Unpacking the Complexities of Armed Conflict Fatalities in Bangladesh: A Data-driven Study of Factors, Actors, and Spatial Patterns

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Abstract—Bangladesh, a developing country, faces various challenges that hinder its progress. One significant issue is the high crime rate, along with its lower resilience score on the global peace scale compared with other Asian countries. This study investigates the underlying factors that contribute to armed conflict in Bangladesh. Key questions were explored, such as identifying the regions most affected by conflicts, understanding the involvement of different actors in these regions and events, and developing predictive models for fatality rates and future crime based on various related attributes. To address these objectives, machine learning algorithms and clustering techniques were employed in this research. The ACLED[1] Bangladesh dataset, encompassing conflict events from 2010 to 2021, was analyzed to obtain valuable insights. Clustering techniques, specifically k-means and hierarchical clustering, were applied to classify Bangladeshi Divisions and Cities based on shared characteristics. Furthermore, this study investigates the events and actors associated with each cluster to identify hidden factors.

Machine learning algorithms are utilized to predict fatality rates by employing various techniques, such as pre-trained models and discretization methods. Finally, the focus shifts towards predicting future crimes by utilizing the Random Forest algorithm, which achieved a 97% accuracy rate. The results of this study demonstrated promising outcomes, with high R2 scores which is Goodness of fit measure, indicating a 99% satisfaction level for predicting fatalities. Overall, this study highlights the potential of machine learning to understand and mitigate conflicts in Bangladesh. It emphasizes the importance of interdisciplinary approaches and stakeholder engagement in developing context- specific tools for effective conflict analysis and mediation. By leveraging the findings of this study, policymakers and relevant authorities can make informed decisions to address the increasing prevalence of crime and work towards a more peaceful and secure Bangladesh.

Index Terms—Conflict events, Fatalities, Armed conflict, Hierarchical Clustering, Machine learning, Spatial analysis, and Predictive modeling.

I. Introduction

Bangladesh emerged in the second decade of the twenty- first century as a country to be reckoned with, but there have been numerous conflicts. The current population of Bangladesh stands at approximately 169.17 million[2]. Studying Bangladeshi armed conflict is crucial for understanding violent conflicts in South Asia and developing effective conflict prevention and peacebuilding strategies in the region. The ACLED[1] Bangladesh dataset provides crucial information on the traits and dynamics of these conflicts, including the type of incident, location, participants, and death tolls. Understanding these patterns and trends is crucial for developing effective conflict prevention and resolution strategies. In this study, we investigated the ACLED[1] Bangladesh dataset using machine learning methods and clustering approaches to gain insights into the patterns and trends of conflict events in Bangladesh. We specifically want to answer several questions, including how event types and actor participation affect the number of fatalities, conflict-prone regions, and the events with the highest fatality rates. Additionally, we investigated the use of machine learning algorithms to anticipate crime rates for the following year and to model and predict deaths based on the given variables. Key Highlights of the Study are:

- Utilizes machine learning algorithms and clustering techniques to examine the ACLED[1] Bangladesh dataset, providing a unique approach to understanding conflict events and fatalities in the region.
- Offers insights into how event types and actor involvement impact the number of fatalities, conflict-prone regions, and the most fatality-prone events.
- Uses a range of machine learning algorithms, including ensemble learning methods, to predict fatalities and anticipate crime rates for the following year, providing valuable information for law enforcement agencies and policymakers.
- Achieved satisfactory results, indicating the effectiveness of the study's methodology and approach.

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The results of this study help us understand the patterns and trends of conflict-related incidents in Bangladesh and may allow us to design strategies for conflict prevention and resolution. Other conflict datasets may benefit from applying the machine learning and clustering techniques used in this study to comprehend conflict dynamics and inform policy choices.

