Svedberg Open
DISSEMINATION OF KNOWLEDGE

International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: https://www.svedbergopen.com/

Research Paper Open Access

Implementation Of Climate Factor Prediction Of Dengue Outbreak With Mosquito Spreading Control Using Optimal Feature Association Of Attention-Based Deep Learning Network

Gopala Varma Kosuri[1]*, Dr. M. Chandra Naik[2], Dr. R. N. V. Jagan Mohan[3]

[1]Research Scholar Department of Computer Science & Engineering Gandhi Institute of Engineering and Technology University Odisha, Gunupur-765022, India. Email:gopalavarma.kosuri@giet.edu
[2]Professor Department of Computer Science & Engineering, Gandhi Institute of Engineering and Technology University Odisha, Gunupur-765022, India. Email:srichandra2007@gmail.com
[3]Associate Professor Department of Computer Science & Engineering SRKR Engineering College (A) Chinaamiram, Andhra Pradesh-534204, India. Email:mohanrnvj@gmail.com

Abstract
Dengue fever and other mosquito-borne illnesses spread quickly and this disease has intricate connections between social, economic, and ecological factors, but weather patterns including variations in temperature, humidity, and rainfall continue to have a significant impact. Therefore, an automated mosquito spreading control system is implemented using climatic data and a deep learning-based dengue outbreak prediction framework. The climate factors data for dengue fever outbreak is predicted in this work for controlling the mosquito spreading. Initially, the requisite climate data such as temperature, humidity, precipitation, and so on is gathered from the benchmark resources and the collected data is fed into the optimal feature selection stage. Here, the necessary feature of the mosquito spreading control process is optimally selected by utilizing the Modified Golden Eagle Optimizer (MGEO). Further, the optimally selected features are forwarded to the Attention-based Temporal Convolutional Network (TCN) with Long Short Term Memory layer (ATCN-LSTM) for predicting the dengue outbreak. Subsequently, the climate factors data for dengue fever outbreak is predicted by analyzing and varying the climatic parameters and its micro-level. Here, the parameter and its micro-level are determined optimally by the same MGEO algorithm to control mosquito spreading.

Keywords-Climate Factor Prediction of Dengue Outbreak; Mosquito Spreading Control; Optimal Feature Selection; Modified Golden Eagle Optimizer; Attention-Based Temporal Convolutional Network With Long Short Term Memory Layer

1. Introduction

Different types of arboviruses are spread by mosquitoes. These viruses typically cause diseases in tropical and subtropical areas [1]. Climate change [2] can further improve virus transmission and the spread of invading mosquito species. The emergence and spread of diseases linked to climate change and extreme weather events [3]. Mosquito-borne diseases are the worst threats to the world and it is the prime example of hazards. Humans have coexisted with the Anopheles mosquito, which spreads the malaria parasite, and the Aedes, which carries several arboviral infections, such as dengue and recently discovered viruses like Zika and chikungunya [4]. Aedes mosquitoes are more prone to transmit diseases, dengue being the most prevalent, because they reside close to human bodies and feed on human blood [5]. The local mosquito species can promote the transmission of the corresponding viruses in humans [6]. However, there is currently limited information available regarding the local mosquito species for the particular arboviruses.

Mosquitoes need a variety of climatic and structural characteristics for their growth [7]. In the most basic scenario, models are created using bioclimatic data which includes precipitation and temperature [8]. The lowlands of northeastern Germany do not experience this climate difference [9]. The invasive organisms are not fully adapted to the local climate, so modeling is frequently necessary in this circumstance [10]. Sub-Saharan African countries are susceptible to malaria-endemic but they are not thoroughly investigated based on climate-related factors [11]. Thus, there is an urgent need to address these problems and provide a state-of-the-art solution to improve choices in the health sector [12].

The acoustic signature of the Birds and bees has been successfully classified by machine learning algorithms [13] [14]. Effective classification of mosquitoes has been demonstrated by log-mel spectral characteristics with Convolutional Neural Network (CNN) models [15]. Healthcare professionals can adopt machine learning algorithms for making decisions about therapies. The Support Vector Machine (SVM) is used to predict the outbreak of malaria diseases based on climate data [16]. The conventional approaches reads meteorological data from geographical Application Programming Interfaces (APIs) and free weather services and then forecast the potential incidence rate of dengue [17]. The majority of these models for forecasting have been successful, but none of them could be considered the best approach for predicting dengue based on climate variability and the prediction techniques vary depending on the area's behavior. The traditional approaches are not suited to predict the dengue mosquito in the tropical and subtropical regions. Further, the conventional approaches fail to learn the complex pattern in the data, which produces in accurate results in the dengue outbreak prediction process. Likewise, the climatic factors are not considered by the conventional approaches, which cause a huge barrier in the outbreak prediction process. In this research, a deep learning-based dengue outbreak prediction with mosquito spreading control is developed to handle the difficulties involved in the conventional model.

The important contributions of the deep model-based dengue outbreak prediction with mosquito spreading control model are listed as follows.

- To design a deep structure-based dengue outbreak prediction with a mosquito spreading control approach to predict the dengue epidemic based on the climatic data for guiding medical professionals to take proactive steps to prevent the dissemination of dengue disease in the country. In addition, the suggested model controls the spread of the mosquito to mitigate the transmission of dengue disease in the human.
- To recommend an MGEO by upgrading the arbitrary number in the conventional GEO for optimally choosing the features and parameters to enhance the relief score and accuracy in the optimal features selection and dengue outbreak prediction process.
- To design the ATCN-LSTM with the combination of attention-based TCN and LSTM for predicting the dengue outbreak based on climatic data. The ATCN-LSTM has the capability to analyze the temporal and long-term dependency in the input data that provides accurate results in the dengue outbreak prediction process. This model also helps to adopt different disease control measures for enhancing the health concerns of the people.
- To optimally determine the parameter and the micro-level for controlling the spread of the mosquito to lower the transmission of the dengue fever in the country and it greatly minimize the impact of the dengue disease on public health.
- To validate the performance of the recommended dengue outbreak prediction with mosquito spreading control for confirming its effectiveness with the existing model.

The ATCN-LSTM-based dengue outbreak prediction with mosquito spreading control approach is presented as follows. The literature works of the dengue outbreak prediction is given in Part II. A novel climate factor prediction of dengue outbreak using deep learning is specified in Part III. The description of the dataset and optimal selection of features for improving detection performance is indicated in Part IV. The attention-based deep learning network for climate factor prediction of dengue outbreak is given in Part V. The results with its discussion are specified in Part VI. The conclusion of the developed model is mentioned in Part VII.

2.Literature survey

2.1 Related Works

In 2021, Li et al. [18] have developed a statistical and regression network to find the occurrences of dengue fever in the country. The key ecological environment for dengue fever was predicted by the Principal Component Analysis (PCA). The key factors including light time night travel and population density were also considered to find the dengue outbreak in the country. The socio-economic factors and endemic factors for the particular region are also considered to find the dengue outbreak in the region.

In 2021, Sierra et al. [19] have suggested a Poisson multilevel analysis for detecting the climatic, socio-demographic and economic factors that lead to the development of dengue disease in the country. The health department provides the required details such as entomological variables to predict the outbreak in the country. The municipality affected by the severe dengue was determined by this model. Based on the temperature, and humidity level, the cases present in the particular area were accurately measured via the Poisson multilevel analysis.

In 2021, Wieland et al. [20] have presented an XGBoost model for analyzing the mosquito species in the German country. The combination of the habitat model and climate model effectively considers climatic factors for accurately detecting the dengue outbreak in the country. Finally, the statistical analysis was performed to find the effectiveness of the recommended model and the infection in the particular region was detected by the recommended approach.

In 2024, Joelianto et al. [21] have offered a real-time CNN for classifying the mosquito species in the particular region. The multi-class classification and binary classification were performed by the CNN approach. The suggested CNN model attained higher accuracy while classifying the mosquito species. The male and the female Ades were determined by the CNN with high precision. This approach was used to control the dissemination of dengue and provides an effective disease management process.

In 2022, Carreto et al. [22] have presented an index mathematical model for eliminating the dissemination of mosquito-borne disease in the country. Here, the viral suitability index was taken into consideration for analyzing the mosquito-borne disease in the country. The temperature, precipitation, and humidity levels were considered by the index mathematical model to get accurate results in the detection of mosquito-borne diseases detection.

In 2022, Mondal et al. [23] have offered a Geographically Weighted Regression (GWR) technique for determining vector-borne disease based on climatic conditions. It considered the temperature and attributes of the rainfall for analyzing vector-borne diseases in humans. Further, the Inverse Distance Weight (IDW) interpolation technique was used to map the positive disease cases and climatic parameters. The final results showed that the vector-borne disease was mainly occurred due to the rainfall and temperature factors and it greatly spread this disease all around the world.

In 2021, Nkiruka et al. [24] have suggested a machine-learning approach for classifying the malaria diseases based on climatic variables. The feature engineering process was initially done to analyze the climatic variables to find the incidence of malaria disease. The outlier in the data was detected by the k-means clustering process. The comparative results were adopted to verify the effectiveness of the proposed model in the classification process. The suggested model helps to save the lives of the people by providing effective treatment approaches

In 2021, Soh and Aik [25] have designed an efficient approach for analyzing the rainfall variability and temperature in the environment to analyze the habitats of the mosquitoes. The characteristic of the abundant Culex mosquito larval was determined by this model. The utilization of weather data in the prediction process helps to prevent the transmission of the virus in urban areas.

2.2 Problem statement

Dengue fever is a widespread disorder and causes serious problems for humanity. The primary climatic factors that contribute to dengue outbreaks must be detected to effectively prevent this issue. Various experiments have been conducted in this area. However, a very limited amount of work has been given successful outcomes and these approaches also still need further improvement. The primary limitations that have been faced in the traditional experiments are listed below.

