



## Machine Learning Model for Predicting Terrorist Attacks in Sub-Saharan Africa

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### Abstract

#### Keywords:

Terrorism,  
Banditry, Attack,  
Security, Model,  
Machine Learning,  
Sub-Saharan Africa

Security of lives and properties is an essential aspect of governance which any serious government of a nation must not toy with. The assurance of safety of the populace however is not to be left in the hands of the government alone. If adequate security is to be achieved, there must be participation from corporate bodies, non-governmental organisation, communities, and even private setup. The Sub-Saharan Africa is probably becoming a den of terrorists. The operations and activities of the terrorists in the Sub-Saharan are so volatile that their next possible move are difficult to predict. To this end, this study is poised to establish machine learning models capable of predicting the terrorists attack in Sub-Saharan African by relying on the past reservoir of attacks data on the continent. The study which considers the peculiarity of attacks in the Sub-Saharan region obtained past data from the Global Terrorism Database, spanning from 1970 to 2017 with data on Sub-Saharan African majorly utilized. The approach adopted sees the study deploying Random Forest Method and the Long-Short Term Memory (LSTM) Technique. The results show that the two methods deployed are capable of predicting terrorist attacks in Sub-Saharan African with prediction accuracy of 85.1% and 80.1% respectively. In the nearest future, it is hoped that this study will be further researched in order to evolve into a data-driven system that predicts with actual data and information, the next probable attacks of the terrorists in terms of time and place.

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#### Background to the Study

Security is a centrally and globally concern issue which no government of any nation could toil with. Security in general tone, refers to protection of lives and properties. Whitman and Mattord (2012) defined it as 'the state of being secured'.

The field of security is a domain that is generally concerned with protection of assets. It refers to a paradigm, a philosophy and a way of thinking defensively. It aims at protecting and mitigating assets against threats. According to Ajayi et al. (2019), security risks are on the rise and it is unfortunate that many organizations do not have necessary security measures to help protect for possible threats.

Security from this study's perspective, can be described as a measure of guarding against the penetration of or attack from an opposition. It is seen as a system that entails putting in place men, method, and mechanism that watches and alerts when the inflow of an intruder is noticed.

Insecurity is an issue of great concern in most countries of the world. Researches have shown that crisis in most part of the countries have led to unsettlement of the citizenry (internally displaced) and majority ending up as refugees and migrants. Many people live in the fear of the unknown, not knowing the next city or country that would be attack and when. This aligns with Beland (2005) assertion, which defined Insecurity as the state of fear or anxiety stemming from a concrete or alleged lack of protection. Even when government deployed troops to certain area for certain period of time, the terrorists in their own wisdom migrate at such a time to attack another location. Insecurity is the direct opposite of security where lives and properties are not secured. Achumba et al. (2013) sees it as the antithesis of security. Among the many duties the United Nations is saddled with is the maintenance and preservation of international peace and security.

Terrorist groups in the West Africa region include Boko Haram and Ansaru in Northern Nigeria, and Ansar Dine (or Ansar Eddine), al-Qaeda in the Islamic Maghreb (AQIM) and the Movement for Oneness and Jihad in West Africa (MOJWA), as well as al-Mourabitoun and *Front de Libération du Macina* (FLM), AQIM affiliates, all in Mali. The Boko Haram also operates in Chad, Niger and Northern Cameroon. The Southern African has al-Shaba on the list of their foreign terrorist; this is aside the presence of al-Qaeda.

Eastern Africa has two primary terrorism hotspots. In Somalia, we have the Al-Qaeda, who have a strong foothold in the region. Ethiopian intervention in 2006 added fuel to the fire after the establishment of the Islamic Courts Union (ICU) earlier in the 2000s. In 2005, Al-Shabaab was established as an offshoot of the ICU to become the most relevant actor in Somalia. Since then it has carried out extended attacks on Uganda, and Kenya. Similar to Somalia, the eastern part of the DR Congo has been a hotspot since its own civil war from 1997 to 2003. Groups such as the Allied Democratic Forces and Lord's Resistance Army from Uganda, under pressure from Ugandan

security forces, established themselves in eastern Democratic Republic of Congo (DRC) along with others in the aftermath of the Rwandan genocide in 1994. The Islamic State in the Central African Province (IS-CAP) also contributed to the instability in northern Mozambique (Anneli, 2021).