II. Related Study

The ACLED dataset [1] we use provides information on armed conflict sites and events in Bangladesh from 2010 to November 2021, including details of the fatalities that occurred during each event. Several studies have been conducted to find the factors related to armed conflict and its impact. Machine learning has promising components for this type of system. Although these studies have contributed valuable insights, it is important to examine their limitations critically. Pavel Rahman et al. conducted a study on crime analysis in Bangladesh and presented performance metrics for dual predictions of geolocation and event types, as well as event count prediction metrics using various models [3]. They put effort to predict future crime only by coordinating values, but related actors in each area are not considered and have a low value of predicting event type. Several smaller forecasting models with sub-models and ensemble methods were used by H. Hegre et al. [4] for Forecasting fatalities in armed conflict up to March 2025. The key challenge of this research is it demands a violent record for a long period, When forecasting 36 months into the future, the model expectantly performed less. An analytical study by SK Chowdhury [5] examined South Asian war and terrorism that employed qualitative and quantitative analyses to compare armed conflict and terrorism in the leading and lagging regions of South Asia. They used already available literature of policy experts to conclusively make a judgment, but they did not provide any specific model to predict factors in conflicted regions. A machine-learning approach to predict crime using time and location data was proposed by Nishat

[6] which Focused on geographical location-based details to predict a type of crime using supervised classification Methods. They did not investigate the actors or events related to the crime and achieved a maximum of 81% accuracy by undersampling. M.M.A. Hashem et al. put forth an approach to predict upcoming crime trends in Bangladesh [7] using Linear Regression. The Lacking of the study is they did not investigate the performance of the other regression methods and only focused on one attribute(murder number) which lacks to capture the non-linearity from multiple attributes.

The Following studies show that armed conflict can depend on various factors and have different impacts on society. This study [8] investigated low-resource nations with weak health systems, armed wars, and natural disasters as major causes of deaths and injuries in armed conflict and trauma worldwide. This research [9] examined the hidden but ongoing cost of conflict to birth weight outcomes in 53 developing countries that have experienced conflict in the preceding 30 years (1990–2018) and showed that armed conflict in the first trimester reduces birth weight by 2.8% and increases low birth weight by 3.2 percentage points. The influence of armed conflict on deforestation in bio-diverse regions of the planet remains poorly understood. Its relationship with illegal agricultural cultivation can hide its effects on deforestation patterns [10]. This Series of studies examined the direct and indirect health effects of armed conflict on women and children (including adolescents) worldwide [3]. This study by badiuzzaman et al. [11] examines rural household liveli- hood decisions, including prospective educational investment in the post-conflict Chittagong Hill Tracts (CHT) region of Bangladesh. The article [12] predicted armed conflict changes globally and regionally for 2010-2050, using a dynamic multi- nomial logit model with core predictors such as population size, infant mortality rates, and education levels. Predictions indicate a decline from 15% to 7% for countries experiencing internal armed conflict. For decades, international societies have attempted to create comprehensive, accurate, and useful early warning systems for political and local disturbances [13]. To reduce conflicts, the UN promotes [14] social progress, human rights, world peace, and peacekeeping cite wars.

Most previous studies have primarily focused on predicting upcoming crime trends and their impact on society. Although previous studies have made significant contributions to the understanding of armed conflict patterns, they lack the detec- tion of hidden actors and events. In addition, identifying the exact areas under larger spatial clusters has not been identified in previous studies. None of the studies used annual fatality rates to predict the upcoming year’s crime rate. This research provides a more nuanced and comprehensive understanding of the complex relationship between the hidden factors of Bangladeshi armed crimes.

III. Methodology

The methodology employed in this study involved the use of machine learning algorithms and statistical analysis techniques to analyze the ACLED Bangladesh dataset. The proposed method is depicted in “Fig. 1”. First, we explain how we preprocessed the data, and how clustering, fatality prediction, and future crime prediction were performed. We then demonstrate the models that provide a better outcome for these investigations.

A. Data Preprocessing

The ACLED Bangladesh dataset was obtained from the Kaggle website. The dataset contains details on armed con- flicts from 2010 to 2021. The dataset includes 31 attributes, including “event type”, “primary and secondary actors”, “ad- ministrative

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regions", "latitude", "longitude", and "fatalities". It covers eight divisions of Bangladesh. Our objective was to identify the areas with the highest fatality rates as well as conflict actors and to forecast fatalities based on the rate of fatalities expected in the following year. The preprocessing and cleaning of the dataset involved handling missing values and removing extraneous data points. Subsequently, we deter- mine the features that are crucial for fatality prediction and clustering.

