International Journal of Nanotechnology

ISSN online: 1741-8151 - ISSN print: 1475-7435
https://www.inderscience.com/ijnt

COVID-19 detection and tracking using smart applications with artificial intelligence

Geeitha Senthilkumar, Rajagopal Kumar, C. Nalini, V.R. Niveditha, Jothilakshmi Ramakrishnan

DOI: 10.1504/IJNT.2023.10056479

Article History:

Received:	31 August 2021
Last revised:	08 March 2022
Accepted:	15 March 2022
Published online:	31 May 2023

COVID-19 detection and tracking using smart applications with artificial intelligence

Geeitha Senthilkumar*

Department of Information Technology,
M. Kumarasamy College of Engineering,
Karur, Thalavapalayam, 639113, Tamil Nadu, India
Email: geeitha.s@gmail.com
*Corresponding author

Rajagopal Kumar

Department of Electronics and Instrumentation Engineering,
National Institute of Technology,
Chumkedima, Dimapur, Nagaland-797103, India
Email: rajagopal.kumar4@gmail.com

C. Nalini

Department of Information Technology,
Kongu Engineering College,
Perundurai, Erode-638 052, Tamil Nadu, India
Email: nalinikec@gmail.com

V.R. Niveditha

Department of Computer Science and Engineering,
Sathyabama Institute of Science and Technology,
Chennai, Tamil Nadu, India
Email: niveditha.cse@sathyabama.ac.in

Jothilakshmi Ramakrishnan

Department of Mathematics,
Mazharul Uloom College Ambur,
Ambur, 635802, Tamil Nadu, India
Affiliated to Thiruvalluvar University, Tamil Nadu, India
Email: jothilakshmiphd@gmail.com

Abstract: Corona Virus Disease 2019 (COVID-19), a newly identified pandemic infection, threatened human life, and disrupted the entire world. Identifying and detecting this pathogenic virus is made essential as it is increasing the mortality rate day by day. In this scenario, alternative technologies play a vital role in monitoring, detecting and diagnosing the disease by deploying smart applications. Today smart applications are incorporated with AI techniques in detecting and monitoring the spread of infection. The proposed work is contributed with multilayer perceptron (MLP) techniques integrating the artificial neural network (ANN) model for extracting COVID-19. The model is equipped with a normalisation process deploying Gaussian process regression (GPR) and radial based function (RBF) for detecting the noise level. The proposed work exploits the publicly available COVID-19 datasets of July month from GitHub and Kaggle. The AI model is measured using the performance metrics in terms of Precision, Recall, F-Measure and Accuracy and MLP model produces higher accuracy.

Keywords: COVID-19; smart applications; sensors; multilayer perceptron; multilayer perceptron; AI; artificial intelligence; detection.

Reference to this paper should be made as follows: Senthilkumar, G., Kumar, R., Nalini, C., Niveditha, V.R. and Ramakrishnan, J. (2023) 'COVID-19 detection and tracking using smart applications with artificial intelligence', *Int. J. Nanotechnol.*, Vol. 20, Nos. 1/2/3/4, pp.433–449.

Biographical notes: Geeitha Senthilkumar is an Assistant Professor, has completed Master of Engineering in Computer Science and Engineering in Anna University. Her research expertise covers medical data mining, machine learning, artificial intelligence, cloud computing, big data, fuzzy, soft computing and ontology. She has published 20 international journals and has presented 18 papers in national and international conferences in the above fields. She has got Senior Educator and Researcher award from National foundation for entrepreneurship development award. She is currently working as Assistant Professor, Information Technology Department in M. Kumarasamy College of Engineering, Karur, Thalavapalayam, Tamil Nadu.

Rajagopal Kumar received his BTech in Electronics and Communication Engineering from Madras University, Tamil Nadu, India in 1991 and MTech in Instrumentation Engineering, Anna university, Tamil Nadu, India in 1994. He received his PhD in Embedded Systems and Control Engineering from NIT, Trichy, 2007. He is currently working as a Professor in Electronics and Instrumentation Engineering and Dean Academic of NIT Nagaland, India. He has 80 publications in international journals and conferences. His areas of interests include MEMS, sensors and actuators, wireless sensor networks (WSN), Internet of Things and embedded systems design.

C. Nalini completed her Bachelor's and Master's degrees in computer science and engineering. She received her PhD in Data Mining from Anna University, Chennai. She has 30 years of expertise as a teacher. She is a Professor at Kongu Engineering College, Department of Information Technology. She has been recognised as a supervisor for Anna University PhD Program in Computer science and Engineering She has around twenty-five research papers that have been published in national and international publications and conferences. Her research interests include data mining, machine learning, database management, and optimisation strategies.

V.R. Niveditha has completed BE in Computer Science Engineering in PB college of Engineering, MTech Information Security and Cyber forensics and pursuing research in the domain of Mobile Security in the Department of Computer Science and Engineering of ABET accredited Dr. M.G.R. Educational and Research Institute, Deemed to be University with Graded

Autonomous Status, Chennai, India. She is presently working as an Assistant Professor, Department, Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, Tamil Nadu, India. She also published 25 papers in international referred journals, six papers in National conferences and applied for the funded proposal to government funding Agencies. She also published six books and four patents.

Jothilakshmi Ramakrishnan is obtained PhD from Thiruvalluvar University, Tamil Nadu, India in 2015. She is presently working as an Assistant Professor and Head, Department of Mathematics, Mazharul Uloom College, Ambur, Tamil Nadu, India. Her area of interest is Difference Equations, Digital Signal Processing, Artificial Intelligence and Internet of Things. She has published more than 30 research papers in the international journals.

