Smart COVIDNet: designing an IoT-based COVID-19 disease prediction framework using attentive and adaptive-derived ensemble deep learning

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Abstract

Since the end of 2019, the world has faced severe issues over Corona Virus Disease of 2019 (COVID-19). So there is a need for some essential precautionary measures until the development of vaccines to battle the COVID-19 pandemic. In addition to that, quarantine and social distancing have become the more significant practice in the world. COVID-19 associated with the virus not only degraded the economy of the world due to the lockdown but also saturated the healthcare system of the people due to its exponential spread. In this case, the Internet of Things (IoT) system offers frequent monitoring facilities to doctors. But, the fight against COVID-19 gets continued until people get vaccinated. Therefore, an IoT-based COVID prediction is designed using deep learning techniques. Firstly, IoT data is collected from online resources. Then, the data is fed to the autoencoder (AE) for attaining the deep features. Further, the deep features are forwarded to the attentive and adaptive ensemble model (AAEM), which includes deep temporal convolution network (DTCN), one-dimensional convolutional neural network (1DCNN), and long short-term memory (LSTM) model for COVID prediction or monitoring. By utilizing the hybrid algorithm fitness position of Eurasian oystercatcher and sewing training (FPEOST), the parameter in the ensemble model is tuned for further improvement in the process. Finally, the COVID-19 disease prediction outcomes are

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attained on the basis of the high-ranking process. Thus, the developed model achieved an effective prediction rate than conventional approaches over multiple experimental analyses.

Keywords COVID-19 disease prediction · Attentive and adaptive ensemble model · Internet of things · Fitness position of Eurasian oystercatcher and sewing training · Autoencoder

1 Introduction

In recent years, the world has changed due to the spread of COVID-19, and thus, it has influenced the daily lives of human beings [1]. Moreover, COVID-19 has minimized the rate of GDP in many countries randomly. The delayed distribution of vaccines and the slow production of vaccines have maximized the pressure on the healthcare system in both developing and developed countries [2]. However, various collaborative effects have been carried out by various countries and the deployment of vaccines for sanitation has aided in the recovery rate of the world [3]. More specifically, the detection of COVID-19 recovered and infected patients is regarded as a great concern for the health department [4]. Thus, the prevention as well as the diagnosis of COVID-19 has been performed with the help of sensor technology combined for big data processing among patients along with the IoT-embedded machine learning algorithm [5]. Whenever the condition for the survival of the strain of virus causing the ongoing pandemic of coronavirus disease (SARS-Co2V) virus has been much more favorable, then the infection rate of COVID-19 is maximized and that is drastically noticed during the winter season [6]. Further, the IoT has been regarded as the most emerging technique and thus it has been incorporated into every part of human life. Thus, the limitation of COVID-19 is effectively reduced by using the IoT system depending upon the smart health monitoring system [7]. This system has been embedded into the bed of COVID-19 patients or is wearable similar to that of a smartwatch [8].

There is a requirement for an automated health monitoring system, which has acquired the ability to raise an alarm while a critical situation for patients [9]. Further, the data has been determined by means of a node microcontroller in order to propagate messages through Twitter and email to the concerned people or doctors [10]. Moreover, it has the potential to record and then manage the earlier diagnostic information in accordance with the patient's health [11, 12]. In addition to that, the actual condition of the patients has been monitored through an online portal by medical professionals and adequate treatment has been carried out to cure the patients [13]. Further, all the values have been transferred to the doctors to determine the state accordingly. The signals of sensors like a heartbeat, electroencephalogram (EEG), and temperature readings have been passed by amplification as well as the signal conditioning system to raise the gain of signals [14]. Further, the measurement of the biomedical signals along with diverse sensors is regarded as the prerequisite in the enhancement of the healthcare monitoring system, which is utilized for real-time tracking and physical rehabilitation of disabled individuals [15].

In such cases, machine learning techniques have been employed to detect COVID-19 patients out of numerous amounts of data by measuring the health parameters with the aid of IoT and then storing them in the cloud. Moreover, the IoT-dependent smart health monitoring system has been minimized [16]. Further, the combination of machine learning along with the IoT has been carried out in more advantageous ways. Moreover, artificial intelligence (AI) has the ability to perform remarkably over IoT in combating the outbreak. Machine learning is regarded as the subset of AI that has processed the data for prediction as well

as for decision-making [17]. Additionally, AI is defined as the better technology, which has enabled computers to emulate the intelligence of humans in order to precede things like virtual reality, augmented reality, and so on. In the context of COVID-19, various ML algorithm models have been utilized to validate on the basis of the onset of confirmed cases of exposure, travel history, and symptoms. The novel IoT-based COVID-19 disease prediction framework using an attentive and adaptive-derived ensemble deep learning model is designed in this work to overcome the limitations of the traditional model.

Major contributions associated with the given model are as follows.

- To implement an IoT-based COVID-19 disease prediction framework using attentive and adaptive-derived ensemble deep learning model to scale up the prediction performance that has aided the healthcare center, hospitals, and so on by accurate prediction.
- To design a new deep learning model termed as AAEM, which is designed via DTCN, 1DCNN, and LSTM for continuously monitoring the COVID patients as well as the AE model is used to attain the deep features from the raw data.
- To develop the hybrid algorithm using Eurasian oystercatcher optimizer (EOO) and sewing training-based optimization (STBO) named as FPEOST, the main intent of this algorithm model is to optimize the parameters like epoch and hidden neuron count over the AAEM model to level up the performance of the prediction model.
- To determine the capability of the implemented model in terms of diverse matrices performance.

Further, the lists of upcoming sections in the implemented model are as follows. Section 2 is about the literature survey, Sect. 3 is about an IoT-derived disease prediction model for COVID-19: hybrid meta-heuristic enhancement and ensemble deep learning model, Sect. 4 is about autoencoder for feature extraction and FPEOST for optimization, Sect. 5 is about disease prediction of COVID-19 using attentive and adaptive ensemble model and its objective function, Sects. 6 and 7 are about results and its conclusion.

2 Literature survey

2.1 Related works

Otoom et al. [18] recommended the "real-time COVID-19 monitoring as well as detection" model. This recommended model has included five major components like Cloud Infrastructure, Health Physicians, Data Analysis Center, and Quarantine/Isolation Center. This model has applied an IoT framework to aggregate data through users to earlier detection of suspected virus cases to determine the patient response to the treatment through aggregating and validating the relevant data. Experimentation was then carried out to determine the classical algorithm involved in this model on the real-time COVID-19 symptom dataset. The outcomes have shown that the given model has attained better accuracy. On considering the outcomes, the real-time symptom data has offered accurate and effective detection of COVID-19.

Wahid et al. [19] developed the AI model depending upon IoT architecture for the earlier identification as well as for monitoring of effective COVID-19 cases. In this case, the researchers have developed a contact tracing application to automatically identify the contacts, which was infected by the index case. Due to the asymptomatic spread of COVID-19 among the people, the virus still transmits to the masses. It also has problems such as cross-app as well as privacy compatibility. In addition to that, the IoT-based COVID-19 monitoring

and privacy model along with the semi-automated and then enhanced contact tracing capability has been presented with applications of real-time data of symptoms aggregated through contact tracing and individuals.

Bhardwaj et al. [20] proposed a new model that has taken the advancement of technology to make patients' life easier for earlier detection and treatment. This system was very useful for villages or rural areas, in which the nearby clinics were in touch along with the city hospitals about patient health conditions. A smart health monitoring system was further designed using IoT technology that was capable of monitoring the temperature, oxygen level, heart rate, monitoring blood pressure of the person. The health monitoring system depending upon the IoT aided the doctors to aggregate real-time data effortlessly. This system has aided the earlier treatment and detection of COVID-19 individual patients.

Narayanan et al. [21] presented an IoT-dependent smart system for determining the occupancy in such entertainment screens and spot public entry when they did not follow the protocol. This presented model was implemented over the "Raspberry Pi 3B + processor" that runs based on the "Broadcom processor." In order to further monitor the occupancy as well as to screen the visitors for masks, they have utilized the Pi camera and passive infrared sensors to count the person entering into the premises. The complete system was designed using Python and the authorities have monitored the remote places so that of propagation of COVID-19 has been restricted in public entertainment spots.

Namdev et al. [22] suggested the "critical IoT technologies," which it was useful in terms of healthcare at the time the COVID-19 pandemic was identified and determined. At last, during the COVID-19 pandemic, the potential fundamental IoT application was detected in the medical industry with a short explanation. The IoT is an up-and-coming technology that has improved as well as provided better solutions in the medical area like the cause of sickness, device integration, samples, and medical record-keeping. Moreover, the IoT has facilitated the work of the surgeon by minimizing the risks as well as improving overall performance. By utilizing these techniques, physicians have effectively detected the changes that occurred over the COVID-19 vital parameters. Further, the proper utilization of IoT has assisted in the handling of various medical difficulties like complexity, affordability, and speed. During the COVID-19 pandemic days, the health management system has improved overall healthcare performance.

Paganelli et al. [23] exploited the "comprehensive IoT-based conceptual architecture," which was utilized to address the major necessity of privacy, reliability, context discovery, network dynamics, interoperability, and scalability of monitoring COVID-19 patients at home and in hospitals. Moreover, the remote monitoring of patients at home has engendered trust issues in accordance with ethical and secure data collection to assure data privacy. It has also offered support for adaptable and configurable scoring systems integrated into wearable devices to improve usefulness as well as flexibility for health care.

Bassam et al. [24] implemented IoT-dependent wearable monitoring devices that determine diverse vital signs related to COVID-19. The wearable sensor was located over the body that has been connected to the edge node over the IoT cloud where the data was processed and then validated to determine the state of health condition. Every layer has its own functionality; in the initial phase the data that has been measured through the IoT sensor layer to determine the health symptoms. The design has majorly served as the essential platform that determines the measurement of COVID-19 symptoms for analysis, management, and monitoring. Moreover, the work disseminates how the digital remote platform is the wearable device that is utilized as the monitoring device to detect the recovery as well as the health of COVID-19 patients.

Khan et al. [25] recommended the IoT-dependent system, in which the real-time health monitoring system that used the measured values of oxygen saturation, pulse rate, and body temperature of the patients was the most significant measurement. This system has acquired the liquid crystal display (LCD), which has shown the measured oxygen saturation, pulse rate, and temperature level, and it was easily synchronized with the mobile application for instant access. The outcomes attained through the system and the data acquired through the system were restored very quickly. IoT-dependent tools have been effectively increased using valuable at the time of the COVID-19 pandemic.

2.2 Problem specifications

Some of the advantages and disadvantages of the traditional COVID-19 disease prediction are listed in Table 1. The ensemble [18] technique has been effectively utilized to apply significant COVID-19 case information. It has effectively minimized the effects of communicable diseases. But, it consumes more time to process the data. The artificial intelligence [19] model is defined as the most reliable process for predicting COVID-19 in its earlier stage. It has also been utilized to track the cluster of affected persons for smart lockdown. It has faced issues with data privacy. Raspberry Pi [20] method has offered ease to doctors for gathering useful information about the patient using the display monitoring at their place. It is more updatable and flexible. However, there is a lack of data availability. The smart assist system [21] model has provided the solution to the disconnectivity issues in the monitoring system. It has more scalability and improves the prediction process. It is expensive in terms of the economic side. Web-based gadgets [22] have the ability to provide trustworthy, relevant, and superior data. It is the more effective technique that is capable of continuous monitoring. There is a lack of bandwidth, connection, and spectrum. Machine learning [23] model has been used to enhance the reliability, scalability, network dynamics; privacy of the COVID-19 disease prediction model. It has effectively maintained the privacy of the patients. A safer, smarter, and more efficient monitoring process is needed to be explored in the future. Application programming interface (API) [24] technique has the ability to gather, restore as well as validate the data and is used in real-time applications. It continuously monitors and updates the status of the patients. It is expensive in both time and space. LCD [25] technique has been considered as a cost-effective, versatile, and noninvasive that makes the monitoring process easier. The addition of more sensors for monitoring the physiological parameters of the human body is limited in this work.