B. Clustering to detect conflicted regions

Two clustering techniques were used in this study to analyze conflict data and identify regions with the highest fatality rates. Administrative area based features namely **'admin1'**, **'admin2'** and **'fatality'** is used to construct the clusters. Here **'admin1'** is the division and **'admin2'** represents the cities inside **'admin1'**. The first technique was k-means clustering. In a straightforward clustering method, the k-means algo- rithm divides a given dataset into a predetermined number of clusters. The ideal number of clusters was established using the elbow method [15]. Three clusters would be the most appropriate for the data according to the elbow plot, shown in "Fig. 2" with a clear elbow at k = 3. The Ward linkage method, a component of hierarchical clustering, was the sec- ond method used. Using iterative merging, a powerful and adaptable hierarchical clustering technique builds a hierarchy of clusters [16]. Cities with the highest fatality rates in each division were identified using hierarchical clustering. The first consideration was the corresponding divisional areas of cities. A distance matrix was then created using the mean fatality rates for the vicinity of each city. Ward's method was used to link the distance matrix, which produced a dendrogram shown in "Fig. 5" illustrating the hierarchical relationships between cities. The two cities with the highest fatality rates were determined using a dendrogram. Overall, the use of k- means and hierarchical clustering to identify the most violent regions based on fatality rates proved to be useful. While hierarchical clustering enabled a more precise analysis of the cities within each k-means cluster, k-means clustering was successful in grouping the divisional areas into distinct groups.

C. *F*atality Prediction using Regression Models

This study utilized a variety of regression models to predict fatality rates. These models included linear regression, ridge regression, elastic net regression, decision tree regression, support vector regression, and K-neighbors regression. The features we accounted for while clustering is 'event type', 'sub event type', 'assoc actor 1', 'inter1', 'assoc actor 2', 'inter2', 'interaction', 'admin1'. The ex- planation of these features can be found here [17]. It is worth noting that some of these are ensemble learning models, such as Random Forest Regression, Gradient Boosting Regression, and AdaBoost Regression, which combine multiple models to increase the predictive power of the overall model. These models were chosen based on their ability to handle regression problems and their widely recognized effectiveness in predic tion tasks. Using a range of models, we aimed to identify the model that provides the best prediction performance for our problem.

D. Predicting the upcoming year's crime rate

We used Multinomial Regression [18] and ARIMA from the state model to forecast the fatality rate for the coming year shown in "Fig. 6" and "Fig. 7". These models were chosen because they have a track record of handling time-series data and excel at comparable prediction tasks. Our analysis found that using a single feature to predict the crime rate is not much efficient as it provides a low R2 value. For this, we have constructed another approach to solve the issue. As we aimed to predict the severity of these crimes based on fatality, the crime rate was calculated by dividing the total number of fatalities by the total count of fatalities for each year. Afterwards, the crime rate was categorized into five bins. This approach allows us to analyze the crime rate in a more granular way by categorizing the crime rate into higher to lower classification bins. After data preprocessing, feature selection, and engineering, we used four classification models: Random Forest Classifier, Gradient Boosting Classifier, Support Vector Machine Classifier, and KNearestNeighbour Classifier. We evaluated the model's performance using accuracy and R2 score metrics stated in "Table. III" and analyzed their classification reports.

E. *Linear Regression*

Linear regression is a statistical method that is used to model the relationship between a dependent variable and one or more independent variables. In our investigation of fatality predictions, Linear Regression performs better than all other Regressor models. The goal was to determine the values of the parameters[19] that best fit the data. The equation for a simple linear regression is:

$$y = \beta_0 + \beta_1 x + \epsilon$$

where y is the dependent variable, x is the independent variable, β_0 is the intercept, β_1 is the slope, and ϵ is an error term.