- Only a limited number of researches is available to predict the dengue outbreak using climatic factors. Hence, to enhance the system efficiency and predict the dengue outbreaks automatically, climatic factors are required.
- Most of the conventional dengue outbreak prediction techniques utilized machine learning mechanisms for predicting the dengue outbreaks. However, these techniques consume more time and create more computational complexities. Hence, the suggested work employed the recent deep learning technique that minimized the mentioned issues.
- Though some of the traditional techniques employ climate data for the prediction process, these techniques didn't consider the optimal features. This reduced the accuracy of the overall process. Thus, the suggested work performed the optimal feature selection task using an improved optimization algorithm that selects very related and effective features from the climate data for the prediction task.
- The conventional dengue fever outbreak techniques only predicted the dengue outbreaks and didn't focus the mosquito spreading control. Hence, the suggested work performed the mosquito spreading control operation by employing the modified optimization algorithm that shows the uniqueness of the presented work.
- Although there are some deep learning techniques employed for prediction purposes, the techniques face overfitting, dimensionality, and generalizability issues. Hence, this work implemented a modern and effective deep learning technique to reduce the mentioned issues.

Thus a novel dengue outbreak prediction mechanism is introduced by employing deep learning in this work. Table 1 elucidates the state-of-the-art technique's features and limitations.

Table 1. Features and challenges of existing dengue outbreak prediction techniques

Author [citation]	Methodology	Features	Challenges
Li et al. [18]	Support Vector Regression (SVR)	It is robust to outliers and has better generalization capability. Its implementation process is simple.	It is not efficient in large-scale datasets. It generates inaccurate outcomes.
Sierra et al. [19]	Poisson multilevel analysis	It effectively forecasts future events. It generates accurate representations of random events.	It increases the risk of false positive rates. It is not suitable for real-world applications.
Wieland et al. [20]	XGBoost	It is very fast and effective. It handles huge-size datasets effectively.	It can be slow to train because of numerous hyperparameters. It is not applicable for low-end devices.
Joelianto et al. [21]	CNN	It automatically learns the necessary features. It reduces the computations.	It demands more memory and time. It has interpretability complexities.
Carreto et al. [22]	Index P analysis	It reveals markedly distinct mosquito disease risk transmission patterns.	It is suitable for very small regions.
Mondal et al. [23]	ANN	It is fault-tolerant ad performs parallel processing. It can generate outcomes with inadequate data.	It is computationally very expensive. It consumes more time to develop.
Nkiruka et al. [24]	XGBoost	It generates high accuracy. It is very simple to understand and interpret.	It is susceptible to overfitting. It is memory intensive.
Soh and Aik [25]	Zero-inflated Poisson (ZIP) regression	It manages high amount of zeros and has better flexibility. It offers interpretable attributes.	It is not applicable for small samples. It is more complex than other regression techniques.

3.A Novel Climate Factor Prediction of Dengue Outbreak Using Deep Learning: Architectural Description

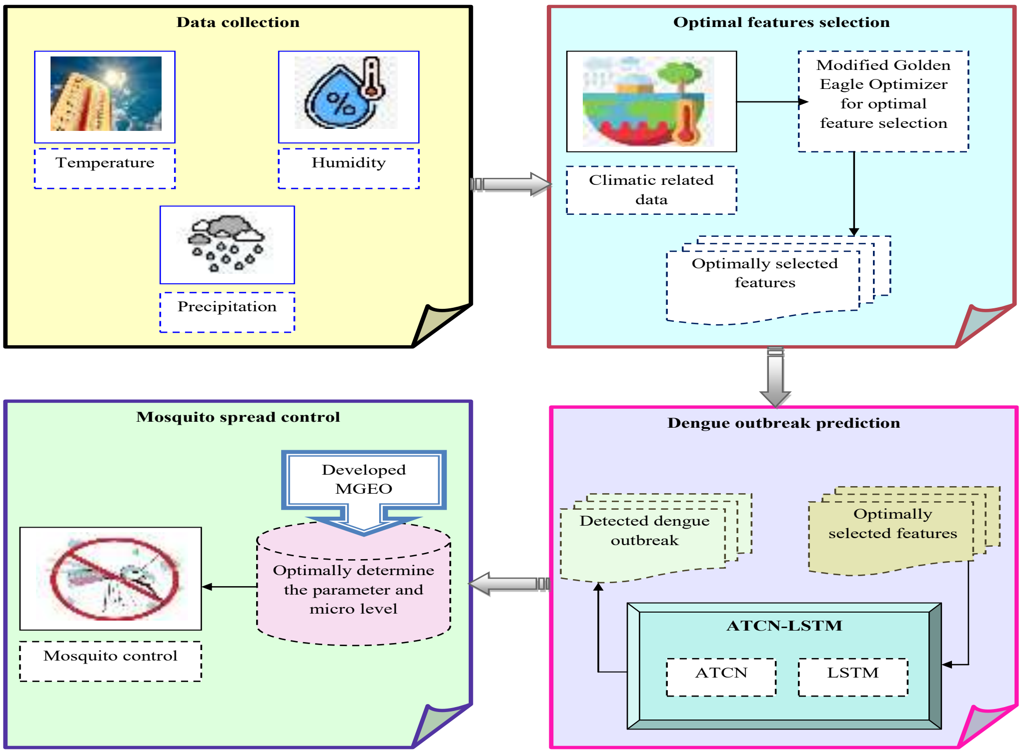
3.1 Importance of Predicting the Climate Factor of Dengue Outbreak

The humid and semi-tropical regions of the world are greatly endangered by the dangerous disease called as dengue. Joint pain, muscle pain, and headache are the frequent symptoms of dengue. The mosquitoes are the primary factor for spreading dengue fever around the world. The accurate forecasting of dengue outbreaks can be used to take proactive steps to prevent the spread of dengue fever in the world. The premature caution system for the dengue outbreak is easily provided by predicting the climatic factors such as rainfall, temperature humidity, etc and it may be helpful to neglect the dissemination of dengue fever by taking the targeted intervention in a timely manner. Further, mosquitoes are the main sources for spreading dengue disease in humans here the reproduction of mosquitoes is mainly depend on the changes in the climatic factors. The dengue transmission changes over time based on the temperature and the rainfall conditions of the country. The disease control measures are effectively adopted with the help of predicting the climatic factors and it entails enhancing the accuracy of the dengue outbreak prediction process. Proactive disease management is done by predicting the climate factor associated with the dengue outbreak.

3.2 Architectural View of Proposed Model

Dengue is a dangerous disease that affects most of the people in the world. Priority health adaptation techniques are developed to significantly provide early warning signals for the dengue disease. The dengue outbreak prediction is performed by numerous approaches. The dengue fever cases in the given area are determined by some of the factors including rainfall, temperature and humidity, etc. However, the conventional approaches attain accurate results while taking these factors into account. In addition, the predictive capability of the traditional model is very low and they fail to capture the complex relationship between the climatic factor data. The dengue outbreak is effectively predicted by the variability of climatic factors. However, the existing model does not find the spatial pattern of the climatic data so it does not provide precise results in the dengue outbreak recognition process. The challenges of the existing approaches prevail by the deep leaning-based dengue outbreak prediction with mosquito spreading control approach. The architectural view of the deep network-based dengue outbreak prediction with mosquito spreading control is specified in Fig. 1.

Figure 1.Architecture of the deep network-based dengue outbreak prediction with mosquito spreading control model



We developed a deep learning-based dengue outbreak prediction with a mosquito spreading control framework for assisting the healthcare professions in taking proactive steps to prevent the spread of dengue in the country. In addition, the suggested deep model also helped to mitigate the risk of transmission of dengue by taking the necessary treatment measures. Further, the developed model reduces the risk of dengue by providing valuable insights to predict the outbreak in the country based on the climatic data. Dengue fever is mainly caused by climatic factors since the mosquitoes are grown in humid areas and spread viruses so the intensity of the dengue in a particular region is enormously increased and develops outbreak in the country, which can be prevented by the suggested methodology as it captures the microclimatic data to control the spread of mosquito in the area and prevent the occurrence of dengue in the particular area. This research uses the climate data that is collected from the online resources. The collected climatic data consists of temperature, humidity, and precipitation details for predicting the dengue outbreak in the country. The collected climatic data is further passed to the feature selection phase here; the feature selection is done in an optimal manner in which the necessary features are optimally attained using the MGEO. Thus, the relief score value is highly enhanced. After that, the optimal features are given to the ATCN-LSTM to predict the outbreak in the country. The TCN requires very minimum resources for processing the time series data and the temporal dependencies of the data are captured by the TCN. Additionally, the relationships among the climatic variables of the optimally selected features are captured by the TCN. Along with the TCN, the attention module is incorporated to enhance the feature learning capability of the TCN. The LSTM can preserve the historical information and spatial features in the given input data to get precise results in the dengue outbreak recognition process. The optimally selected features are given to the ATCN-LSTM and here the features from the optimal features are approved by the LSTM to make the prediction regarding the dengue outbreak. After the dengue prediction, the parameters and its micro level such as maximum and minimum temperatures as well as maximum and minimum humidity is optimally selected to prevent the spreading of mosquitoes around the country which enhances the accuracy of the mosquito outbreak prediction process. The optimal control of mosquito spread prevents the occurrence of dengue disease in humans. The mosquito-spread control can help to prevent the risk of dengue outbreaks in the public healthcare system. It has the ability to handle the spread of dengue viruses by minimizing the mosquito population. At last, the recommended model is contrasted with the conventional techniques to verify its effectiveness in the dengue outbreak prediction with mosquito spreading control process.

4.Description of Dataset and Optimal Selection of Features for Improving Detection Performance

4.1 Representation of Climate Factor Dataset

The Local Epidemics of Dengue Fever is the first dataset and it is taken from the link https://www.kaggle.com/datasets/arashnic/epidemy with access date: 2024-07-16. The tropical and subtropical parts of the world are affected by the dengue disease. The symptoms such as fever and flu are occurring due to the presence of the dengue disease. The Asian and Pacific islands are mostly affected by the dengue disease.

Global Dengue Outbreak Prediction Challenge is the second dataset and it is loaded from the link of https://www.kaggle.com/competitions/global-dengue-outbreak-prediction-challenge/data with access date: 2024-07-16. The individual health records of the patient are available in this dataset. This dataset has symptomatic cases that can be used to identify the disease in humans.