Security challenges throughout Africa have evolved in nature and are a lot more complex. Sierra Leone has also become a central player in a growing arms trade on the continent, along with the Democratic Republic of the Congo, Liberia, Somalia, Sudan, and others. Estimates place the value of the arms trade in Africa at \$1 billion annually and include everything from handguns and assault rifles to rocket-propelled grenades and even antitank and anti-air missiles. In some countries, AK-47 automatic assault rifles are available for only \$6. This trade fuels conflict in many places throughout the continent and has contributed to violence on a dramatic scale. In South Africa, for example, small arms have become the leading cause of unnatural deaths in the country (Matt and Guy, 2006). An additional facet of this problem is the increasing rate of arms trafficking that originates on the continent. Some have argued that Eastern European arms such as the AK-47 no longer constitute the bulk of trafficking. They point instead to a growing arms production industry on the continent in countries such as Egypt, Nigeria, and South Africa (Eric, 2007).

According to Global Terrorism Index (2022), Sub-Saharan Africa accounted for almost half of global terrorism deaths in 2021. The report found that violent conflict remains a primary driver of terrorism, with more than 97% of terrorist attacks in 2021 taking place in countries in conflict.

The report found that 48% (3,461 people) of all terrorism deaths globally occurred in the four sub-Saharan African countries of Burkina Faso, the Democratic Republic of the Congo, Mali and Niger. ISIS, an Islamist militant jihadist group, replaced the Taliban as the world's deadliest terror group in 2021, with 15 deaths per attack in Niger. Terrorism deaths in Niger more than doubled in 2020, rising to 588.

Nigerian President Muhammadu Buhari wrote at the time of the Taliban takeover of Afghanistan last year that the "war on terror" was not over, it was instead shifting to Africa. He cited the rising threat of terrorist groups in Africa, from Boko Haram in

Nigeria and the Sahel region to al-Shabaab in Somalia, and the rising insurgency in Mozambique. The Foreign Minister for Algeria, Mourad Medelci added his voice by saying: 'For countries bordering the Sahara Desert, terrorist attacks continue to pose real threat' (Anathi, 2022).

The fire of Xenophobia has not been totally quenched in South Africa. Claasen (2017) said South African Xenophobia has national and regional consequences. The violence that took place in 2008 and 2015, as well as the hate crimes that occur with everyday regularity, present a pressing human rights concern. Gavin (2008) pointed out overwhelming poverty, marginalization and inequality within and between SADC member states, exacerbated in many cases by globalization, as the bedrock of human insecurity in Southern Africa. The author further highlighted unemployment and human development challenges as additional pressures on states to meet the human security needs of citizens. Apart from poverty and underdevelopment, the author picked out weaknesses and failures of governance as the single most important threat to the security of both citizens and states. Calcott (2021) put it that, given this reality of relative deprivation, as well as abject deprivation and poverty, South Africans sought an outlet for their frustration, and foreign immigrants provided an easy target.

Busher (2014) stated that, One of the most striking features of the way terrorism and counter-terrorism have evolved in Sub-Saharan Africa during the last 3–5 years has been the apparent resilience of terrorist groups to increasingly large-scale national and international responses, as well as the scaling up of domestic counter-terrorism efforts. The African Union has continued to support counter-terrorism both through the various plans and protocols associated with its Counter-Terrorism Framework and through the deployment of African Union peacekeeping forces.

In spite of these different strategies adopted, several of Sub-Saharan Africa's most prominent terrorist groups have thrived. The Boko Haram resurgent, after a large-scale assault on the group by Nigerian security forces succeeding in killing its leader and around 800 Boko Haram members in 2009 (Agbibo, 2013, Zenn, 2013), and with the attack on the Westgate shopping mall in Nairobi, it is worrisome to see how the group regroup, re-strategize and resurface.

The Global Terrorism Index (2020) reported in 2021, stated that, the expansion of ISIL affiliates into Sub-Saharan Africa led to a surge in terrorism in many countries in the region. This study therefore, using available data in the Global Terrorism Database and that specifically related to Sub-Saharan Africa, experiments and establishes the capability and accuracy of machine learning model in predicting bandits attacks in the Sub-Saharan region of Africa.