The goal of linear regression is to estimate the values of parameters β_0 and β_1 which minimize the sum of the squared errors:

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$$\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

where y_i denotes the actual value of the dependent variable, $\hat{y}_i$ denotes the predicted value of the dependent variable, and n denotes the number of observations. The least-squares method is commonly used to estimate the parameters. This involves finding the values of β_0 and β_1 that minimize the sum of the squared errors:

$$\beta_1 = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sum_{i=1}^{n}(x_i - \overline{x})^2}$$

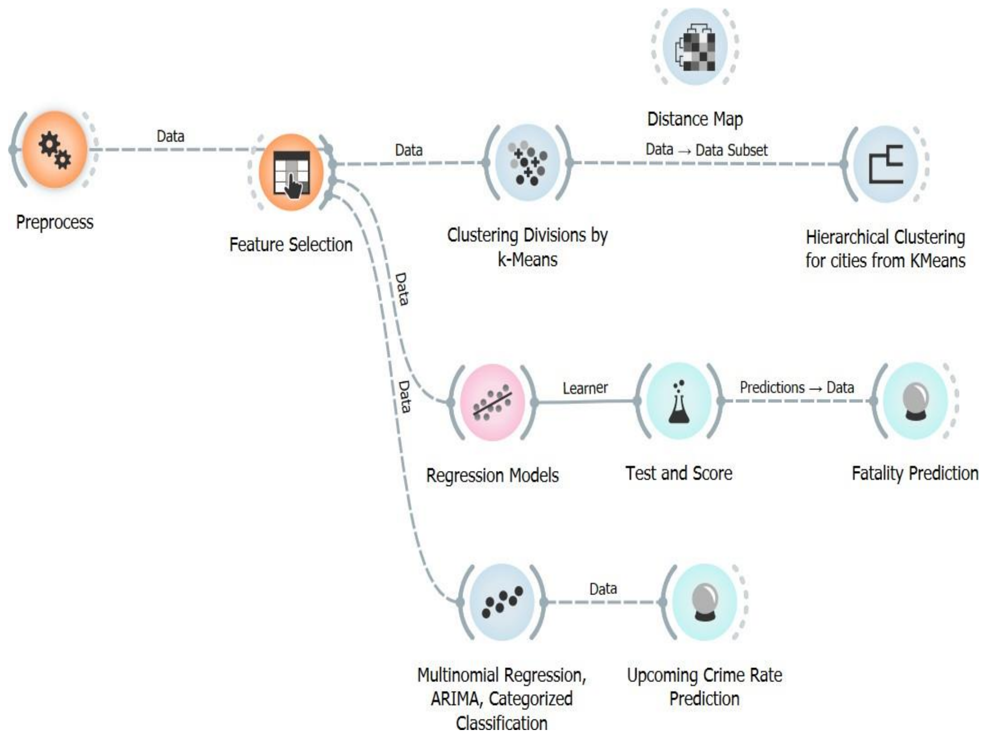

Fig. 1. Methodology Diagram

$$\beta_0 = \overline{y} - \beta_1 \bar{x}$$

where $\bar{x}$ and $\bar{y}$ are the sample means of independent and dependent variables, respectively. In the result of coefficients, b0 (intercept) is approximately **0.0001264** which is reasonable cause many of the events do not contain any fatality.

The quality of the fit can be assessed using measures such as the coefficient of determination (R^2 Score), which represents the proportion of the variation in the dependent variable that is explained by the independent variable.

F. Random Forest Classifier

A random forest classifier is a machine-learning algorithm that builds a set of decision trees and combines their outputs to make predictions. We try to classify the years based on the fatality rate of the years. We convert the regression problem of predicting crime into a discretization problem diving them into 5 groups based on fatality rate. Among different classification algorithms, Random Forest provides maximum accuracy of 97%. The algorithm builds a forest of decision trees [20] by randomly selecting a subset of features and using them to split data at each node. The trees were built independently and the final prediction was made by aggregating the predictions of all trees in the forest. Random forests are highly effective in handling classification tasks and their output can be described by the following equation:

$$\hat{y} = \frac{1}{T}\sum_{i=1}^{T} f_i(x)$$

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the forest. Random Forest utilizes features from the encoded categorical ACLED[17] dataset columns **[sub event type, assoc actor 1, and admin1]**, numerical column **[year]**, and the **mean crime rate** to make predictions through an ensemble of decision trees.

