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Optimized Triple Memristor Hopfield Neural Network fostered Automated Outbreak Prediction of Epidemic Diseases using Internet of Things

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Abstract

The paper presents a comprehensive system for predicting and preventing epidemic outbreaks using the Internet of Things (IoT), combined with an Optimized Triple Memristor Hopfield Neural Network (TMHNN) and the Northern Goshawk Optimization (NGOA) algorithm. This approach, referred to as AOPE-TMHNN-NGOA-IoT, gathers real-time health data from individuals through wearable IoT devices. Critical health parameters like body temperature, blood pressure, and heart rate are monitored using a Dengue dataset. The collected data is first subjected to pre-processing using Nanoplasmonic Ultra Wideband Bandpass Filtering (NUWBF) to remove noise and outliers. Following this, feature extraction is performed using the Two-sided Offset Quaternion Linear Canonical Transform (TOQLCT), which extracts the essential features for disease detection. These features are then fed into the TMHNN, which is optimized by the NGOA algorithm to classify individuals as either infected or healthy. When an infection is detected, the system immediately alerts the individual via the IoT device, enabling early intervention. The AOPE-TMHNN-NGOA-IoT system is implemented using Python and demonstrates superior performance compared to existing methods, including AOPE-SVM-IoT, AOPE-KNN-IoT, and AOPE-NB-IoT. Specifically, the proposed system achieves 25.45%, 19.12%, and 27.11% higher accuracy, and 15.36%, 21.55%, and 18.74% higher specificity than these techniques, respectively. By integrating IoT, advanced neural networks, and optimization algorithms, AOPE-TMHNN-NGOA-IoT provides a robust, efficient solution for predicting and preventing epidemic outbreaks. This system significantly enhances health monitoring, offering a proactive method for controlling the spread of infectious diseases globally.

Keywords: *Automated Outbreak Prediction, Dengue data set, Nano plasmonic Ultra-Wideband Band pass Filtering (NUWBF), Dengue data set, Two-sided Offset Quaternion Linear Canonical Transform (TOQLCT), Triple Memristor Hopfield Neural Network (TMHNN), Northern Goshawk Optimization (NGOA) algorithm.*

1. Introduction

Digital electronics and information technologies (IT) have seen tremendous growth in recent years, and there has been an exponential rise in creation of 5G networks for the IoT. These technologies used in a variety of ways to diagnose medical conditions, smart medical care for illnesses [1]. The focus of diagnosis and prevention is on advancing healthcare technologies to improve human health by the application of smart technology at every level [2]. Because of the idea of the advancements in information technology importance of smart healthcare grown over time. Smart healthcare uses cutting-edge information technologies likes AI, cloud computing, big data, loT, to completely change traditional medical system and provide more convenient, effective, and individualized care [3]. Today, virus called SARS-CoV-2 that discovered at Wuhan, China, is the cause of a serious illness known as COVID-19. When COVID-19 first enters a person's respiratory system, it can induce fever, coughing, dyspnea, and a host of other dangerous symptoms like pneumonia. One type of illness brought on by lung inflammation is pneumonia [4]. Severe infections are caused by bacteria, fungus, the SARS-CoV-2 virus, and other hazardous organisms. Ageing, asthma, recurrent infections, low immunity, and other medical factors all contribute to the severity of pneumonia. Depending on the organ involved, there are several effective treatments for pneumonia. These include painkillers, cough vaccines, antibiotics, and antipyretics. The diagnosis of COVID-19 becomes crucial as the idea of smart healthcare is introduced. A patient admitted to hospital based on the signs, and in more serious situations, admitted to ICU. The COVID-19 pandemic thought to be serious illness as to increased permeability, contagiousness [5]. Furthermore, pandemic sickness has a significant effect on patients' health, resulting in a large number of ICU admissions, lengthy treatment times, and a shortage of hospital resources. Therefore, initiate an effective defensive mechanism, it handles the issues experienced with the existing methodologies accuracy and computational time to guarantee précised forecast. This attempt to suggest a solution for primary problems, likes merging data from various sources due to increased sensitivity of data in collaborative domains.