3 An IoT-derived disease prediction model for COVID-19: hybrid meta-heuristic enhancement and ensemble deep learning model

3.1 IoT framework

In order to upgrade physical objects into tiny objects, the IoT model has utilized the sensor as well as communication techniques. In general, the IoT architectural model has included three layers application, network, and physical. This model has assured the delivery of smart service to users in order to enhance the quality of their lives. Further, the physical data has been equipped along with the sensor for gathering the heterogeneous data. This sensor has restricted the lifetime and computational capacity. But, the data processing complexity has become a bottleneck. The networking model is not only utilized to upload the gathered data

Table 1 Advantages and disadvantages in the traditional COVID-19 disease prediction

Author [Refs.]	Methodology	Features	Challenges
Chakraborty et al. [18]	Ensemble	• This technique has been effectively utilized to apply significant COVID-19 case information • It has effectively minimized the effects of communicable diseases	• But, it consumes more time to process the data
Wahid et al. [19]	Artificial intelligence	• This model is defined as the most reliable process for predicting COVID-19 in its earlier stage • It has also been utilized to track the cluster of affected persons for smart lockdown	• It has faced issues with data privacy
Bhardwajet al. [20]	Raspberry Pi	• This method has offered ease to the doctors for gathering useful information about the patient using the display monitoring at their place • It is more updatable and flexible	• But, there is a lack of data availability
Narayanan et al. [21]	Smart assist system	• This model provides the solution to the disconnectivity issues in the monitoring system • It has more scalability and improves the prediction process	• It is expensive in terms of the economic side
Namdevet al. [22]	Web-based gadgets	• This method has the ability to provide trustworthy, relevant, and superior data • It is the more effective technique that is capable of continuous monitoring	• There is a lack of bandwidth, connection, and spectrum
Paganelliet al. [23]	Machine learning	• This model has been used to enhance the reliability, scalability, network dynamics, and privacy of the COVID-19 disease prediction model • It has effectively maintained the privacy of the patients	• A safer, smarter, and more efficient monitoring process is needed to be explored in the future
Bassamet al. [24]	API	• This technique has the ability to gather, restore as well as validate the data and is used in real-time applications	• It is expensive in both time and space

Table 1 (continued)

Author [Refs.]	Methodology	Features	Challenges
Khanet al. [25]	LCD	• It continuously monitors and updates the status of the patients • This technique has been considered cost-effective, versatile, and noninvasive which makes the monitoring process easier	• The addition of more sensors for monitoring the physiological parameters of the human body is limited in this work

Fig. 1 Depiction of IoT-based COVID-19 disease prediction framework
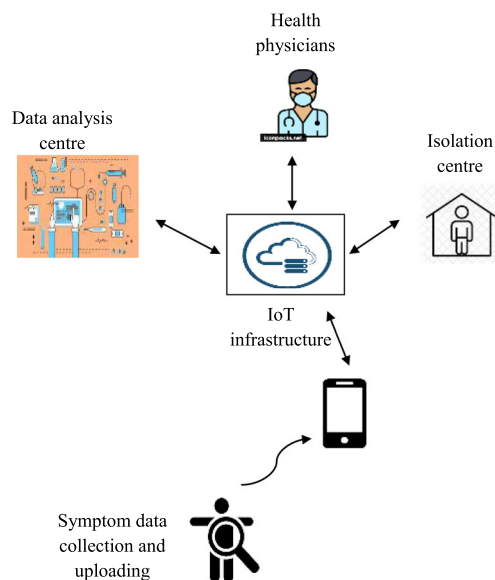
for validation but it is used to assure communication among heterogeneous IoT objects. Further, the network layer has aided the scalability of the model. Consequently, it has offered privacy as well as security for IoT devices. In addition to that, the uploaded data through the IoT devices has been validated deeply in order to produce insights as well as aid in making decisions. In recent years, the deep learning and machine learning algorithm has been utilized due to its ability. Moreover, the wide range of applications in the IoT has been effectively utilized in the power grid, agriculture, and smart cities, health care. IoT is sometimes called as Internet of Medical Things (IOMT). Thus, it has acquired more advanced features than the traditional models. The IoT-based framework in the prediction model is given in Fig. 1.

3.2 Proposed model and description

More specifically, healthcare is regarded as the most significant application field, which acquires accurate and real-time outcomes. Some of the technology has involved fog and

cloud computing, IoT and big data have attained more attention to offer various services depending on the real-time and latency-sensitive applications. Thus, manual processing is not effective, and the utilization of AI in healthcare is prominent for diagnosis, prognosis, and monitoring. COVID-19 is rapidly propagated all over the world in the initial phase. At that point, there is a necessity for automatic detection of COVID-19 [37] with rapid and accurate diagnostic techniques. Computed tomography (CT) is defined as a noninvasive imaging technique, that is used to identify the lesions in the lung that are associated with COVID-19 disease [38]. Chest CT is regarded as a diagnostic tool. Most artificial intelligence includes deep learning and machine learning model that has proven their efficiency over the medical image, thus it has strengthened feature extraction and classification. Consequently, convolutional neural network (CNN) is used to detect as well as differentiate the disease in a simpler way. But, there is much lack in the standard of diagnosis model. Some of the traditional models failed to acquire instant steps for identifying the patients and also failed to tackle multiple medical sensor data for disease prediction. The architectural model for an IoT-based COVID-19 disease prediction framework using attentive and adaptive-derived ensemble deep learning is given in Fig. 2.

Thus, an IoT-based COVID-19 disease prediction framework using attentive and adaptive-derived ensemble deep learning is implemented in this work. IoT-related data is aggregated in the initial phase to perform the diagnosis model of COVID-19. Then, for attaining the deep features, the data is fed to the AE model. Further, the deep features are forwarded to AAEM, which includes three diverse standard approaches like DTCN, 1DCNN, and LSTM model for COVID prediction or monitoring. By utilizing the hybrid algorithm termed as FPEOST, the parameters in the ensemble AAEM model are tuned for further improvement in the process. Finally, the COVID-19 disease prediction outcomes are attained on the basis of the high-ranking process. Thus, the developed model achieved an effective prediction rate than conventional approaches over multiple experimental analyses.

3.3 IoT-based data collection

The novel IoT-based COVID-19 disease prediction framework using an attentive and adaptive-derived ensemble deep learning model is designed in this work, where the initial phase including the gathering of IoT-related data is considered. Thus, the data-related details and their links are discussed.

Dataset: it has two datasets. Dataset 1: "https://www.kaggle.com/datasets/meirnizri/covid19-dataset: Access Date: 2023–06–12." It provides information about the medical history, status, and symptoms about the patients affected by COVID-19. Dataset 2: "https://www.kaggle.com/datasets/iamhungundji/covid19-symptoms-checker?select=Raw-Data.csv: Access Date: 2023–06–12." It has included seven main variables like contact; experience of any symptoms, symptoms, age, and country, and so on. It has 316,800 combined labels in it.

From utilizing the above dataset, the data that is relevant to performing the prediction model is aggregated and indicated as CVD_s^{dt}, $s = 1, 2, \ldots, S$ is the total number of aggregated data.
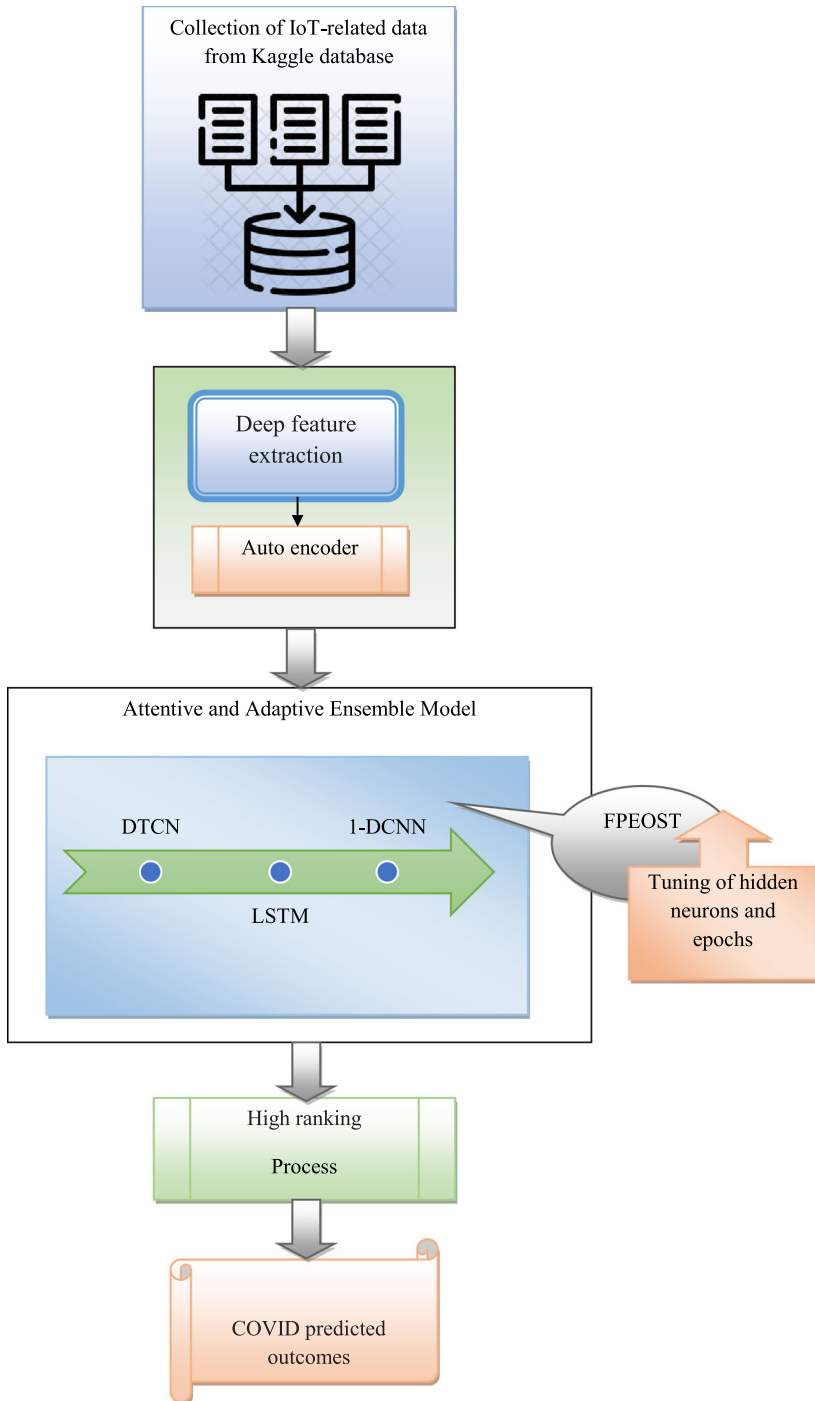
Fig. 2 Architectural depiction of IoT-based COVID-19 disease prediction framework using attentive and adaptive-derived ensemble deep learning

4 Autoencoder for feature extraction and FPEOST for optimization

4.1 Autoencoder-based feature extraction

Here, the AE model is used for the process of retrieving the deep features from the aggregated raw data CVD_s^{dt}. The extraction deep features are helpful to boost the performance of the given model by minimizing the redundant data.

AE [26]: one of the unsupervised machine learning techniques is defined as the AE model over the artificial neural network. In general, the AE model has been trained in order to reconstruct the output layer near the input layer. It includes the input, output, and hidden layer which usually has a smaller dimension than the input. In general, the AE model has the ability to detect the structure of the data by minimizing the data along with the nonlinear transformation. In the initial phase, the input is transformed to the lower-dimensional layer as well as then extended to reproduce the initial data. The main intent of the process is to minimize the dimension of input data.

The neural network along with the hidden layer has been derived in Eq. (1) and (2) for the encoder and decoder.

$$CVD_s^{dt} = a_\omega(B) = b(CB + c_B) \tag{1}$$

$$B' = d_{\omega'}\left(CVD_s^{dt}\right) = b\left(C'A + c_A\right) \tag{2}$$

Here, the function activation is given as b, a bias for data is termed as c, the weighting parameter is indicated as C, the decoded function is indicated as $d(A)$, and the encoded function is denoted as $a(B)$. Further, the decoder function d has mapped the hidden depiction of A to reconstruct B'.

Moreover, the training process of AE has been used to validate the parameter $\omega = (C, c_B, c_A)$ for reducing the loss of reconstruction along with the objective function that is derived in Eq. (3).

$$\omega = \min D(B, B') = \min D(B, d(a(B))) \tag{3}$$

Here, the loss reconstruction D_1 in the case of linear reconstruction is given in Eq. (4).

$$D_1(\omega) = \sum_{y=1}^{z} \left\| e_y - e'_y \right\|^2 \tag{4}$$

Here, the loss reconstruction D_2 in the case of nonlinear reconstruction is given in Eq. (5).

$$D_2(\omega) = -\sum_{y=1}^{z} \left[e_y \log(f_y) + (1 - e_y) \log(1 - f_y) \right] \tag{5}$$

Thus, by utilizing the AE model, the deep features from raw data are attained and termed as df_u^{ae}, $u = 1, 2, \ldots, U$ is the total number of deep features. It is represented in Fig. 3.