IV. Results and Discussion

In this section, we discuss the outcomes acquired during the training and testing phases. Each algorithm was trained using the training set, and its performance was assessed using a variety of performance measures.

A. Result of K-Means and Hierarchical Clustering

The clusters created by the K-Means clustering algorithm are displayed in this “Fig. 3”. “Fig. 2” shows the approach to find the best value of clusters and it is visible that the effective value of k for the elbow method is 3. First, we detected clusters based on the fatality rates of the divisions. They hold the values of Cluster 1: [’Chittagong’ ’Khulna’ ’Mymensingh’ ’Rajshahi’ ’Rangpur’] Cluster 2: [’Dhaka’ ’Sylhet’] Cluster 3: [’Barisal’] with the fatality rate of **0.45, 0.32, 0.23** accordingly. Later, we used agglomerative hierarchical clustering, which starts with each data point as its cluster and iteratively merges the most similar clusters until only one cluster remains. The top three cities with the highest fatality rates were considered while creating the dendrogram for Cluster 1. The height of the branches in the dendrogram indicates the distance between the clusters being merged or split, with longer branches indicating a greater distance between city fatalities.

According to the analysis, Barisal has the lowest fatality Where $\hat{y}$ is the predicted output, $f_i(x)$ is the output of and Rangpur holds the highest fatality. “Fig. 4” shows the the i^{th} decision tree, and T is the total number of trees in contribution of each division to construct the cluster. When

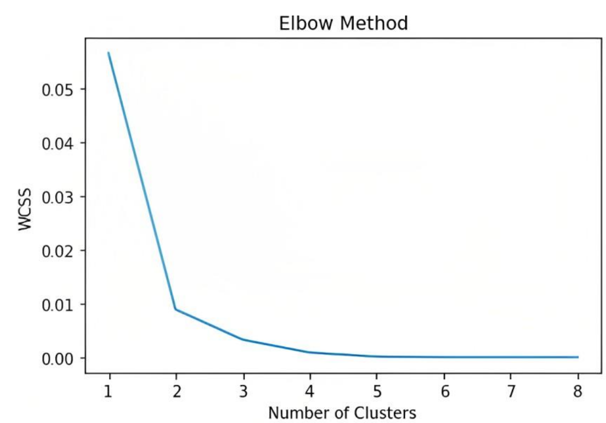

Fig. 2. Detecting optimal value using Elbow Method

Fig. 3. K-Means Cluster for Divisions

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armed conflict is considered in cities, Rangamati has the highest fatality rate. We should also be concerned with Rajbari, Noagaon, Nilphamari, and Maulavibazar among others.

B. Events and associated actors in the clusters

In this section, we continue our investigation to detect the events and actors, that work as a hidden factor in each cluster. As we already detected areas by clustering, by analyzing the actors and events we can take preventive measurements to control the fatality. We can see from “Table. I”, when “Riots” occurred, the majority of fatalities in Cluster 1 occurred.

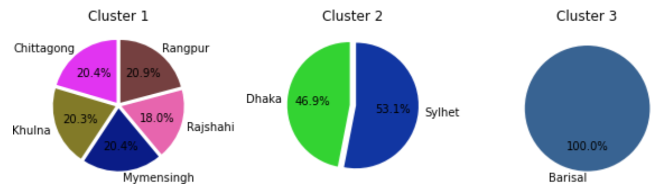

Fig. 4. Fatarity rate score of Divisions in each cluster

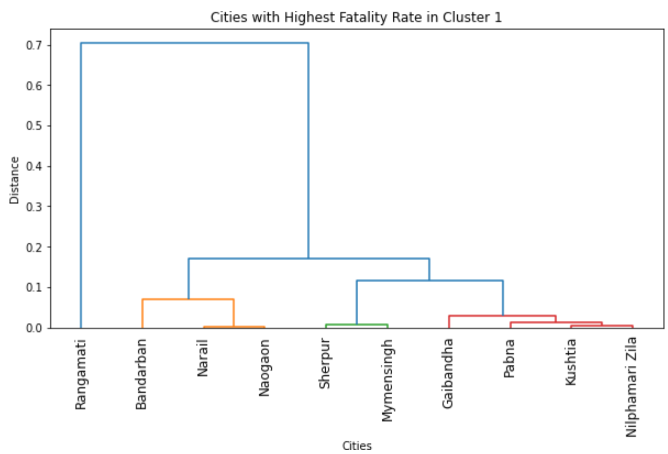

Fig. 5. Hierarchical Clusters from K-Means Results

Violence against civilization was linked to Cluster 2. Law enforcement agencies can conclude statements like “when there are Riots happening in Rangpur and what can be the fatality rate?”

