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IoT-based systemic lupus erythematosus prediction model using hybrid genetic algorithm integrated with ANN

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Abstract

Internet of things (IoT) is commonly employed to detect different kinds of diseases in the health sector. Systemic lupus erythematosus (SLE) is an autoimmune illness that occurs when the body's immune system attacks its own connective tissues and organs. Because of the complicated interconnections between illness trigger exposure levels across time, humans have trouble predicting SLE symptom severity levels. An effective automated machine learning model that intakes IoT data was created to forecast SLE symptoms to solve this issue. IoT has several advantages in the healthcare industry, including interoperability, information exchange, machine-to-machine networking, and data transmission. An SLE symptom-predicting machine learning model was designed by integrating the hybrid marine predator algorithm and atom search optimization with an artificial neural network. The network is trained by the Gene Expression Omnibus dataset as input, and the patients' data are used as input to predict symptoms. The experimental results demonstrate that the proposed model's accuracy is higher than state-of-the-art prediction models at approximately 99.70%.

KEYWORDS

artificial neural network, atom search optimization, internet of things, marine predators algorithm, systemic lupus erythematosus

1 | INTRODUCTION

Internet of things (IoT) is a popular communication technology that has the potential to transform many aspects of our daily lives. This "new frontier" comprises various techniques that enable the intelligent operation of everyday objects, owing to the integration of sensors, low-power computing, and wireless communications. Such devices (e.g., clocks, smart bracelets, air conditioners, umbrellas, and refrigerators) maintain their own control and transmission capabilities. Furthermore, they can accept data input from multiple people and even other appliances, passing the compiled data to the internet for collection and analysis. Such scenarios have led to the idea of "ubiquitous computing" [1], which would allow hidden machines to perform scientific reasoning about human living conditions without knowing the identity or personality of the persons being evaluated [2]. Over time, the number of IoT devices and their applications are anticipated to increase [3], as their configurations and utility are already more efficient than employing dedicated high-power phones, laptops, tablets, and medical devices [4].

Recently, IoT systems, including wearable devices, have been made available for healthcare purposes [5, 6], as they provide the ability to capture necessary information about the user's vital signs and surroundings in near real-time [7, 8]. These medical-related services must be accompanied by reliable machine learning models and robust data that produce outputs compatible with extant medical systems [9, 10]. Hence, by monitoring the health of patients, remote healthcare is expected to soon to become widely accessible, most likely with distributed cloud-based processing capabilities [11–13]. Therefore, IoT healthcare, learning, and travel support capabilities are becoming increasingly popular in real-world applications [14]. These approaches improve user comprehension by allowing users to selectively choose new services selectively, based on their context and profile information. Notably, these enabling technologies must be designed and deployed with patient safety, privacy, and security in mind [15, 16], as governments and society will not tolerate IoT solutions that place citizens and increased risk and fall short of the performance standards set by cutting-edge medical practice.

To prepare for ubiquitous IoT-based healthcare systems, several new algorithms and wearable sensors are being developed in various forms for telemedicine services, hospital screening, healthcare for the elderly, and in-home medical treatment [17–19]. This is the right direction as long as it is accompanied by resilient connectivity methods that allow quick access to medical decisions and essential prophylactic measures. Extensive research has been conducted on the best criteria for deploying and sustaining such services, as they require certain intelligent conflict-resolution protocols that are currently lacking.

Interestingly, with rapid advancements, researchers have recently focused on specific areas of healthcare to prepare them for eventual IoT integration. Based on the authors' backgrounds and their work with medical systems in the past, systemic lupus erythematosus (SLE) prediction lacks the appropriate machine learning decision support needed for eventual IoT healthcare integration. SLE is a dangerous and sometimes fatal autoimmune disease that affects approximately five million individuals worldwide. When stricken by SLE, the body's immune system targets its own connective tissues and organs, leading to debilitating and often fatal consequences. Therefore, patients must recognize and restrict their exposure to environmental and biometric triggers that have the potential to generate these reactions. However, the complexity of the disease and its symptoms is very difficult to predict, and the causes seem to change over time. Many patients perceive this complexity as unmanageable and terrifying. Hence, the emotional burden alone can become crippling.