We utilize the climatic factor dataset for performing the dengue outbreak prediction and mosquito prediction. The accuracy of the dengue outbreak prediction is enhanced by considering the climate factor dataset. The collected climatic data from the data source is denoted as G_c^l and $c = 1,2 \ldots C$ here the total quantity of the climatic data is elucidated as C .

4.2 Optimal Feature Selection

The feature selection process is optimally carried out on the climatic data G_c^l collected from the data sources. The collected climatic data consist of several features that enhance the complexity of the dengue outbreak prediction process. The optimal feature selection processes select the appropriate features from the data, which seriously augment the recognition capability of the deep model in the outbreak prediction process. Because of this process, the model utilized for the prediction process only concentrates on the relevant feature thus the process of overfitting is greatly reduced. The MGEO algorithms optimally choose the features from the collected climatic data in an optimal way and it is expressed by the term G_c^{mego} . The feature selection in an optimal manner increases the value of the relief score and attains precise results. The optimally selected features enhance the outbreak prediction accuracy and reduce the time necessary for the outbreak prediction process. The objective function of the MGEO-based feature selection is specified in Eq. (1).

$$ob = \underset{\{G_c^{mego}\}}{\arg\min}\left(\frac{1}{rel}\right) \tag{1}$$

Here, the relief score is denoted by the term rel and it is calculated using Eq. (2). The optimally selected feature is expressed by the term G_c^{mego} .

$$rel = R\left(d.of.G_c^{mego} \mid n.d.c\right) - R\left(d.of.G_c^{mego} \mid n.s.c\right) \tag{2}$$

Here, the probability is expressed by the term R , the different value of G_c^{mego} is expressed as $d.of.G_c^{mego}$, the nearest illustration from the similar class is expressed as $n.s.c$, and the adjacent illustration from the dissimilar class is expressed as $n.d.c$. The maximized relief score value is used to get accurate results in the outbreak recognition process.

4.3 Developed MGEO

The MGEO is derived from the GEO algorithm for optimally selecting the features and micro-level in the dengue outbreak prediction with mosquito controlling process. The optimal selection of feature and micro-level parameters simultaneously augments the relief score and accuracy in the feature selection and dengue outbreak prediction process. The GEO is motivated by the behavior of the eagle that solves the global optimization issues in the search space. In addition, the real-time engineering issues are also defeated by the GEO. However, the balancing capability of the GEO in the exploitation and exploration phase is very low. The adaptability and the generalizability of the GEO are very low. By considering these difficulties, an MGEO is developed by upgrading the random attributes. The MGEO enhances the relief score and accuracy in the selection of features and the dengue outbreak prediction process. For calculating the random number, the current, best, worst, and mean fitness values are adopted. The mathematical form of the upgraded arbitrary number is specified in Eq. (3).

$$\vec{s} = \frac{fct}{bct + wct + mct} \tag{3}$$

Here, the upgraded random number is represented as $\vec{s}$ and it is applied in Eq. (7) of the conventional GEO, the best fitness is elucidated as bct, the term fct delineates the current fitness, the worst fitness is delineated as wct and the mean fitness is denoted as mct. The upgraded arbitrary number enhances the balancing capability of the MGEO thus exploitation and exploration are greatly increased. In addition, the generalizability of the MGEO is also enhanced by the upgraded arbitrary number. The tuning of parameters using the MGEO also enhances the accuracy and the relief score values.

Golden Eagle Optimizer (GEO) [26]: The global optimization issues are solved by the GEO. The speed of the golden eagle during the hunting process is taken as the inspiration of the GEO. Then exploitation and the exploration of the GEO are analyzed in the following sections.

The golden eagle follows the spiral motion to catch its prey and the eagle has excellent memory capability so it does not forget the place visited by the eagle to perform the hunting process.

The cruise hunting operation is performed by the golden eagle since it adopts the new prey at each iteration process. The best solution in the GEO is considered from the prey. The best solution is easily memorized by the golden eagle.

From the present position, the attack process is initiated in the direction of the eagle's memory. Eq. (4) is used to determine the vector attack of the golden eagle j.

$$\vec{B}_j = \vec{Y}_g^* - \vec{Y}_g \tag{4}$$

The vector attack of the eagle j is denoted as $\vec{B}_j$, the eagle g visiting the best location represented as $\vec{Y}_g^*$, and the existing location of the present eagle g is denoted as $\vec{Y}_g$.

Exploration (cruise): Based on the attack vector, the cruise vector is calculated. For the circle, the cruise vector is tangent in nature and for the attack vector, it is perpendicular in nature. The inner side of the circle consists of a tangent hyperplane with a cruise vector. In the o dimensional space, the scalar of the hyperplane is calculated using Eq. (5).

$$i_1 y_1 + i_2 y_2 + \ldots + i_o y_o = e \Rightarrow \sum_{k=1}^{o} h_k y_k = e \tag{5}$$

$$e = \vec{I} * \vec{Q} \tag{6}$$

Here, the variable vector is specified as $Y = [y_1, y_2 \ldots y_o]$ and the normal vector is represented as $\vec{I} = [i_1, i_2 \ldots i_o]$, and the arbitrary point is elucidated as $\vec{Q} = [q_1, q_2, \ldots q_o]$.

Displacement to the new position: The attack and vector are comprised in the displacement process of the golden eagle. In the iteration u, the step vector of the golden eagle is specified in Eq. (7).

$$\nabla y_j = \vec{s}_1 q_b \frac{\vec{B}_j}{\|\vec{B}_j\|} + \vec{s}_2 q_d \frac{\vec{D}_j}{\|\vec{D}_j\|} \tag{7}$$

The Euclidean standard of the attack is expressed as $\|\vec{B}_j\|$ and the Euclidean standard of the cruise vector is expressed as $\|\vec{D}_j\|$. At the iteration u, the attack coefficient is expressed as q_b, and the cruise coefficient is expressed as q_d, the random vectors are specified as $\vec{s}_1$ and $\vec{s}_2$, respectively and this arbitrary number is upgraded using Eq. (3) of the recommended MGEO. At u^{th} iteration, the vector of step and the location are added to get the point of the golden eagle and it is given in Eq. (8).

$$y^{u+1} = y^u + \Delta y_j^u \tag{8}$$

The reminiscence of the golden eagle is upgraded with the new position if the fitness value of the new location is superior to the position in the memory of the golden eagle.

Conversion from the exploration and exploitation: This process is done by considering the factors like q_b and q_d. At the initial stage, the value of q_b is very low and the value of q_d is higher. While beginning the iteration process, the value of q_b is increased and the value of q_d is decreased. The linear transition is used to find the value of the intermediate values and it is displayed in Eq. (9).

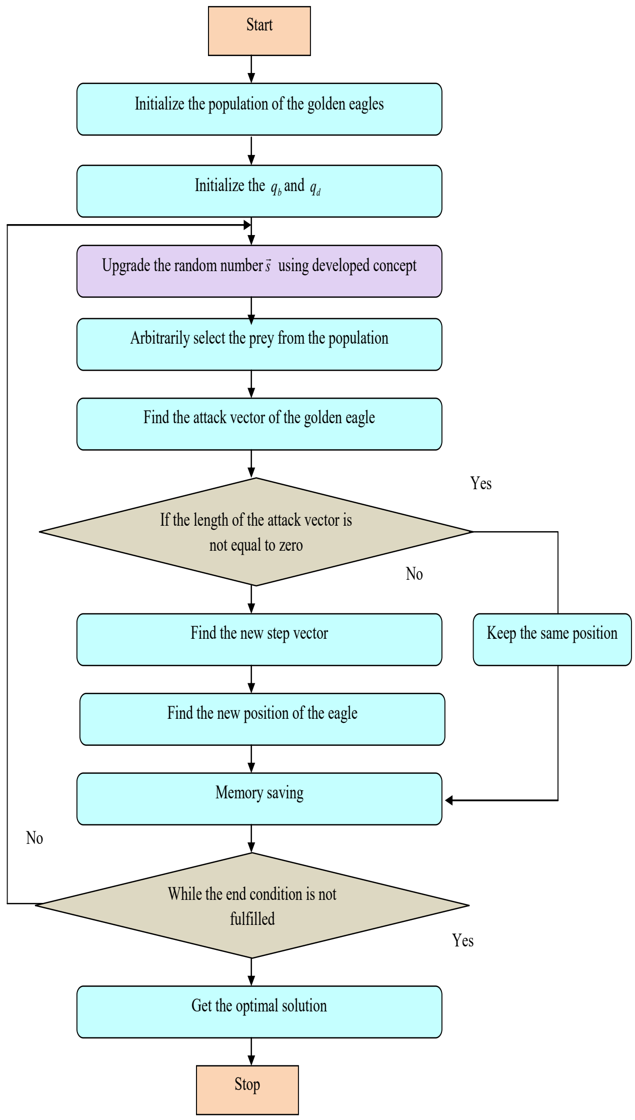
$$\begin{cases} q_b = q_b^0 + \dfrac{u}{U}\left(q_b^U - q_b^0\right) \\ q_d = q_d^0 - \dfrac{u}{U}\left(q_d^U - q_d^0\right) \end{cases} \tag{9}$$

In the tendency to the attack, the initial and the final values is represented as q_b^0 and q_b^U, respectively. In the tendency of the cruise, the initial and the final values are represented as q_d^0, q_d^U, respectively.

The pseudocode of the MGEO is expressed in Algorithm 1 and the flowchart of the MGEO is offered in Fig. 2.