No doubt, the effects of bandit and terrorist attacks on African Cities and Countries cannot be over-emphasized. Aside thousands of lives that have been lost, several habitations are no more habitable as the inhabitants have fled for refuge somewhere safer. Africa Report on Internal Displacement (2021) reported that around thirty million Africans were forcibly displaced in 2021 as a result of different insurgent attacks. The Global Terrorism Index (2021) also features nineteen (19) African Countries among the first fifty (50) countries most affected by terrorism.

Therefore this study seeks to come up with machine learning model capable of predicting terrorist attacks in Sub-Saharan African, with high accuracy. Alongside the main aim, the study is also expected to achieve the following objectives:

- i. researched into literature on insecurity and terrorisms around the unsettled, crisis-stricken cities and countries in Sub-Saharan Africa;
- ii. relative analysis of the various models used in terms of prediction accuracy;
- iii. report the peculiar nature of attacks on countries in the region.

Many researches have been conducted on security issues (Albert, 2003; Beland, 2005; Nwoli, 2006; Booth, 2007; Hettne, 2010; Aliyu, 2012; Omede, 2012; Achumba et al., 2013; Onifade et al., 2013; Udeh et al., 2013; Ewetan & Urhie, 2014; Ivancik et al., 2014; Onoja, 2014; Chinecherem & Iregbenu, 2015; David & Dominika, 2015; Omede & Omede, 2015; Abdulrahman & Zuwaira, 2016; Robin, 2016; Ede, 2018; Sulaiman et al., 2018; Ajayi et al., 2019; Obarisiagbon & Akintoye, 2019; Glusac, 2020). Review of these works however shows that emphasis was not specifically on Sub-Saharan African region which as at the time of writing this article is gradually being taken over and probably becoming the deadliest region in the world when it comes to terrorism.

The two wings to this study are to examine the trends of terrorists' attacks and activities in the Sub-Saharan African region, and also to establish machine learning model capable of predicting these terrorist attacks.

### Related Works

Different approaches have been adopted as counterterrorism to achieve sustainable cities. However and most recently, machine learning techniques have been adopted to ensure accuracy of the prediction. Few of the most recent works on this subject that adopted machine learning methods are discussed.

In Ding et al. (2017), the study demonstrated a novel method using relatively popular and robust machine learning methods (NNET, SVM and RF) to simulate the risk of terrorist attacks at a global scale based on multiple resources, long time series and globally distributed datasets. Historical data from 1970 to 2015 were used to train and evaluate the model. GIS Software and C++ Programming Language were used to preprocess the datasets. The model predicted with an accuracy of 96.6%. The author however acknowledged the need to make better analysis and prediction of terrorist attacks across different regions, countries and continents between different years, to further validate the level of accuracy of the result.

M.Irfan et al. (2020) investigated AI-based solutions to understand the different factors of terrorism in order to make accurate future prediction of terrorist attack. The work which identified five different factors, deployed three (3) different traditional machine learning techniques, Neural Network, and Deep Neural Network. The result of the experiment carried out on data from the Global Terrorist Database (from 1970 to 2018) shows DNN as the best predictor with an accuracy value of 95% compared to other deployed techniques which returned 83% accuracy.

Xiaohui (2021) developed a classifier framework for the accurate and efficient prediction of different terrorist organizations and their attacks. The study made use of data from the GTD (Global Terrorist Database) from 1970 to 2017 and applied feature selection (SelectKBest) to select the most important variables and filter the redundant ones. The study constructed five classification and prediction models (Decision Tree, bagging, Random Forest, Extra Tree, and XGBoost) and utilized a 10-fold cross validation method to verify the performance and stability of the model. The

result shows XGBoost and Random Forest give the best accuracies of 97.16% and 96.82% respectively, of the activities of the various terrorist organization.