"It is natural to feel unhappy, frustrated, angry, or depressed when you have symptoms that come and go, illness flares and remissions, and the uncertainty of what each day will bring."

According to studies, 15%–60% of people with chronic illnesses (e.g., SLE) will develop clinical depression at some point throughout their condition [20]. One way to help alleviate the emotional burden is to deploy a technology that can intelligently predict SLE symptom severity levels accurately and automatically in near real-time. Doing so would help patients not only manage their symptoms by predicting and avoiding triggers but also would also help them lead reasonably normal lives.

To pave the way for this objective, this study provides a machine learning SLE prediction model that combines the marine predator algorithm (MPA) and atom search optimization (ASO) into an artificial neural network (ANN) that intakes IoT data from SLE patients. The model is trained using the Gene Expression Omnibus (GEO) dataset, and the MPA–ASO ANN predicts patient triggers based on their current activities and input signals. Patient details are uploaded anonymously to the internet for easy access, data transfer, processing, and security.

The experimental results show that the proposed model provides better performance with a much lower low mean square error (MSE) than generic state-of-the-art models. This effort and the results are fully explained in the remainder of this paper, which is organized as follows. The associated efforts in this field are described in Section 2, and Section 3 presents the preliminaries of the proposed methodology and model. The suggested workflow and machine learning techniques are described in Section 4. Section 5 discusses the experimental findings, and Section 6 concludes this paper.

2 | LITERATURE REVIEW

Recent improvements in healthcare systems have resulted in the development of attractive new smart healthcare applications. In medical industries, various new low-power and lightweight sensors have been produced that can accurately analyze and transmit vital human biometric indicators (e.g., pulse rate, body pressure, temperature, and oxygen levels). Researchers have leveraged these sensors to investigate the IoT opportunities in healthcare. This section briefly reviews the relevant healthcare system studies that apply sensor networks viable to IoT machine learning integration.

Dhar and others [21] suggested an interference-aware sensor scheduler for a real-time smart health-monitoring system to enable IoT healthcare monitoring. Using a shared fixed-bandwidth channel with collision prevention protocols, several sensors were linked to a nearby data-processing unit to test bandwidth and communication latency for use by smart health-monitoring systems.

Based on the need to provide prioritized discrete communications, the IoT-based scheduling strategy reduced data loss and sensor interference. Zhang and others [22] reviewed user-centric prehospitalization communication technologies to provide a design strategy for resolving data transmission problems while improving user-friendliness in time-critical medical settings.

Vaishya and others [23] identified potential new cutting-edge applications for disease prevention and treatment, including IoT, big data consumption, and machine learning opportunities. Utilizing outcome-oriented technologies, current and potential patients were accurately evaluated, analyzed, forecasted, and followed. The utility of the described concepts in applying machine learning to prevent and regulate COVID-19 was discussed by Adly and others [24], and artificial intelligence (AI) was found to contribute to new and dependable healthcare paradigms. Arora [25] examined recent digital AI healthcare breakthroughs, highlighting both the dangers and benefits. By changing clinical practices and streamlining workflows, AI is expected to enhance healthcare opportunities and provisions.

3 | PRELIMINARIES

3.1 | ANNs

An ANN leverages a set of connected artificial neurons that mimic the biological processing methods of the human brain, in which one neuron receives inputs and provides outputs to other neurons. With the ANN, the input may comprise external data (i.e., images or documents) or adjacent neuron output [22]. Tasks such as identifying an object in an image are accomplished when the final output neuron of the network provides its product. An ANN consists of several stacked layers, and Figure 1 shows the input layer, some of the hidden layers, and the output layers.