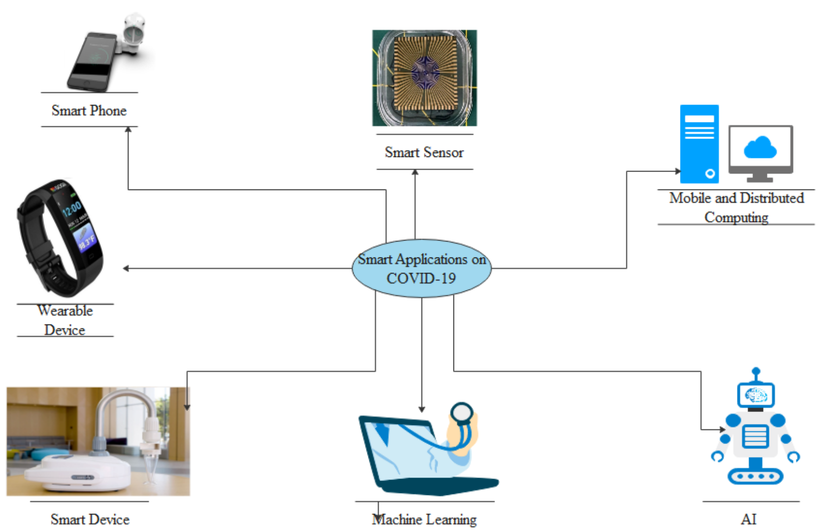
1 Introduction

Coronavirus is an infectious disease caused by a virus, called severe acute respiratory syndrome coronavirus2 (SARS-CoV-2). This novel virus is now universally called COVID-19 [1, 2]. National and State Governments have introduced various measures such as lockdown, social distancing, wearing personal protective equipment (PPE). However, still, the fallout of COVID-19 has created a significant impact on society disrupting the economy of the world, the supply of food and other raw materials [3] to reduce the transmission of disease. Many researchers and scientists putting up with vaccines and medicines, none has been approved until now in the world [4, 5]. The world meters have reported a total of 14,684,666 COVID-19 cases and 609,747 deaths as of 20th July 2020. In this potential crisis, it becomes essential to track, monitor and detect this infectious disease. Today smartphone technology has increased the footprints in mobile health and driven positive implications towards the patient-doctor relationship [6]. It is evolving 5G cellular network expansion which plays a significant role in healthcare systems. Pervasive computing is a benchmark in communication that includes information gathering and sharing [7]. These were undergoing technology when combined with smartphones, sensor devices, and wireless communication creating a pervasive environment [8, 9]. Modelling the pandemic virus infection is paramount in this scenario [10]. Besides conventional modelling [11] Artificial Intelligence (AI) could offer a significant contribution in predicting the models [12], classifying the X-ray images, specifying the infection stage of the patient whether the infection is mild or severe using image segmentation problem (ISP) [13]. Artificial neural networks (ANNs) an AI technique can easily extract the visual features that help in decision making and further treatment of the infected patients [14]. A novel ML model named adaptive neuro-fuzzy inference system (ANFIS) tracks the disease's progress based on historical data imputed from the cloud [15]. IoT devices are most probably imposed in detecting the spread of infection. An IoT-based biometric face detection technique is implemented in the places where lockdown has been announced during COVID-19 outbreaks. It is a three-phase technique designed under the edge computing architecture [16]. Though many smart devices are deployed in detecting COVID-19 cases, the existing systems are facing some challenges in medications and decision making which take a long duration in this pandemic crisis which can be overcome by AI techniques. The proposed study is organised into five sections. Section 2 describes a pervasive environment, including the applications of smartphones, technologies of smart devices, the contribution of AI and ML tools in COVID-19 detection and diagnosis. Section 3 presents the contribution of ML and AI in monitoring and detecting infectious disease and Section 4 discusses the results and experiments.

2 Smart applications

Today smart applications are embedded with a pervasive environment embedded with network devices that provide continuous and reliable connectivity. This system helps us by focusing on sensing data, supporting information technologies to provide better communication capabilities in both mobile and distributed computing [17]. AI provides an automatic monitoring and treatment of COVID –19 patients using the ANN technique [18]. The CAD4COVID-XRay tool was deployed to aid the tuberculosis diseases from chest X-Ray images relevant to pneumonia. [19]. A novel technique named COVID-MTNet and NABLA-3 network was used for detecting and localising the region of interest from two images especially from chest x-ray images [20]. The schematic diagram of smart applications is shown in Figure 1. The proposed work discusses the contribution of various sensors, smartphones and wearable devices in detecting COVID-19 diseases. The paper also provides insight into a pervasive environment by identifying, tracking and monitoring COVID-19 cases. AI models with machine learning techniques such as support vector machine (SVM), Random Forest (RF) and multilayer perceptron (MLP) have been incorporated in analysing COVID-19 cases.

Figure 1 Smart applications towards COVID-19 (see online version for colours)



2.1 Mobile-based Covid-19 tracking

A smartphone-based portable test has been launched to detect COVID-19. It identifies the viral and bacterial pathogens. It comprises a cartridge that contains testing reagents. Furthermore, a port is present where nasal extract or blood sample can be inserted. Then the whole device is clipped to the smartphone. RNA is accessed inside the cartridge. Genetic material is amplified into millions within 10–15 min, and with the help of blue LED light, the stains glow in green colour. The camera detects this on the smartphone.