The work of Steven et al. (2022) presented a machine learning model that uses localized data to predict the occurrence of terrorist attacks in the United States. The study employed Ensemble method, comprising of Random Forest, AdaBoost, and Neural Networks (FFN and LSTM) techniques. The model was trained on multimodal inputs, utilizing localized news data from the Global database of Events, Language and Tone (GDEL) and Global Terrorism Database (GTD). Data considered for the experiment were from 2015 to 2018. The result proved that machine learning (Random Forest) can predict likely terrorist attacks. The result also showed the potency of multimodal approach to the dataset used. However, the authors pointed out that, better machine model that controls noise should be adopted. Dataset used can also be of larger quantum.

### Methodology

Steven et al (2022) which came up with Random Forest approach as the most accurate method, recommended a better model that controls noise. To this end, this study adopts Ensemble Machine Learning approach deploying Random Forest Machine Learning approach and Long Short Term Memory Recurrent Neural Network Deep Learning approach.

The following procedures shall be followed in achieving a successful analysis and actualizing the objectives of this study:

- i. **Data Collection:** Previous data on security/insurgent/militant attacks on cities and countries across Sub-Saharan Africa were collected from the Global Terrorism Database (from 1970 to 2017).
- ii. **Data Preprocessing:** Collected data were further processed using data cleaning technique (removal of incomplete/missing data)
- iii. **Feature Selection:** Filter feature selection technique was deployed to remove noisy or unwanted/irrelevant features.
- iv. **Model Building:** 80% of the data were subjected to training, while 20% were used for the testing.
- v. **Model Prediction:** Ensemble technique, using Random Forest and LSTM RNN deep

learning technique were deployed in the prediction by the model.

vi. **Model Evaluation:** The level of prediction accuracy were also measured using precision, recall and f-score, and reported in Table 8.