Later we focus on detecting the actors associated with each cluster. In our investigation, we found the following results Top actors in cluster 1: **[“Unidentified Armed Group (Bangladesh)”, “Police Forces of India (2004-2014) Border Security Force”]** Top actors in cluster 2: **[“Rioters (Bangladesh)”]** Top actors in cluster 3: **[“PL: Political Party”, “PLS: Political Party of Students”]** From this analysis questions like “When Unidentified Armed Group (Bangladesh) is the actor, which area should we focus” can be answered.

TABLE I RELATED EVENTS IN EACH CLUSTER

Cluster	Riots	Violence against civilians	Battles	Explosions
1	7050	1151	891	168
2	1288	1827	866	47
3	53	6	33	3

C. Predicting fatalities using Regressor Algorithms

The regression model results, when applied to the selected features, indicate that the linear regression model, which has the lowest mean squared error and highest R-squared value, best fits the data. The Decision Tree Regressor and Random- Forest Regressor models showed low mean squared errors and high R-squared values [21], respectively, and tree-based models performed well. The Gradient Boosting Regressor and Ada Boost Regressor models also performed reasonably well despite having marginally higher mean squared errors and lower R-squared values. Results are summarized in "Table. II". By contrast, the Elastic Net models underperformed, displaying higher mean squared errors and lower R-squared values. Compared to the other models, KNeighbors Regressor model also performed comparably poorly, with higher mean squared errors and lower R-squared values which is Goodness of fit measure of any model while measuring the performance.

TABLE II PERFORMANCE OF REGRESSION MODELS

Model	MSE	RMSE	R2
Linear Regression	< 0.01	< 0.01	0.99
Elastic Net	0.67	0.82	0.11
Decision Tree Regressor	0.05	0.23	0.93
Random Forest Regressor	0.06	0.24	0.93
Gradient Boosting Regressor	0.03	0.17	0.96
Ada Boost Regressor	0.03	0.17	0.96
Suppoet Vector Regressor	0.07	0.27	0.91
K Neighbors Regressor	0.14	0.37	0.82

Since they had the lowest mean squared errors and highest R-squared values, it can be concluded that the linear regression is the best one. Overall, the results suggest that the linear re- gression model may be the best choice for predicting fatalities based on selected features.

V. Predicting upcoming years crime

Our goal was to use various machine-learning algorithms to predict the severity of crimes based on the number of fatalities. However, our analysis based on ARIMA [22] and multinomial regression found that the crime rate in the upcoming years had a lower correlation with the predicted values. However, both models predict an increasing crime rate in the upcoming years.

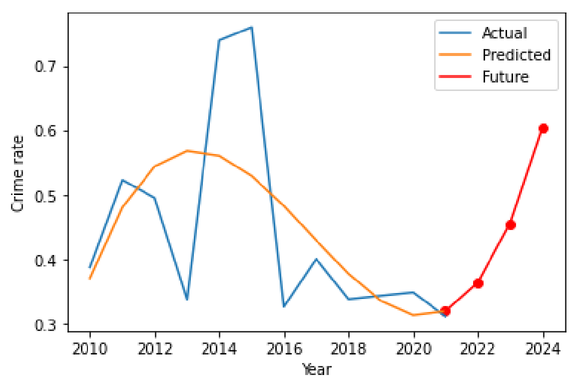

Fig. 6. Prediction of Multinomial Regression

To transform the regression problem into a classification problem, we categorized the crime rate into five bins, based on the total number of fatalities per year. Each bin was indexed with a mean value ranging from [(0.31, 0.338], (0.338, 0.345], (0.345, 0.395], (0.395, 0.517], (0.517, 0.76]]. Index values represent the lowest and highest crime rates, respectively. The aim of this transformation was to classify years into categories based on the fatality rate. For the upcoming years when we somehow conceive the related events in advance, we can use this model to predict the crime rate in advance. To achieve this, the crime rate was calculated by dividing the total number of fatalities by the total number of fatalities per year.