Luminostics and Sanofi together combined to launch a mixture of hardware and software platforms with a smartphone to detect COVID-19. It is a home testing device and is used for global health applications. It comprises an adapter that is clipped onto the smartphone. A cartridge is loaded into the adapter and diagnosed with swab samples applied to the sensor.

A new Aranet PRO100 base station with a wireless battery has been designed to sense the body temperature. The sensors attached to every patient's bed send measurements to a centralised monitoring system for every minute wirelessly. The history of every patient can be viewed, and alerts are sent to the most severe cases that require immediate care. These communications are made available through a smartphone [21, 22]

A portable and reusable sensor embedded with smartphones has been developed by scientists from the University of Utah in the US. It detects coronavirus by taking saliva samples within 60 s. The sensor is about a quarter size that uses parameters containing single-strand DNA. This DNA strand attaches to the protein of the COVID-19 virus. It can be used by plugging the sensor into the mobile phone by launching an app relevant to the device [23]

2.2 Sensor-based Covid-19 tracking

Plasmonic biosensor with dual functioning with a combination of plasmonic photothermal (PPT) effect and localised surface plasmon resonance(LSPR) sensing transduction is designed for diagnosing COVID-19 disease. It comprises gold nan islands (AuNIs) embedded with DNA receptors that detect RNA samples with severe acute respiratory syndrome coronavirus2 (SARS-CoV-2) via nucleic acid hybridisation [24].

Portable Air Sampler, a monitoring device is used to trap the coronavirus tested through DNA analysis. This device traps the virus particles by sucking a huge amount of air, and then the virus is taken for diagnostic purposes. DejiAkinwande devised an electronic sensor at the University of Texas in Austin with his engineering team to detect both flu and COVID-19, and it has the capacity of differentiating between two viruses by testing the patient's saliva. This sensor is inbuilt with graphene circuits containing antibodies of COVID-19 infections which is linked to the biosensors that measure the sensitivity and specificity readings [25].

A new platform, namely the plasmonic fibre optic absorbance (P-FAB) sensor was developed to detect viruses. To realise the detection, Murugan et al. [26] proposed two types of bioanalytical approaches: Label-free bioassay and labelled bioassay. It is a U-bent-shaped sensor device used for the early detection and diagnosis of coronavirus. GOQii has launched a wrist band with sensors used to detect symptoms of COVID-19. This device tracks vital systems such as body temperature, heart rate, blood pressure. It comprises a temperature display and thermal sensor. A comparative analysis of various sensors is presented in Table 1.

Table 1 Applications and challenges of smart devices in detecting COVID-19 cases

References	*Device*	*Description*	*Applications*	*Challenges*
Kohli [27]	Smartphone-based portable test	It is made of a small cartridge with testing reagents	Used to test passengers before getting on a flight, people going to a theme park	Uncertainty regarding individuals quarantined
Luminostics [28]	Hardware/Software platform with smartphone	The Cartridge is loaded into the adapter and is clipped on a smartphone. Swab samples are prepared to place on the sensor	Used as home testing, point of care testing and global health applications	It takes 30 min to get the result
Wang [29]	An Optical Sensor for RNA samples	Integrate two types of effects to identify a virus: thermal effect and an optical effect	Used in detecting viruses with RNA sequences	The device is not ready to quantify the concentration of the coronavirus in the environment
GOQii [30]	Vital 3.0	Wrist band with sensors to detect the early symptom of COVID–19 infection	Used to track pulse, body temperature, blood pressure and sleep	Used only for screening purposes and not a medical device
Waltz [31]	Portable Air Sampler	A gooseneck-shaped instrument is used to trap any particles inside a liquid	The device can be used in office buildings, airplanes, etc.,	Fails to produce a beep to alert people nearby detecting viruses
Crotti [32]	Breathalyser	The device is designed to detect specific breath and examine metabolites even in asymptomatic patients	Used for monitoring gases in automotive exhaust	It is just an early-stage work
Brussels [33]	Ultrasensitive laser sensor	The detector works by looking at the binding of coronavirus molecules to the sensor surface	Used in Biological Laboratories, hospitals	It takes 30 min for diagnosis

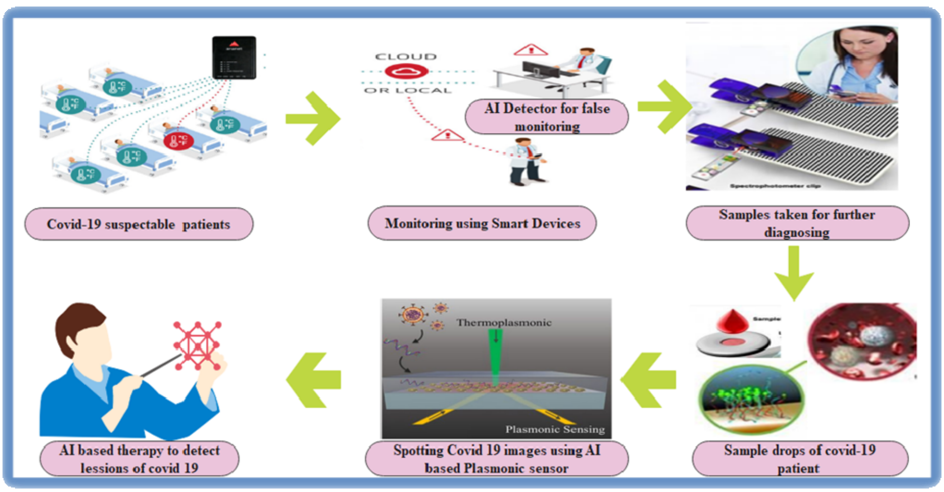
3 Proposed work

Smart applications comprise connected devices and systems communicating with other environments such as sensors with AI detectors to detect and monitor diseases. In the proposed work, applications of smart devices and their challenges in handling COVID-19 cases are furnished in Table 1. The work also implements the AI techniques in harnessing the COVID-19 dataset using SVM and MLP.