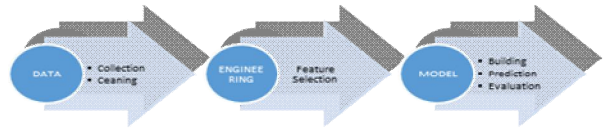


Figure 1: Methodology Procedures

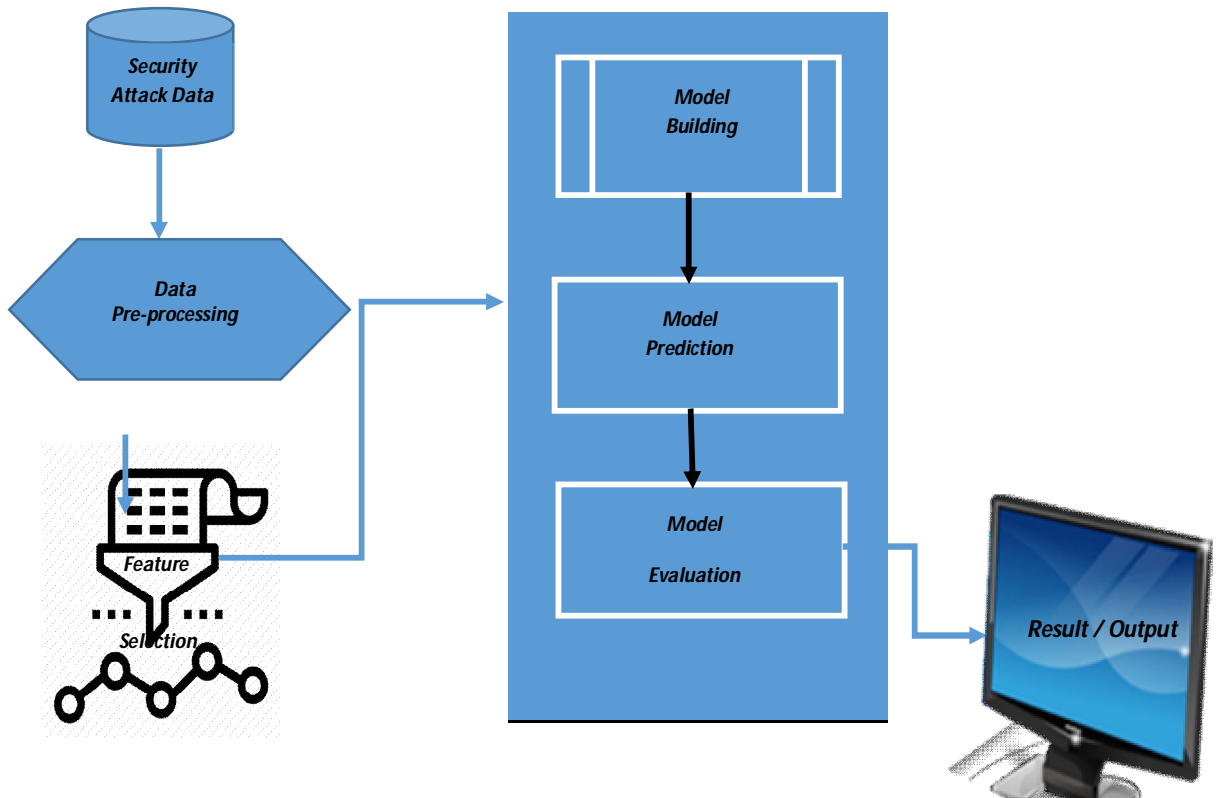


Figure 2: System Architecture

### Data Collection

The data used for this study were collected from the repository of Global Terrorism Database. The data which span from 1970 to 2017 contain 17,550 records with 135 columns.

```

In [7]: print(f"The dimension is {df.ndim} and the shape is {df.shape}")
The dimension is 2 and the shape is (17550, 135)
  
```

### Data Pre-processing

The collected data were pre-process using data cleaning technique to remove unwanted or incomplete/missing data.

## DATA CLEANING STARTS

```
In [8]: df_clean = df.dropna(axis=1)
df_clean = df_clean.drop("eventid", axis=1)
```

```
In [9]: df_clean.head()
```

After the cleaning, the data were reduced to 27 columns of data, and these were used for the analysis and predictive work.

```
In [11]: df_clean.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17550 entries, 0 to 17549
Data columns (total 27 columns):
```

```
In [13]: print(f"The new data dimension is {df_clean.ndim} and the shape is {df_clean.shape}")
The new data dimension is 2 and the shape is (17550, 27)
```

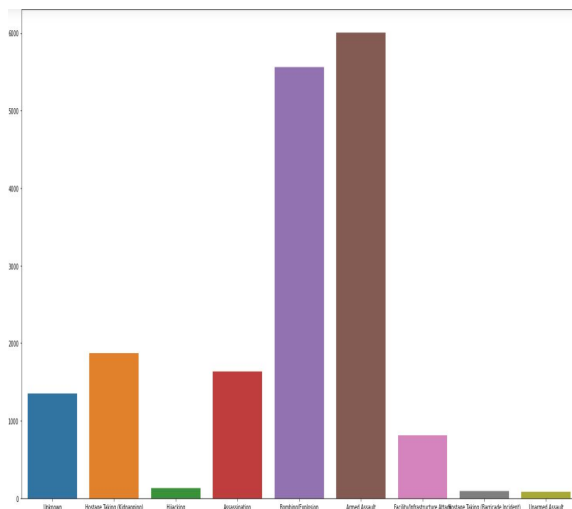
## Results

Tables 1 and Figure 3 present and capture the visualization of the bandits' various activities.

**Table 1: Exploring and Visualizing Bandit Types**

```
df_clean["attacktype1_txt"].value_counts()

Armed Assault                6004
Bombing/Explosion            5557
Hostage Taking (Kidnapping)  1872
Assassination                1638
Unknown                     1355
Facility/Infrastructure Attack  810
Hijacking                    136
Hostage Taking (Barricade Incident)  95
Unarmed Assault              83
```



**Figure 3: Bandits' Activities Types**

Merging data with some level of similarities and applying data cleaning, we have a new set of data (Table 2).

**Table 2: Bandits' Activities Types**

Assault	6087
Bombing	5557
Kidnapping	1967
Assassination	1638
Unknown	1355
Facility Attack	810
Hijacking	136

Table 4 presents the different types of weapons used by the terrorists, while Table 5 shows the various terrorist groups that exist.

