the proposed model, SHapley Additive exPlanations (SHAP) were employed to quantify the contribution of each feature toward model predictions. SHAP assigns an importance value to every feature for both global and local explanations. This is done on cooperative game theory [18]. This facility explains the importance of the variables along with their influence on individual predictions.

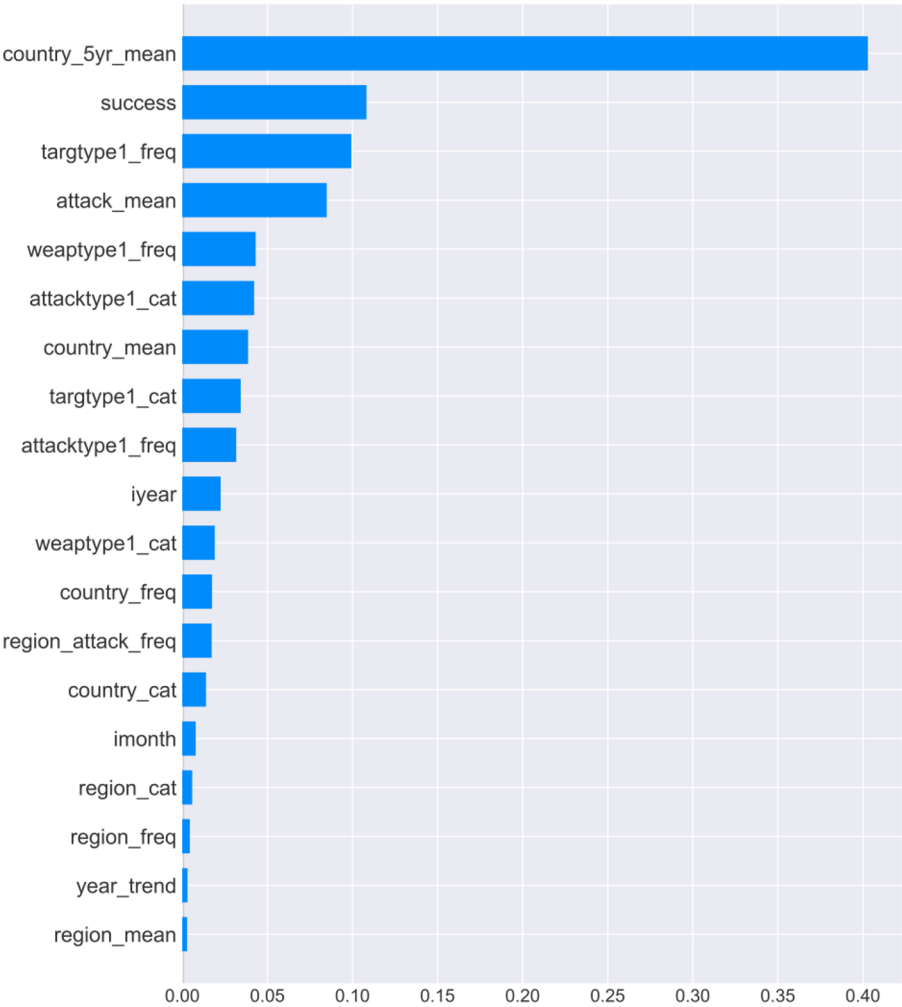


Fig. 13.SHAP Feature Importance (Mean SHAP Value)

Importance of Global Feature: The global feature importance is depicted in the figure 13 which is showing the mean absolute SHAP values for all input features. This indicates the contribution of the global features into the model’s predictions. It is observed that the country_5yr_mean has the maximum influence with a clear margin, compared to the other variables. This indicates that historical casualty patterns within a country have the maximum prediction capabilities of casualty severity.

Some other important features are success, targtype1_freq and attack_mean. Their importance is due to their contribution in prediction in terms of historical trends and operational characteristics. It has also been found that there is a major contribution of the rolling historical mean. It suggests that temporal persistence exhibited by terrorism severity, along with countries experiencing sustained violence tending to face more severe incidents over time.

