Journal of Contemporary Technology and Applied Engineering (JCTAE)

Home Page: https://jctae.journals.ekb.eg/
Published by: Faculty of Engineering, Kafrelsheikh University

Volume: 3 **Issue:** 2 **Year:** 2025
Pages: 103 – 113
DOI: 10.21608/jctae.2025.364093.1045

Print ISSN: 2812-5797
Online ISSN: 2812-5800

PROPOSED LOSS FUNCTIONS FOR ACCURATE PREDICTION OF TERRORIST EVENT LOCATIONS IN EGYPT

Received: 26-02-2025
Accepted: 04-03-2025

Ghada Hamisa[a], Loai Abdalslam[b]

[a] *Electrical Engineering Department, Faculty of Engineering, Kafrelsheikh University, Kafrelsheikh 33516, Egypt*
[b] *Computer Science Developer, BSc. Alexandria University, Egypt*
[*] Corresponding author: G. Hamisa (ghada.hemesa@eng.kfs.edu.eg)

ABSTRACT. At the last decades, human security is threatened by terrorism. A rapidly expanding field of work seeks to analyze terrorist attack trends in order to inform counter-terrorism policy. Terrorist attacks can be analyzed and predicted with detailed historical data for better prevention and early warning. In this research, we use predicting geolocation in an open area space. It is aimed to predict the terrorist action location before it being occurred. Two novel ideas are presented in this research. *The first idea* is using spherical-distance measurements between two points instead of traditional straight-line distance measurements as previously used in predicting locations. Spherical-distance measurements depends on coordinate-form(x,y). *The second proposed idea* is coupling geolocation-functions to famous loss functions, like *Mean Square Error* (***MSE***) loss function to achieve accurate performance. The proposed geolocation-functions are "*Haversine formula*", and "*Equirectangular Projection formula*". The two proposed geolocation loss functions are hybrid to *MSE* loss function. The deep learning algorithm, ***LSTM*** (*Long Short-Term Memory*) is used for training our model. Experimental results indicated that the proposed loss functions achieved high accuracy compared to the traditional one. In this research, we use dataset of terrorist events in Egypt.

KEYWORDS: Long Short-Term Memory; Deep Learning; Loss Function; Haversine Formula; Terrorist Events Location Prediction.

1. INTRODUCTION

Terrorism is a pressing global issue involving the utilize of violence by non-state actors to achieve economic, religious, political, or social objectives, resulting in significant loss of life, property damage, and disruptions to economic and political stability. In the 21st century, it has emerged as a critical threat to human security, driving extensive research into attack patterns to develop effective counter-terrorism strategies. The GTD (Global Terrorism Database) defines terrorism as the threat or utilize of violence and illegal force by a non-state actor to achieve a political, religious, economic, or social purpose through fear, intimidation or coercion [1]. The Global Terrorism Database is a well-known database that contains over 190,000 terrorist events and occurrences worldwide from 1970 to 2020 and includes a variety of factors such as the type of weapons utilized, whether the attack was successful or not, the sort of attack, and the category of terrorist.

Several studies have employed advanced computational techniques to analyze and predict various aspects of terrorist activities. For instance, deep learning-based recommender systems have been developed to estimate the dissemination rate of online terrorist propaganda [2]. Hazard grading models utilizing K-Means clustering have been proposed to quantify the severity of terrorist attacks [3], while Decision Tree Algorithms have been applied to predict the success of such activities [4]. Additionally, researchers have used machine learning to classify terrorist targets, such as government officials, civilians, military personnel, or businesses [5]. Further studies have explored computational methods for terrorism prediction [6-8], using machine learning to identify whether a terrorist act will be claimed by a known group [9]. Others, have been published for prediction of continents susceptible to terrorism using machine learning models [10], forecast the likelihood of criminals engaging in activities that assist crime [11]; or to find the behavior patterns of terrorist groups by combines the context of previous attacks, social networks, and individual terrorist groups' prior acts [12].

However, none of these studies have focused on predicting the geographical locations (e.g., geolocation) where specific types of terrorism are likely to occur. This research represents a novel contribution of the current work, which proposes an ensemble computational model to identify specific zones for terrorist attacks. Such predictions can enhance counter-terrorism efforts, improve security awareness, and provide valuable guidance for travelers.

The spatial temporal predicting [13] and predicting geolocation, based on an unlimited open space, are employed to enhance the accuracy of predicting the locations of future terrorist incidents.

The (geographic coordinate system) GCS [14] is a ellipsoidal or spherical coordinate systems utilized to communicate and measure positions directly on the Earth, such as latitude and longitude [15], as illustrated in Fig. 1. It is the oldest and most commonly utilized of the spatial reference system now in utilize. Although latitude and longitude create a coordinate tuple similar to Cartesian coordinate systems, the GCS is not Cartesian since the measurement are angles rather than points on a plane.

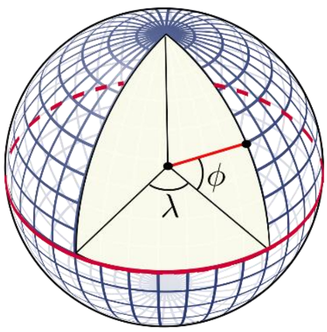

Fig. 1. Schematic representation of the longitude λ and latitude ϕ angle measurements for a spherical coordinate of the Earth.

Geographical distance, also known as geodetic distance [16], refers to the distance measured along the earth's surface. In Euclidean space, the distance between 2 points is the length of a straight line that connects them; however there are no straight lines on the sphere. Geodesics replace straight lines in curved spaces. Geodesics on the sphere are circles whose centers are the same as the sphere's center. They are called huge circles [15], as indicated in Fig. 2. The formulas used in this work calculate distances between points defined by geographical coordinates (longitude and latitude). The distance, D, is determined between 2 points, P and Q. The geographical coordinates of the 2 points, as (longitude and latitude) pairs, are (λ_1, ϕ_1) and (λ_2, ϕ_2), respectively. Which of the 2 points is designated as *P* is not important for the calculation of distance, shown in details at section 3.