Major contributions of this research work brief below

- In this research, Optimized Triple Memristor Hopfield Neural Network fostered Automated Outbreak Prediction of Epidemic Diseases using Internet of Things (AOPE-TMHNN-NGOA-IoT) is proposed.
- Nanoplasmonic Ultra Wideband Band pass Filtering (NUWBF) to remove random noise of the data signal.
- The features are extracted based Two-sided Offset Quaternion Linear Canonical Transform (TOQLCT).
- IoT based TMHNN to identify and detect the disease. Propose Northern Goshawk Optimization process to enhance TMHNN.
- Therefore, in this strategy, utilizing these novel methods alert patients whoever affected by epidemic diseases.
- AOPE-TMHNN-NGOA-IoT model is implemented at python and effectiveness examined with several performance metrics.
- The efficiency of proposed model analyzed with the existing techniques like AOPE-SVM-IoT, AOPE-KNN-IoT and AOPE-NB-IoT respectively.

Rest of these manuscripts structured as below: part 2 reviews literature review, part 3 defines proposed method, part 4 proves the results, part 5 conclusion.

2. Literature Review

Numerous research works suggested in literature related to deep learning based automated outbreak prediction of epidemic diseases, few current works were reviewed here,

In 2023, Hemdan, E.E.D, et.al [6] have suggested that framework for primary detection of COVID-19 cough audio signals utilizing ML processes for automated medical diagnosis applications. Here, this paper suggests a hybrid system that uses different machine learning methods from cough audio signals to efficiently detect and diagnose COVID-19. By using ML approaches in conjunction with a genetic algorithm, this framework's accuracy is increased. It also evaluates the CR19 system, which is a suggested method for diagnosis, using measures like F-measure, precision, and recall. It provides high Accuracy and low specificity.

In 2022, Mubarak, A.S, et.al, [7] have presented that a local binary pattern with DL feature extraction fusion for COVID-19 recognition on CT images. Here, to improve the classifier's performance, a concatenated local binary pattern, DL feature suggested train KNN, SVM. On the basis of performance conditions, methods VGG-19 + LBP attained higher accurateness. It provides high sensitivity and low precision.

In 2022, Deepa, N, et.al, [8] have presented that Towards applying IoT and ML for risk prediction of COVID-19 pandemic situation utilizing NB classifier for refining accuracy. Here, sensor-assisted data collection yields predictions using RF, NB classifiers. Certain populations were identified, burden of the sickness can be mitigated for those in that group.. It provides high f-measure and low error rate.

In 2021, Le, D.N, et.al, [9] have suggested that IoT allowed depth wise separable CNN by deep support vector machine for COVID-19 diagnosis, classification. Here, binary, multiple class labels of COVID-19 were found utilizing DSVM model. The DWS-CNN methods improved performance was confirmed by the experimental findings, which achieved maximum classification performance with accuracy on binary and multiclass, respectively. It provides high specificity and low Accuracy.

In 2023, Rezazadeh, B, et.al, [10] have suggested that computer-assisted techniques for combating Covid-19 in prevention, recognition, service provision techniques. Here, fog-cloud computing-based Internet of things, which makes utilize of AI methods like ML and DL is a useful idea. The purpose of this article is to review computer-based strategies for prevention, detection, and service delivery in the fight against COVID-19. It offers high sensitivity, low computational time.

3. Proposed Method

AOPE-TMHNN-NGOA-IoT is discussed in this section. This section presents the clear description about the research methodology used in automated Outbreak Prediction of Epidemic Diseases from Dengue dataset. The block diagram of AOPE-TMHNN-NGOA-IoT is represented by Figure 1. Thus, the detailed description about AOPE-TMHNN-NGOA-IoT is given below,

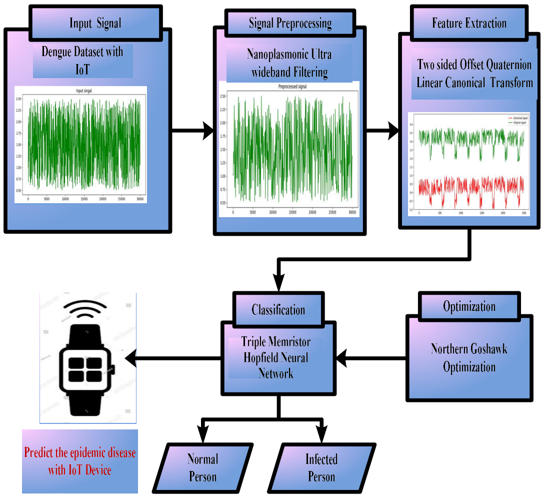

Figure 1: Block Diagram of the proposed AOPE-TMHNN-NGOA-IoT automated Outbreak Prediction of Epidemic Diseases