3.2 | MPA

The MPA was inspired by observing the behaviors of ocean predators as they identify and locate prey, particularly in austere selection environments. Lévy strategies are used, and when there is an abundance of prey, Brownian techniques are applied [26]. Based on the prey search space, the MPA initially allocates random values to a set of solutions. The following expression calculates these values:

$$I_0 = L_{\min} + r \times (L_{\max} - L_{\min}), \tag{1}$$

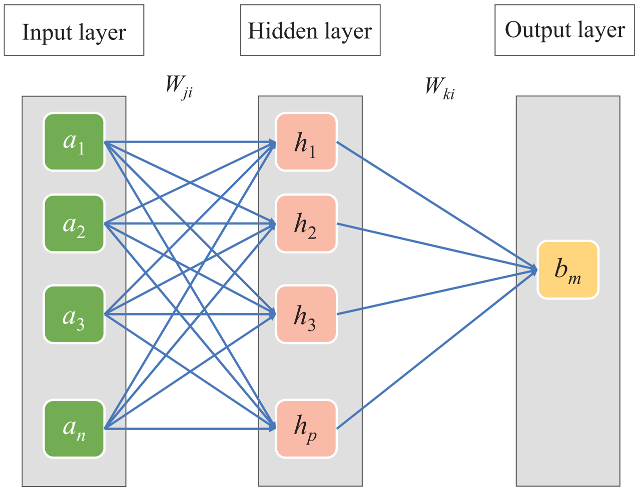

FIGURE 1 Artificial neural network diagram.

where $L_{\min}$ denotes the minimum search space boundary, $L_{\max}$ denotes the maximum, and a random value between 0 and 1 is represented as r.

Both the predator and prey are search agents, and the predator searches for the prey's food as the prey searches for its meal. After each search process, the matrix of the uppermost predator (i.e., the elite) is updated.

$$\text{Elite} = \begin{bmatrix} I_{11}^1 & I_{12}^1 & \dots & I_{1d}^1 \\ I_{21}^1 & I_{22}^1 & \dots & I_{2d}^1 \\ \vdots & \vdots & & \vdots \\ I_{s1}^1 & I_{s2}^1 & \dots & I_{sd}^1 \end{bmatrix}, \tag{2}$$

$$\text{Prey} = \begin{bmatrix} I_{11} & I_{12} & \dots & I_{1d} \\ I_{21} & I_{22} & \dots & I_{2d} \\ \vdots & \vdots & & \vdots \\ I_{s1} & I_{s2} & \dots & I_{sd} \end{bmatrix}. \tag{3}$$

The number of agents is represented by s, the number of dimensions is d, and I_{lm} denotes the m^{th} dimension of the l_{th} prey. The predicted location of prey is improved at each cycle by simulating the entire predator–prey hunting process and altering the velocity ratios.

3.2.1 | High velocity ratio

When the velocity ratio is high, the predator may proceed faster than the prey, implemented during the initial optimization phase. The following equation changes the position of the prey after each repetition:

$$L_p = R_{BM} \otimes (\text{Elite}_k - R_{BM} \otimes P_k),\ k = 1,2,\ldots,s, \tag{4}$$

$$P_k = P_k + C.R \otimes L_{\mathrm{p}}, \tag{5}$$

where L_{p} represents the location of the prey, the Brownian motion of the random vector is denoted as R_{BM}, R represents a random number that varies from 0 to 1, p is set to a constant (i.e., 0.5), and s denotes the number of search agents.

3.2.2 | Unit velocity ratio

When searching for prey or food, both predator and prey travel to the same location. The MPA then switches from an exploration phase to one of exploitation. This affects the unit velocity ratio so that the hunter travels using a Brownian motion pattern, and the prey continues to travel using a Lévy pattern. Exploitation phase patterns are represented by the following equations:

$$L_{\mathrm{p}} = R_{\text{Lévy}} \otimes \left(\mathrm{Elite}_k - R_{\text{Lévy}} \otimes I_k\right),\ k = 1,2,...,s, \tag{6}$$

$$I_k = I_k + C.R \otimes L_p, \tag{7}$$

where the random Lévy distribution value is $R_{\text{Lévy}}$. The equations applied during the exploration phase are computed as follows:

$$L_{\mathrm{p}} = R_{\mathrm{BM}} \otimes \left(R_{\mathrm{BM}} \otimes \mathrm{Elite}_k - I_{\text{Lévy}}\right),\ k = 1,\ 2,\ ...,\ s, \tag{8}$$

$$I_k = I_k + P.SM \otimes L_{\mathrm{p}},\ SM = \left(1 - \frac{t}{t_{\mathrm{gen}}}\right)^2 \frac{t}{t_{\mathrm{gen}}}, \tag{9}$$

where SM regulates the step-size motion of the hunter and the total number of generations is t_{gen}

3.2.3 | Low velocity ratio

This is the final exploitation step, during which the hunter moves faster than the prey. This scenario is represented by the following equation:

$$L_{\mathrm{p}} = R_{\text{Lévy}} \otimes \left(R_{\text{Lévy}} \otimes \mathrm{Elite}_k - I_k\right),\ k = 1,\ 2,\ ...,\ s, \tag{10}$$

$$I_k = I_k + P.SM \otimes L_{\mathrm{p}},\ SM = \left(1 - \frac{t}{t_{\mathrm{gen}}}\right)^2 \frac{t}{t_{\mathrm{gen}}}. \tag{11}$$

3.2.4 | Eddy formation and the fish-aggregating device (FAD) effect

Eddy formulations and FADs can change the behaviors of marine predators. Equation (12) depicts their influence:

$$I_k = \begin{cases} I_k + SM[R \otimes B_{\max} - B_{\min}] \otimes BS & r_5 < FAD \\ I_k + [FAD(1-r) + r](I_{r1} - I_{r2}) & r_5 > FAD. \end{cases} \tag{12}$$

Here, BS denotes the binary solution, and the FAD is assigned a value of 0.2. The prey indices are denoted by $r1$ and $r2$.

3.3 | ASO approach

The ASO [27] method is a heuristic algorithm that leverages the properties of molecular dynamics. It depicts the relationships between atomic restriction and interaction forces in various positions using atomic weights to calculate movements in the search space. The mutual action of the interaction and restriction forces denotes the acceleration of the l_{th} atom at the r_{th} iteration as follows:

$$at_l^d(r) = \frac{T_l^d(r)}{M_l^d(r)} + \frac{C_l^d(r)}{M_l^d(r)}, \tag{13}$$

where $T_l^d(r)$ denotes the total force, $C_l^d(r)$ is the constraint force, and $M_l^d(r)$ is the mass of the l_{th} atom at the r_{th} iteration.

Thus, the velocity and search position of the atom at the $(l+1)_{\mathrm{th}}$ iteration are calculated as follows:

$$s_l^r(r+1) = \mathrm{rand}_l^d s_l^r(r) + at_l^d(r), \tag{14}$$

$$p_l^d(r+1) = p_l^r(r) + s_l^r(r+1), \tag{15}$$

where $s_l^r(r)$ represents the velocity of the l_{th} atom at the r_{th} iteration and p_l^d denotes its search position.

4 | PROPOSED SLE PREDICTION MODEL

4.1 | Proposed architecture

The IoT-based SLE prediction model is illustrated in Figure 2. The objective of this study is to evaluate the influence of several patient-related characteristics on SLE symptom prediction. For the experiments, data were acquired from the GEO dataset, which was supplemented with additional artificially created data to avoid local minima traps. Data security was ensured during the subsequent transfer of the obtained data via the IoT. Relevant data were downloaded from the internet for hybrid MPA–ASO ANN model training.