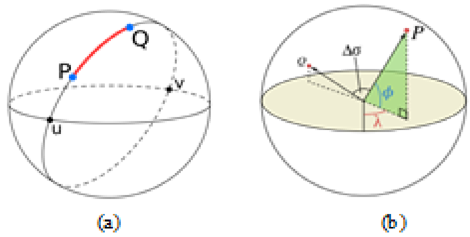

*Fig. 2. A diagram showing great-circle distance (red color) between 2 points on a sphere, P and Q., and **(b)** An illustration of the central angle, $\Delta\sigma$, between P and Q. φ and λ are the latitudinal and longitudinal angles of P.*

RNNs (Recurrent neural networks) contain cyclic connections that make them a more powerful tool to model such types of sequence data. One of the specific recurrent neural network architecture is the (*Long Short-Term Memory*) ***LSTM*** that was designed to model temporal sequences and their long-range dependencies more accurately than conventional recurrent neural networks. ***LSTM*** [17] overcomes some modeling weaknesses of recurrent neural networks, is conceptually attractive for the task of acoustic modeling. ***LSTM*** and traditional recurrent neural networks have been effectively applied to a variety of sequence prediction and sequencing problems.

Our research concerns in designing an accurate model that predict the location of the next terrorist events based on the previous events that took place through a specific date and specific area. The novelty in our research divided into two proposed ideas.

The first proposed idea is proposing the next events using the geographic methods, which is measuring the latitude and longitude coordinate-values between two coordinates instead of measuring the absolute straight-line distance-value between two points. As known in mathematical basics, the distance-value between two coordinate points located on a curve path gives differs results from the distance between the same two points when being measured as straight line. So, our approach presents the ultimate outcome of the learning network to be in the form of coordinate-values. Also, it trains the distance-value between two points upon curve as the same as training the distance-value in straight line.

The second idea is proposing two novel loss functions, which evaluate the validity and accuracy of the results. This novel loss functions depend on the geolocation case problem.

Our paper arranged as follows. Section 2 presents some research related to our work. Our proposed model is presented in details with equations and graphs, in section 3. Data set and data preparation presented in section 4. Section 5 describes the preprocess and procedure of our model. Section 6 shows experimental results with their analysis. Conclusion and future work present in section 7.

2. Related Work

In 2021, Olusola A. Olabanjo et al. [18] developed an ensemble ML model (machine learning model). This combines K-Nearest Neighbor and Support Vector Machine to predict the continents susceptible to terrorism. The data utilized in their work is from Global Terrorism Database. They applied Chi-squared; Information Gain and a hybrid of both were to the dataset before modeling. The accuracy for Chi-squared, the hybrid-based features and information Gain is 94.17%, 97.81% and 97.34% respectively. The specificity scores were of 98%, 90.5% and 99.67% and Predicting danger zones were of 82.3%, 88.7% and 92.2%. The results indicated that their ML model can accurately predict terrorism locations

At 2022, Firas Saidi and Zouheir Trabelsi [12] were interested in studying the correlation between the occurrence of attacks and its relation with the type of weapons utilized, and the types of terrorist attacks and their success rates. They proposed a hybrid DL (Deep Learning) algorithm based on CNN (Convolutional Neural Network) and LSTM (*Long Short-Term Memory*) models to learn the temporal features from the GTD (Global Terrorism Database) [19] and to predict the activities characteristics future terrorist. They utilized the Convolutional Neural Network to extract complex features of the data, and then these features are forwarded to *Long Short-Term Memory* model to learn the temporal relationship of data. Their results indicate that the convolutional neural network and *Long Short-Term Memory* models, for bi-classification tasks, accomplishes more than 96% accuracy. Moreover, the Convolutional Neural Network outperforms the utilized hybrid model with 99.2% accuracy.

In 2022, Xiaohui Pan and Wei-Chuen Yau [20] propose a classification framework this relies on ensemble learning to predict and classify terrorist groups. They used GTD from 1970 to 2017 in their analysis. 5-classifications and predictions models for terrorist organizations were utilized. The 5 models are: decision tree, extra tree, bagging, XGBoost and random forest. They used a cross-validation method to verify the performance and stability of the proposed model. According to the experimental outcomes the random forest models and XG Boost obtained the best accuracies 96.82% and 97.16%, of predicting the thirty two terrorist organizations with the highest attack rates.

In 2016, Liu et al. [13] proposed ***ST-RNN*** (Spatial Temporal-Recurrent Neural Network) to spatial and temporal contexts model. Their proposed approach was too complex to train and use with so many pars per meter. Furthermore, its continuous spatial modeling method prevents it from being used with the discrete location prediction scene.

Wang et al. [21] presented a unique hybrid Markov-LSTM model for indoor location prediction. First, a multi-step Markov transition matrix was created to deconstruct the k-MCs into many 1-MCs, so overcoming the k-MC's dimensional problem. The LSTM (Long Short-Term Memory) model is used to combine numerous 1-MCs to improve model prediction performance.

Depending on the previous researches, we have detected two directions for treating the Terrorist attacks. The first, few researches interest in the locations of terrorist's location and using traditional mathematical method in calculating and predicting terrorist locations. The second, LSTM is the famous deep learning algorithm used in predicting sites. The standard loss function used in all of these methods is a MES function to evaluate algorithms; where the calculation of predicted locations forecasts depends on measuring the distance between two points in a straight line. We construct our model to predict locations that depends on measuring the distance between two points in curved surface.