4.2 Hybrid meta-heuristic improvement: FPEOST

The new hybrid algorithm model termed as FPEOST is designed in the novel IoT-based COVID-19 disease prediction framework using attentive and adaptive-derived ensemble deep learning model by using two diverse algorithm models like EOO and STBO models. This

Fig. 3 Depiction of AE model used for extracting the deep features
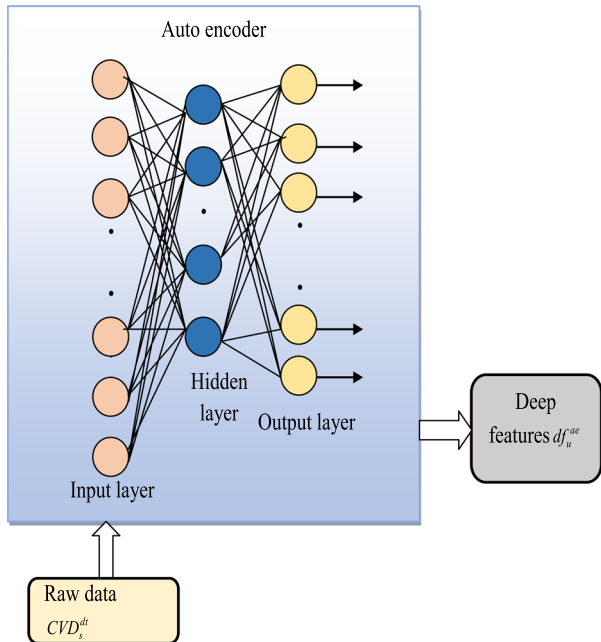
model has provided better value for unimodal functions as well as offers distinguished outcomes for multimodal functions. But, there is a difficulty over complex issues. For STBO, it has the capability to perform fixed-dimensional multimodal, high-dimensional multimodal as well as unimodal. It offers diverse real-time applications. But, there are some optimization application issues. Thus, the FPEOST is designed in this model to tackle all the limitations in the classical by designing a new formulation and it is derived in Eq. (6).

$$ps = mean(ps1, \ ps2) + \left(\frac{(it_{bst} - cr_{ft})}{(it_{wst} - cr_{ft})} \right) \tag{6}$$

Here, the best fitness, worst fitness, and current fitness are indicated it_{bst}, it_{wst}, and cr_{ft}. Here, the terms $ps1$ and $ps2$ indicate the position update takes place in terms of EOO and STBO algorithm models accordingly.

4.2.1 EOO [27]

It mimicked the food behavior of the EO while searching for the mussels. Every bird in the population acts as the search agent. The mathematical model of search as well as the appropriate mussel chosen through EO. The major intent of EO is to balance the energy and also calories attained through mussels. When the mussel's length has been maximized, and then the time and calories acquired for opening have also been maximized. Then, the high energy is acquired through EO waste. Equations (7) and (8) have depicted the behavior of EO in the searching process.

$$EE = FF + GG + HH * g * (E_{bst} - E_{h-1}) \tag{7}$$

$$E_h = E_{h-1} * F \tag{8}$$

Here, the length of the mussel that depicts the range of optimal length FF is depicted as HH, the position of the candidate mussel is represented as E_h, and the final energy of EO in every solution is given as EE. Further, the EO energy at the current time is indicated as GG that is attained through Eq. (9). The random number among 0 to 1 to offer more randomness is termed as g. The caloric value is given in Eq. (10).

$$FF = \left(\left(\frac{HH - 3}{5 - 3} \right) * 10 \right) - 5 \tag{9}$$

$$GG = \left(\frac{h - 1}{i - 3} \right) - 0.5, \quad \text{where} \quad h > 1 \tag{10}$$

$$F = \left(\left(\frac{HH - 3}{5 - 3} \right) * 2 \right) + 0.6 \tag{11}$$

Here, the iterative value is indicated as h. This condition permits EO to attain any position in the searching space as well as tackle the local minimum issues, thus it has emphasized the explorations.

4.2.2 STBO [28]

The activity of teaching sewing skills has been made through training instructors to beginner tailors. Moreover, the interactions among training instructors and beginner tailors have represented the high capability of the sewing training process is regarded as designed for the optimizer. The given STBO algorithm has been regarded as the population-based metaheuristic algorithm model, where the members are training instructors and beginner tailors. The STBO population is defined by the matrix representation is in Eq. (12).

$$G = \begin{bmatrix} G_1 \\ \vdots \\ G_j \\ \vdots \\ G_H \end{bmatrix}_{H \times k} = \begin{bmatrix} l_{1,1} & \cdots & l_{1,m} & \cdots & l_{1,n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ l_{j,1} & \cdots & l_{j,m} & \cdots & l_{j,n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ l_{H,1} & \cdots & l_{H,m} & \cdots & l_{H,n} \end{bmatrix}_{H \times k} \tag{12}$$

Here, the number of problem variables is given as n, the number of STBO population members is termed as H, the jth STBO member is depicted as G_j, and the STBO population matrix is denoted as G. In the initial stage of STBO implementation, all population members have been initialized randomly in Eq. (13).

$$\begin{aligned} &l_{j,m} = bl_m + o \cdot (bu_m - bl_m), \\ &j = 1, 2, \ldots, H \\ &m = 1, 2, \ldots, n \end{aligned} \tag{13}$$

Here, the upper and lower bound of mth the problem variable is indicated as bu_m and bl_m. Random number in the interval is indicated as o, and the value of mth the variable determined through jth STBO is given as $l_{j,m}$.

Training phase: in the initial phase of updating STBO member has been depending upon the simulating process of choosing the training instructor and then requiring the sewing skill through beginner tailors. Further, the set of all candidate members has considered as the

group of possible training instructors for every STBO member G_j, $j = 1, 2, \ldots, H$ has been determined using Eq. (14).

$$TI_j = \left\{ G_p | I_p < I_j, \, p \in \{1, 2, \ldots, H\} \right\} \cup \{G_{bst}\} \tag{14}$$

Here, the set of all possible candidates for training instructor is given as TI_j, the selected instructor is termed as SI_j. The new population for every population member has been produced in the initial phase by using Eq. (15) to update the population members depending on this phase.

$$l_{j,m}^{aa1} = l_{j,m} + o_{j,m}.\left(SI_{j,m} - ss_{j,m}.l_{j,m}\right) \tag{15}$$

Here, the random number among the interval [0, 1] is given as $o_{j,m}$, numbers that have been chosen randomly from the set $\{1, 2\}$ is termed as $ss_{j,m}$, the objective function value is termed as $SI_{j,m}$, dth dimension is depicted as $l_{j,m}^{aa1}$.

Further, the new position has enhanced the objective function value, it replaces the previous position of the population members. The updating condition is expressed in Eq. (16).

$$G_j = \begin{cases} G_j^{aa1} & I_j^{aa1} < I_j \\ G_j & \text{else} \end{cases} \tag{16}$$

Here, the new position of the jth STBO member based on the initial phase of STBO is given as G_j^{aa1}.

Imitation of the instructor's skills: it has been dependent upon the simulating beginner tailors that have tried to mimic the instructor's skills. Every STBO member imitates im_{sk} the skills of the chosen instructors $1 \le im_{sk} \le im$. In addition to that, this procedure has been utilized in order to propagate the population of the algorithm model into diverse areas over the searching space which has shown the exploration ability of the STBO model. Further, a set of variables, that imitates STBO members, has been derived in Eq. (17).

$$DS_j = \left\{ dd_1, dd_2, \ldots, dd_{im_{sk}} \right\} \tag{17}$$

Here, the set of the indexes of decision variables that are used for detecting imitation from the instructor is indicated as DS_j, the total number of iterations is given as IT, the number of skills selected to mimic is termed as $im_{sk} = 1 + \frac{it}{2IT}$, and the iteration counter is denoted as it.

Then, the new orientation of every STBO member has been determined on the basis of simulation of imitating the skills of instructors by using Eq. (18).

$$l_{j,m}^{aa2} = \begin{cases} SI_{j,m} & m < DS_j; \\ l_{j,m} & \text{else} \end{cases} \tag{18}$$

Here, the dth dimension of G_j^{aa2} is termed as $l_{j,m}^{aa2}$, a newly generated position for the jth STBO member is given as G_j^{aa2}. When the value of the objective function is enhanced, then the new position in STBO is replaced by the previous position that it is given in Eq. (19).

$$G_j = \begin{cases} G_j^{aa2} & I_j^{aa2} < I_j \\ G_j & \text{else} \end{cases} \tag{19}$$

Here, the objective function value of G_j^{aa2} is termed as I_j^{aa2}.

Exploitation: here, the local search has been carried out around the candidate solution along to determine the best possible solution around the candidate solution. Further, the new

position around every member of the STBO is expressed in Eq. (20).

$$l_{j,m}^{aa3} = \begin{cases} bl_m, & l_{j,m}^* < bl_m; \\ l_{j,m}^*, & l_{j,m}^* < [bl_m, bu_m]; \\ bu_m, & l_{j,m}^* > bu_m \end{cases} \tag{20}$$

Here, the random number among [0, 1] is given as $l_{j,m}^* = l_{j,m} + bl_m + o_{j,m}(bl_m, bu_m)/it$ and $o_{j,m}$. Further, the position has been replaced by the previous position of STBO and it is derived in Eq. (21).

$$G_j = \begin{cases} G_j^{aa3} & I_j^{aa3} < I_j \\ G_j & else \end{cases} \tag{21}$$

Here, the objective function value is given as I_j^{aa3}, dth the dimension value is given as l_j^{aa3}, newly generated position for the jth STBO is termed as G_j^{aa3}. At last, the hybrid FPEOST model's pseudo code is given in Algorithm 1.

Input both the EOO and STBO populations
Determine the optimization problem information
Fitness for every searching agent is calculated
For $it = 1 \, to \, it_{mx}$
$i = 1 \, to \, N_p$
While $it > it\max$
Update the position using EOO by Eq. (7) and (8)
Else
Update the position using STBO by Eq. (16), (18) and (21).
Formulate the new derivation $ps = mean(ps1, ps2) + \left(\frac{(it_{bst} - cr_{fi})}{(it_{wst} - cr_{fi})} \right)$
End while
End for
End
Return better solution

Algorithm 1: FPEOST

The hybrid FPEOST model's flowchart is given in Fig. 4.

5 Disease prediction of COVID-19 using attentive and adaptive ensemble model and its objective function

5.1 Models employed for prediction

The deep features df_u^{ae} are fed as the input to the AAEM model for attaining the classified outcomes, in which it includes three standard techniques like DTCN, 1DCNN, and LSTM model.