Algorithm 1: Designed MGEO					
Initialize the attributes of the MEGO					
Find the fitness value					
Initialize the population's memory					
Initialize the q_b and q_d					
While the end condition is not fulfilled					
	For each iteration u				
		Upgrade the random number using Eq. (3).			
		Upgrade the value of the q_b and q_d			
		For each golden eagle j			
			Arbitrarily select the prey from the memory of the population		
			Find the attack vector using Eq. (4).		
			If the length of the attack vector is not equivalent to zero		
				Find the step vector using Eq. (7).	
				Upgrade the position value using Eq. (8).	
				Find the fitness of the new position.	
				If the fitness is greater than the fitness of the eagle's memory	
					Replace the position with the position in the memory of the eagle
				End	
			End		
		End for			
	End for				
End while					
Get the optimal solution					
Stop					

Figure 2.Flowchart of the MGEO



5.Attention-based Deep Learning Network for Climate Factor Prediction of Dengue Outbreak

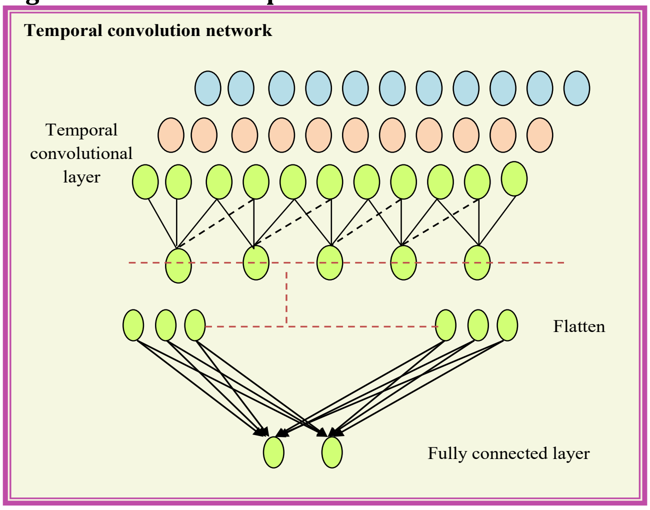
5.1 Temporal Convolutional Network

The TCN [27] is a well-known deep learning architecture that uses dilations and casual convolution layers for interpreting sequential data. The TCN model provides the output at each given time step depending on previous inputs and future input, they are referred to as causal. The TCNs employ dilated fundamental convolutions, which reduce memory requirements or increase the number of parameters needed to store the model while enabling a broad receptive field. The convolutional layers of the TCN model work on a distinct segment of the input sequence. The TCN can construct a representation of the complete input sequence by feeding the output of each layer. While extracting the information from the input data, the vanishing gradient issues are solved by dilated casual convolution and the residual block of the TCN. The utilization of the casual convolution enhances the receptive field to get precise outcomes in the outbreak prediction process. The dilated casual convolution maintains the identical time step for input and output values at the same time it prevents the loss of information in the features retrieval operation. Eq. (10) expresses the operation of the casual dilated convolution in the TCN.

$$z_{i,u} = \sum_{j=0}^{l} g_j * z_{i-1,u-2je} \tag{10}$$

At the time u and for the layer i, the size of the convolutional layer is denoted as l, the series of the value is stated as $z_{i,u}$, the filter is denoted as g_j, and the dilation rate of the TCN is expressed as e. The structural representation of the TCN is given in Fig. 3.

Figure 3.Structural representation of the TCN



5.2 Long Short-Term Memory

The LSTM [28] model is used to predict the dengue outbreak for controlling mosquito spread in the country. In several countries, dengue is considered as a severe health issue and outbreak in a particular region. The time series data is effectively handled by the LSTM and it also effectively handles the flow of data within the network. The gates of the LSTM can capture the long-term dependencies in the data thus it provides effective results in the dengue outbreak prediction process. The LSTM structure provides more accurate prediction results since it can prioritize the features in the input data to get effective results in the dengue outbreak prediction. The performance of the RNN is hindered by the exploding gradient issues so it does not provide accurate results in the dengue outbreak prediction process. In order to solve the difficulties of the RNN, the LSTM is developed and this structure adopts the memory blocks that prevent the exploding gradient issues in the outbreak prediction process. LSTM structure substitutes the multiplicative gates like output, input forget gates rather than the hidden neuron of the RNN. The behavior of the memory block is controlled by the three gates of the LSTM. The resetting, wiring, and reading operations in the memory cell are also embarrassed by the gates of the LSTM. The LSTM can effectively capture and retain the information and allows for getting accurate prediction results.

The flow of new information is controlled by the input gate of the LSTM and it is represented in Eq. (11).

$$j = sigmoid(X_{jj} \times y + X_{jk} \times y + d_j) \tag{11}$$

The input gate's bias value is represented as d_j, the prior hidden state is denoted as y, the input given to the LSTM is represented as y, the prior hidden state, and the input state is connected to the input gates via weights X_{jk} and X_{jj}. The decision to retain or forget the information in the memory block is decided by the forget gate g and it is represented in Eq. (12).

$$g = sigmoid(X_{jg} \times y + X_{ig} \times i + d_g) \tag{12}$$

The input and preceding hidden state is connected to the forget gate with the help of weight values is represented as X_{jg} and X_{ig} correspondingly. The forget gate's bias value is represented as d_g, the provision of output from the memory block is decided by the output gate p and it is represented in Eq. (13).

$$p = sigmoid(X_{jp} \times y + X_{ip} \times i + d_p) \tag{13}$$

The input and previous hidden state is connected to the output gate with the help of weight values represented as X_{jp}, X_{ip}, correspondingly, and the forget gate's bias value is represented as d_g. The memory cell d store the attributes in the memory block d' and it is upgraded using forgets and the input gate is given in Eq. (14).

$$d' = g \times d + j \times \tan i(X_{jd} \times y + X_{id} \times i + d_d) \tag{14}$$

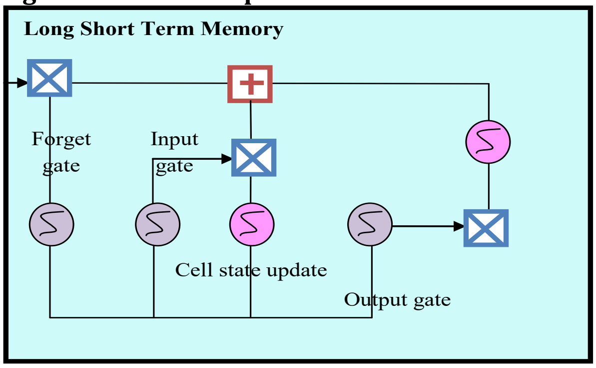
The input and preceding hidden state is connected to the memory cell with the help of weight values represented as X_{jd}, X_{id}. The memory cell's bias value is represented as d_d.

The update gate and the memory cell are used to upgrade the hidden state i and it is elucidated in Eq. (15).

$$i = p \times \tan i(d') \tag{15}$$

The basic operation of the LSTM is expressed by the above expressions. The pictorial representation of the LSTM is given in Fig. 4.

Figure 4.Pictorial representation of the LSTM



5.3 ATCN-LSTM for Climate Factor Prediction of Dengue Outbreak

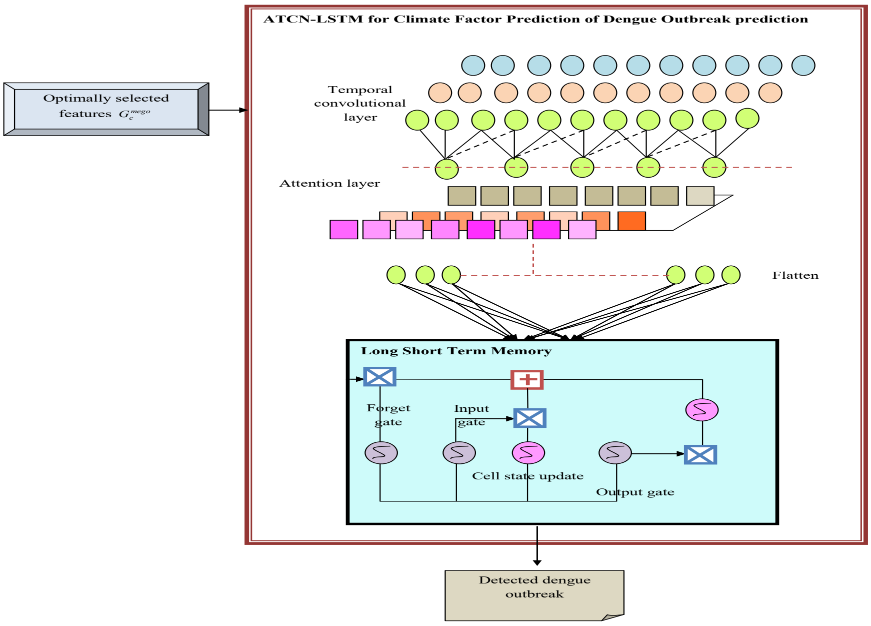
The ATCN-LSTM is developed by incorporating the attention TCN and LSTM. The climate factors related to the dengue outbreak are predicted by the combination of the TCN and LSTM. The TCN requires very minimum time and computational resources for predicting the dengue outbreak. In addition, it enhances the receptive field to get precise grades in the outbreak prediction process The TCN [29] can have the capability to extract significant characteristics from the input data. Likewise, the long-term dependencies in the data are captured by the LSTM so it gives accurate results in the climate factor prediction for the dengue outbreak. The focus of the TCN on the relevant features is enhanced by adding the attention mechanism with the TCN. The optimally selected features G_c^{mego} are given to the ATCN-LSTM for predicting the dengue outbreak based on climatic factors. Here, the ATCN structure retrieves the significant features and they are passed to the LSTM to predict the climate factors related to the dengue outbreak, which includes precipitation, humidity, and temperature that greatly influence the population of the mosquito in the dynamic environment. Based on the above climatic factors, the suggested model predicts the chance of dengue outbreak at the high mosquito region. Predicting the microclimatic variation helps to control the dissimilation of the mosquito that can be used to prevent the development of an outbreak in the country. The ATCN-LSTM-based climate factor detection provides valuable insights to the healthcare department for taking effective treatment to prevent the transmission of dengue in the specific region.

Attention [28]: The long-term dependencies are effectively modeled by incorporating the attention mechanism with the deep network. The utilization of the attention mechanism prioritizes the features in the given input data and provides accurate results in the outbreak prediction process. When making the prediction, the incorporation of the attention mechanism guides the deep model to focus on the most relevant information to get accurate prediction results within the minimum time period. The context vector is produced by the attention module at the given time step and it is represented in Eq. (16).

$$d_u = \sum_{k=1}^{U} \kappa_{uk} i_k \tag{16}$$

The total number of time steps is expressed as U, for each state i_k, and the weight value at each time step u is denoted as κ_{uk}. The structural demonstration of the ATCN-LSTM-based climate factor prediction is presented in Fig. 5.