3. Machine Learning Model

In machine learning prediction tasks, datasets often comprise hundreds of attributes, many of which may be redundant or irrelevant to the specific analysis objective, necessitating the application of feature selection. Feature selection is a critical process that enhances the understanding and preliminary analysis of a dataset, while also serving as a key step in data preprocessing, particularly for machine learning models [22, 23]. It involves evaluating and scoring predictive variables based on their contribution to explaining the target variable [24].

Feature importance can be determined through manual, statistical, or machine learning-based methods. An effective method is information gain, which quantifies the relevance of features based on their ability to reduce uncertainty about the target variable. These techniques are essential for optimizing model performance and reducing computational complexity.

Since the main purpose of this research is to predict the location of terrorist attacks, it is important to measure the distance between two points by their coordinates on earth; as the earth is a spherical surface. One of the proposed ideas is to use a geographic coordinate system, shown in section 2, as the input of the machine learning model to predict locations.

3.1. LSTM MODEL

Fig. 3 presents a block diagram of used ***LSTM*** model [21], which is the machine learning model used to apply our research.

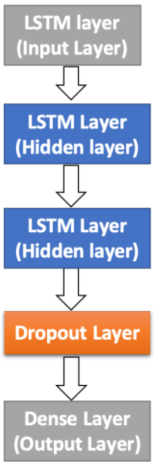

Fig. 3. Architecture of LSTM (RNN)

The architecture of the model consists of LSTM input layer, LSTM hidden layer, dropout layer, and LSTM output layer. The input layer rearranges the input data sequence. The hidden layers train the data and prepare it to the third layer. The *DropOut* Layer concerns for preventing the model from overfitting -it is 20% in our model as a normal percentage. The last layer is *Dense* Layer. It has a linear activation function; to accept all result values (positive and negative values). The optimization technique uses *Adam Optimization* algorithm [25].

The output of our ***LSTM*** model is an array of *dual values* (x_i,y_i) *points*; which is the predicted locations of the terrorist events. The dual values (x_i,y_i) express the latitude and longitude coordinate values among the spherical surface of the earth, respectively. Our learning model use the resulted values to predict terrorist locations.

4. PROPOSED LOSS FUNCTIONS

The loss function is a tool for evaluating how well the algorithm models the dataset. It is a mathematical function dependent on the machine learning algorithm's parameters. It gives a quantitative measure of how well the model performs. So, choosing the right loss function is not as easy as it is supposed to. One of the common and famous loss functions is MSE, shown in equation (1),

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \widehat{Y}_i)^2 \tag{1}$$

MSE is a traditional measure when calculating the linear distance between 2 points. But if the distance between two points upon spherical path, the results will be different. Therefore, there are no accurate measurements, until now, to calculate the distance between two GPS coordinates because conventional calculations do not take into account the curvature of the earth.

In our research, we propose *two hybrid loss functions* based on geographical functions methodology. These two functions called: 1) *Haversine formula* [26, 27] and 2) *Equirectangular Projection formula* [28]. The first proposed hybrid loss function is based on coupling *Haversine formula* and MSE loss function. The second one is based on coupling *Equirectangular Projection formula* and MSE.

4.1. HAVERSINE FORMULA

The *Haversine formula* (***HAV***), shown in the equation (2), has been used for hundreds of years as a navigational tool. It calculates the great circle distance between 2 points on the sphere surface.

$$hav(\theta) = sin^2(\theta/2) \tag{2}$$

$\theta = d / r$, where:

- d : is the distance between the 2 points along a great-circle of the sphere,
- r : is the sphere radius.

that is, d to be computed directly from φ (latitude) and λ (longitude) of the 2 points where,

φ_1, φ_2 are the latitude (in radians)of points 1 and 2,

λ_1, λ_2 are the longitude (in radians) of points 1 and 2.

To compute the distance d, shown in equations (3),(4),(5)

$$a = sin^2(\varphi2 - \varphi1/2) + cos\ \varphi1 * cos\ \varphi2 * sin^2(\lambda2 - \lambda1/2) \tag{3}$$

$$c = 2 * a * tan2(\sqrt{a}, \sqrt{(1-a)}) \tag{4}$$

$$d = R \cdot c \tag{5}$$

where, R is the earth's radius (mean radius = 6,371km)

4.2. EQUIRECTANGULAR PROJECTION FORMULA

Equirectangular Projection formula (***EQR***) is one of the famous map projection [28]. It becomes a standard for global raster datasets, such as Natural Earth, NASA World Wind, and Celestia, because of the especially straightforward link between the position of an image pixel on the map and its corresponding geographical location on Earth [29], shown in Fig. 4.

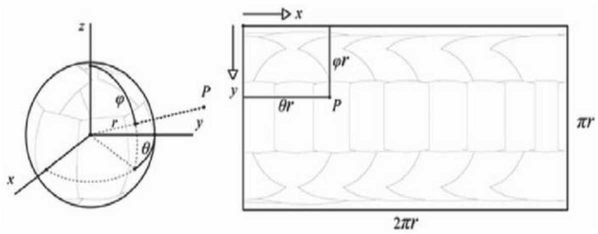

Fig. 4. Relationship between spherical coordinates and equirectangular coordinates

The forward projection converts spherical coordinates to planar coordinates. The formulae assume a spherical model and use the following definitions, shown in equation (6):

$$x = R\,(\lambda - \lambda_0) \cos \varphi_1$$
$$y = R\,(\varphi - \varphi_0) \quad (6)$$

Where,

R, the radius of the earth.

x, y, horizontal and vertical coordinates of the projected location on map;

φ, λ, latitude and longitude of the locations to project;

φ_1, north and south of the equator (the standard parallels) where the scale of the projection is true;

λ_0, φ_0, central meridian and central parallel of the map;

Latitude and longitude variables in radians terms.