5.1.1 DTCN [29]

The most essential, as well as the crucial part of the DTCN networking model, is regarded as the convolutional sequence prediction architecture and which is validated in the starting
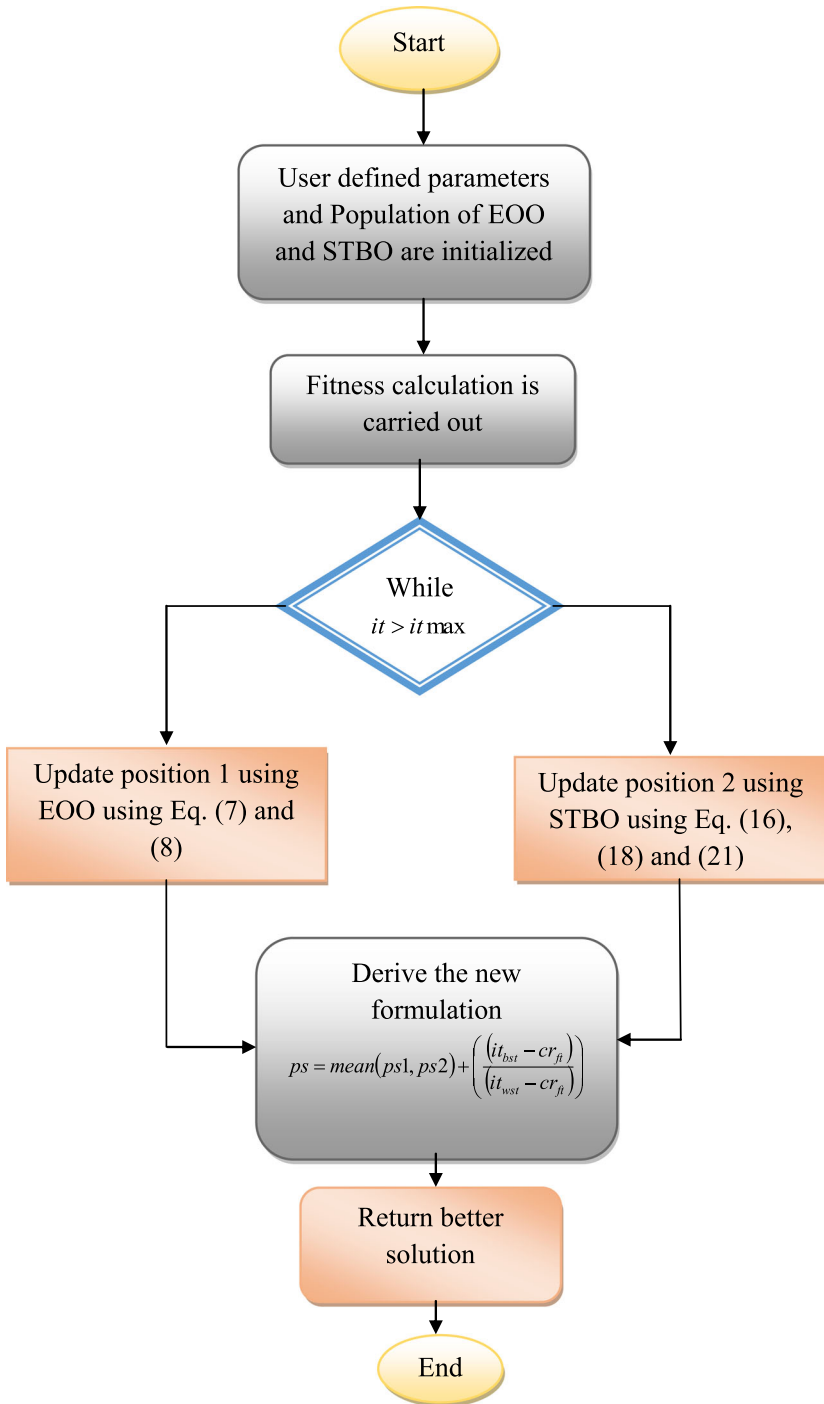
Fig. 4 The flowchart for FPEOST model-representation

stage. In this process, the input $(jd_0, \ldots, jd_{q-1})$ is forwarded to the next level to attain the output value dj_q in accordance with time q. Further, a series of flow data $(jd_0, \ldots, jd_{q-1})$ and the data used in the case of validating the flow data is given as $\left\{ \hat{d}j_0, \ldots, \hat{d}j_q \right\}$. Then, the sequence of the network model is attained as the function for fc that is analyzed in terms of the mapping function, which is derived in Eq. (22).

$$\left\{ \hat{d}j_0, \ldots, \hat{d}j_q \right\} = fc(jd_0, \ldots, jd_q) \tag{22}$$

When the causal condition is satisfied by the value of a function fc, then the term dj_q dependent upon $(jd_0, \ldots, jd_{q-1})$ rather than the input future $(jd_{q+1}, \ldots, jd_q)$. Moreover, the function fc is utilized to detect the data flow at dj_q, which is expressed in Eq. (23).

$$\hat{d}j_q = fc(jd_0, \ldots, jd_{q-1}) \tag{23}$$

Moreover, the DTCN has used causal convolution in the initial phase, where the output at a time q is convoluted over the previous layer. Further, it is considered as the essential block over deep learning techniques. It has offered better tackling techniques to the data sequence input with its length and is used for the detection process as well.

Subsequently, the dilated convolution and the residual layer are integrated together over the DTCN to exhibit the accurate rate. Particularly, the dilated convolution has been assured the large receptive field in an exponential manner. Thus, it may lead to complicated network models as well as heavy computation. Then, in accordance with both the filter $ft : (0, \ldots, hc - 1) \rightarrow J$ and the input BB, the data flow ZZ over time q is expressed in Eq. (24).

$$ZZ(q) = (jd * dft)(q) = \sum_{ee}^{hc-1} ft(ee).jd_{q-dt.ee} \tag{24}$$

Here, dt is the dilation factor, hc is the filter size, and $q - dt.ee$ is the orientation of the past. Here, the enhancement in terms of dilation has assured the development of the receptive field. Thus, it may lead to the output being attained at the top level for representing the wider range.

The residual connection, which gets included over the branch that carries out the series of ξ transformations, is regarded as the most essential factor of the DTCN model. Further, the output is get added up with the input ee. Then, the residual block is given in Eq. (25).

$$dj = \xi(ee, wg_{ee}) + ee \tag{25}$$

Here, the residual mapping is given as $\xi(ee, wg_{ee})$, where the weight over the layer is termed as wg_{ee} and dj depicts the output vector of the layer.

5.1.2 1DCNN [30]

Commonly, the 1DCNN model is regarded as a kind of CNN. In order to implement the feature mapping, both, the sub-sampling and the one-dimensional convolutions are utilized. By utilizing the shared weights in a deep network as well as a local receptive field, the feature extraction from one-dimensional data has been carried out in 1DCNN, in which it includes multiple pooling and convolution layers. Moreover, the feature map over the sub-sampling and convolution layers has the ability to retrieve the depiction of the discriminate feature through the multiple vector segments.

Convolution layer: by utilizing the multiple convolution filters, the most adequate information from the raw data has been retrieved. In addition to that, the representative expression

of the given one-dimensional data has been mapped into the convolution layer by means of diverse feature filters zz_{yy} from various segments. Further, the output features of the convolution layer produced through nonlinear transformation depending upon the multiple convolution kernels are expressed in Eq. (26).

$$yy_{jj}^{ii} = zz\left(\sum_{hh=L_{jj}} yy_{hh}^{ii-1} * xx_{hhjj}^{ii} + ww_{jj}^{ii}\right) \tag{26}$$

Here, the convolution kernel is indicated as xx, bias is given as ww_{jj}^{ii}, the amount of layer over 1DCNN is termed as ii, and the input feature is denoted as L_{jj}. Here, the activation function yy has included the sigmoid function and hyperbolic convolution.

Pooling layer: in order to further attain the feature map for the low-resolution, the subsampling has been utilized in this layer. By means of maximum sampling operation, the feature map produced in this layer has been minimized to one-half of the output.

Fully connected layer: a classifier in the 1DCNN has been constructed along with the label information over the training phase that has been utilized for updating the parameters in the networking model. Here, the pooling layer that has further mapped the input to a smaller output is given as in Eq. (27).

$$M_{jj}^{ii} = \max\left(vv_{hh}^{ii}\right), hh \in N_{jj}^{ii} \tag{27}$$

Here, the size of the kernel is denoted as $mm * 1$, features in the pooling domain of index ii are indicted as vv_{hh}^{ii}, and the jjth pooling domain in iith the layer is termed as N_{jj}^{ii}.

The cascaded feature map cd_{kk} has been retrieved through 1DCNN and has been subjected to the top classifier as derived in Eq. (28).

$$O = cd(uu_O + vv_O cd_{kk}) \tag{28}$$

Here, the weight and bias are given as uu_O and vv_O accordingly.

5.1.3 LSTM [31]

Most commonly, the LSTM networking model is used to generate the task relevant to machine translation and sequence generation. Further, the input vector acquired over the LSTM model is given in Eq. (29).

$$fg_t = \psi\left(si_{be}^{MF} \cdot \left[ov_{t-1}, ns_t\right] + bt_{fg}\right) \tag{29}$$

Here, the output vector of the previous layer is given as ov_{t-1}, and the new element of the sequence that concatenated with output is termed as ns_t. Further, it is converted into a vector through the sigmoid activation function layer and it is given in Eq. (30).

$$K_t = fg_t * K_{t-1} + in_t * \tilde{K}_t \tag{30}$$

Here, the state update is multiplied along with the past state by fg_t to "forgot state" The data is detected as unnecessary in accordance with the previous phase and then get added up with $in_t * \tilde{K}_t$. Further, the terms K_{t-1} and K_t are used to state updates. It is expressed in Eqs. (31) and (32).

$$in_t = \psi\left(si_{be}^{MF} \cdot \left[ov_{t-1}, ns_t\right] + bt_{in}\right) \tag{31}$$

$$\tilde{K}_t = \tanh\left(si_{be}^{MF} \cdot \left[ov_{t-1}, \, ns_t\right] + bt_K\right) \tag{32}$$

To develop the vector of new candidates, tanh is termed as $\tilde{K}_t$ as well as the values get added up to the cell state and the input gate is utilized to detect the value for the update. It is derived in Eq. (33).

$$ov_t = ot_t * \tanh(K_t) \tag{33}$$

Here, the terms ov_t and K_t have been further fed to the neural networking input at a time $t + 1$.

$$ot_t = \psi\left(si_{be}^{MF} \cdot \left[ov_{t-1}, \, ns_t\right] + bt_{ot}\right) \tag{34}$$

$$pp_t = sft\max(ov_t) \tag{35}$$

Here, $\psi(.)$ is the nonlinearity that is produced by the sigmoid function and ov is the hyperbolic tangent. The term ov_t is fed to the softmax function for validating the probability distribution pp_t. The multiplicative filter allows adequate training of the LSTM model and then prevents the exploding and vanishing gradients.

5.2 AAEM-based disease prediction

In the novel, IoT-based COVID-19 disease prediction framework, a new deep learning technique termed as AAEM is designed, in which the model is developed via some of the standard techniques like DTCN, 1DCNN, and LSTM model. Here, the adaptive mechanism is by optimizing the parameters in three models using the FPEOST algorithm. Consequently, the attention mechanism has been involved in all three models to scale up the performance of the prediction model. This process is given in Eq. (8).

$$attn(hh, \, gg) = \sum_{z=1}^{X} \sigma_z(hh, \, gg_z)Y_z \tag{36}$$

Here, $\sigma_z(hh, \, gg_z)$ is the similarity function, hh is the query task, Y_z and gg_z is the key. Further using the softmax function, it is determined in Eq. (37)

$$sfmx(t_z) = \frac{\exp(t_z)}{\sum_{z'} \exp(t_{z'})'} \tag{37}$$

To score function $hh, \, gg_z$:

$$\sigma_z = \frac{\exp(sco(hh, \, gg_z))}{\sum_{z''=1}^{X} \exp(sco(hh, \, gg_{z''}))} \tag{38}$$

Then, the feed-forward neural network is used to determine the score function and given in Eq. (39).

$$sco(hh, \, gg_z) = Y_{gc} \tanh\left[Y_{gc}\left[(hh, \, gg_z)\right]\right] \tag{39}$$

Here, the linear function of hh and gg_z is indicated as $(hh, \, gg_z)$, and the matrix is given as Y_{gc}.

Attention-based DTCN model is designed to enhance the ability of the machine translation process. It has assisted the final predicted outcome with accurate values. In general, it gets added up with the deep learning model to attain attention to the adequate part.

Then, the attention mechanism in 1DCNN is intended to focus on learning the most significant data features as well as to level up the prediction performance. It further provides enough attention to the key information.

Finally, the attention to the LSTM model has permitted it to focus on the specified part of the input sequence at the time of prediction.

In addition to that, the entire traditional attention-based model has acquired some limitations, so the FPEOST algorithm is used to optimize such parameters. In the end, the final classified or predicted from the designed IoT-based COVID-19 disease prediction framework is attained in terms of high-ranking procedure. This model is represented in Fig. 5.

5.3 Objective function for AAEM

In this phase, some of the parameters included in the AAEM model are optimized with the aid of the FPEOST algorithm along with the derivation of the new objective functions is discussed.

DTCN: it provides more attention during the prediction process. But, it consumes more time as well as the parallelization of the system in DTCN is also very difficult.
1DCNN: it enhances the performance as well as the accuracy rate of complex issues. But, the association among variables needs to be explored further.
LSTM: it enhanced the tackling ability of long sequences as well as the diversity of the output value. But, it adds more parameters related to weight that affect the model.