3.1 COVID-19 detection with AI

The AI-based approach is helpful for better tracking, monitoring and predicting COVID-19 cases [34]. This technology is well suited for alert messages, notifications, and suggestions about the spread of viral infection [35–37]. Figure 2 furnishes the contribution of AI towards COVID-19. The major applications of AI in this pandemic COVID-19 include: Early detection of disease, monitoring the patient's health, proximity and contact tracing, Identifying COVID-19 cases and their mortality, inventing new drugs and vaccines [38, 39].

Figure 2 AI-based COVID-19 diagnosis and treatment (see online version for colours)



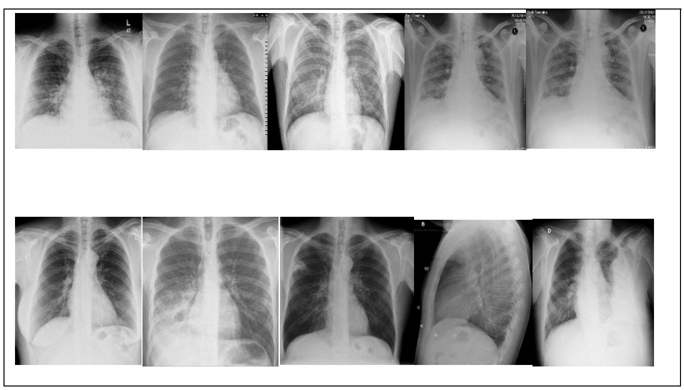
In the proposed study, the COVID-19 dataset belonging to the US country-region is explored with machine learning techniques to predict infected cases. The dataset contains 58 cases with different province states. The demographic features are described in Table 2.

It is compatible with diagnosing infections with medical imaging such as computed tomography (CT) and scanned parts of the human body with Magnetic resonance imaging (MRI). Figure 3 shows the CT images of 10 COVID-19 cases taken in July from the COVID-Chest Xray-Dataset. AI builds an intelligent platform for monitoring and predicting the spread of infection. AI- image acquisition method helps much in the automating scanning that reduces the contact of the patients and provides accurate delineation of infections by visualising the X-ray [40] and CT images that improves the clinical decision [41, 42]. The automated process is carried out by constructing a neural network that extracts the visual features of the infection. This extracted feature aids in further treatment of the infected cases [43, 44].

Table 2 Demographic features of COVID-19 of the US as of 10th July 2020

S. No.	*Demographic features*	*Description*
1	Province State	Number of Province States affected by COVID–19
2	Country Region	COVID–19 dataset belonging to the US in July 2020
3	Lat	The Latitude range of the Province State affected by infection
4	Long	The Longitude range of Province State affected by infection
5	Confirmed	Number of Confirmed cases as of 10th July 2020
6	Deaths	Number of Deaths occurred as of 10th July 2020
7	Recovered	Number of cases recovered from the disease
8	Active	The number of cases that remained active
9	Incident Rate	The incident rate of the Coronavirus cases
10	People Tested	Number of people who undergone a screening process
11	People Hospitalised	Number of people hospitalised due to infection
12	Mortality Rate	Mortality Rate of different Province States of US

Figure 3 Sample image data of COVID-19 Chest_Xray (July 2020)



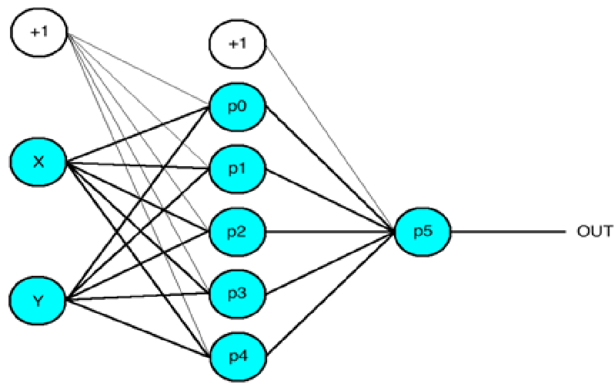
3.2 SVM technique

The SVM classifier is mainly designed for classification and regression purposes. It is one of the AI techniques that helps to detect outliers. It is well suited when the dimensions are more significant than the samples. It is mainly dependent on training small data [45]. The cost function ignores the sample of closed prediction. In the proposed method, SVM is used to detect corona patients with multi-class labels. SVM classifier is efficient for medical analysis, especially COVID-19 disease [46]. This technique combines with ANN by extracting 12 features and classifies corona patients into three categories, namely active, confirmed and recovered.

3.3 MLP technique

MLP is an ANN, well suited for nonlinear modelling via training algorithms based on a stochastic gradient or meta-heuristics [47]. This ANN model consists of three layers such as input, output, and hidden layers Figure 4 [48] There can be any number of hidden layers in MLP. The function of MLP can be denoted as $f(X)$: $X^m \rightarrow X^o$, where m represents input data and o represents the number of outputs in dimensions. For a set of 12features $X = x_1, x_2, \ldots, x_m$ and y are considered as a target. Here, the three target variable is taken such as active, recovered and confirmed.