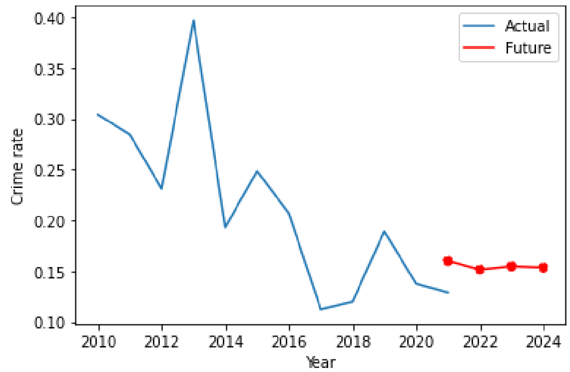

Fig. 7. Prediction of ARIMA Model

Then the classification was performed using multiple features namely **[‘event type’, ‘sub event type’, ‘assoc actor 1’, ‘admin 1’], ‘inter 1’, ‘fatalities’, ‘year’]**

TABLE III PERFORMANCE METRICS OF DIFFERENT CLASSIFICATION MODELS

Model	Accuracy	Precision	Recall	F1-score
Random Forest	0.978	0.98	0.98	0.98
Gradient Boosting	0.948	0.96	0.95	0.95
Support Vector Machine	0.849	0.85	0.82	0.83
K-Nearest Neighbors	0.866	0.87	0.86	0.86

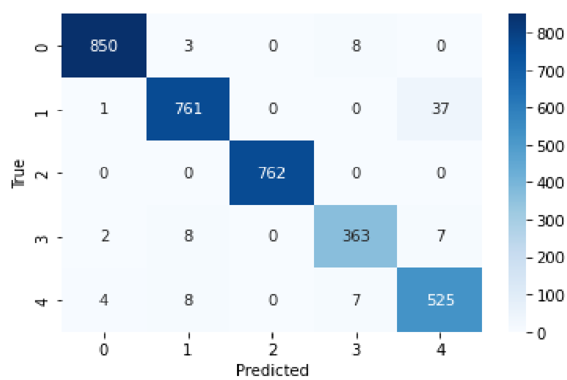

Fig. 8. Confusion matrix of Random Forest

The results in “Table. III”, showed that the Random Forest classifier achieved the highest accuracy and F1-score compared with the other models. The crime rate severity is classified into five bins with f1-score metrics of 0.99 for the first bin, and 0.95, respectively, for the fifth bin. The maximum accuracy of Random forest comes to 98% after tuning the model with the parameters max depth=20, max features=’sqrt’, min samples leaf=1, min samples split=5, and n estimators=200.

VI. Conclusion and future work

The research concluded that the clustering and regression methods can be useful in predicting and analyzing conflict- related fatalities and crime rates. In this study, we conducted a comprehensive analysis of the conflict areas and crime rates. From the previous data, an interesting pattern shows that violence increases greatly after the national election. **Our predictive models suggest that the crime rate will be increased accordingly**. To prevent such events we clustered conflict areas based on fatality

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rates, the actors involved, and the reasons for fatalities. We also predicted fatality and crime rates using various regression algorithms and found that our models performed well. Our findings have important implications for conflict prevention and crime reduction. By identifying the factors that contribute to conflict and crime, we can develop effective strategies to address these issues and promote peace and security. There are several possible directions for future studies based on this research. First, we could integrate additional data sources, such as socioeconomic or political data, to gain a more comprehensive understanding of the factors contributing to conflict and crime. We can also investigate temporal patterns in more detail by exploring weekly or daily fatalities, for example, to gain a more nuanced understanding of the dynamics of conflict and crime over time. Overall, this study provides a foundation for future work on conflict prevention and crime reduction. By continuing to explore and analyze the factors contributing to conflict and crime, we can promote peace and security in our communities.

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