4.3. PROPOSED HYBRID HAVERSINE-MSE LOSS FUNCTION

The proposed hybrid Haversine-MSE loss function is used as a metric for evaluating the performance of a machine learning model in terms of the accuracy of its coordinate predictions. The following algorithm describes the hybrid function.

4.3.1. Proposed Hybrid Haversine-Mse Loss Function Algorithm

The proposed hybrid Haversine-MSE algorithm is summarized in the following steps.

hybrid Haversine-MSE (y_true, y_pred):

A) Convert decimal degrees to distance: deg2rad (deg)

1. pi_in_180 = 0.017453292519943295
2. output = deg * pi_in_180
3. return output

B) Apply the Haversine function:

1. lon1, lat1 = y_true[:,1], y_true[:,0]
2. lon2, lat2 = y_pred[:,1], y_pred[:,0]

#calculate distance from true points on the sphere

3. lon1, lat1 = deg2rad(lon1), deg2rad(lat1)
4. lon2, lat2 = deg2rad(lon2), deg2rad(lat2)
5. dlon = lon2 - lon1
6. dlat = lat2 - lat1
7. a = sin(dlat/2)^2 + cos(lat1) * cos(lat2) * sin(dlon/2)^2
8. c = 2 * asin(sqrt(a))
9. r = 6371 (Radius of earth in km and 3956 for miles)
10. f_output = c * r
11. return (MSE (f_output))

The *Haversine-MSE* algorithm calculates the mean of the great-circle distance between two points on the earth using the Haversine formula, which takes into account the earth's curvature.

First step, it converts decimal degrees to distance by a function called “deg2rad”. The second step is to compute the radius (d). The inputs of our model are the start and end points on the sphere. These are the true longitude and latitude (lon1, lat1 and lon2, lat2 respectively) which is converted from degree to distances, as shown in equations (3), (4),(5). The final result is the mean square error of the predicted distances for all points.

4.4. PROPOSED HYBRID EQUIRECTANGULAR-MSE LOSS FUNCTION

The proposed hybrid Equirectangular -MSE loss function is used as a metric for evaluating the performance of a machine learning model in terms of the accuracy of its coordinate predictions. The following algorithm describes the hybrid function.

4.4.1. Proposed hybrid Equirectangular-MSE loss function algorithm

The following steps show the proposed hybrid Equirectangular –MSE algorithm.

hybrid Equirectangular -MSE (y_true, y_pred)

1. R = 6371 (Earth's radius)
2. true_lng = y_true[:,1]
3. true_lat = y_true[:,0]
4. pred_lng = y_pred[:,1]
5. pred_lat = y_pred[:,0]
6. o = (pred_lat - true_lat) ^ 2
7. y = pred_lng - true_lng
8. x = o + (y * cos(0.5 * (pred_lat - true_lat))) ^ 2
9. d = R * sqrt(x)
10. return (MSE (d))

The *Equirectangular –MSE* algorithm calculates the mean of the great-circle distance between two points on the earth using the Equirectangular formula, shown in equation (6), which takes into account the earth's curvature. The input is two arrays, y_true and y_pred, each of shape (n x 2), where n is the number of samples and the two columns represent the longitude and latitude respectively. The longitudes and latitudes of the true location (true_lng and true_lat, respectively) and predicted location (pred_lng and pred_lat, respectively). The Earth's radius R is used in the calculation, and the “cos” and “sqrt” functions are used to find the distance d between the two points. The final result is the mean square error of the distances for all points.

5. DATA SET AND DATA PREPARATION

The dataset used in this research is from the Global terrorism corpus. Global Terrorism Database (***GTD***) [30] includes more than 125,000 terrorist incidents that have occurred around the world since 1970 till 2020. The information concerns the time is collected based on the day level. For public good, we try to predict the occurrence of the terrorist action attacks in countries or locations. Therefore, an appropriate response can be taken towards this terrorist act.

In our paper, we consider only the data of the terrorist actions taken place in Egypt. The data set contains 16 columns. It presents the date, the geographical information (country, city, latitude and longitude), and other statistical information about the terrorist action (the dead and the injured). We use only the events that happened in Egypt because our target was to predict the location of the potential next terrorist action in Egypt.

Weisstein tool was used for data augmentation processing. It produced many random points around each event. Thus, 10 additional events were created for each event in a range of two kilometers (2 *KM*) to expand the data samples. ***LSTM*** predicts the next events around the 10 prior calculated events –the time step in our case will be 10.

6. PREPROCESS AND PROCEDURE

In this section, we perform several experiments to demonstrate the effectiveness of our model. We use two cases of dataset samples (training and testing samples). In the first case, ***LSTM*** is trained on 1891 events and tested on 77 events (test samples are approximately 4% of training samples). The second case used 1498 in training and 470 in testing where the testing samples are approximately 31% of training). The dataset used in training (training set) is the terrorist events that taken place in Egypt from 2016 till 2018. The data of terrorist events of 2019 is used as testing set.

The two proposed loss functions, ***hybrid Haversine-MSE*** and ***hybrid Equirectangular -MSE***, are used for testing our model to measure the accuracy predicted locations. A comparison was performed between three experimental results: traditional ***MSE***, ***hybrid Haversine-MSE*** and ***hybrid Equirectangular -MSE***. We evaluate the model on distance basis regarding different tests with modified ***MSE***. The evaluation is based on real-world samples.

7. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we will illustrate the performance of the LSTM model depending on the proposed hybrid loss functions. The output of the ***LSTM*** model will be in the form of geographical point; (x_i, y_i) coordinate values. The difference between the performance of calculating the predicted geographical points and calculating the predicted points measured traditionally determines the efficiency of proposed hybrid loss functions. Two cases are preformed using two different sizes of datasets.