In this case, to overcome all those restrictions in the classical attention-based model, the new objective function is derived and the new AAEM model is attained. The given AAEM model is developed with the integration of DTCN, 1DCNN, and LSTM models which helps to enhance the prediction performance and improve the bagging and boosting of deep learning strategies. It is formed with the combination of algorithm-level methods and data-level approaches. It helps to modify the data distribution and also to deduce the data imbalance issues. It is utilized to improve the sensitivity of the developed model. The new objective function is expressed in Eq. (40).

$$obfc = \underset{\{hn^{dt}, hn^{ls}, hn^{1-d}, eo^{dt}, eo^{ls}, eo^{1-d}\}}{\arg\min} \left(\frac{1}{(acr + prc + mcc)} + fd \right) \tag{40}$$

Here, hn^{dt}, hn^{ls}, hn^{1-d}, eo^{dt}, eo^{ls}, eo^{1-d} are terms that represent the hidden count among the range [5–255] in DTCN, 1DCNN, and LSTM as well as the epoch among the range [5–50] in DTCN, 1DCNN, and LSTM models. Then, acr, prc, mcc, and fd terms are accuracy, precision, Matthews correlation coefficient (MCC), and false discovery rate (FDR) and it is expressed as in Eqs. (41)–(44).

$$acr = \frac{(vrr + vaa)}{(vrr + vaa + brr + baa)} \tag{41}$$

$$prc = \frac{vrr}{vrr + brr} \tag{42}$$

$$mcc \frac{vrr \times vaa - brr \times baa}{\sqrt{(vrr + brr)(vrr + baa)(vaa + brr)(vaa + baa)}} \tag{43}$$
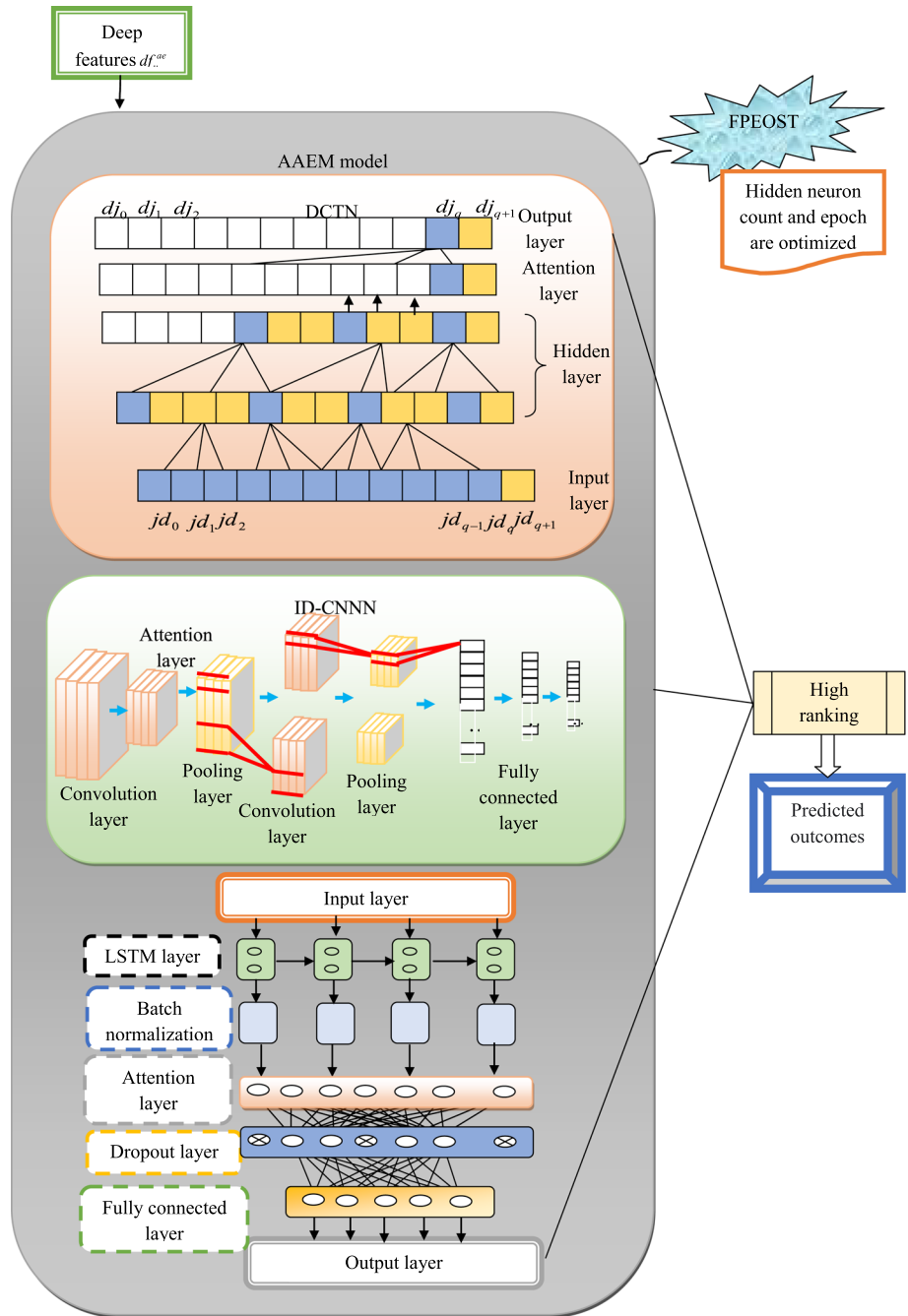
$$fd = \frac{brr}{brr + vrr} \tag{44}$$

Fig. 5 Disease prediction by using a newly designed AAEM model along with the FPEOST approach

Here, the term vrr is defined as true positive and the variable vaa is denoted as the true negative. Moreover, the term brr is represented as a false positive, and the variable baa is noted as a false negative. Finally, predicted or classified outcomes are attained for the given IoT-Based COVID-19 disease prediction framework.

6 Results and discussion

6.1 Simulation setup

The proposed novel IoT-Based COVID-19 disease prediction framework using an attentive and adaptive-derived ensemble deep learning model was implemented in Python. Approaches like the reptile search algorithm (RSA)-AAEM [32] and chameleon swarm algorithm (CSA)-AAEM [33] were used for the assimilation process. The "population size was 10, chromosome length was 6, and maximum number of iterations was 50" were used in this model.

6.2 Performance measures

The novel IoT-based COVID-19 disease prediction framework using an attentive and adaptive-derived ensemble deep learning model is analyzed as follows.

(a) Sensitivity in Eq. (45)

$$stt = \frac{vrr}{vrr + baa} \tag{45}$$

(b) Specificity in Eq. (46)

$$spc = \frac{vaa}{vaa + brr} \tag{46}$$

(c) False positive rate (FPR) in Eq. (47)

$$fp = \frac{brr}{brr + vaa} \tag{47}$$

(d) False negative rate (FNR) in Eq. (48)

$$fn = \frac{baa}{vaa + vrr} \tag{48}$$

(e) Net present value (NPV) in Eq. (49)

$$np = \frac{baa}{baa + vaa} \tag{49}$$

(i) F1-score in Eq. (50)

$$f1s = \frac{stt \cdot prc}{prc + stt} \tag{50}$$

(j) Cohen-kappa-score in Eq. (51)

$$cks = \frac{2 * (vrr * vaa - baa * brr)}{(vrr + brr) * (brr + vaa) + (vrr + baa) * (baa + vaa)} \tag{51}$$

(k) G-mean in Eq. (52)

$$G \text{-} \text{mean} = \sqrt{\text{Sensitivity} \times \text{Specificity}} \tag{52}$$
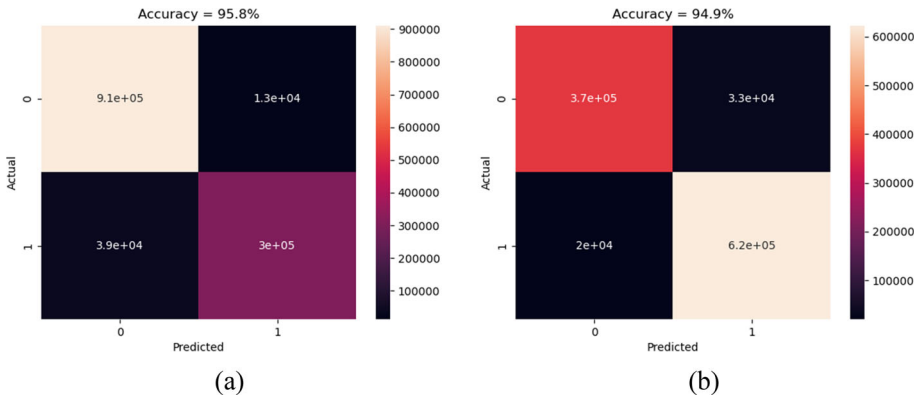
Fig. 6 Analysis of the performance of the given prediction model in terms of a confusion matrix for **a** dataset 1 and **b** Dataset 2

(l) Log-loss in Eq. (53)

$$\text{log - loss} = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{M} y_{ij} \log(p_{ij}) \tag{53}$$

From Eq. (53), the term N and M is defined as the count of rows in the given test set and also the count of error deliverance sets. Consequently, the variables y_{ij} and p_{ij} are presented as the study belongs to class and the predicted probability distribution of the given study.

6.3 Analysis of confusion matrix for two datasets

Figure 6 represents the confusion matrix of both datasets 1 and 2 for predicting the COVID-19 model. It is keenly shown that the proposed FPEOST-AAEM offers a better rate of accuracy in both datasets and enhances the entire performance.

6.4 Analysis of ROC and cost function

The analysis of the ROC curve and cost function for performing the prediction model is given in Figs. 7 and 8. The ROC analysis has been carried out by assimilating over diverse classifier models and the cost function is carried out by comparing with various algorithm models. Both datasets have provided better and outperformed values for the given FPEOST-AAEM model. Thus, the performance ability of the given model is maximized.

6.5 K-fold validation for diverse algorithms and classifiers for two datasets

Figures 9 and 10 as well as Figs. 11 and 12 represent the k-fold validation for diverse algorithms model and classifier model. In accordance with various algorithms like RSA-AAEM, CSA-AAEM, EOO-AAEM, and STBO-AAEM model, the given FPEOST-AAEM model provides 11, 10, 7, and 4% higher values of F1-Score at 4% for dataset 1. Consequently, in some of the classifiers like DTCN, 1DCNN, LSTM, and DTCN + 1DCNN + LSTM model, the given FPEOST-AAEM model provides 5, 4, 3, and 2% higher for the value of precision
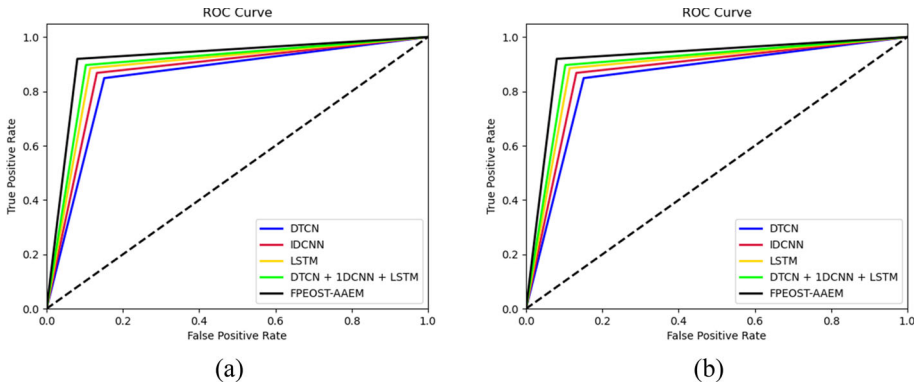
Fig. 7 Analysis of the performance of the given prediction model in terms of ROC for **a** dataset 1 and **b** dataset 2
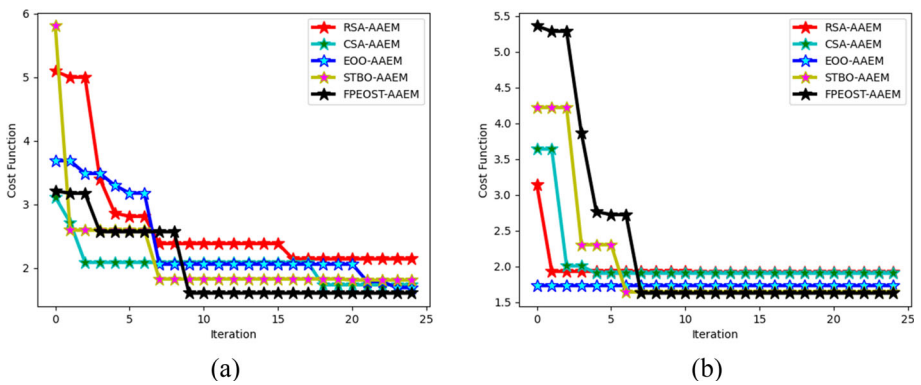

Fig. 8 Analysis of the performance of the given prediction model in terms of the cost function for **a** dataset 1 and **b** dataset 2

for dataset 2 at 4%. Thus, the prediction model has shown better rates for all the positive measures.