Figure 5. Structural representation of the ATCN-LSTM-based climate factor prediction



5.4 Optimal Control of Mosquito Spreading

The mosquito is the major cause of dissemination of dengue fever all around the world. To control mosquito spreading in a specific region, the micro level and its parameters are optimally determined using the MGEO. The MGEO optimizes the micro level variables like air temperature minimum level, air temperature maximum level, station temperature minimum level, station temperature maximum level, dew point temperature minimum level, dew point temperature maximum level, relative humidity minimum level, relative humidity maximum level, specific humidity minimum level and specific humidity maximum level to get accurate results in the Mosquito spreading control process. Here, the mean value of the five micro-level attributes is determined by averaging the maximum and the minimum level values of the individual micro-level attributes. The attained mean dew point temperature, mean station temperature, mean air temperature, mean relative humidity, and mean specific humidity are utilized to control the spread of the mosquito in the country. The metabolism of the mosquito is slowed down under the particular air temperature and also the high air temperature in the environment can affect the breeding process of the mosquito thus it helps to control the spreading of mosquitoes in the country. The station temperature is used to find the temperature in a particular area to take effective control measures to prevent the spread of mosquitoes in the country. The humidity of the particular area is determined by the dew points. The survival rate of the mosquito is controlled by maintaining a particular level of relative humidity. The optimal identification micro-level parameters manage the population of the mosquito and neglect the breeding sites of the mosquito. Further, the favorable condition for mosquito breeding is predicted by continuously monitoring the rainfall, humidity, and temperature conditions of the particular sites. Because of the optimal control of mosquito spreading, the burden of the dengue outbreak is greatly reduced. The objective of the optimal control of mosquito spreading is given in Eq. (17).

$$S = \underset{\left\{\begin{matrix} AT_1^{\min}, AT_2^{\max}, ST_1^{\min}, ST_2^{\max}, \\ DT_1^{\min}, DT_2^{\max}, RH_1^{\min}, RH_2^{\max}, \\ SH_1^{\min}, SH_2^{\max} \end{matrix}\right\}}{\arg\min} \left(outbreak\right) \qquad (17)$$

Here, the objective function is delineated as S, the main objective of considering the micro-level attributes is to minimize the chance of dengue outbreak in the country.

6.Results and discussion

6.1 Experimental setup

The recommended ATCN-LSTM-based dengue outbreak prediction with mosquito spreading control approach was implemented using Python software. The reliability of the ATCN-LSTM-based dengue outbreak detection model was compared with the conventional algorithms such as "Seagull optimization algorithm (SOA) [30], Golf Optimization Algorithm (GOA) [31], Namib Beetle Optimization Algorithm (NBOA) [32]", GEO [26] and the prior approaches like XGBoost [33], TCN [27], and LSTM [28] were employed to find the effectiveness of the dengue outbreak prediction model. We take the value of the chromosome length as 5, population as10, and maximum iteration as 50.

6.2 Evaluation indices

The evaluation indices like “False Negative Rate (FNR), False Positive Rate (FPR), and Precision” are taken for the comparison process.

$$accuracy = \frac{vv + vb}{vv + vb + nn + nm} \tag{17}$$

$$FPR = \frac{nn}{vb + nn} \tag{18}$$

$$FNR = \frac{nm}{vv + nm} \tag{19}$$

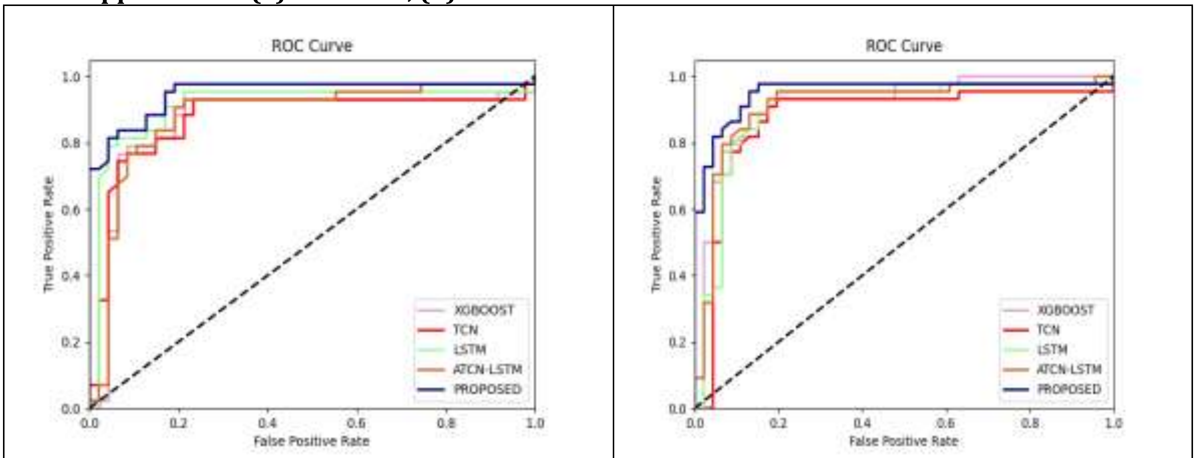
$$precision = \frac{vv}{vv + nn} \tag{20}$$

Here, the true positive rate is represented as vv and the true negative rate is denoted as vb, the false positive is expressed as nn, and the false negative is delineated as nm.

6.3 Roc curve evaluation

The ROC curve analysis of the ATCN-LSTM-based dengue outbreak prediction with mosquito spreading control approach is specified in Fig. 6. The ROC curve analysis is carried out to assess the relative efficiency of the suggested dengue outbreak prediction framework. Here, the proposed ATCN-LSTM (blue line) has a higher ROC area in comparison with the traditional approaches like XGBoost, TCN, LSTM, and ATCN-LSTM. The huge ROC curve indicates that the designed approach attained a higher accuracy value in the dengue outbreak prediction so it is more effective in managing the dissemination of mosquitoes in society. The results comparison show that the combination of the ATCN-LSTM is more effective for predicting the dengue outbreak and it helps to control the mosquito control, which may influence the spreading of dengue in the country. The dengue outbreaks influenced by the long and short-term factors are significantly predicted by the recommended ATCN-LSTM. The suggested ATCN-LSTM is helpful in dengue outbreak prediction and enhances public health efforts.

Figure 6.ROC curve analysis of the suggested dengue outbreak prediction with mosquito spread control approach for (a) Dataset 1, (b) Dataset 2

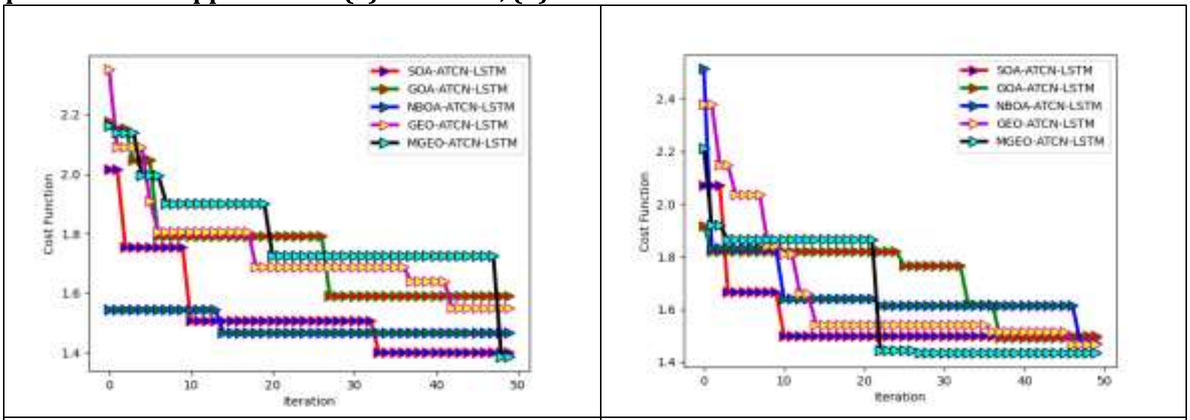


(a) (b)

6.4 Convergence analysis

Fig. 7 presents the convergence assessment of the MGEO-ATCN-LSTM-based dengue outbreak prediction with a mosquito spreading control approach. Here, the convergence assessment is performed by comparing it with traditional algorithms like SOA, GOA, NBOA, and GEO. Here, the iteration value ranges from 0 to 50. Overall, the MGEO-ATCN-LSTM model performs best as it converges within limited iteration values. It is worth to note that the recommended MGEO-ATCN-LSTM initially gets a similar convergence value with the GOA. At 1st iteration, the convergence of the MGEO-ATCN-LSTM is suddenly lowered and it ultimately lowered after the 20th iteration. As the iteration is increased, the cost function of the developed MGEO-ATCN-LSTM tends to degrade, which indicates that the suggested MGEO-ATCN-LSTM provides an optimal solution with a minimum convergence rate. The suggested MGEO-ATCN-LSTM model predicts the dengue outbreak and controls the dissemination of the mosquito in the country. The suggested model is also useful for seeking the proper diagnosis and treatment for saving one’s life from dengue fever.