7.1. CASE 1

In this case, the testing dataset is 4 % of the training data. A comparison between performance of the three loss function traditional ***MSE***, hybrid Haversine-MSE (***HAV-MSE***) and hybrid Equirectangular –MSE (***EQR-MSE***) are presented in the Table 1.

Table 1. Number of predicted locations for LSTM model in different location ranges (in km) (testing data is 4% of training data)

	3 *km*	**5 *km***	**10 *km***	**20 *km***	**30 *km***	**40 *km***	**50 *km***	**60 *km***	**70 *km***
MSE	2	2	2	3	5	6	10	15	19
HVS-MSE	2	23	28	30	32	40	48	50	53
EQR -MSE	2	3	22	28	38	39	48	51	54

Table 1 shows the number of predicted locations in different location-ranges after applying three different loss function. The first is the traditional loss function ***MSE***. The second and third are the proposed loss functions ***HAV-MSE*** and ***EQR-MES***, respectively. In our experiments, different distance-ranges are presented; small and wide ranges of coordinates: 3, 5, 10, 20, 30, 40, 50, 60 and 70 kilometers.

From Table 1, it is shown that using traditional ***MSE*** results in few number of predicted events in range from 3 to 40 km. The maximum predicted location number is 10 to 19 events in rang 50 to 70 km, which is so small compared to tested events.

The proposed hybrid loss function ***HAV-MSE*** gives different predicted events in different ranges. It is observed that the number of predicted locations in the range of 5 to 30 *km* is greater that the number of predicted locations resulted from traditional ***MSE*** loss function. It gives 23 locations in small range of 5 *km* and reaches from 28 to 32 locations in range of 10 t0 30 *km*. While in wide ranges from 40 to 70 *km*, the predicted locations increases and is going to be near the testes values. It reaches to 53 predicted locations from 77 which is the total test samples.

The proposed hybrid loss function ***EQR-MSE*** gives different results than the previous two loos functions. It results in less range of values (predicted locations) between 3 and 5 *km*. The results show that the number of predicted locations within range 10 to 20 km are less than resulted in ***HAV-MSE.*** While in ranges from 30 to 70 km, the predicted location gives better results than traditional ***MSE*** and ***HAV-MSE*** loss functions.

It is noticed that the two proposed hybrid loss functions ***HAV-MSE*** and ***EQP-MSE*** have approximately the same ranges of predicted location values.

Figs. 5, 6, and 7 show the performance curves; for traditional ***MSE***, hybrid ***HAV-MSE*** and ***EQP-MSE*** respectively. In our model, the learning curve represents the performance of loss functions and the epochs, where learning is at the y-axis over experience at the x-axis. The blue curve represents the training results, whereas the red line represents the testing results (predicted locations).

Fig. 5 illustrates the performance of traditional MSE loss function for the experiment using the LSTM model with testing data is 4% of training data. It is known that, as the epochs increase during the model configuration, more accuracy is acquired during testing and training the model. But, we can observe that curve shows that the model is *underfit curve* and noisy values are found of relatively high loss at the beginning of learning. This indicates that the model was unable to learn the training data at all.

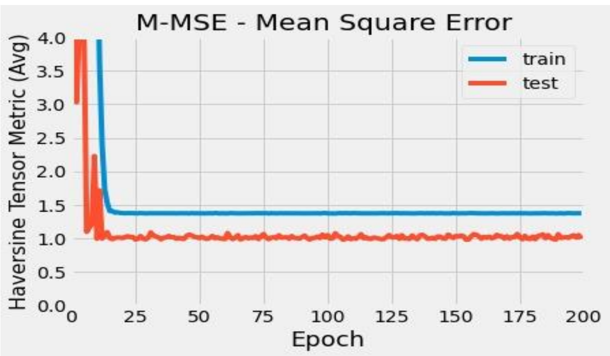

Fig. 5. MSE test result of LSTM (testing data is 4% of training data)

Fig. 6 shows that for 200 epochs, the ***HAV*** test gives more accuracy between the actual and predicted data. The number of learning up to 20 (5 times the case of using ***MSE***). The training model indicates a *good fit performance curve*. As, the plot of actual data decreases to a point of stability and the plot of predicted data also decreases to a point of stability and has a small gap with the training one.

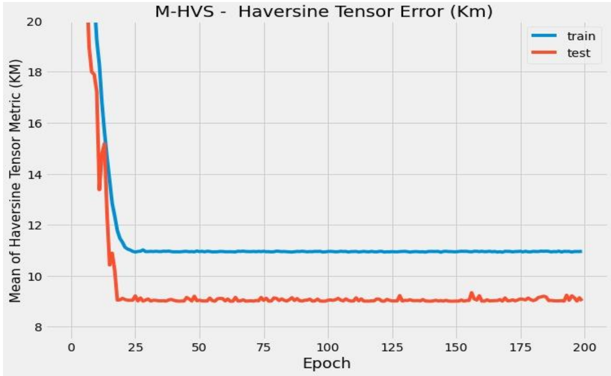

Fig. 6. Hybrid HAV-MSE test result of LSTM (testing data is 4% of training data)

Fig. 7 is the result of ***EQR-MES*** test. It shows that for 200 epochs, the error between the actual and predicted data has disparate ranges of accuracy ranges at the beginning of the plot (in small ranges of kilometers). The learning model ***LSTM*** is an *Overfitting curve*. It has learned the training data too well, including the statistical noise or random fluctuations at the beginning of learning data. It shows the learning is up to 100 (5 times ***HAV***). The plot of training (actual data) continues to decrease with experience and the plot of predicted data is disparate; it decreases to a point and begins increasing again. But the problem with overfitting, is that the more specialized the model becomes to training data, the less well it is able to generalize to new data, resulting in an increase in generalization error. This increase in generalization error can be measured by the performance of the model on the validation dataset.