3.1 Data Acquisition

Initially, the data were taken from Dengue Dataset [11].It outlines dual primary, secondary data sources that utilized to acquire dengue data. Secondary data gathered in area of healthcare in medical centres, while primary data were collected using the questionnaire system. ID, age, gender, pulses, acute fever, platelet count, rashes, vomiting, stomach discomfort, skin peeling, body ache, cold, vomiting, crunchiness, bleeding gums, headache, nausea, tourniquet test, tiredness, fast breathing, antigen dengue, IgM, platelet discrepancy, IgG, NS1 dengue were among attributes that were observed in the dataset. As a result, there will be little delay when transmitting the dataset over IOT, and the heart rate will occur more frequently.

3.2 Preprocessing using Nanoplasmonic Ultra Wideband Band pass Filter (NUWBF)

In this step, NUWBF performs the data pre-processing [12] which is utilized for removing noise and outliers of signal in the dataset. Typically, cascaded resonators are used to create filters, which are then synthesized based on predetermined specifications, likes center frequency, bandwidth, insertion loss for band-pass filter. It can be evaluated using equation (1),

$$\frac{\vartheta^!}{\vartheta_1^!} = \frac{1}{\vartheta}\left(\frac{\vartheta}{\vartheta_0} - \frac{\vartheta_0}{\vartheta}\right), \tag{1}$$

Where $\vartheta = \frac{\vartheta_2 - \vartheta_1}{\vartheta_0}$ and $\vartheta_0 = \sqrt{\vartheta_1 \vartheta_2}$ is the lower and upper frequency band-pass centres. With the use of the ladder network components b_1, b_2, b_3, b_4, and b_5, as listed the 5th-order prototype may be created. A capacitor (b_1), an inductor (b_2), a capacitor (b_3), an inductor (b_4), and a capacitor (b_5) make up this circuit which is evaluated in equation (2) and (3),

$$b_0 = b_4 = b_6 = 1,\; b_n = 4 \times \left(\frac{w_{n-1} \times w_n}{u_{n-1} \times b_{n-1}}\right), \tag{2}$$

Where, $n = 2,3,....,k$

$$w_n = \sin\left(\frac{(2n-1)\gamma}{2k}\right),\; u_n = \beta^2 + \sin^2\left(\frac{n\gamma}{k}\right) \tag{3}$$

Where, $\frac{n\gamma}{k}$ are the signal variance coefficient. The coupling structure in this instance is a configuration of asymmetrically connected lines. Characteristic impedance (I_{in}) of three-wire linked utilizing three-wire TL method given by SRR with the ring-coupled line shown in equation (4)

$$I_{in} = I_0 \frac{I_d + iI_0 \tan(\lambda f)}{I_0 + iI_d \tan(\lambda f)}, \quad (4)$$

Where I_d and I_0 represent the open stub's load and input impedances, respectively and the noises and the outliers are removed. Then, pre-processed data fed feature extraction process.

3.3. Feature Extraction using Two-sided Offset Quaternion Linear Canonical Transform (TOQLCT)

Following preprocessing, method called feature extraction is used to extract a number of signal features. After preprocessing, the features likes body temperature, blood pressure, heart rate are extracted from pre-processed output through Two-sided Offset Quaternion Linear Canonical Transform (TOQLCT) [13]. It helps to extract variable correlation. First, it reviews the quaternion valued function's logarithmic upper bound for the two-sided QLCT and computed as in equation (5),

$$\int_{\mathrm{A}^2} \ln|h| |g(h)|^2 dh + \int_{\mathrm{A}^2} \ln|r| |\mathrm{E}_Z g(r)|^2 dr \geq G \int_{\mathrm{A}^2} |g(h)|^2 dh \quad (5)$$

Where, $\mathrm{E}_Z g(r)$ is the offset value , $|g(h)|^2$ is the generated signal and by converting real 2D signal to quaternion valued frequency domain signal, is essential for representation of signals and colour pictures A quaternion signals function two-sided QLCT is defined as in equation (6).

$$g(a) = \frac{1}{\sqrt{(2\pi)^2}} \int_{A^2} e^{-ia_1 s_1} E_z\{g\}(s) e^{ja_2 s_2} ds \quad (6)$$