Figure 4 Multi-layer perceptron with input layer, 2 hidden layers and output layer (see online version for colours)



The leftmost layer is the input layer consisting of n neurons $\{x_1, x_2, x_3, \ldots, x_n\}$. Every neuron present in the hidden layer transforms the values from the previous layer by computing the weights such as $w_1x_1, w_2x_2, \ldots, w_nx_n$. With a nonlinear activation function. The output layer present at the rightmost end receives values from the hidden layer and then transforms them into output values. The MLP classifier supports multi-class classification. In the proposed work, a dataset with multi-class labels is used with backpropagation. MLP is trained on two arrays *X* and *Y*. *X* consists of 58 samples and 12 features. These training samples are considered as floating-point feature vectors and array *Y* consists of 58 samples holding class labels as target values. The MLP classifier uses parameter alpha for the regularisation process and continuous monitoring maximum likelihood estimation (MLE) is deployed [49]. It helps in avoiding overfitting by adjusting weight values. The MLP Classifier performs as follows (Figure 5).

MLP Classifier

1 *Parameters*:

 i hidden layer size = No. of tuples(58); length: n_layers; *i*th element denotes the number of neurons in the hidden layer.

 ii Activation function: rectified linear unit function(relu) returns $f(X) = \max(0, X)$

 iii Solver: adam(Stochastic gradient-based(SGD) optimiser

 iv alpha: 0.001 to 1000; learning rate = constant

 v *X* is defined as the input variable, *Y* as output variable.

2 *Create model*: Initialise the activation function as sigmoid

i Sum of weights is computed as:

$$s_i = \sum_{i=1}^{n} w_{ij\,X_i} + \alpha_i \tag{1}$$

where X_i denotes the input variable, w_{ij} denotes weight amidst X_i and *j* neuron and α_i is the bias.

ii Activation function: Sigmoid function is implied:

$$f_i(X) = \frac{1}{1+e^{-s_i}} \tag{2}$$

where f_i denotes a sigmoid function for i and S_i denotes the sum of weights

iii *Computing output*: The output of neuron j is computed as:

$$y_i = \sum_{i=1}^{k} w_{ij\,f_i\ +\alpha_i} \tag{3}$$

where y_i denotes the output of neuron *j*, w_{ij} represents the weight between the output variable y_i and the neuron *j*, f_i is the activation function for neuron *j* and α_i is the bias term.

3 Fit the model: Epochs = 100, batch size = 12

4 *Model evaluation*:

i Predict with MLP classifier and return the estimates of the log of probability.

ii Return the mean accuracy score on the test data and class labels.

iii Adjust the parameters according to this estimator.

5 *Iteration*: Final computations for forward and backward are iterated until the criterion is met. Bias values adjust the momentum and learning rate parameters.

4 Results and discussion

In this proposed work, the COVID-19 dataset of US province States is taken for analysis. The dataset is analysed with 12 features with 3 class labels. As the growth of the epidemic diseases is increasing at an exponential rate, the research work undergoes analysis of active, confirmed and recovered cases for July. Figure 6 shows COVID-19 infection concerning Latitude and Longitude for 24 Provinces. Similarly, Figure 7 depicts three classes of COVID-19 cases: Confirmed, Active, Recovered per day.

Figure 5 MLP classifier working process (see online version for colours)

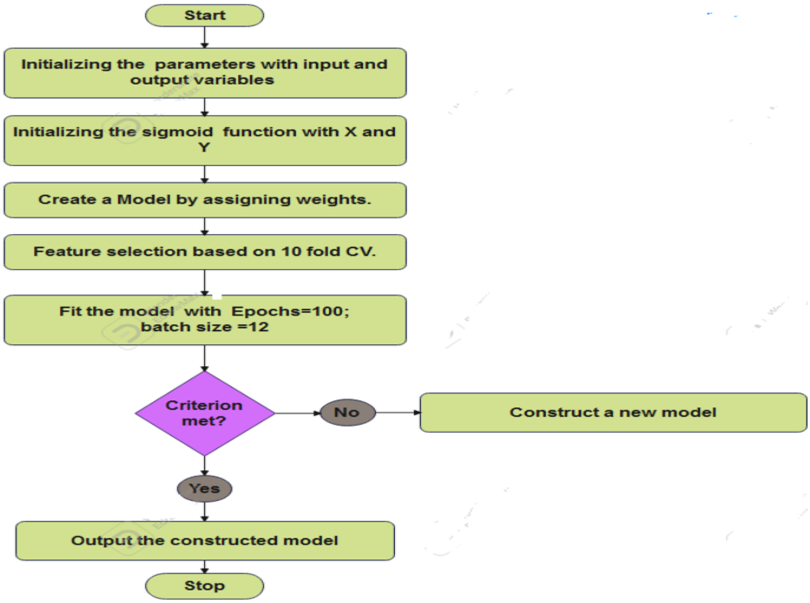


Figure 6 COVID-19 infection as of 10th July 2020 (see online version for colours)