Figure 7.Convergence investigation of the suggested dengue outbreak prediction with mosquito spread control approach for (a) Dataset 1, (b) Dataset 2

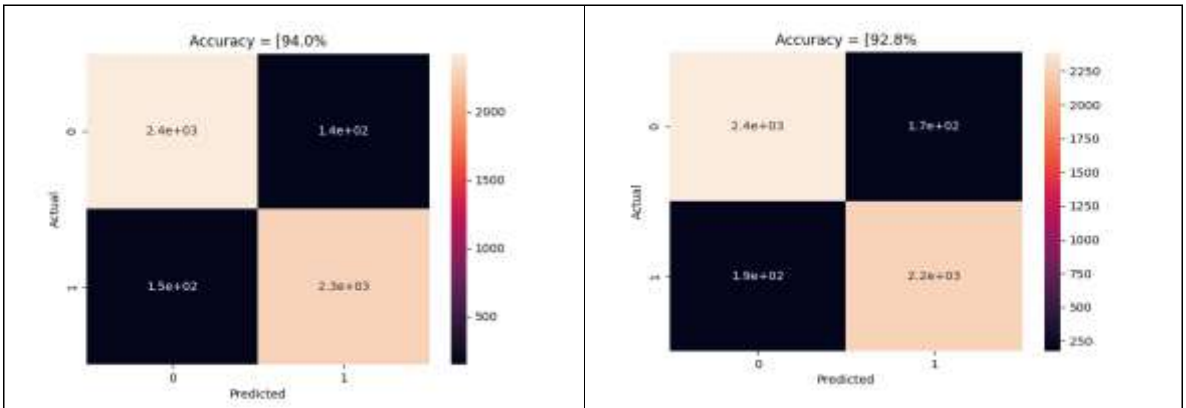


(a) (b)

6.5 Confusion matrix evaluation

The convergence examination of the developed MGEO-ATCN-LSTM-based dengue outbreak prediction with mosquito spreading model is given in Fig. 8. To find the overall performance of the MGEO-ATCN-LSTM, the convergence analysis is carried out. The convergence analysis uses four factors like true positive and negative, false positive and negative to find the overall accuracy of the recommended MGEO-ATCN-LSTM. On the dengue outbreak prediction, the suggested MGEO-ATCN-LSTM outperformed other approaches especially it considering the climatic data to perform the prediction process. The proposed MGEO-ATCN-LSTM was successfully applied for predicting the dengue outbreak and offered convenient results. The suggested model also controls the spread of mosquitoes for controlling the spread of the dengue disease. In addition, the developed MGEO-ATCN-LSTM controls the mosquito as it carries viruses for dengue fever and causes the endemic situation. The dengue disease causes severe complications and death in humans. The controls of mosquito spreading prevent the major causes of dengue fever. Thus, the recommended MGEO-ATCN-LSTM is obviously suited for the dengue outbreak prediction process.

Figure 8.Confusion matrix of the suggested dengue outbreak prediction with mosquito spread control approach for (a) Dataset 1, (b) Dataset 2



(a) (b)

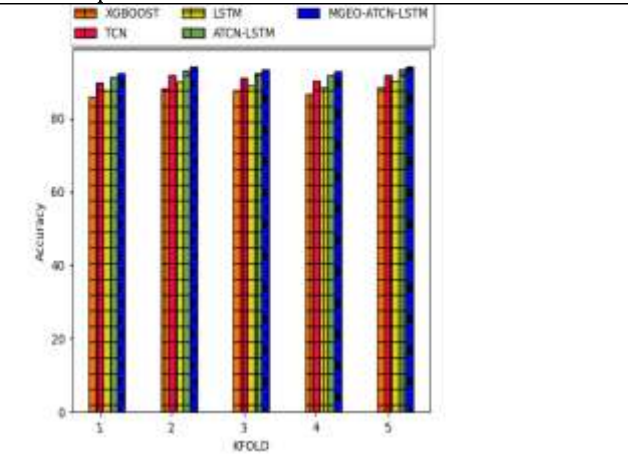
6.6 Accuracy analysis

The accuracy analysis of the ATCN-LSTM-based dengue outbreak prediction with mosquito spreading control approach for the two datasets is given in Fig. 9. Here, the accuracy of the recommended ATCN-LSTM is examined by varying the K fold metric in the axis X and its ranges from 1-5. At the 2nd K fold value, the accuracy of the recommended ATCN-LSTM is reaches maximum value and it is slightly lower at the 1st k fold value. Again at the 5th K fold value, the accuracy of the recommended ATCN-LSTM reaches maximum value. In all K fold values, the least accuracy is attained by the XGBoost. The results showed that the developed ATCN-LSTM was able to accurately predict the progression of the dengue outbreak by consuming minimum time and it developed superior grades in the outbreak detection process. The person around the globe is greatly affected by dengue fever, which is a kind of mosquito-borne disease.

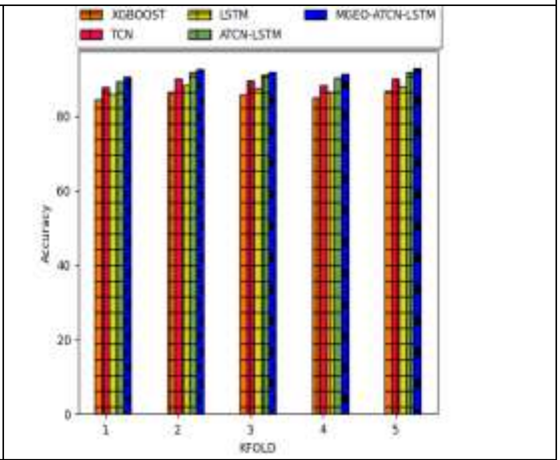
The developed ATCN-LSTM helps healthcare officials take preventative actions by providing timely information regarding dengue diseases.

Figure 9.Accuracy examination of the suggested dengue outbreak prediction with mosquito spread control approach for (a) Dataset 1, (b) Dataset 2

Techniques

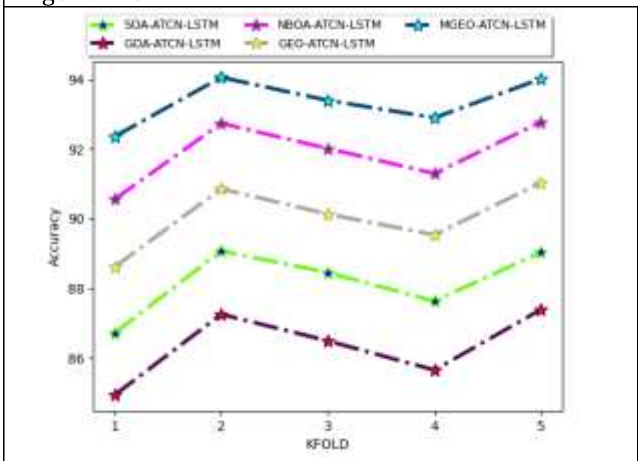


(a)

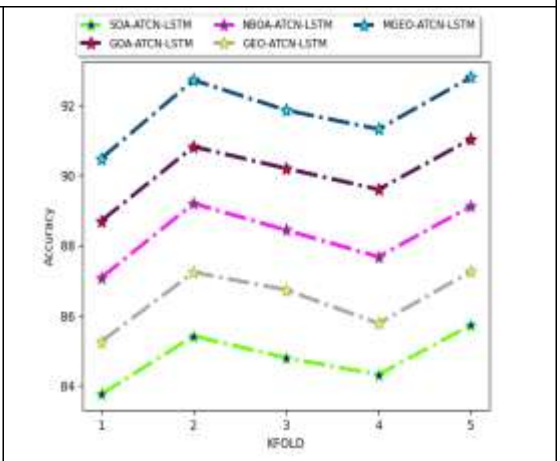


(b)

Algorithms



(a)



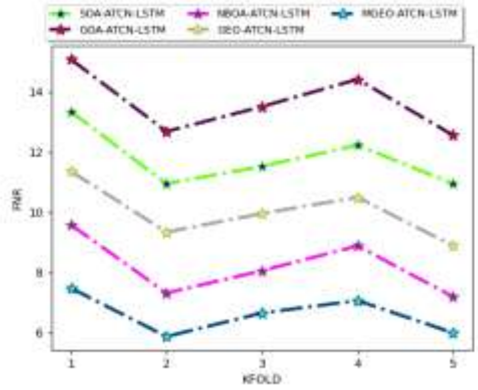
(b)

6.7 Performance analysis over numerous algorithms

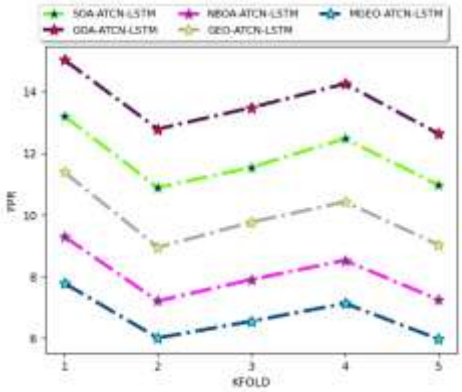
Fig. 10 exemplifies the performance comparison of the suggested MGEO-ATCN-LSTM with the traditional algorithms. The recommended model is analyzed in terms of numerous evaluation indices. From the visualized graph, the precision of the developed MGEO-ATCN-LSTM is greater than the SOA-ATCN-LSTM, GOA-ATCN-LSTM, NBOA-ATCN-LSTM, and GEO-ATCN-LSTM with 5.3%, 7.44%, 1.06%, and 3.72% at the 2nd K fold value. With the increase in K fold values, the precision of the MGEO-ATCN-LSTM is greatly enhanced. At the 5th K fold value, the MGEO-ATCN-LSTM gains a higher value of precision. The results revealed that the suggested model predicts the dengue outbreak in the country to prevent mosquito spreading. In addition, the suggested MGEO-ATCN-LSTM is more robust for predicting the dengue disease from the climatic factors. Moreover, the developed MGEO-ATCN-LSTM provides effective prevention efforts by providing vital information regarding the dengue outbreak based on climatic data. Thus, the developed MGEO-ATCN-LSTM is potentially applied in the dengue disease outbreak prediction for taking the necessary action to prevent the spreading of mosquitoes in the country.