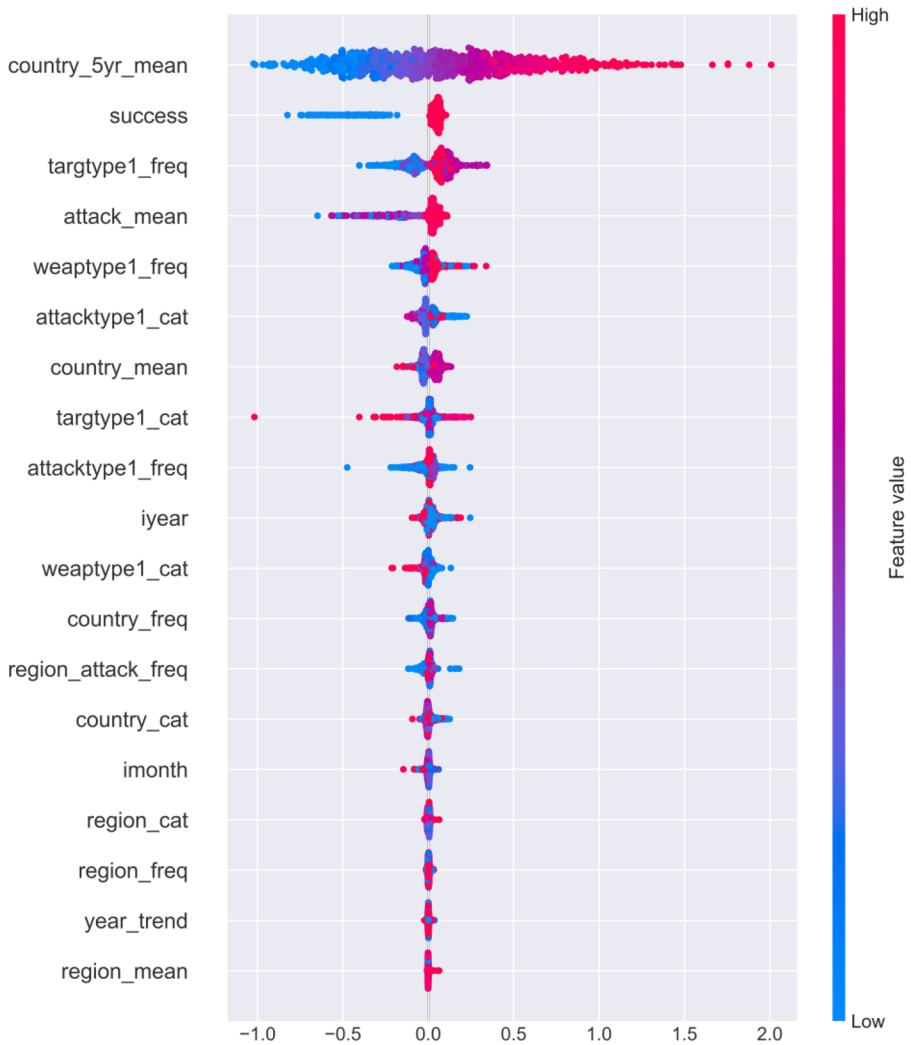


Fig. 14. SHAP Summary Plot (Bee-swarm)

Interpretation of SHAP Values: The SHAP summary plot is depicted in Figure 14. It shows the importance of each feature and along with its influences in the model's predictions. The color red indicates higher feature values and blue indicates lower feature values. On the other hand, the features with a broader horizontal spread indicate a high effect on the output.

The increased casualty severity is indicated by higher values and the lower values indicate a reduction in the predicted outcome. The success feature has also a positive contribution in terms of showing that successful attacks are more likely to result in higher casualties. Some other variables like attack_mean and targettype1_freq has a significant role in the prediction, in which their effects are minimal. As a result we can

see that the model mainly depends on historical trends and operational characteristics for predicting casualty severity.