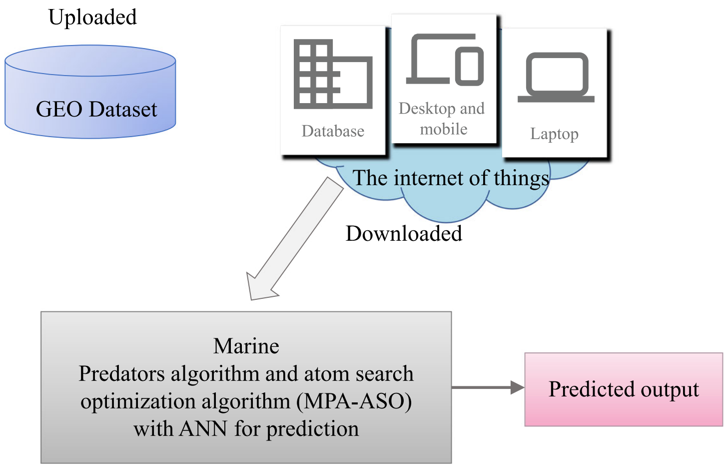

FIGURE 2 Block diagram of the proposed IoT-integrated SLE prediction model.

4.2 | IoT integration

With the IoT, patient information is saved on a remote hidden server that can be accessed as needed to carry out the appropriate prediction actions. Different ANNs were tested in this case, trained using the GEO dataset. Results were sent to the remote server via the IoT, where it was securely processed. Two types of security risks are involved in the data exchange. The first type concerns application security, meaning that the data must be secured while being processed. The second type is user security [8], which implies authentication and session cryptography. Hence, the three most important characteristics of secure IoT services are as follows:

- The data exchange must be protected from unauthorized access.
- Services must be accessible only by authorized users, regardless of context or location.
- Data privacy preservation should be properly guaranteed, and it should never be removed.

Assuring that the user data and private information remain shielded from malevolent entities is the most important security aspect of this case [4]. Figure 3 presents a flow diagram of these IoT security needs.

4.3 | Novel MPA–ASO ANN

ANNs utilize weight and bias variables to optimize features during training, and it is necessary to obtain these values for each node. The weights and biases are treated as part of each predator's structure, and real values are determined randomly to generate their vectors. A flowchart of this process is presented in Figure 4.

MPA is a universal algorithm used for optimization, and the iterations are divided to accomplish various functions. Global exploration is completed in the first third of

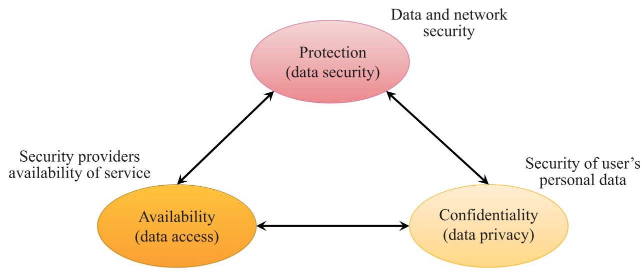

FIGURE 3 Requirement of security in the IoT environment.

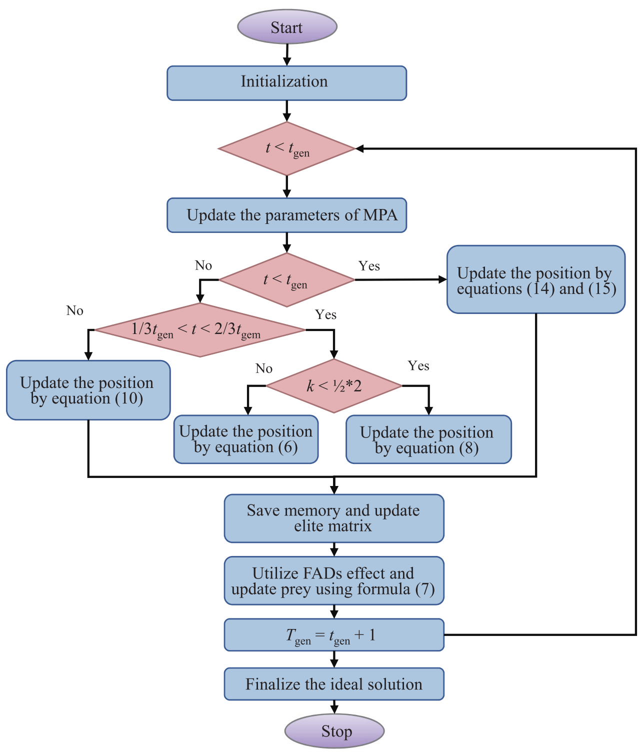

FIGURE 4 Flowchart for Proposed MPA-ASO based on ANN.