**Table 4: Exploring and Visualizing Weapon Types**

```
df_clean['weaptype1_txt'] = df_clean['weaptype1_txt']
df_clean.weaptype1_txt.value_counts()
```

Firearms	7499
Explosives	6319
Unknown	2371
Incendiary	840
Melee	478
Other	19
Chemical	12
Sabotage Equipment	7
Biological	3
Vehicle	1
Fake Weapons	1

**Table 5: Exploring and Visualizing Terrorist Types**

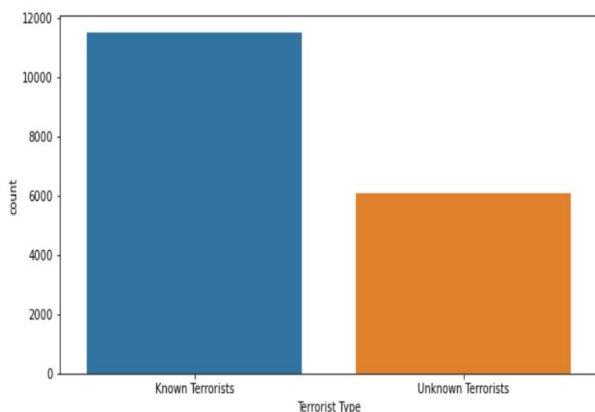
```
df_clean.gname.value_counts()
```

Unknown	6057
Al-Shabaab	3288
Boko Haram	2418
African National Congress (South Africa)	606
Fulani extremists	511
National Union for the Total Independence of Angola (UNITA)	432
Lord's Resistance Army (LRA)	322
Mozambique National Resistance Movement (MNR)	311
Allied Democratic Forces (ADF)	216
Janjaweed	213
Hutu extremists	187
Sudan People's Liberation Movement in Opposition (SPLM-IO)	181
Democratic Front for the Liberation of Rwanda (FDLR)	99
Movement for the Emancipation of the Niger Delta (MEND)	87
Muslim extremists	80
Movement of Democratic Forces of Casamance	79
Al-Qaida in the Islamic Maghreb (AQIM)	74
Anti-Balaka Militia	72
Mayi Mayi	68
Revolutionary United Front (RUF)	65
South-West Africa People's Organization (SWAPO)	63
Sudan People's Liberation Movement - North	59
Jamaat Nusrat al-Islam wal Muslimin (JNIM)	59
Amsan al-Dine (Mali)	54
Niger Delta Avengers (NDA)	50
Inkatha Freedom Party (IFP)	50
Movement for Oneness and Jihad in West Africa (MUJAO)	50
Patriotic Resistance Front in Ituri (FRPI)	49
Sudan People's Liberation Army (SPLA)	45
Tuareg extremists	40
Party for the Liberation of the Hutu People (PALIPEHUTU)	39
Seleka	34
National Liberation Front (FNL) (Burundi)	32
Azawad National Liberation Movement (MNLA)	27
Zimbabwe African Nationalist Union (ZANU)	27
Murle Tribe	26
Nyatara Militia	25
Tutsi extremists	23
Mujahideen Youth Movement (MYM)	23

Further data cleaning was done to classify the terrorists, to known and unknown terrorists (Figure 4).

```
# Cleaning the terrorist type by co
df_clean['gname'] = df_clean['gname']
df_clean['gname'].value_counts()
```

Known Terrorists            11493  
 Unknown Terrorists        6057

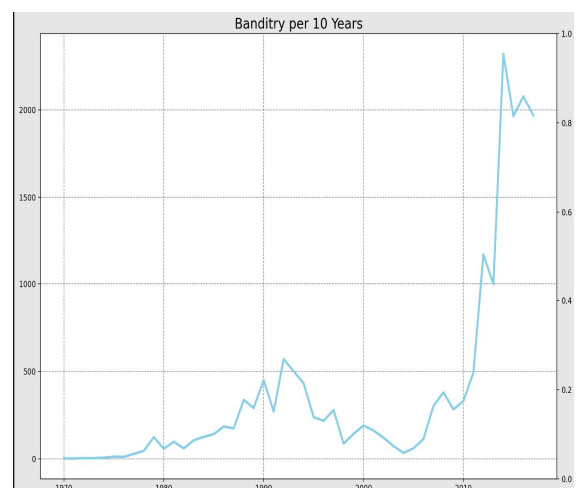


**Figure 4: Terrorists' Types**

Table 6 shows the top twenty (20) countries with the most terrorists' banditry attacks, while Figures 5 and 6 show the rate of banditry attacks for every 10 years and the types of banditry activities for each year, from 1970 to 2017