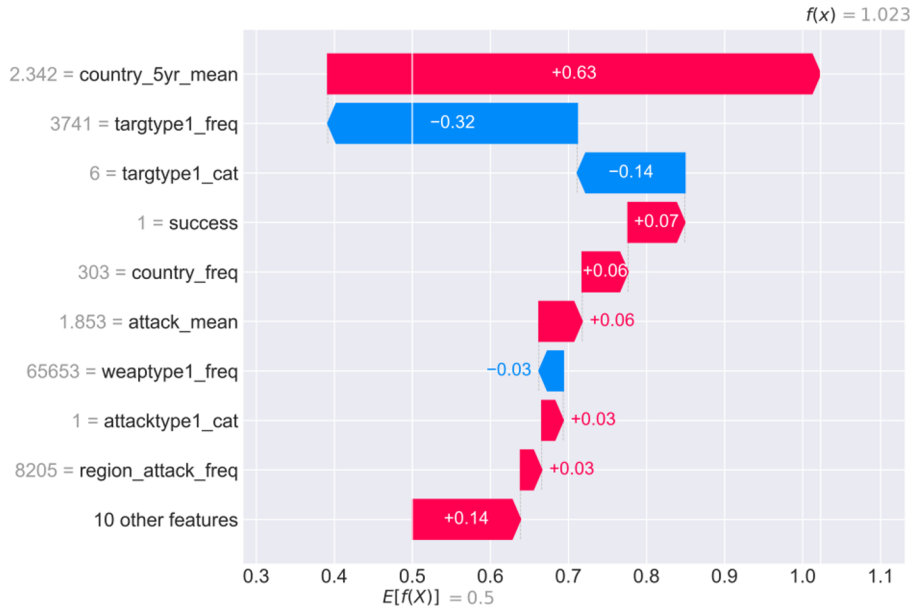


Fig. 15. SHAP Waterfall Plot for Individual Prediction

Explanation of Local Predictions: A SHAP waterfall plot in figure 15 depicts an individual prediction feature. It depicts the flow of the individual features of the model in estimating the casualty severity. From the model's baseline prediction till the final prediction, how each feature is contributing for the final output. The output is either increased or decreased by the feature.

Hence, the feature `country_5yr_mean` is making the largest positive contribution indicated by +0.63, this is responsible for increasing the predicted severity. On the other hand, `targtype1_freq` has the maximum negative effect indicated by -0.32, reducing the predicted value. Some other variables like attack success, historical attack severity, target type and weapon frequency have small positive and negative contributions. So, it can be said that a single feature is not responsible for the final prediction. An integrated influence of several historical and contextual factors is responsible for the final outcome.

Finally, it can be said that the proposed model is affected by interpretable temporal and operational characteristics, five-year rolling country mean, attack success and target-related variables for the final prediction. The combination of global feature importance and local explanations provides greater transparency into the model's behavior and helps explain how individual predictions are produced.

7. Discussion

As we know that terrorism activities are highly uncertain. The present framework can predict moderate terrorism. The data in GTD is highly skewed. It has been seen in the dataset that most attacks result in less number of casualty and a very small percentage of it causes high losses. This skewed data and missing records results to a very challenging accurate prediction.

This XGBoost framework has better predictive performance compared with the other baseline models. The better performance is due to the innovative feature engineering, rolling historical mean, frequency encoding etc. This enabled the model to make efficient capturing of temporal patterns and nonlinear relationships which tree-based methods lagged. This is reflected in the proposed model achieving the highest R^2 score and less MAE compared to other models. This is depicted by the figure 10.

Another significant approach SHAP make the proposed framework work efficiently by identifying the variables which have major contribution in the prediction. It has been observed that the five-year rolling country casualty mean had influenced strongly. On the other hand, attack success severity of historical attack etc have significant contribution. All these make the model more reliable on meaningful historical and contextual information. It is not based on arbitrary correlations in the prediction process.

However, this work has not considered any new Machine Learning algorithm. But a major contribution is the terrorism casualty prediction which combines domain specific feature engineering, XGBoost and SHAP-based explainability. This end-to-end framework improves the predictive performance, maintains transparency and making it appropriate for accurate prediction. As the future work, the proposed framework can work in deep learning, graph-based and spatiotemporal models. This will provide a more efficient model.

There are certain limitations like the Global Terrorism Database comprising missing record, inconsistent reporting including suppressing terrorism data on certain regions. These all are great hindrance in accurate predictions. Apart from this to enhance the model performance socioeconomic, political and environmental factors may be considered. Hence, this framework is capable of estimating the expected casualty severity rather than predicting the actual time or event of the terrorist activity.

8. Conclusion

The proposed system is successful in capturing severity trends. The model achieved ($R^2 \approx 0.49$ - 0.51) for severity estimation, which is a moderate one. On the other hand, the successful integration of data management, data processing, predictive modelling with interactive visualization dashboards has made a user-friendly tool to explore the terrorism data patterns.

As a future work, to improve the system for more accurate predictions the modern deep learning, graph-based and spatiotemporal modelling can be incorporated.

9. Future Work

- Incorporation of Hawkes process models or spatiotemporal GNNs.
- Real-time data ingestion and incremental retraining.
- Fusion with socio-economic, political, and climate indicators.
- Expanded uncertainty quantification and XAI techniques.
- Cloud-native scalable deployment.

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