6.6 Determination over epoch-diverse algorithms and classifiers for two datasets

Determination over epochs in accordance with various algorithms and classifiers is given in Figs. 13 and 14 and 15 and 16. The given FPEOST-AAEM model provides 18, 16, 12, and 6% higher values compared to various algorithms like RSA-AAEM, CSA-AAEM, EOO-AAEM, and STBO-AAEM model of precision at 500 for dataset 1when. Thus, the prediction model has shown better rates for all the positive measures.
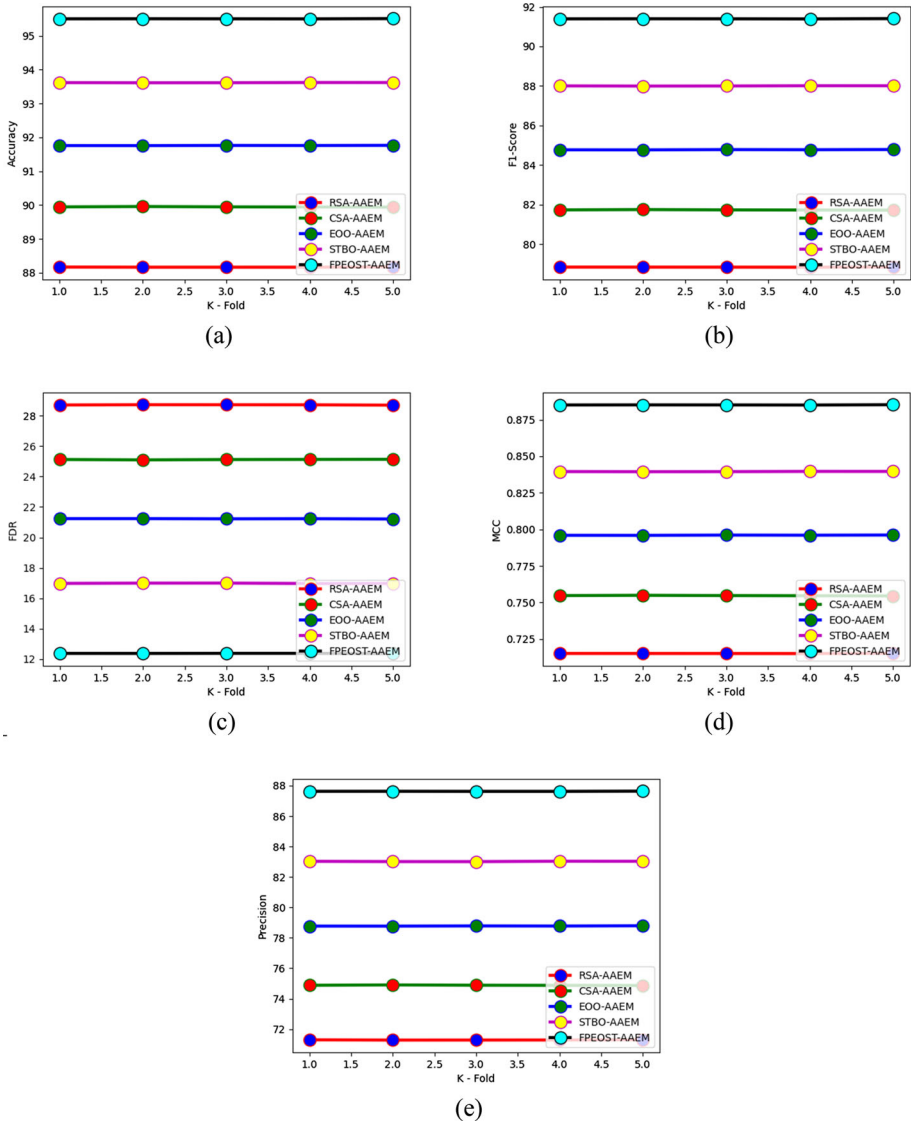
(a)

(b)

(c)

(d)

(e)

Fig. 9 K-fold validation for the given prediction model of COVID-19 when compared to diverse algorithms for dataset 1 concerning **a** accuracy, **b** F1-score, **c** FDR, **d** MCC, and **e** precision

6.7 Validation of with and without optimization of designed approach for two datasets

Validation of with and without optimization of designed IoT-based COVID-19 disease prediction approach is given in Figs. 15 and 16. Thus, the given prediction result reveals that with optimization approach named FPEOST-AAEM model attains elevated performance than the without optimization like DTCN + 1DCNN + LSTM existing approaches.
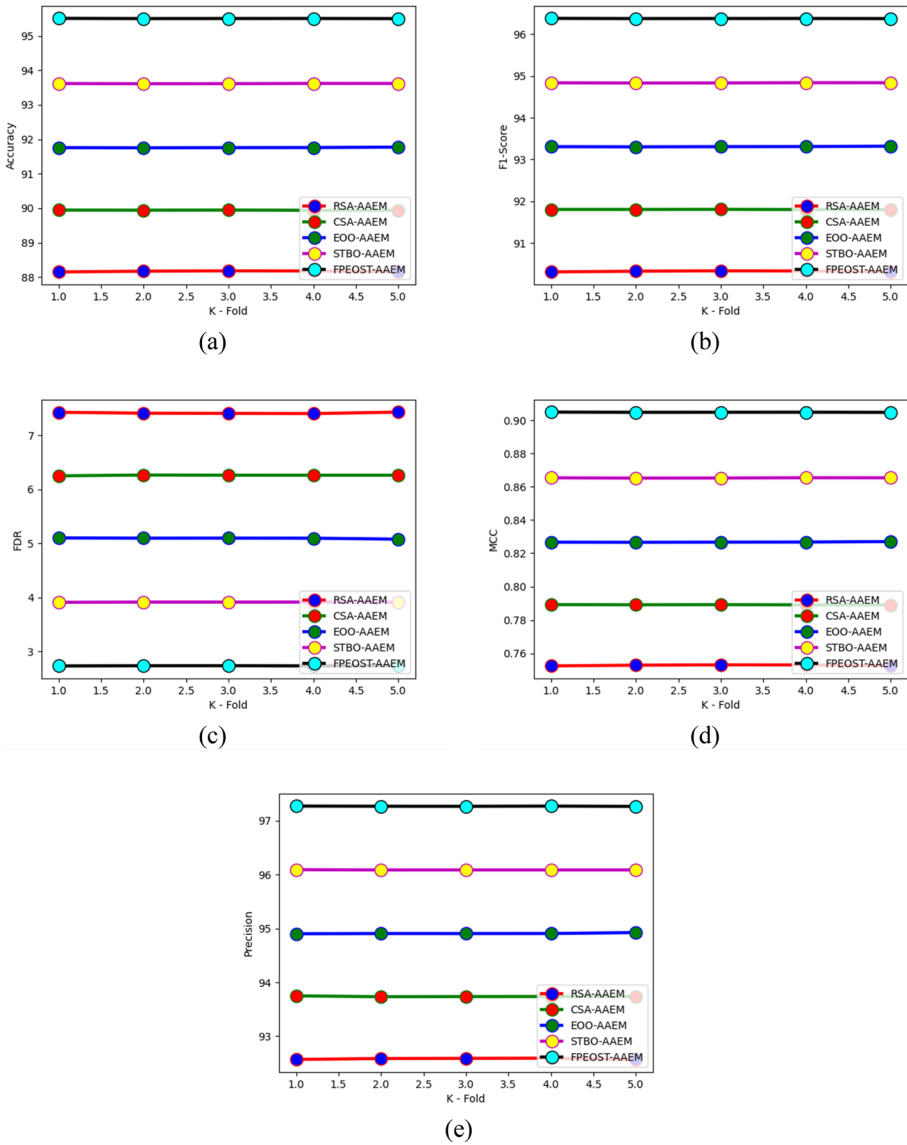
Fig. 10 K-fold validation for the given prediction model of COVID-19 when compared to diverse algorithms for dataset 2 concerning **a** accuracy, **b** F1-score, **c** FDR, **d** MCC, and **e** precision

6.8 Validating the prediction model using diverse algorithms and classifiers

Validating the prediction model using diverse algorithms and classifiers for datasets 1 and 2 are given in Tables 2 and 3. The sensitivity value for the given FPEOST-AAEM model when compared to various algorithms like RSA-AAEM, CSA-AAEM, EOO-AAEM, and STBO-AAEM models provides 7, 5, 4, and 2% higher values. Thus, the prediction model of COVID-19 offers better outcomes.
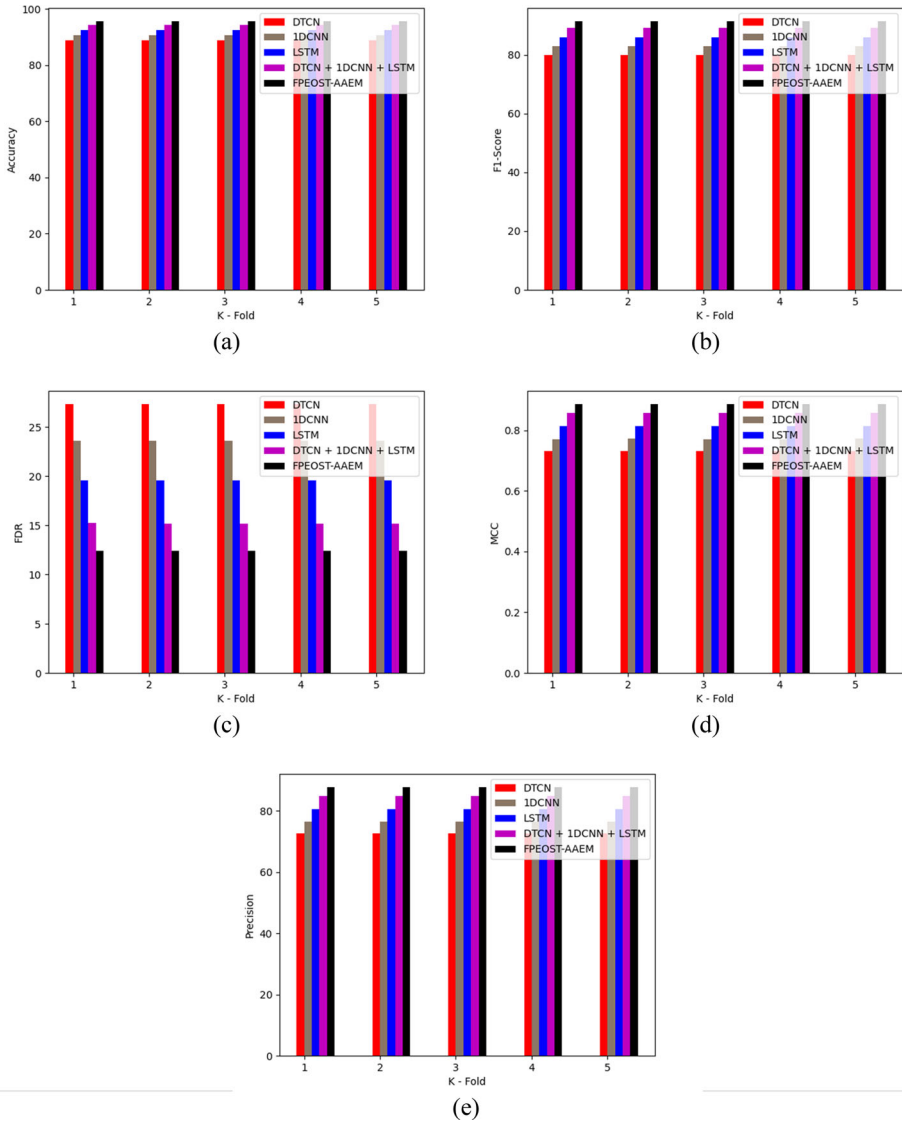
Fig. 11 K-fold validation for the given prediction model of COVID-19 when compared to diverse classifiers for dataset 1 concerning **a** accuracy, **b** F1-score, **c** FDR, **d** MCC, and **e** precision