**Table 6: Top 20 Most Attacked Sub-Saharan Countries**

Somalia	4142
Nigeria	3907
South Africa	2016
Sudan	967
Democratic Republic of the Congo	775
Kenya	683
Burundi	613
Mali	566
Angola	499
Uganda	394
Mozambique	363
Cameroon	332
Central African Republic	283
South Sudan	225
Ethiopia	190
Rwanda	159
Niger	154
Namibia	151
Senegal	118
Zimbabwe	101
Sierra Leone	101
Chad	91
Rhodesia	83
Ivory Coast	74
Zambia	62



**Figure 5: Banditry Activities in every 10 years**

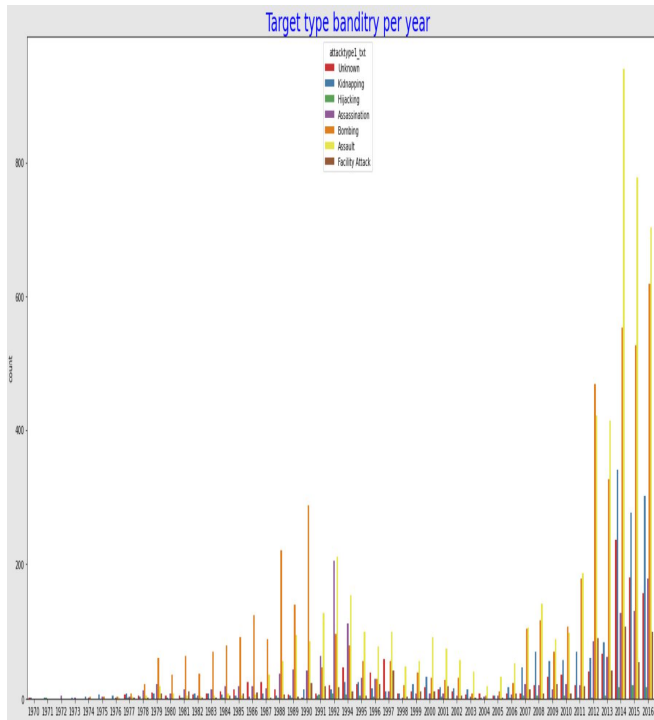


Figure 6: Various Banditry Activities per year

### Model Building

For the building of this model, 80% of the preprocessed data were used for training, were 20% were used for the testing.

```
In [210]: # Outputting the final dataset for the model
print(f"The dimension is {df_test.ndim} and the shape is {df_test.shape}");
print(" ")
df_test.info()

The dimension is 2 and the shape is (17550, 22)
```

```
In [212]: print(y_test.shape)
print(y_train.shape)
print(X_train.shape)
print(X_test.shape)
```

```
(3510,)
(14040,)
(14040, 19)
(3510, 19)
```

### USING RANDOM FOREST

```
In [222]: model = RandomForestClassifier(n_estimators=200)
model.fit(X_train, y_train)
predictionss = model.predict(X_test)
print(" ===== Accuracy Score ===== ")
print(" ")
print(f"{accuracy_score(y_test, predictionss)} or {round(accuracy_score(y_test, predictionss), 2)}")
print(" ===== Confusion Matrix ===== ")
print(" ")
print(confusion_matrix(y_test, predictionss))
print(" ")
print(" ===== Classification Report ===== ")
print(" ")
print(classification_report(y_test, predictionss))
```

Tables 7 and 8 present the prediction accuracy results of random forest and LSTM respectively.

Table 7: Random Forest Results Table

```
===== Accuracy Score =====
0.8527065527065527 or 85.3%

===== Confusion Matrix =====
[[ 117 145  29  3  0  8 12]
 [ 23 1088 99 29  0 29 1]
 [ 13  16 1060  0  0  3  3]
 [  0  32  0 107  0  3 17]
 [  3  4  0  0  1 13  2]
 [  4  9  2  2  1 369  0]
 [  8  0  0  2  0  2 251]]

===== Classification Report =====
```

	precision	recall	f1-score	support
0	0.70	0.37	0.49	314
1	0.84	0.86	0.85	1269
2	0.89	0.97	0.93	1095
3	0.75	0.67	0.71	159
4	0.50	0.04	0.08	23
5	0.86	0.95	0.91	387
6	0.88	0.95	0.91	263
accuracy			0.85	3510
macro avg	0.77	0.69	0.70	3510
weighted avg	0.84	0.85	0.84	3510