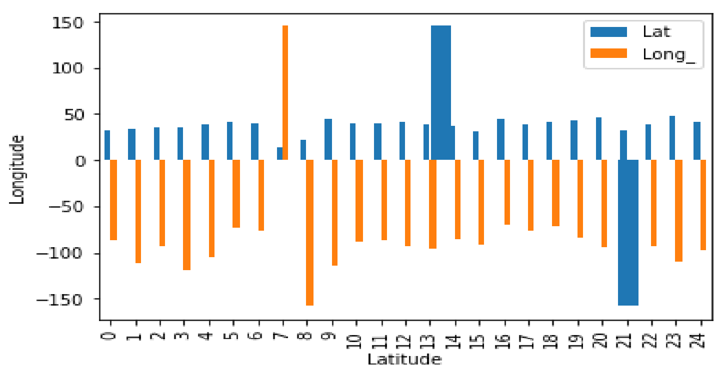
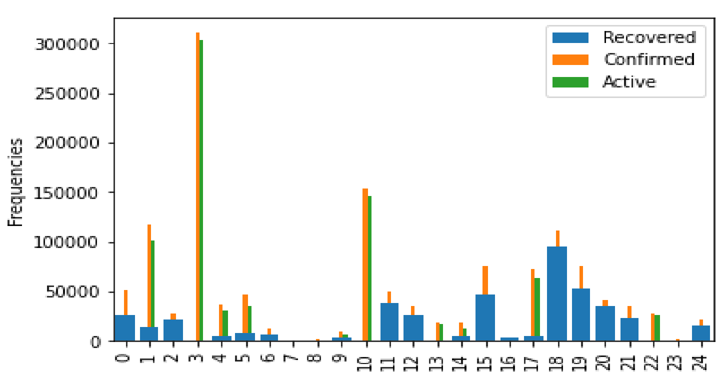
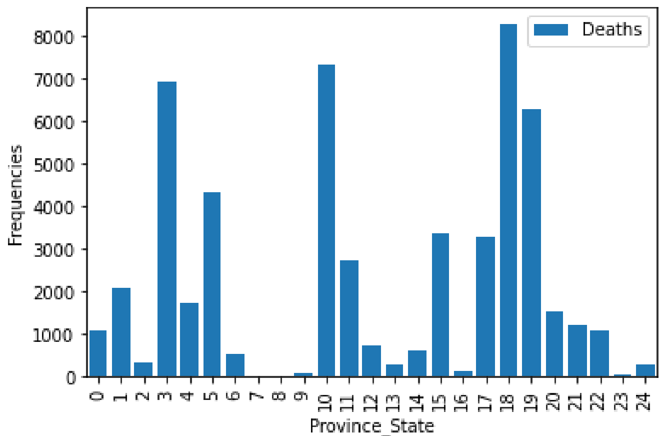


Figure 7 Classification of COVID-19 cases as of 10th July 2020 (see online version for colours)



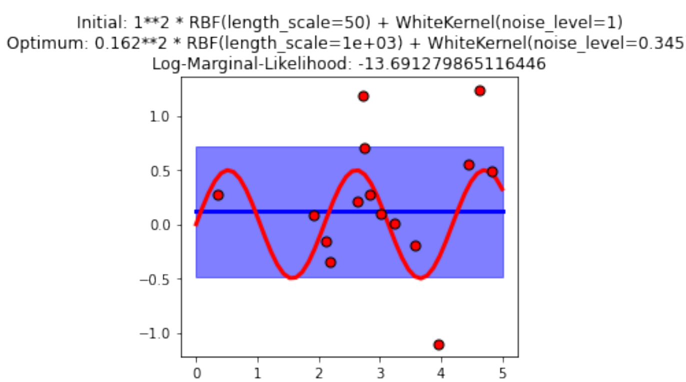
As the death rate of COVID-19 is spreading violently, the deaths of 24 province states are portrayed in Figure 8 showing the high peak rate in some states of the US. The dataset is downloaded from Kaggle. The analysis is carried out with 58 instances among which training is done with 58 states and testing with 24 states.

Figure 8 Death frequencies of COVID-19 as of 10th July 2020 (see online version for colours)



To remove the noise level of the data, supervised learning method, namely Gaussian process regression (GPR) is implemented as a preprocessing method. The initial mean value is assumed to be zero, and the covariance calculated is passed by the kernel object. Hyperparameters are optimised during this GPR process. Radial based function (RBF) is implemented for normalisation and by maximising log-marginal-likelihood (LML) with the help of local optimal shown in Figure 9. The parameter α specifies the noise level.

Figure 9 Noise level with LML in COVID-19 dataset (see online version for colours)



Support vector machine solves unbalanced problems as the dataset comprises three class labels. By assigning weight values to the samples, the unbalanced problem can be solved. Figure 10 depicts the decision boundary with and without weight values.

Figure 10 Non-weighted and weighted values of samples (see online version for colours)

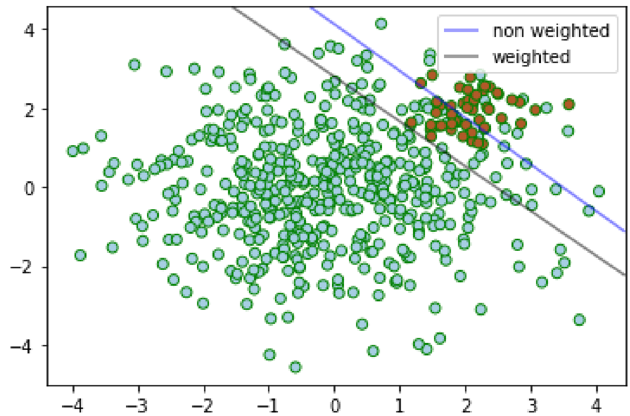
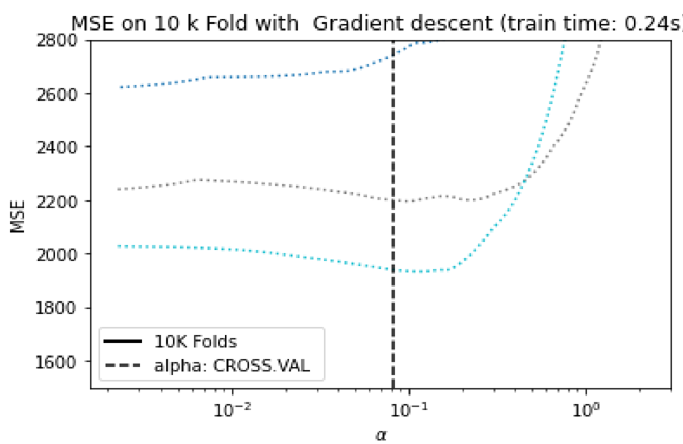