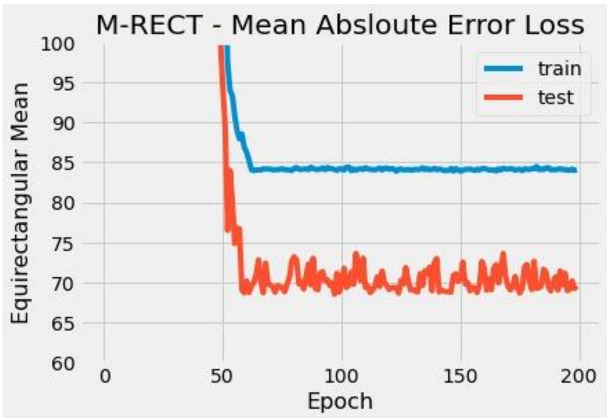

Fig. 7. Hybrid EQR-MSE test result of LSTM (testing data is 4% of training data)

7.2. CASE 2

In case 2, the testing dataset is 31% of the training data. A comparison between performance of the three loss function-traditional ***MSE***, ***HAV*** and ***EQR*** - is presented in the Table 2.

Table 2. Number of predicted locations of our LSTM modelin different location ranges (in km) (testing data is 31% of training data)

	3 km	5 km	10 km	20 km	30 km	40 km	50 km	60 km	70 km
MSE	0	0	1	2	14	16	17	23	50
HVS-MSE	154	159	180	193	209	277	333	335	361
Eq_Rect-MSE	152	162	179	194	204	275	333	335	359

Table 2 shows the number of predicted locations in different location ranges (3, 5, 10, 20, 30, 40, 50, 60 and 70 kilometers) after applying the three loss functions: traditional ***MSE***, proposed hybrid ***HAV-MSE*** and proposed hybrid ***EQR-MSE***.

In using traditional ***MSE***, approximately, the accuracy is Zero in ranges of distances 3 and 5 *km*; and small in range of 10 to 20 *km*. In ranges from 30 to 60 km, it has light small changes. The predicted values are small compared to tested samples. In the proposed loss function ***HAV-MSE,*** it gives large values of results among different ranges compared to the traditional ***MSE***. The number of predicted locations (events) was ascending gradually from 154 (at 3 *km*) to 361 (at 70 *km*) which is the best case.

In the case of using proposed loss function ***EQR-MSE,*** it gives results near to the results of the loss function ***HAV-MSE.*** The predicted events increases from 152 (at 3 *km*) to 359 (at 70 *km*).

Figs. 8, 9, and 10 present the *learning performance curves* of our model using the; for traditional ***MSE***, proposed hybrid ***HAV-MSE*** and proposed hybrid ***EQR-MSE***, respectively. As mention before, the metric used to evaluate our model is that the better the scores (larger numbers) indicate more learning and more accuracy.

Fig.s 8, 9 and 10 indicate that our ***LSTM*** model has a *good fit performance curve* than in *Case 1* (that is acceptable because number of tested data is larger than in *Case 1*).

Fig. 8 shows the performance of traditional MSE loss function for the **LSTM** model with testing data is 31% of training data. The curve shows that the model less noisy than in Fig. 5, but still *under-fit* curve.

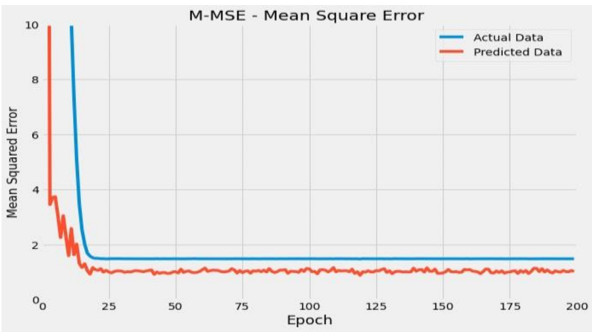

Fig. 8. MSE test result of LSTM (testing data is 31% of training data)

In Fig. 9, the plot of predicted data has less noisy and fit to the actual data, especially when using proposed hybrid ***HAV-MSE***.

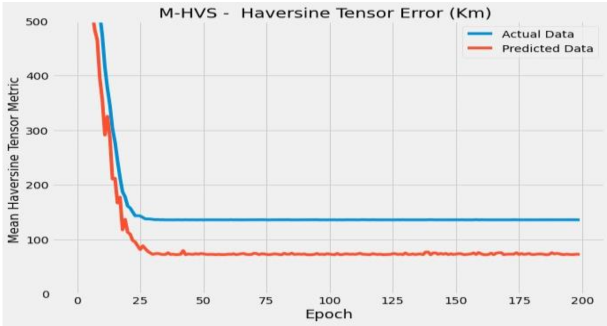

Fig. 9. Hybrid HVS-MSE test result of LSTM (testing data is 31% of training data)

While in Fig. 10, the curve of the predicted data in overfitting with small gap with the training curve. This shows the efficiency of the proposed hybrid ***EQR-MSE***.

Comparing the results of the two cases 1 and 2, it is shown that the traditional loss function ***MSE*** is less accuracy than modified ones, hybrid ***HAV-MSE*** and hybrid ***EQR-MSE*** at the two cases. Each of the proposed hybrid loss functions gives high accuracy than traditional loss function ***MSE*** because of using different way for distance measurements which is the coordinate instead of traditional ways in measuring distances.