6.9 Statistical analysis of the prediction model

The statistical analysis of the prediction model is given in Table 4. When assimilated over DTCN RSA-AAEM, CSA-AAEM, EOO-AAEM, and STBO-AAEM, the given FPEOST-AAEM model gives 33, 1, 18, and 7% lower values for the value of mean at dataset 1. It improves the efficiency of the prediction model.
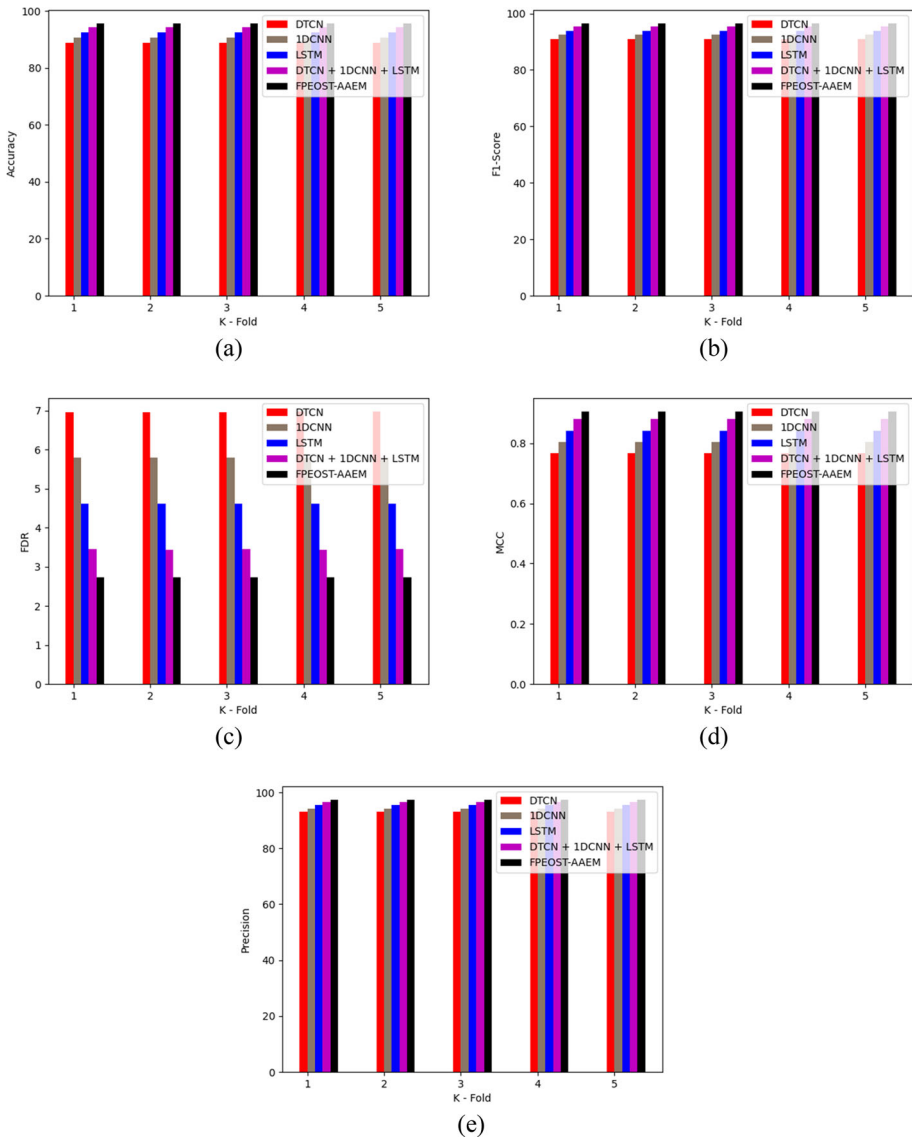
Fig. 12 K-fold validation for the given prediction model of COVID-19 when compared to diverse classifiers for dataset 2 concerning **a** accuracy, **b** F1-score, **c** FDR, **d** MCC, and **e** Precision

6.10 Validation of the recommended approach using recent existing approaches

The estimation of the designed IoT-based COVID-19 disease prediction framework for datasets 1 and 2 using new metrics like Cohen-kappa-score, G-mean, and log-loss is shown in Table 5. Therefore, the empirical result proved that it attains elevated performance.
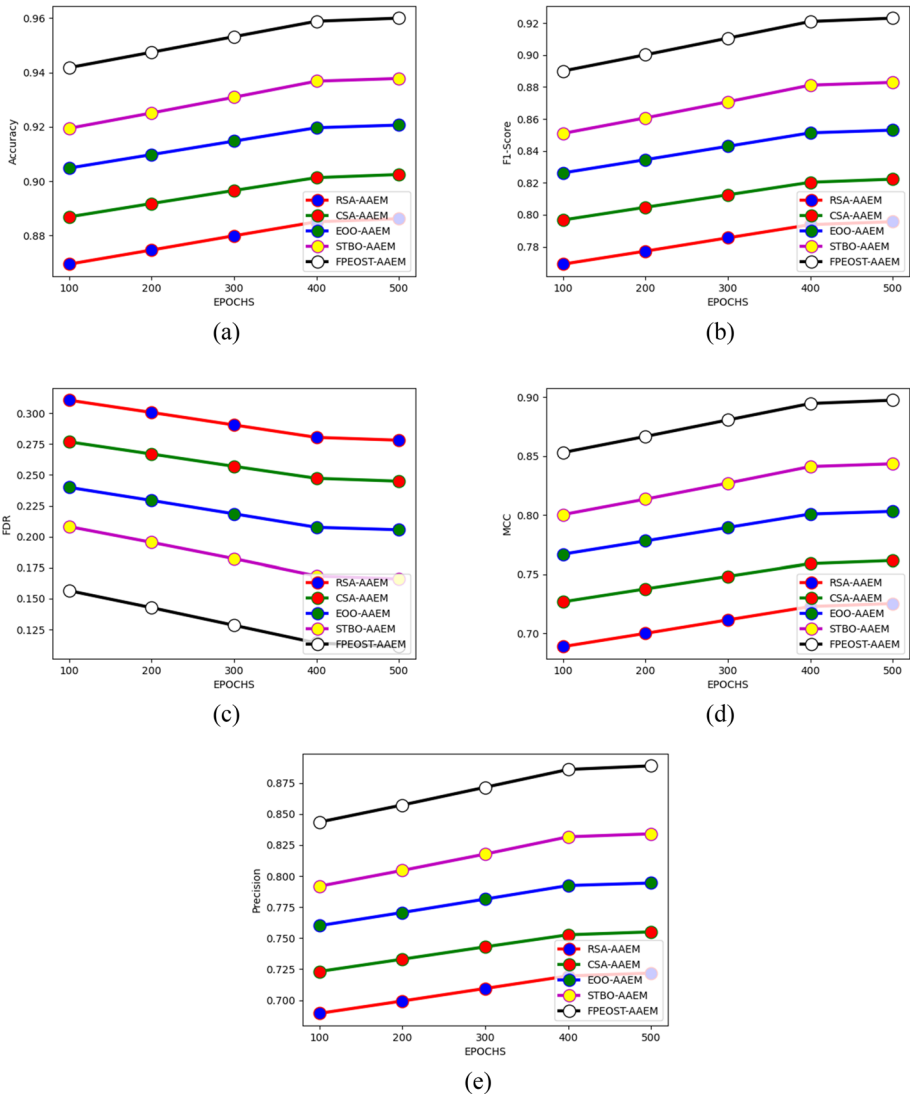
Fig. 13 Determination over epoch for the given prediction model when compared to diverse algorithms for dataset 1 concerning **a** accuracy, **b** F1-score, **c** FDR, **d** MCC, and **e** precision

7 Conclusion

Thus, an IoT-based COVID-19 disease prediction framework using attentive and adaptive-derived ensemble deep learning was implemented using Python in this work. IoT-related data was aggregated in the initial phase to perform the diagnosis model of COVID-19. Then, for attaining the deep features, the data is fed to the AE model. Further, the deep features were forwarded to AAEM, which includes three diverse standard approaches like DTCN, 1DCNN, and LSTM model for COVID prediction or monitoring. By utilizing the hybrid algorithm
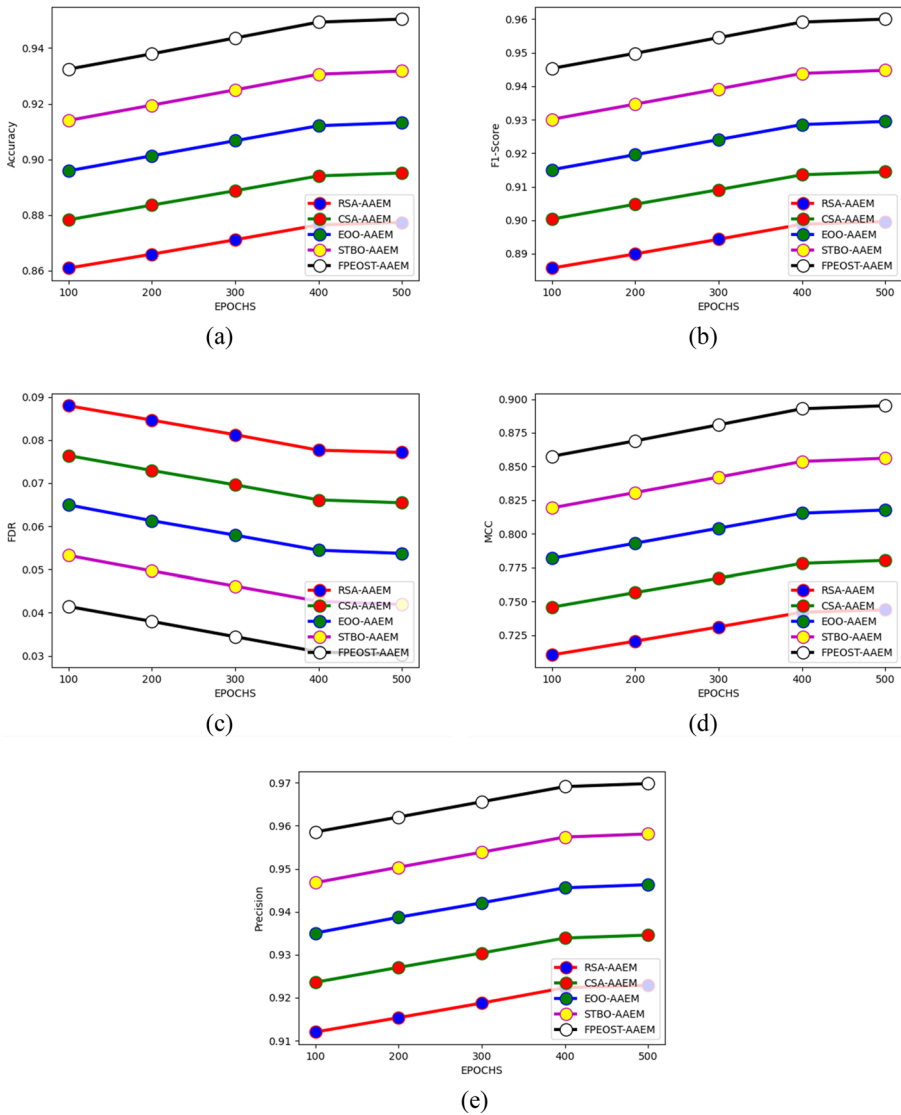
Fig. 14 Determination over epoch for the given prediction model when compared to diverse algorithms for dataset 2 concerning **a** accuracy, **b** F1-score, **c** FDR, **d** MCC, and **e** precision