each iteration, half of the particle exploration and exploitation is completed in the middle third, and partial production is completed in the final third. The global searching ability effect at the beginning should provide an ideal path for the next stage of local growth, leading to the best solution. To overcome constraints, the MPA is integrated with ASO to improve its efficacy by replacing the ASO algorithm's location update strategy with MPA's initial stage strategy.

5 | EXPERIMENTAL RESULTS

The proposed model was implemented in the COLAB framework on an Intel Core i3 2.3-GHz processor with 8-GB RAM. The GEO database provided gene screening data (http://www.ncbi.nlm.nih.gov/geo) [29] for GSE144390, GSE4588, GSE50772, and GSE81622 sequences, which are associated with SLE. The original data were classified using a variety of performance measures, including kappa, Matthews correlation coefficient (MCC), MSE, recall, specificity, F_1 score, precision, accuracy, and recall. The proposed technique was contrasted with different approaches to assess MPA [28], ASO [29], chaotic ASO (CASO) [27], and opposition-based learning (OBL) performance [28].

The parameters used to evaluate the functionality of the proposed framework are as follows:

$$\text{Accuracy} = \frac{(tpv + tnv)}{(tpv + tnv + fpv + fnv)}, \tag{16}$$

$$\text{Precision} = \frac{tpv}{tpv + fpv}, \tag{17}$$

$$F_1\,\text{score} = 2 \times \text{precision} \times \frac{\left(\frac{tpv}{(tpv + fnv)}\right)}{\text{precision} + \left(\frac{tpv}{(tpv + fnv)}\right)}. \tag{18}$$

$$\text{Kappa} = \frac{\text{Accuracy} - \text{Expectedaccuracy}}{1 - \text{Expectedaccuracy}}, \tag{19}$$

$$\text{Expectedaccuracy} = \frac{((tpv + fnv) \times (tpv + fpv)) + ((fpv + tnv) \times (fnv + tnv))}{(tpv + tnv + fpv + fnv)^2}, \tag{20}$$

$$\text{Sensitivity} = \frac{tpv}{tpv + fnv}, \tag{21}$$

$$\text{Specificity} = \frac{tpv}{fpv + tnv}, \tag{22}$$

where tpv indicates true positives, fpv indicates false positives, indicates true negatives, and fnv indicates false negatives.

Table 1 compares the performance of the proposed strategy in terms of recall, specificity, precision, accuracy, F_1 score, MCC, kappa, and MSE. As can be seen, the proposed technique outperforms existing approaches in all measures. Compared with existing techniques, the proposed methodology has an extremely low error rate.

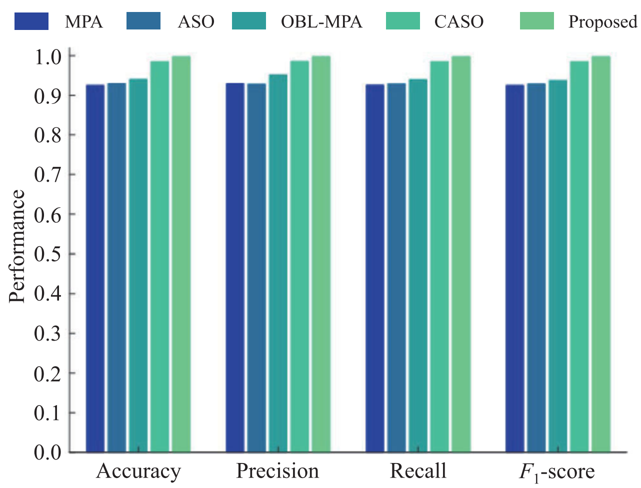

FIGURE 5 Comparing the accuracy of the proposed approach with other models.

TABLE 1 Performance comparison of proposed approach with other approaches.