Where, $E_z\{g\}(s)$ is the two sided offset value and $e^{ja_2 s_2} ds$ is the signal provider. UPs on non-zero function, offset quaternion linear canonical transform decrease quickly and it is evaluated using the equations (7) and (8) as follows,

$$\langle d_k, d_l \rangle = \frac{1}{x_1 x_2} T_S \left(\int_{A^2} g(a) \overline{m(a)} da \right) \quad (7)$$

$$\int_{\mathrm{A}^2} \ln|h| |g(h)|^2 dh + \int_{\mathrm{A}^2} \ln|r| \left| D^{\mathrm{K}}_{Z_1,Z_2} \{g\}(r) \right|^2 dr \geq (G + \ln|e|) \int_{\mathrm{A}^2} |g(h)|^2 dh \quad (8)$$

Where, $g(a)\overline{m(a)}$ is the quaternion valued function and $G + \ln|e|$ is the linear valued status $D^{\mathrm{K}}_{Z_1,Z_2}\{g\}(r)$ is the domain constant. In addition, each of aforementioned UPs in TOQLCT domains resolve quaternion-valued signals in real-world applications and the features are extracted. Feature extraction is performed on data which includes a comprehensive set of features likes' body temperature, blood pressure, heart rate and to capture complete nature of distribution in real time signals are explained as

Body temperature: Abnormal spikes in body temperature can be an early indicator of an infectious disease.

Blood Pressure: Abnormalities in blood pressure can be an indicative of certain disease.

$$Blood\ pressure = \frac{Systolic\,\mathrm{Pr}\,essure}{Dystolic\,\mathrm{Pr}\,essure}$$

Heart rate: Changes in heart rate patterns may suggest the presents of illness. Then it undergoes classification process.

$$Heartrate(bpm) = \frac{Nunber\ of\ heartbeats}{Time(\mathrm{min})}$$

Then it undergoes Classification process.

3.4 Classification using Triple Memristor Hopfield Neural Network

In this section, the input signal is given to TMHNN [14] to classify the person as infected person and normal person is discussed. Memristors established great promise constructing memristive NN by complex dynamics. The complex dynamical behaviors of TMHNN which have observed in preceding Hopfield networks comprise space multi-structure chaotic attractors, spatial initial-offset coexisting behaviors. Initially, the TMHNN perform two functions multi-structure chaotic attractors, spatial initial-offset coexisting behaviors. Hopfield Neural Network is deliberate as of brain-like network structure, complex chaotic dynamics. The active memristor of the structured data can be calculated in following equation (9)

$$\begin{cases} j = X(\beta)u = a\beta u \\ d\phi / dt = cu - dg(\beta) \end{cases} \tag{9}$$

Where, $d\phi$ is the position of the spatial Memristor and $a\beta u$ is the structural space type. Then the chaotic attractors can be calculated in following equation (10)

$$g_1(\beta) = \begin{cases} \beta, N = 0 \\ \beta - \sum_{i=1}^{N} (\tan g) q(\beta + (2i-1)) + \tan g\,(q(\beta - (2i-1))) \\ N = 1,2,3,.... \end{cases} \tag{10}$$

Where, $\sum_{i=1}^{N} (\tan g)$ is the exponential function of the weighted signal data. Then the multi-structure chaotic of the data signal characters can be calculated in following equation (11)

$$g_2(\beta) = \begin{cases} \beta - \tan g\,(q\beta), M = 0 \\ \beta - \tan g\,(q\beta) - \sum_{j=1}^{M} (\tan g(q(\beta + 2j))) + \tan g(q(\beta - 2j)) \\ M = 1,2,3,...... \end{cases} \tag{11}$$

Where, $\beta - 2j$ is the fixed coefficient of memristor N, M denotes control parameters. Then intrinsic properties of the signal can be calculated in following equation (12)

$$d\beta / dt = -dg(\beta) \tag{12}$$

Where, $d\beta$ denotes space initial-offset behavior of signal. Then the final chaotic Hopfield neural network can be calculated in following equation (13)

$$C_i y_i = -\frac{y_i}{R_i} + \sum_{j=1}^{n} x_{ij} \tan g(y_j) + I_i \tag{13}$$

Where, C_i, y_i, R_i denotes membrane capacitance, membrane resistance, membrane resistance of i^{th} neuron, $\tan g$ signifies neuron activation action, I_i denotes external input current. Finally, Triple-Memristor Hopfield Neural Network (TMHNN) predicts the epidemic disease and classifies the person as the infected person and the normal person. The TMHNN classifier considers AI-based optimization strategy due to its relevance, ease of use. Here, NGOA employed to enhance TMHNN optimum parameter β. The NGOA employed for tuning weight, bias parameter of TMHNN.