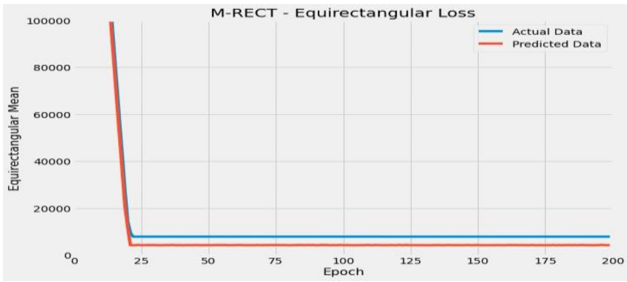

Fig. 10. Hybrid EQR-MSE test result of LSTM-C (testing data is 31% of training data)

8. Conclusions

In this paper, we proposed two novel ideas. The first is using the *Geodetic Distance system*, the distance along earth surface which has the property of curvature shape. The Geodetic Distance system depends on the latitude and longitude coordinate-values in measuring distance. This leads to accurate results in predicting terrorist location.

The second proposed novel idea is using two geolocation functions as loss functions to achieve more accurate performance, which are: *Haversine formula* and *Equirectangular Projection formula*. The two proposed loss functions are: hybrid ***HAV-MSE*** and hybrid ***EQR-MSE***.

Two experiments are performed on our machine learning model ***LSTM*** with two different ranges of datasets in training and testing. The model used actual data of terrorist action taken place in Egypt at 2019.

The first experimental case (*Case 1*) uses testing data is 4% of training data and the second experimental case (*Case 2*) uses testing data is 31% of training data.

For each experiment, three loss functions are applied to determine the model performance. These loss functions are: traditional ***MSE***, hybrid ***HAV-MSE*** and hybrid ***EQR-MSE.***

The following Tables summarize a compression between the three loss functions: traditional ***MSE***, hybrid ***HAV-MSE*** and hybrid ***EQR-MSE*** for the two experiments in *Case1* and *Case2*; to measure the accuracy (in %) for each loss function.

From Table 3, it is shown that using traditional ***MSE;*** in both two experiments; is not accurate (or useless) and give bad response in the case of geolocation prediction for sequenced data. The number of predicted location was 0% for distance is less than 20 *km* and approximately of range 2.5% to 13% in distance range from 20 to 70 *km*, in *Case 1*. While, in *Case 2*, ***MSE*** was 0% for distance less than 10 *km* and approximately of rang 0.2 % to 10.7% in distance range from 10 to 70 *km*.

Table 4 shows in *Case-1*, the use of hybrid ***HAV-MSE*** resulted in the number of predicted location was 0% for distances less than 20 *km*; and of rang 28.5% to 66.2% for distance range from 20 to 70 *km*. In *Case-2*, using the hybrid ***HAV-MSE*** resulted in range of 32.7% to 76.8%; in distance range from 3 to 70 *km*.

In Table 5, the using of hybrid ***EQR-MSE*** in *Case-1*, the number of predicted location was approximately of range from 5.19% to 68.8%.While in *Case-2*, the predicted location accuracy is from 32.3% to 76.4%.

From Tables 3, 4 and 5, we find that the traditional ***MSE*** is not accurate when using (latitude and longitude coordinate value) for the predicted location of the next event.

The proposed hybrid ***HAV-MSE***, works well in the moderate range of distances between 10 and 20 *km* with accuracy reaches approximately to 29 % than traditional ***MES*** and hybrid ***EQR-MSE***

But it gives Zero accuracy in certain ranges of distances. The proposed hybrid ***EQR-MSE*** loss function has less accuracy than ***HAV*** in ranges in few cases (as shown in Tables 4 and 5). While has no Zero accuracy in any range of distances. Both ***HAV*** and ***EQR*** give more accurate results than the traditional ***MSE.***

Finally, two conclusions are noticed. The first conclusion is using *Geodetic Distance system* are more accurate and effective in predicting geographic locations at open area among earth surface than using the traditional straight-line distance measurements.

The second conclusion is, it is appeared that using geographic formula as loss function gives accurate and best performance that using only traditional loss functions. Using hybrid ***HAV-MSE*** and hybrid ***EQR-MSE*** gives accuracy more that 75% in large scales (50 to 70 km) compared to low accuracy reaches to 10 % for using traditional **MSE** loss function.

Table 3. Accuracy (%) of Traditional MSE in the LSTM

		3*km*	**5*km***	**10*km***	**20*km***	**30*km***	**40*km***	**50*km***	**60*km***	**70*km***
MSE	**Case 1**	0	0	0	26	2.6	6.5	7.8	10.4	13
	Case 2	0	0	0.21	0.42	2.97	3.4	3.6	4.89	10.7

Table 4. Accuracy (%) of the hybrid HAV-MSE in LSTM

		3*km*	**5*km***	**10*km***	**20*km***	**30*km***	**40*km***	**50*km***	**60*km***	**70*km***
HAV	**Case 1**	0	0	28.5	35	46.7	55.8	58.4	63.6	66.2
	Case 2	32.7	33.8	38.2	41	44.4	58.9	70.8	71.2	76.8

Table 5. Table 5: Accuracy (%) of the hybrid EQR-MSE in LSTM

		3*km*	**5*km***	**10*km***	**20*km***	**30*km***	**40*km***	**50*km***	**60*km***	**70*km***
RCT	**Case 1**	5.2	5.2	35	41.55	41.55	54.5	62.3	64.9	68.8
	Case 2	32.3	33.2	38	41.3	43.4	58.5	70.8	71.2	78.3

REFERENCES

[1] Study of terrorism and responses to terrorism (START), Global Terrorism Database Codebook: Methodology, Inclusion Criteria, and Variables, 2021.