Figure 10.Performance assessment of the deep model-based dengue outbreak prediction model over various algorithms for (a) FNR, (b) FPR, (c) Precision

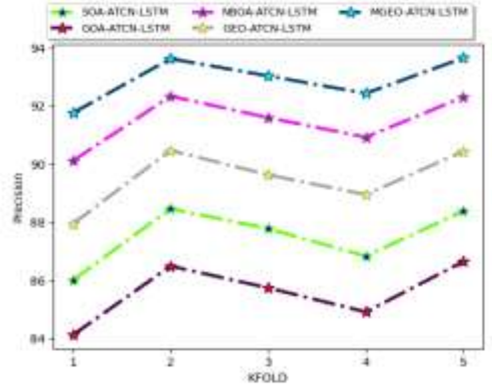
Dataset 1



(a)

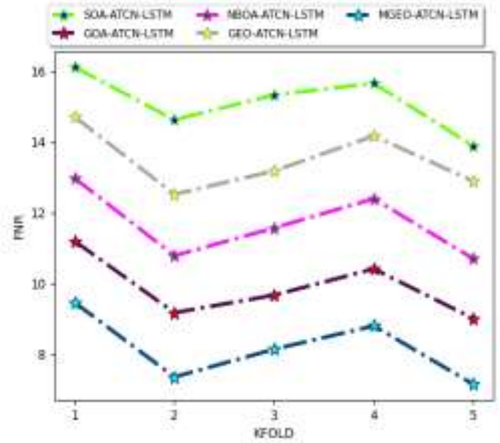


(b)

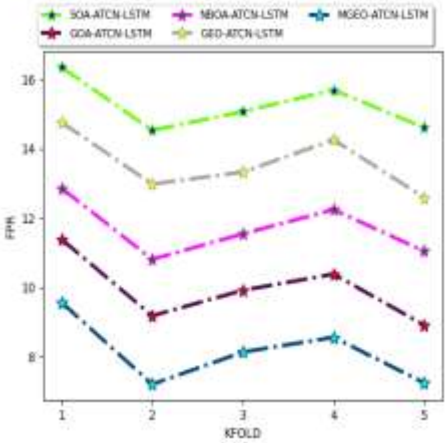


(c)

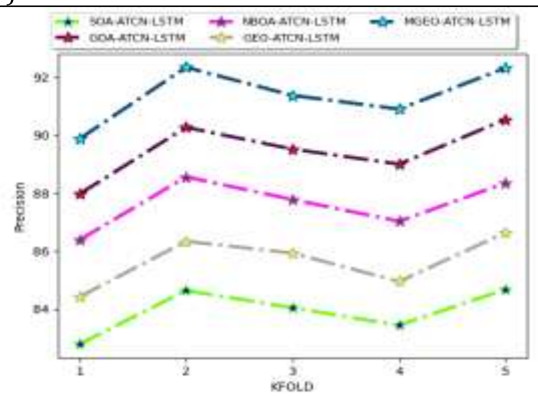
Dataset 2



(a)



(b)



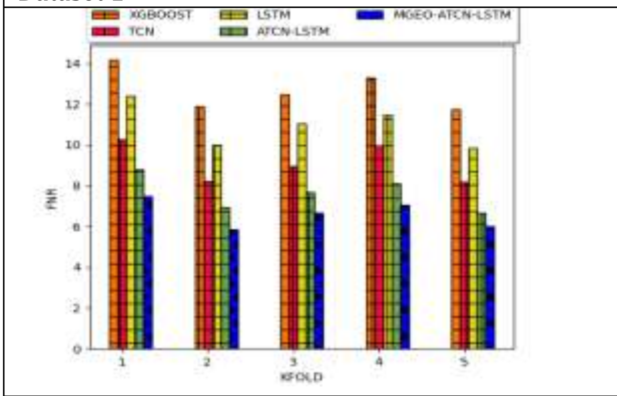
(c)

6.8 Performance examination over numerous techniques

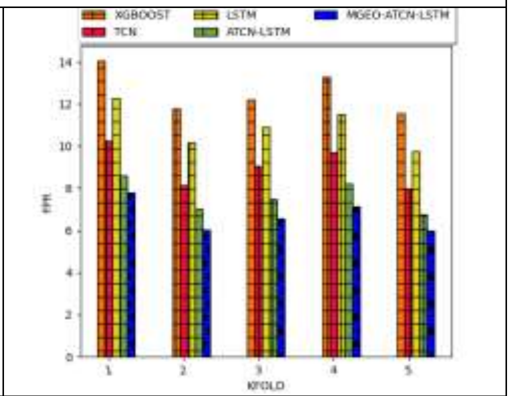
The analyses of the developed MGEO-ATCN-LSTM with numerous existing approaches are specified in Fig. 11. The FPR of the recommended MGEO-ATCN-LSTM is nearly the same as the ATCN-LSTM at the 1st, 2nd, 3rd, and 4th K fold values. But, in the 2nd K fold value, the FPR of the developed MGEO-ATCN-LSTM is comparatively superior to all other K fold values. The extreme least value of FPR is attained by the XGBoost model at the 4th K fold value. The results showed that the suggested MGEO-ATCN-LSTM model helps to predict the dengue outbreak and warn the healthcare authorities and international community to take the proper actions to treat the disease. Dengue outbreak means the dissemination of dengue disease to a huge quantity of people around a specific region within a limited time period. The developed MGEO-ATCN-LSTM determines the escalating number of dengue diseases in the specific area to take mitigative efforts to prevent the transmission of the disease. The suggested MGEO-ATCN-LSTM provides valuable insights to manage the mosquito and avoid the dissemination of dengue in the community and it also reduces the risk of dengue for the human.

Figure 11.Performance assessment of the deep model-based dengue outbreak prediction model over various approaches for (a) FNR, (b) FPR, (c) Precision

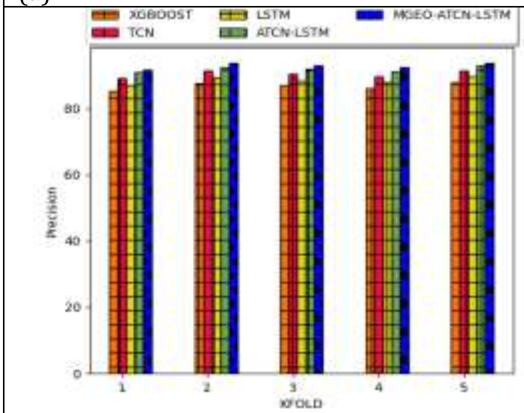
Dataset 1



(a)

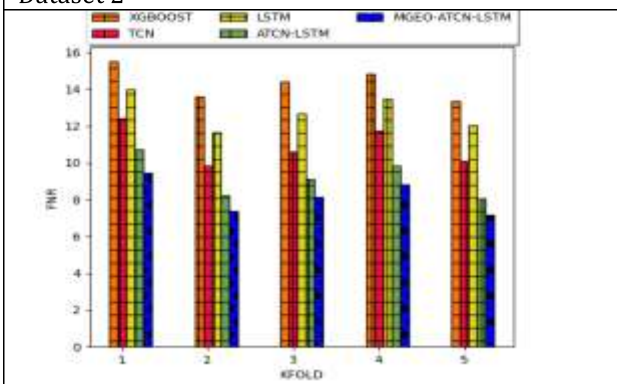


(b)

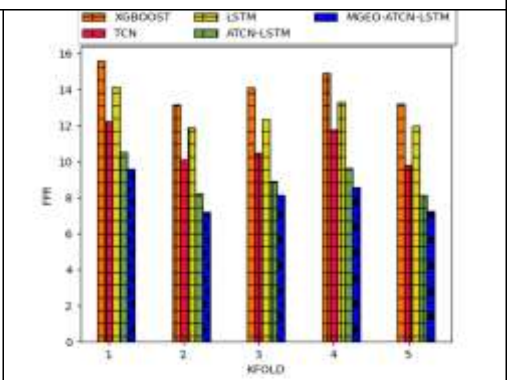


(c)

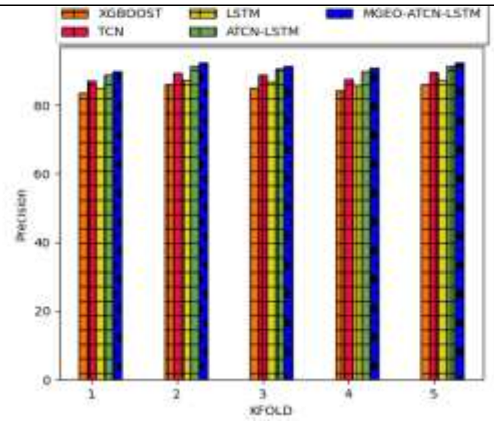
Dataset 2



(a)



(b)



(c)

6.9 Results on climate factor prediction

Table 2 provides the results comparison of the climate factor prediction. The proposed model attains a higher value of the best solution at all values. The higher value of the best solution indicates the proposed model effectively handles the mosquito spreads in the country and that is used to prevent the occurrence of dengue outbreaks in the country.

Table 2. Numerical comparison of the climate factor prediction over existing approaches

Algorithms	**SOA-ATCN-LSTM [30]**	**GOA-ATCN-LSTM [31]**	**NBOA-ATCN-LSTM [32]**	**GEO-ATCN-LSTM [26]**	**MGEO-ATCN-LSTM**
Dataset 1					
Best solution					
1	300.2542	300.2782	300.3211	298.0396	297.4
2	300.3226	299.1103	297.4579	303.1203	295.9318
3	28.13168	26.06711	29.25618	26.79288	28.5339
4	26.1637	30.44196	27.56242	24.34714	29.71558
5	299.2428	292.9717	294.575	297.8279	297.4099
6	291.2535	294.4545	298.1457	292.0521	294.4103
7	64.8471	60.863	96.06894	61.52085	61.92936
8	80.01053	81.0595	60.16241	77.96079	95.69852
9	12.10666	19.3642	15.14827	18.13716	14.29423
10	19.00764	17.73197	11.82847	15.52466	12.164
Dataset 2					
Best solution					
1	295.9995	303.5421	300.724	301.4916	299.5368
2	296.3619	300.4504	298.6159	295.5329	300.5252
3	24.02119	27.34597	26.73286	28.89802	24.50348
4	25.54381	25.39802	25.38118	26.89531	29.26834
5	298.9994	296.0202	297.3164	293.807	292.6047
6	293.1828	296.3427	294.8772	290.615	299.2921
7	97.31472	98.09631	81.40052	60.45921	95.58092
8	84.73472	77.27927	97.15618	77.84167	88.33067
9	10.31421	15.57662	14.64184	10.91658	12.05327
10	11.33798	11.02	19.19397	19.85986	13.24889

7.Conclusion

The major contribution of the works was to develop a deep learning model to forecast the outbreak in the country based on climatic factors to help doctors take the treatment measures for enhancing the quality of life of humans. The suggested model adopts the climatic data from the online resources to perform the dengue outbreak prediction process. From the collected data, the optimal features were selected using MGEO. The features selected in an optimal manner were passed to the ATCN-LSTM to predict the outbreak in the country. Further, the micro-level and its parameters were optimally determined using the MGEO. From the visualized graph, the precision of the developed MGEO-ATCN-LSTM was greater than the SOA-ATCN-LSTM, GOA-ATCN-LSTM, NBOA-ATCN-LSTM, and GEO-ATCN-LSTM with 5.3%, 7.44%, 1.06%, and 3.72% at the 2nd K fold value. The output showed that the suggested ATCN-LSTM surpassed the conventional approaches in the dengue outbreak prediction process. In the future, the non-climatic factors will be considered to find the dengue outbreak in the specific region.