Figure 11 shows the mean square error (MSE) by setting the alpha parameter with a 10k fold cross-validation method. As the dataset contains some collinear features, cross-validation provides advantages for selecting relevant features. In the proposed work, MLP uses backpropagation without activation function in the output layer. It uses the MSE as a loss function. Figure 12 shows the usage of the alpha parameter for regularisation to avoid the overfitting problem by assigning weights with large magnitudes. It displays the mutable decision function with an alpha value of up to 1000 iterations

Figure 11 Gradient descent with 10k cross-validation (see online version for colours)



The classifiers are validated with the performance metrics in terms of precision, recall, F-measure and accuracy. MLP classifier produces higher accuracy when compared to SVM classifier. Figure 13 shows the comparison results of two classifiers in terms of performance measures producing a higher value of 64% for precision, recall, F-measure, and accuracy when compared to the SVM classifier.

Figure 12 Varying regularisation in MLP for COVID-19 dataset (see online version for colours)

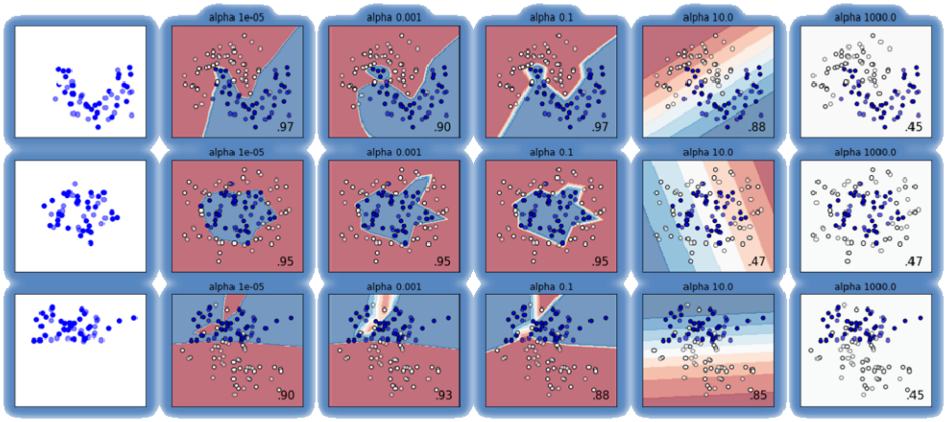
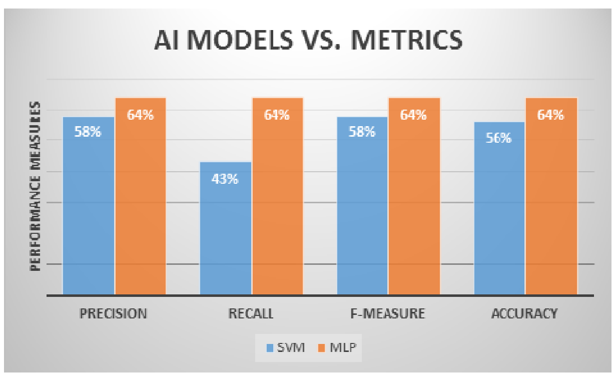


Figure 13 Performance measure of AI models (see online version for colours)



Nevertheless, many sensors and AI detectors are deployed in predicting the COVID-19 cases, sensors and AI detectors are not reachable in all environments. But clinicians make use of these AI detectors for the analysis and detection of diseases and help in clinical decisions within a short duration. And it has a high potential to diagnose CT scans when compared with other clinical entities. It is a contingent of various training data with performance metrics in classifying the chest CT in COVID –19 infection.

5 Conclusion

The proposed study discussed the various sensors and their applications in tracking, monitoring and detecting COVID-19 infection. In this paper, the applications of pervasive computing are presented in terms of sensors, smart devices, and smartphones in COVID-19 analyses. Based on the present situation, the research work has reviewed the importance of sensor-based tracking by deploying smart applications. The paper also discussed the existing techniques and compared them against the performance metrics in terms of Precision, Recall, F-Measure and Accuracy producing 64% for the proposed MLP when compared to the SVM model that produced 58%, 43%, 58% and 56% for respective performance measures. The noise level is reduced from 1 to 0.34 by optimising the SVM model using the RBF kernel. The study also furnishes some challenges of the sensors in real-time. Although some drawbacks prevail in sensor-based tracking of disease, it is prominent to realise the importance of smart devices in this pandemic situation. AI algorithms with ML-based techniques assist a lot in smart applications. In the future, this study helps in promoting sensor-based approaches with the AI model using deep learning concepts.

References

1 Liu, Y., Gayle, A.A., Wilder-Smith, A. and Rocklöv, J. (2020) 'The reproductive number of COVID-19 is higher compared to SARS coronavirus', *J. Travel Med.*, Vol. 27, No. 2, Computational and Mathematical Methods in Medicine 9.

2 Center for Disease Control and Prevention (2020) *Coronavirus Disease 2019 (COVID-19) – How It Spreads*, 4 March, https://www.cdc.gov/coronavirus/2019-ncov/prepare/transmission.html

3 World Health Organization (2020) *Coronavirus Disease (COVID-19) Advice for the Public*, https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public; 2020.