3.5 Optimization using Northern Goshawk Optimization algorithm

The proposed NGOA algorithm [15], followed by its mathematical modeling. NG is medium-sized hunter of Accipitridae family, initialy defined under present scientific name, Accipitridae. The NG is member of Accipiter genus, which hunts variation of prey, comprising small, large birds, along with maybe various birds of prey, small mammals likes mice, rabbits, squirrels, even animals likes foxes, raccoons. Northern goshawk's hunting technique separated into dual stages: firstly, after spotting prey, moves it higher speed, secondly, it chases prey in short tail-chase method.

Step 1: Initialization

At start of method, population members are randomly initialized at search space. The suggested NGOA algorithm, population matrix is shown in equation (14)

$$\begin{bmatrix} Y_1 \\ \vdots \\ Y_i \\ \vdots \\ Y_M \end{bmatrix}_{M\times u} = \begin{bmatrix} y_{1,1} & \cdots & y_{1,j} \cdots y_{1,u} \\ \vdots & & \vdots \quad\quad \vdots \\ y_{i,1} & \cdots & y_{i,1} \cdots y_{i,u} \\ \vdots & & \\ y_{M,1} & \cdots & y_{M,1} \cdots y_{M,u} \end{bmatrix}_{M\times v} \tag{14}$$

Where M denotes the number of population member, Y indicates the population algorithm of northern goshawks, $y_{i,j}$ is j^{th} variable stated by i^{th} proposed solution, u denotes problem variables.

Step 2: Random Generation

In first phase of hunting, northern goshawk finds target random, attacks swiftly. As random selection of prey at search space, phase boosts NGOA's exploration power.

Step 3: Fitness function

From initialized valuations, outcome is random answer. Evaluation of the fitness function utilizes outcomes of weight parameter optimization β . It shown in equation (15),

$$fitness\ function = Optimizing[\beta] \tag{15}$$

Step 4: Exploration phase

This phase initiates global search of search space to determine best area. Northern goshawk behavior through this stage, includes prey selection, attack. The phase notions are quantitatively modeled using in following equation (16)

$$Y_i = \begin{cases} Y_i^{New,B2}, E_i^{New,B2} < E_{i.}, \\ Y_i \quad , E_i^{New,B2} \geq E_{i.}, \end{cases} \tag{16}$$

Where $Y_i^{New,B2}$ is denoted by novel status for ith proposed solution, $E_i^{New,B2}$ signifies the objective function value of NGOA.

Step 5: Exploration phase

The prey at search space chosen at random during phase, NGO's exploring power is increased. To find ideal location, this step outcomes in thorough search at search space. The conceptions stated in phase exactly modeled utilizing equation (17)

$$y_{i,j}^{New,B1} = \begin{cases} y_{i,j} + v(b_{i,j} - J\, y_{i,j}), E_{Bi} < E_i, \\ y_{i,j} + v(y_{i,j} - b_{i,j}), E_{Bi} \geq E_i, \end{cases} \tag{17}$$

Where J denotes the random numbers to generate random NGOA, v denotes the random number interval, b_i shows the position of the ith NGOA.

Step 6: Termination

The weight parameter β values ofTriple-Memristor Hopfield Neural Network (TMHNN) optimized with support NGO process, will iteratively repeat until halting criteria $r = r + 1$. Then finally AOPE-TMHNN-NGOA-IoT predicts Epidemic Diseases with higher precision by lessening the specificity. Ultimately, a global preventive plan based on IoT has prevented neighbour from contracting the epidemic disease and has used IoT to automatically notify the public. Therefore, automated alarm systems stop epidemic disease detection, morbidity rate, and death.

4. Result with discussion

Experimental results of suggested technique discussed in this section. The AOPE-TMHNN-NGOA-IoT method executed in python utilizing Dengue dataset. Obtained outcome of the proposed AOPE-TMHNN-NGOA-IoT approach is analyzed with existing systems like AOPE-SVM-IoT [6], AOPE-KNN-IoT [7] and AOPE-NB-IoT [8] methods respectively.