termed FPEOST, the parameters in the ensemble AAEM model were tuned to further improve the process. Finally, the COVID-19 disease prediction outcomes are attained on the basis of the high-ranking process. The accuracy value for the given FPEOST-AAEM model provides 7, 5, 4, and 2% higher values when compared to various algorithms like RSA-AAEM, CSA-AAEM, EOO-AAEM, and STBO-AAEM models. Thus, the developed model achieved an effective prediction rate than conventional approaches over multiple experimental analyses.
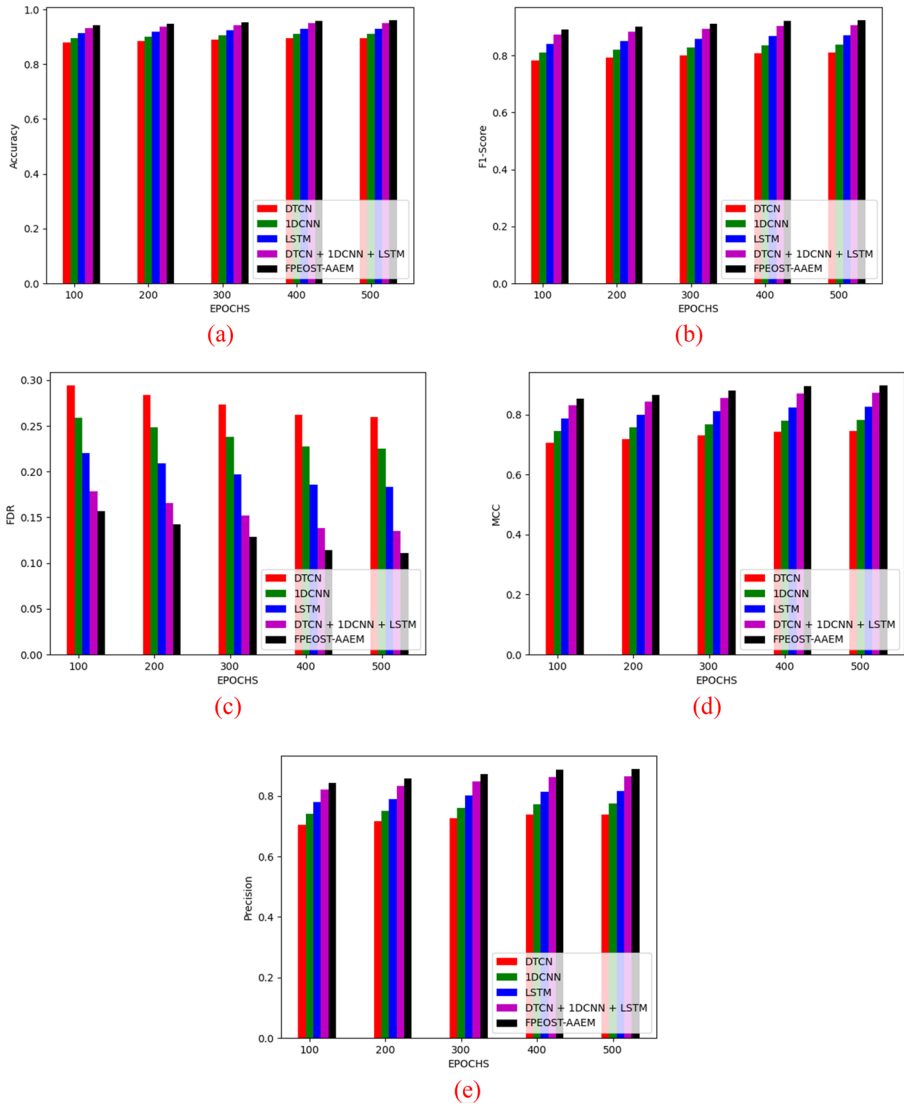
Fig. 15 Validation over with and without optimization of IoT-based COVID-19 disease prediction framework for dataset 1 concerning **a** accuracy, **b** F1-score, **c** FDR, **d** MCC, and **e** precision

7.1 Use of IoT data and deep learning techniques to predict and monitor COVID-19 cases

Here, IoT data and deep structured architectures are utilized to detect and observe COVID-19 cases in early diagnosis and quick recover from the disease. Early recognition and diagnosis help to reduce infections and it provides the way to better health care for those who affected the COVID-19 diseases. Imposing lockdowns, quarantining proven and isolating sick persons from others can help to reduce the count of COVID-19 infections. In this research work,
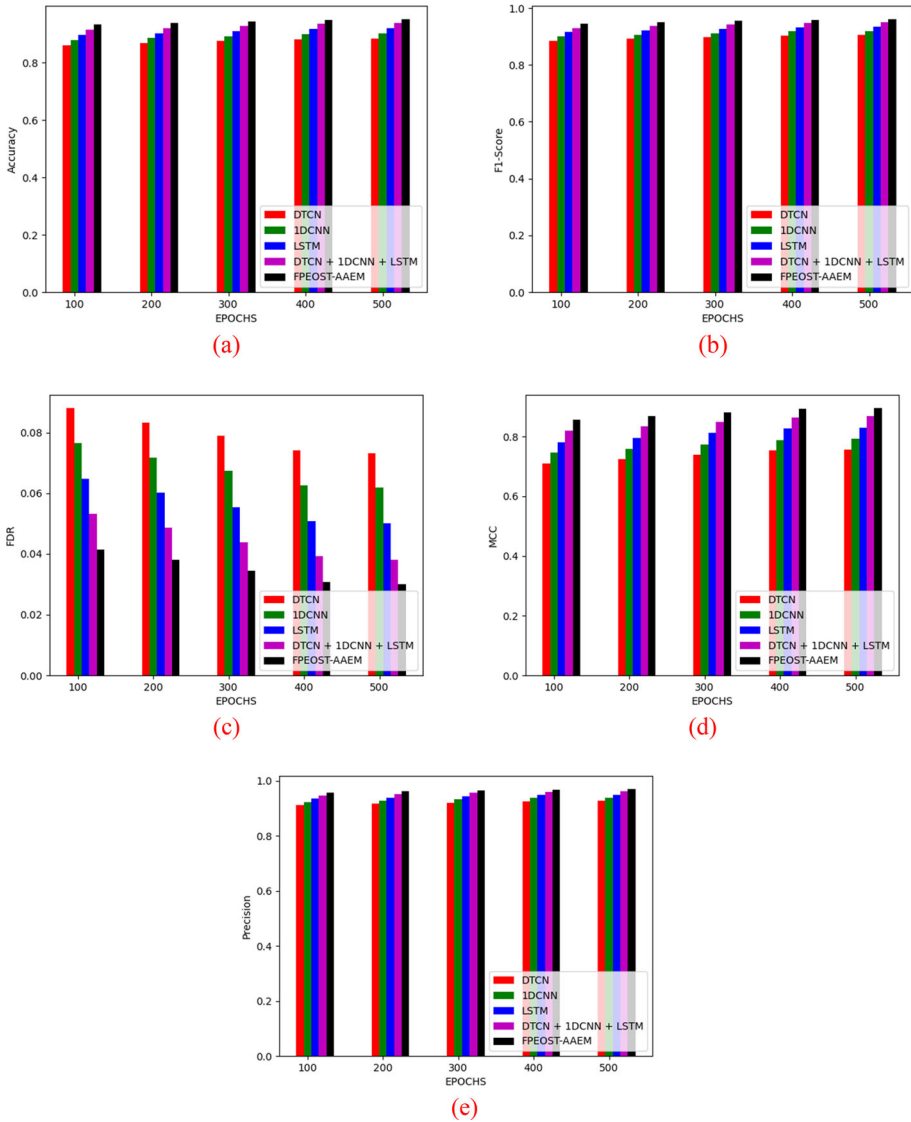
Fig. 16 Validation over with and without optimization of IoT-based COVID-19 disease prediction framework for dataset 2 concerning **a** accuracy, **b** F1-score, **c** FDR, **d** MCC, and **e** precision

IoT technology has been established to be a safe and effective means of dealing with the COVID-19 pandemic. Accordingly, observing and following up on after recovering COVID-19 patients will help to reduce infections from other people.

Table 2 Validating the prediction model using diverse algorithms for datasets 1 and 2

Measures	RSA-AAEM [32]	CSA-AAEM [33]	EOO-AAEM [27]	STBO-AAEM [28]	FPEOST-AAEM
Dataset 1					
Accuracy	8.861963	9.028583	9.194492	9.375576	9.587366
Sensitivity	8.8625	9.028883	9.19416	9.376263	9.587184
Specificity	8.861785	9.028483	9.194602	9.375347	9.587426
Precision	7.218697	7.559704	7.918932	8.334292	8.856599
FPR	1.138215	0.971517	0.805398	0.624653	0.412574
FNR	1.1375	0.971117	0.80584	0.623737	0.412816
NPV	9.589689	9.653872	9.71615	9.783046	9.858504
FDR	2.781303	2.440296	2.081068	1.665708	1.143401
F1-score	7.956585	8.229234	8.509033	8.824626	9.207422
MCC	7.25189	7.623806	8.003055	8.42851	8.941906
Dataset 2					
Accuracy	8.773268	8.951043	9.119434	9.307021	9.495067
Sensitivity	8.773096	8.951121	9.119337	9.307321	9.495215
Specificity	8.773557	8.950913	9.119596	9.306519	9.49482
Precision	9.229722	9.346075	9.455061	9.574133	9.692159
FPR	1.226443	1.049087	0.880404	0.693481	0.50518
FNR	1.226904	1.048879	0.880663	0.692679	0.504785
NPV	8.10212	8.359191	8.607634	8.891456	9.182278
FDR	0.770278	0.653925	0.544939	0.425867	0.307841
F1-score	8.995618	9.144335	9.284165	9.438842	9.592676
MCC	7.438472	7.80303	8.150337	8.539393	8.932049

Table 3 Validating the prediction model of COVID-19 using diverse classifiers in datasets 1 and 2

Measures	DTCN [29]	1DCNN [30]	LSTM [31]	DTCN + 1DCNN + LSTM [29–31]	FPEOST-AAEM
Dataset 1					
Accuracy	8.951807	9.098295	9.279356	9.489244	9.587366
Sensitivity	8.953188	9.098927	9.278346	9.489931	9.587184
Specificity	8.951347	9.098085	9.279693	9.489015	9.587426
Precision	7.39985	7.707903	8.110961	8.609298	8.856599
FPR	1.048653	0.901915	0.720307	0.510985	0.412574
FNR	1.046812	0.901073	0.721654	0.510069	0.412816
NPV	9.62481	9.680418	9.747326	9.823975	9.858504
FDR	2.60015	2.292097	1.889039	1.390702	1.143401
F1-score	8.102745	8.345851	8.655469	9.02819	9.207422
MCC	7.451622	7.782169	8.200703	8.701833	8.941906
Dataset 2					
Accuracy	8.829392	8.998345	9.177922	9.351339	9.495067
Sensitivity	8.829402	8.997892	9.17814	9.351504	9.495215
Specificity	8.829376	8.999105	9.177558	9.351062	9.49482
Precision	9.266553	9.377285	9.492212	9.602207	9.692159
FPR	1.170624	1.000895	0.822442	0.648938	0.50518
FNR	1.170598	1.002108	0.82186	0.648496	0.504785
NPV	8.182757	8.427931	8.695613	8.959235	9.182278
FDR	0.733447	0.622715	0.507788	0.397793	0.307841
F1-score	9.042697	9.183672	9.332534	9.475197	9.592676
MCC	7.553318	7.900524	8.271336	8.631715	8.932049

Table 4 Statistical analysis for the given prediction model in terms of algorithms for dataset 1 and 2

Measures	RSA-AAEM [32]	CSA-AAEM [33]	EOO-AAEM [27]	STBO-AAEM [28]	FPEOST-AAEM
Dataset 1					
BEST	5.091572	3.113076	3.684987	5.802518	3.209819
WORST	2.141853	1.734636	1.690759	1.810261	1.605088
MEAN	2.707656	2.055098	2.390861	2.166588	2.026138
MEDIAN	2.382252	2.088014	2.05881	1.826984	1.605088
STD	0.906353	0.302608	0.66509	0.811095	0.587939
Dataset 2					
BEST	3.138994	3.641106	1.727838	4.221672	5.361368
WORST	1.917359	1.905745	1.727838	1.643212	1.628312
MEAN	1.97206	2.052721	1.727838	2.03197	2.293043
MEDIAN	1.917359	1.905745	1.727838	1.643212	1.628312
STD	0.238304	0.469197	0	0.836148	1.238807

Table 5 Estimation of the designed IoT-based COVID-19 disease prediction approach for datasets 1 and 2

Terms	NAS [34]	GAN [35]	DL-MFM [36]	FPEOST-AAEM
Dataset 1				
Cohen-kappa-score	0.870757	0.892567	0.907869	0.947333
G-mean	0.934606	0.944936	0.952447	0.973452
Log-loss	0.064	0.054	0.046667	0.026
Dataset 2				
Cohen-kappa-score	0.868089	0.886672	0.904663	0.946989
G-mean	0.937741	0.946816	0.955441	0.97512
Log-loss	0.065	0.0555	0.0465	0.026

Declarations

Conflict of interest The authors declare no conflict of interest.

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