Method	Accuracy	Sensitivity	Specificity	Precision	F_1 score	Matthews correlation coefficient	Kappa	Mean square error
Proposed	0.9970	0.9970	0.9992	0.9970	0.9970	0.9963	0.9906	0.0030
Chaotic atom search optimization (ASO)	0.9840	0.9843	0.9960	0.9850	0.9840	0.9805	0.9500	0.0160
Opposition-based learning marine predator algorithm (MPA)	0.9401	0.9391	0.9850	0.9511	0.9374	0.9284	0.8127	0.0599
ASO	0.9295	0.9292	0.9824	0.9281	0.9286	0.9111	0.7797	0.0705
MPA	0.9251	0.9258	0.9813	0.9294	0.9248	0.9083	0.7659	0.0749

Figure 5 displays the recall, precision, F_1-score, and accuracy of the recommended strategy compared with MPA, ASO, CASO, and OBL-MPA models. Overall, the proposed model produced better prediction accuracies for patients with SLE symptoms.

Figure 6 illustrates the confusion matrix of the proposed technique versus the alternative models. These parameters reflect the number of times the planned model becomes too confused to provide useful output. The matrix comprises rows and columns, where the rows represent the actual number of patients with SLE symptoms and the columns represent the predicted number. The classifier predicts the projected count, and if it has only true positives and true negatives, it is considered to be effective and accurate. The diagonal values should all be nonzero, indicating that the model is effective. The proposed MPA–ASO ANN performs well in recognizing different SLE symptoms with an accuracy greater than 99.70%. Hence, the proposed model is the best thus far.

By analyzing Figure 7, the proposed MPA–ASO ANN has the best searching capability because it can increase its search area dynamically, unlike the others. This shows that the new ANN model has a better solution preservation capability.