References

1. Tahir, F., Bansal, D., Rehman, A.U., Ajjur, S.B., Skariah, S., Belhaouari, S.B., Al-Romaihi, H., Al-Thani, M.H., Farag, E., Sultan, A.A. and Al-Ghamdi, S.G., "Assessing the impact of climate conditions on the distribution of mosquito species in Qatar", Frontiers in Public Health, vol.10, no.970694, 2023.
2. Polineni, S., Shastri, O., Bagchi, A., Gnanakumar, G., Rasamsetti, S. and Sundaravadivel, P., "MOSQUITO EDGE: an edge-intelligent real-time mosquito threat prediction using an IoT-enabled hardware system", Sensors, vol.22, no.695, 2022.
3. Francisco, M.E., Carvajal, T.M., Ryo, M., Nukazawa, K., Amalin, D.M. and Watanabe, K., "Dengue disease dynamics are modulated by the combined influences of precipitation and landscape: A machine learning approach", Science of The Total Environment, vol.792, no.148406, 2021.
4. Ma, J., Guo, Y., Gao, J., Tang, H., Xu, K., Liu, Q. and Xu, L., "Climate change drives the transmission and spread of vector-borne diseases: An ecological perspective", Biology, vol.11, no.1628, 2022.
5. Giesen, C., Roche, J., Redondo-Bravo, L., Ruiz-Huerta, C., Gomez-Barroso, D., Benito, A. and Herrador, Z., "The impact of climate change on mosquito-borne diseases in Africa", Pathogens and Global Health, vol.114, pp.287-301, 2020.
6. Li, C., Wu, X., Wang, X., Yin, J., Zheng, A. and Yang, X., "Ecological environment and socioeconomic factors drive long-term transmission and extreme outbreak of dengue fever in epidemic region of China", Journal of cleaner production, vol.279, no.123870, 2021.
7. Morgan, J., Strode, C. and Salcedo-Sora, J.E., "Climatic and socio-economic factors supporting the co-circulation of dengue, Zika and chikungunya in three different ecosystems in Colombia", PLoS Neglected Tropical Diseases, vol.15, no.e0009259, 2021.
8. Wang, T., Fan, Z.W., Ji, Y., Chen, J.J., Zhao, G.P., Zhang, W.H., Zhang, H.Y., Jiang, B.G., Xu, Q., Lv, C.L. and Zhang, X.A., "Mapping the distributions of mosquitoes and mosquito-borne arboviruses in China", Viruses, vol.14, no.691, 2022.
9. Nguyen, V.H., Tuyet-Hanh, T.T., Mulhall, J., Minh, H.V., Duong, T.Q., Chien, N.V., Nhung, N.T.T., Lan, V.H., Minh, H.B., Cuong, D. and Bich, N.N., "Deep learning models for forecasting dengue fever based on climate data in Vietnam", PLoS Neglected Tropical Diseases, vol.16, no.e0010509, 2022.
10. Ordonez-Sierra, G., Sarmiento-Senior, D., Gomez, J.F.J., Giraldo, P., Ramírez, A.P. and Olano, V.A., "Multilevel analysis of social, climatic and entomological factors that influenced dengue occurrence in three municipalities in Colombia", One Health, vol.12, no.100234, 2021.
11. G. Adhane, M. M. Dehshibi and D. Masip, "A Deep Convolutional Neural Network for Classification of Aedes Albopictus Mosquitoes," IEEE Access, vol. 9, pp. 72681-72690, 2021.
12. H. Mayrose, N. Sampathila, G. M. Bairy, T. Nayak, S. Belurkar and K. Saravu, "An Explainable Artificial Intelligence Integrated System for Automatic Detection of Dengue From Images of Blood Smears Using Transfer Learning," IEEE Access, vol. 12, pp. 41750-41762, 2024.
13. Vasconcelos, D., Nunes, N.J., Förster, A. and Gomes, J.P., "Optimal 2D audio features estimation for a lightweight application in mosquitoes species: Ecoacoustics detection and classification purposes", Computers in Biology and Medicine, vol.168, p.107787.
14. Anoopkumar, A.N. and Aneesh, E.M., "A critical assessment of mosquito control and the influence of climate change on mosquito-borne disease epidemics", Environment, Development and Sustainability, vol.24, pp.8900-8929, 2022.
15. Agboka, K.M., Wamalwa, M., Mutunga, J.M. and Tonnang, H.E., "A mathematical model for mapping the insecticide resistance trend in the Anopheles gambiae mosquito population under climate variability in Africa", Scientific Reports, vol.14, no.9850, 2024.

16. Lee, D.S., Lee, D.Y. and Park, Y.S., “Interpretable machine learning approach to analyze the effects of landscape and meteorological factors on mosquito occurrences in Seoul, South Korea”, Environmental Science and Pollution Research, vol.30, pp.532-546, 2023.
17. Herdicho, F.F., Chukwu, W. and Tasman, H., “An optimal control of malaria transmission model with mosquito seasonal factor”, Results in physics, vol.25, no.104238, 2021.
18. Li, C., Wu, X., Wang, X., Yin, J., Zheng, A. and Yang, X., “Ecological environment and socioeconomic factors drive long-term transmission and extreme outbreak of dengue fever in epidemic region of China”, Journal of cleaner production, vol.279, no.123870, 2021.
19. Ordonez-Sierra, G., Sarmiento-Senior, D., Gomez, J.F.J., Giraldo, P., Ramírez, A.P. and Olano, V.A., “Multilevel analysis of social, climatic and entomological factors that influenced dengue occurrence in three municipalities in Colombia”, One Health, vol.12, no.100234, 2021.
20. Wieland, R., Kuhls, K., Lentz, H.H., Conraths, F., Kampen, H. and Werner, D., “Combined climate and regional mosquito habitat model based on machine learning”, Ecological Modelling, vol.452, no.109594, 2021.
21. Joelianto, E., Mandasari, M.I., Marpaung, D.B., Hafizhan, N.D., Heryono, T., Prasetyo, M.E., Tjahjani, S., Anggraeni, T. and Ahmad, I., “Convolutional neural network-based real-time mosquito genus identification using wingbeat frequency: A binary and multiclass classification approach”, Ecological Informatics, vol.80, no.102495, 2024.
22. Carreto, C., Gutiérrez-Romero, R. and Rodríguez, T., “Climate-driven mosquito-borne viral suitability index: measuring risk transmission of dengue, chikungunya and Zika in Mexico”, International journal of health geographics, vol.21, no.15, 2022.
23. Mondal, J., Das, A. and Khatun, R., “Predicting climate change and its impact on future occurrences of vector-borne diseases in West Bengal, India”, Environment, Development and Sustainability, vol.24, pp.11871-11894, 2022.
24. Nkiruka, O., Prasad, R. and Clement, O., “Prediction of malaria incidence using climate variability and machine learning”, Informatics in medicine Unlocked, vol.22, no.100508, 2021.
25. Soh, S. and Aik, J., “The abundance of Culex mosquito vectors for West Nile Virus and other flaviviruses: A time-series analysis of rainfall and temperature dependence in Singapore”, Science of The Total Environment, vol.754, no.142420, 2021.
26. Abdolkarim Mohammadi-Balani, Mahmoud Dehghan Nayeri, Adel Azar, and Mohammadreza Taghizadeh-Yazdi, "Golden eagle optimizer: A nature-inspired metaheuristic algorithm," Computers & Industrial Engineering, Vol.152, pp. 107050, February 2021.
27. Ali Raza, Waleed Alam, Shahzad Khan,Muhammad Tahir, And Kil To Chong, "iPro-TCN: Prediction of DNA Promoters Recognition and Their Strength Using Temporal Convolutional Network," IEEE Access, 2023.
28. Mokhalad A. Majeed, Helmi Z. M. Shafri, Aimrun Wayayok, Zed Zulkafli,"Prediction of dengue cases using the attention-based long short-term memory (LSTM) approach," Geospatial Health, vol. 18, pp. 1176, 2023.
29. Wenlin Li & Xuchu Jiang, "Prediction of air pollutant concentrations based on TCN-BiLSTM-DMAttention with STL decomposition," Scientifc Reports, vol. 13, pp. 4665, 2023.
30. Gaurav Dhiman, Vijay Kumar, "Seagull optimization algorithm: Theory and its applications for large-scale industrial engineering problems," Knowledge-Based Systems, vol. 165, pp. 169-1961, February 2019.
31. Montazeri, Zeinab, Taher Niknam, Jamshid Aghaei, Om Parkash Malik, Mohammad Dehghani, and Gaurav Dhiman, "Golf optimization algorithm: A new game-based metaheuristic algorithm and its application to energy commitment problem considering resilience," Biomimetics, vol. 8, pp. 386, no. 5, 2023.
32. Chahardoli, Meysam, Nafiseh Osati Eraghi, and Sara Nazari, "Namib beetle optimization algorithm: a new meta-heuristic method for feature selection and dimension reduction," Concurrency and computation: practice and experience, vol. 34, pp. e6524, no. 1, 2022.
33. Anggraeni, Wiwik, Humaira Nur Pradani, Surya Sumpeno, Eko Mulyanto Yuniarno, Reza Fuad Rachmadi, and Mauridhi Hery Purnomo, "Prediction of Dengue Fever Outbreak Based on Climate and Demographic Variables Using Extreme Gradient Boosting and Rule-Based Classification," In 2021 IEEE 9th International Conference on Serious Games and Applications for Health (SeGAH), pp. 1-8, 2021.