[2] R.S. Alhamdani, M.N. Abdullah, and I.A. Sattar, "Recommender System for Global Terrorist Database Based on Deep Learning," Int. J. Mach. Learn. Comput. 8, 2018.

[3] Y. Jun, X. Tong, H. Zhiyi, and L. Yutong, "Hazard Grading Model of Terrorist Attack Based on Machine Learning," 2019.

[4] T. Jani, "Predicting success of global terrorist," 2019.

[5] S.B. Salem, S. Naouali, "Pattern recognition approach in multidimensional databases: application to the global terrorism database," Int. J. Adv. Comp. Sci. Appl. (IJACSA) 7, 2016.

[6] M.M. Khorshid, T.H. Abou-El-Enien, G.M. Soliman, "Hybrid Classification Algorithms For Terrorism Prediction in Middle East and North Africa," Int. J. Emerg. Trend. Tech. Comp. Sci. 4, 23–29, 2015.

[7] S. Nieves and A. Cruz, "Finding Patterns of Terrorist Groups in Iraq: a Knowledge Discovery Analysis," 9th LACCEI Latin American and Caribbean Conference (LACCEI'2011), Engineering for a Smart Planet, Innovation, Information Technology and Computational Tools for Sustainable Development., Medellín, 2011.

[8] M. Adnan, M. Rafi, "Extracting patterns from Global Terrorist Dataset (GTD) Using Co-Clustering approach," J. Independ. Stud. Res. 13, 7, 2015.

[9] V. Kumar, M. Mazzara, A. Messina, J. Lee, "A Conjoint Application of Data Mining Techniques for Analysis of Global Terrorist Attacks," International Conference in Software Engineering for Defense Applications, pp. 146–158, 2018.

[10] Olusola A. Olabanjo et al, "An ensemble machine learning model for the prediction of danger zones: Towards a global counter-terrorism," Elsevier, Soft Computing Letters 3, 2021.

[11] Momita Rani Giri1, Prof. Preeti Rai, "Detecting and classifying human terrorist attack type involvement using machine learning," International Research Journal of Engineering and Technology (IRJET), Volume: 11 Issue: 08, 2024.

[12] Firas Saidi and Zouheir Trabelsi "A hybrid deep learning-based framework for future terrorist activities modeling and prediction", Egyptian Informatics Journal, ScienceDirect Vol.23(437–446), Issue 3, September 2022.

[13] Liu, Q.; Wu, S.; Wang, L.; and Tan, T., "Predicting the next location: A recurrent model with spatial and temporal contexts", In Proceedings of the 13th AAAI Conference on Artificial Intelligence, February 12-17, Phoenix, Arizona, USA, 194–200, 2016.

[14] Bolstad Paul, "GIS Fundamentals,"(5th ed.), Atlas books. p. 102. ISBN 978-0-9717647-3-6, 2012.

[15] Chang, Kang-tsung, "Introduction to Geographic Information Systems," (9th ed.). McGraw-Hill. p. 24. ISBN 978-1-259-92964-9, 2016.

[16] Frank van der Wouden , and Hyejin Youn, "The impact of geographical distance on learning through collaboration", Research Policy, Elsevier, Vol. 52, Issue 2, 104698, March 2023.

[17] S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural Computation, vol. 9, no.8, pp. 1735–1780, Nov. 1997.

[18] Olusola A. Olabanjo, Benjamin S. Aribisala, Manuel Mazzara, Ashiribo S. Wusu , " An ensemble machine learning model for the prediction of danger zones: Towards a global counter-terrorism" , Soft Computing Letters, Elsevier, Vol 3, 100020, December 2021.

[19] T. Jani, "Predicting success of global terrorist," 2019.

[20] Xiaohui Pan and Wei-Chuen Yau, "Quantitative Analysis and Prediction of Global Terrorist Attacks Based on Machine Learning", Scientific Programming (Published Special Issues: Theory, Algorithms, and Applications for the Multiclass Classification Problem), Vol. 2021,Article ID 7890923, 2022.

[21] Wang, P.; Wang, H.; Zhang, H.; Lu, F.; and Wu, S., "A hybrid markov and LSTM model for indoor location prediction", IEEE Access 7:185928–185940, 2019a.

[22] S. Hooker, D. Erhan, P.-J. Kindermans, and B. Kim, "Evaluating feature importance estimates," 2018.

[23] G. K¨onig, C. Molnar, B. Bischl, M. Grosse-Wentrup, "Relative feature importance," 25th International Conference on Pattern Recognition (ICPR), pp. 9318–9325, 2021.

[24] C. Liu, S. Gong, C.C. Loy, "On-the-fly feature importance mining for person reidentification," Pattern Recognition 47, 1602–1615, 2014.

[25] Z Fei, Z Wu, Y Xiao, J Ma, W He , "A new short-arc fitting method with high precision using Adam optimization algorithm", Elsevier, Optik, 2020.

[26] Nichat, M., "Landmark based shortest path

detection by using an algorithm and Haversine formula", International Journal of Innovative Research in Computer and Communication Engineering, 2013.

[27] van Brummelen, Glen Robert, "Heavenly Mathematics: The Forgotten Art of Spherical Trigonometry," Princeton University Press. ISBN 9780691148922.0691148929, 2015.

[28] John P. Snyder, "Flattening the Earth: Two Thousand Years of Map Projections," pp. 5–8, ISBN 0-226-76747-7, 1993.

[29] Qi Wang, Yue Ma, Kun Zhao & Yingjie Tian, "A Comprehensive Survey of Loss Functions in Machine Learning," springer link, 2020.

[30] Xia T, Gu Y., "Building terrorist knowledge graph from global terrorism database and wikipedia." IEEE International Conference on Intelligence and Security Informatics (ISI). IEEE; p. 194–6, 2019.