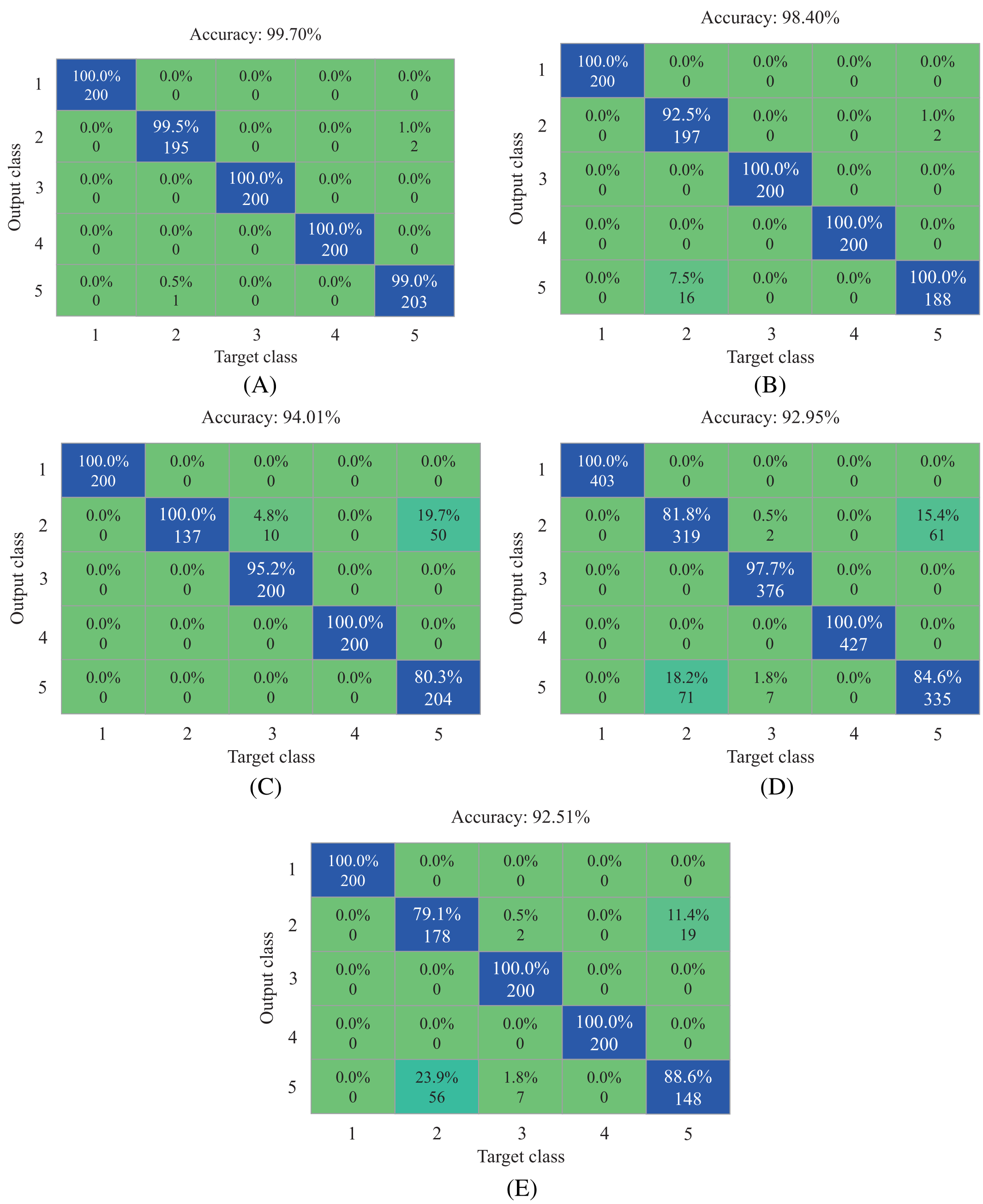

FIGURE 6 Confusion matrix for the proposed approach and other models: (A) proposed algorithm, (B) chaotic atom search algorithm, (C) opposition-based learning marine predator algorithm, (D) atomic search algorithm, (E) marine predator algorithm.

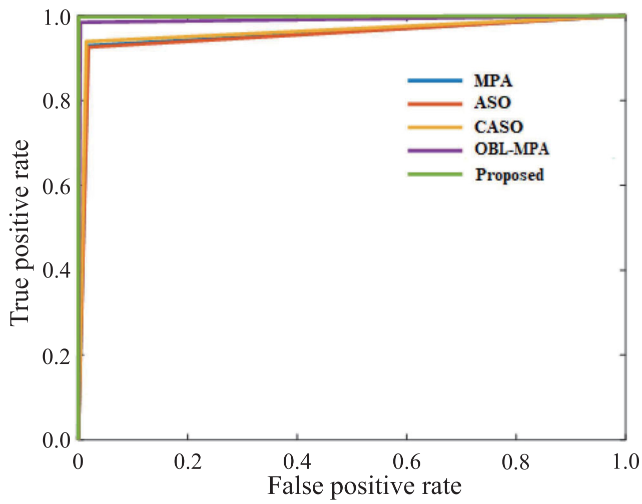

FIGURE 7 ROC curve for the proposed ANN with MPA-ASO and existing model.

6 | CONCLUSION

In this study, a new machine learning model that integrates IoT was developed to detect SLE symptoms and triggers. The IoT used with this model provides effective, timely, and secure communication among cloud-based servers and user devices. The proposed MPA–ASO ANN method reduces biases, tunes the number of neurons, and appropriately weighs each neuron's hyperparameters to obtain the lowest MSE values. Compared with MPA and ASO alone, the proposed technique is more effective, with an average prediction accuracy of 99.70%. Compared with the outcomes of baseline MPA+ASO and ASO +OBL-MPA, it is evident that the recommended MPA–ASO ANN produces the best results. Therefore, we can conclude that the model's architecture is reliable and useful for prediction, particularly for diagnosing SLE symptoms and triggers. In the future, this approach can be expanded by manually collecting more data and testing for generalizability for other disease types.

CONFLICT OF INTEREST STATEMENT

The authors declare no potential conflicts of interest.

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