4.1 Performance measures

It is crucial step for selecting the optimal classifier. Performance measures evaluated to assess performance, comprising accuracy, specificity. To scale performance metrics, the performance metric is estimated.

4.1.1 Accuracy

The ratio of accurately forecast samples to total input samples indicates a model's accuracy and it is given by the equation (18),

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{18}$$

Where, TN, TP, FP, FN signifies True Negative, True Positive, False Positive, False Negative.

4.1.2 Specificity

It is known as by classifying the samples as negative, the trained model was able to identify how many negatives it could accurately predict from the whole collection of negative values. It is given by the equation (19)

$$Specificity = \frac{TN}{TN + FP} \tag{19}$$

Where, TN, FP, represents True Negative and False Positive respectively.

4.2 Performance Analysis

Fig 2-3 portrays simulation results of AOPE-TMHNN-NGOA-IoT method. Then, the proposed AOPE-TMHNN-NGOA-IoT method is likened with existing BTGC-CNN-SS, BTGC-RCNN-SS and BTGC-ADNet-SS methods respectively.

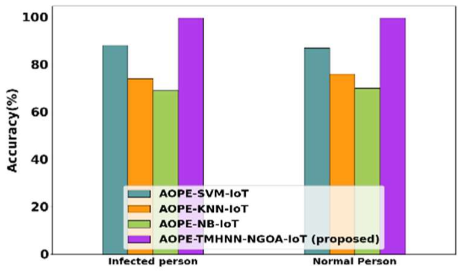

Figure 2: Accuracy analysis

Figure 2 displays accuracy analysis. Here, AOPE-TMHNN-NGOA-IoT attains 25.45%, 19.12% and 27.11% high accuracy for infected person; 25.41%, 24.11% and 19.50% higher Accuracy for normal person estimated to the existing method such as AOPE-SVM-IoT, AOPE-KNN-Io T and AOPE-NB-IoT models respectively.

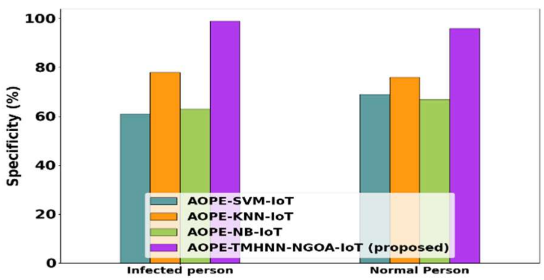

Figure 3: Specificity analysis

Figure 3 displays performance of specificity. Here, AOPE-TMHNN-NGOA-IoT attains 15.36%, 21.55% and 18.74% higher specificity for infected person; 25.12%, 23.11% and 27.10% higher specificity for normal person estimated to the existing method such as AOPE-SVM-IoT, AOPE-KNN-IoT and AOPE-NB-IoT models respectively.

4.3 Discussion

A novel AOPE-TMHNN-NGOA-IoT model to predict the infected person and normal person from Dengue Database is developed in this paper. It is clear from the recommended approach that IoT wearable device gathers data from people, integrates it using AOPE-TMHNN-NGOA-IoT model. This effectively resolves the class distribution issue by eliminating outliers, lessens scaling issue by missing values. By removing noise and demographic bias, the NUWBF technique greatly outperforms itself in the prediction task. The illness outbreaks cannot be controlled even when individuals are treated and diseases are predicted. Human movement is one of the primary causes of disease outbreaks. To stop this epidemic, a TMHNN based on the Internet of Things has been proposed. This system effectively identifies affected person by main signs of the epidemic. Once the device detects disease, notifies person if they are affected person. For this reason, illness prevention is very helpful in helping people anticipate and stop disease outbreaks.

5. Conclusion

In this section, Optimized Triple Memristor Hopfield Neural Network fostered Automated Outbreak Prediction of Epidemic Diseases using Internet of Things (AOPE-TMHNN-NGOA-IoT) is successfully implemented. The proposed AOPE-TMHNN-NGOA-IoT approach is implemented in python utilizing Dengue dataset. The performance of the proposed AOPE-TMHNN-NGOA-IoT approach contains 25.45%, 19.12% and 27.11% high accuracy; 15.36%, 21.55% and 18.74% high specificity when analyzed to the existing methods like AOPE-SVM-IoT, AOPE-KNN-IoT and AOPE-NB-IoT methods respectively. In future work comprises improvement of proposed method through AI for prediction of epidemic disease outbreak.

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