### USING RNN

```
In [335]: from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
import tensorflow as tf

In [336]: early_stop = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=25)

In [337]: model = Sequential()
model.add(Dense(512, activation='relu'))

model.add(Dropout(0.2))
model.add(Dense(10, activation='softmax'))

model.compile(optimizer='sgd', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

In [338]: model.fit(X_train, y_train, epochs=50, validation_data=(X_test, y_test), callbacks=[early_stop])
```

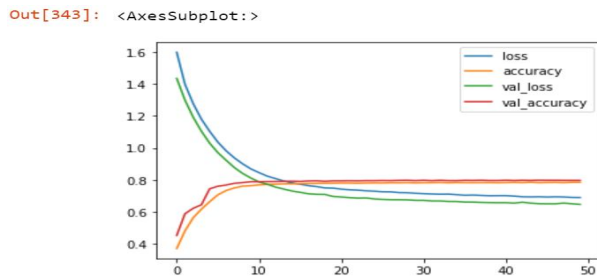


```
In [342]: model_loss = pd.DataFrame(model.history.history)
          model_loss
```

```
Out[342]:
```

	loss	accuracy	val_loss	val_accuracy
0	1.597070	0.371011	1.433876	0.452422
1	1.397406	0.480769	1.298303	0.588034
2	1.276196	0.563105	1.191410	0.622222
3	1.178952	0.616880	1.103445	0.644160
4	1.103149	0.663462	1.029098	0.744160

```
In [343]: model_loss.plot()
```



**Table 8: LSTM RNN Results Table**

```
===== Accuracy Score =====
0.8011396011396011 or 80.1%

===== Confusion Matrix =====

[[ 62 171  58  0  0  3 20]
 [ 27 1108 101  4  0 28  1]
 [  0  15 1074  0  0  3  3]
 [  2 123  0 12  0  3 19]
 [  1  11  1  0  0  7  3]
 [  8  54  4  2  0 297 22]
 [  0  0  0  0  0  4 259]]

classification_report:
      precision    recall  f1-score   support

   0           0.62     0.20     0.30         314
   1           0.75     0.87     0.81        1269
   2           0.87     0.98     0.92        1095
   3           0.67     0.08     0.14         159
   4           0.00     0.00     0.00          23
   5           0.86     0.77     0.81         387
   6           0.79     0.98     0.88         263

 accuracy
macro avg           0.65     0.55     0.55        3510
weighted avg           0.78     0.80     0.77        3510
```

**Discussion**

The results show that the two methods deployed, Random Forest and Long Short-Term Memory, are capable of predicting terrorist attacks in Sub-Saharan African with prediction

```
model.evaluate(X_test, y_test)

print(" ")
print(" ")

predictions = model.predict(X_test)
prediction_classes = [np.argmax(element) for element in predictions]
print(" ===== Accuracy Score ===== ")
print(" ")
print(f"{{accuracy_score(y_test, prediction_classes)}} or {{round(accuracy_scc
print(" ")
print(" ===== Confusion Matrix ===== ")
print(" ")
print(confusion_matrix(y_test, prediction_classes))
print(" ")
print("classification_report: \n", classification_report(y_test, prediction
```

accuracy of 85.1% and 80.1% respectively. This is in tandem with previous research results that proved Random Forest as a suitable supervised machine learning technique for prediction of this nature.

Further analysis on the data shows armed assault as the most terrorist activities type (6,004). Firearms is the most used weapon types (7,499). Known Terrorists accounted for 11,493 while unknown Terrorists are 6,057. The five most attacked Sub-Saharan countries are Somalia, Nigeria, South Africa, Sudan, and DR Congo.

**Conclusion**

The two models presented in this study were applied to global terrorism data of 1970 to 2017. The results show the ability and suitability of the two models in the prediction of terrorists' activities. It is intended that this study would be further investigated in the near future to develop into a data-driven system that forecasts the likely timing and location of the next bandit assaults using actual data and information.

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