4 Velavan, T.P. and Meyer, C.G. (2020) 'The COVID-19 epidemic', *Trop. Med. Int. Health.*, Vol. 25, No. 3, pp.278–280.

5 Letko, M., Marzi, A. and Munster, V. (2020) 'Functional assessment of cell entry and receptor usage for SARS-CoV-2 and other lineage B beta coronaviruses', *Nat. Microbiol.*, Vol. 5, No. 4, pp.562–569.

6 Kumanan, W. (2018) 'Mobile cell phone technology puts the future of health care in our hands', *Can. Med. Assoc. J. Apr.*, Vol. 190, No. 13, E378e9.

7 Yu, C., Yao, D., Yang, L.T. and Jin, H. (2014) 'Energy conservation in progressive decentralized single-hop wireless sensor networks for the pervasive computing environment', *IEEE Syst. J.*, Vol. 11, pp.823–834.

8 Bansod, G., Pisharoty, N. and Patil, A. (2017) 'BORON: an ultra-lightweight and low power encryption design for pervasive computing', *Front. Inf. Technol. Electron. Eng.*, Vol. 18, pp.317–331.

9 Jayalakshmi, M. and Gomathi, V. (2018) 'Pervasive health monitoring through video-based activity information integrated with sensor-cloud oriented context-aware decision support system', *Multimed. Tools. Appl.*, https://doi.org/10.1007/s1104 2-018-6716-8

10 Vynnycky, E. and White, R. (2010) *An Introduction to Infectious Disease Modelling*, OUP Oxford.

11 Lawson, A.B. (2013) *Statistical Methods in Spatial Epidemiology*, John Wiley & Sons, Hoboken, New Jersey, USA.

12 Wong, Z.S., Zhou, J. and Zhang, Q (20) 'Artificial intelligence for infectious disease big data analytics', *Infect. Dis. Health*, Vol. 24, No. 1, pp.44–48.

13 Abdel-Basset, M., Chang, V. and Mohamed, R. (2020) 'HSMA_WOA: a hybrid novel slime mould algorithm with whale optimization algorithm for tackling the image segmentation problem of chest X-ray images', *Appl. Soft Comput.*, Vol. 95, p.106642.

14 Hussain, A.A., Bouachir, O., Al-Turjman, F. and Aloqaily, M. (2020) 'AI techniques for COVID-19', *IEEE Access*, Vol. 8, pp.128776–128795.

15 Kumar, R., Al-Turjman, F., Srinivas, L.N.B., Braveen, M. and Ramakrishnan, J. (2021) 'ANFIS for prediction of epidemic peak and infected cases for COVID-19 in India', *Neural. Comput. Appl.*, pp.1–14.

16 Kolhar, M., Al-Turjman, F., Alameen, A. and Abualhaj, M.M. (2020) 'A three layered decentralized ioT biometric architecture for city lockdown during COVID-19 outbreak', *IEEE Access*, Vol. 8, pp.163608–163617.

17 Gollagi, S.G., Math, M.M. and Daptardar, A.A. (2019) *A Survey on Pervasive Computing over Context-Aware System*, CCF Transactions on Pervasive Computing and Interaction.

18 Vaishya, R., Javaid, M., Khan, I.H. and Haleem, A. (2020) 'Artificial intelligence (AI) applications for COVID-19 pandemic', *Diabetes Metab. Syndr.*, Vol. 14, No. 4, pp.337–339, https://doi.org/10.1016/j.dsx.2020.04.012

19 Murphy, B.K., Smits, H., Knoops, A.J.G., Korst, M.B.J.M., Samson, T., Scholten, E.T. and Schalekamp, S., Schaefer-Prokop, C.M., Philipsen, R.H.H.M., Meijers, A., Melendez, J., van Ginneken, B., Rutten, M. (2020) 'COVID-19 on chest radiographs: a multireader evaluation of an artificial intelligence system', *Radiology*, Vol. 296, No. 3, E166–E172, https://doi.org/10.1148/radiol.2020201874

20 Alom, M.Z., Rahman, M.M.S., Nasrin, M.S., Taha, T.M. and Asari, V.K. (2020) 'COVID_MTNet: COVID-19 detection with multi-task deep learning approaches', *Preprints*, pp.1–11.

21 'Smart blog, aranet body temperature monitoring solution for hospitals, smart industry', *IoT Business Magazine*, April, https://iotbusinessnews.com/2020/04/10/20704-aranet-releases-a-large-scale-wireless-body-temperature-monitoring-solution-for-hospitals-battling-covid-19/

22 Garg, L., Chukwu, E., Nasser, N., Chakraborty, C. and Garg, G. (2020) 'Anonymity preserving ioT-based COVID-19 and other infectious disease contact tracing model', *IEEE Access*, Vol. 8, pp.159402–159414, doi: 10.1109/ACCESS.2020.3020513.

23 Basu, M. (2020) *ThePrint*, May, https://theprint.in/health/scientists-develop-sensor-that-can-help-smartphones-detect-coronavirus-in-60-seconds/417100/

24 Qiu, G., Gai, Z., Tao, Y., Schmitt, J., Kullak-Ublick, G.A. and Ang, J. (2020) 'Dual-functional plasmonic photothermal biosensors for highly accurate severe acute respiratory syndrome coronavirus 2 detection', *ACSNaNo*, Vol. 14, No. 5, pp.5268–5277.

25 Alan (2020) *Single Sensor to Detect COVID*-19, *FLU in Works*, Science and Enterprise, June.

26 Murugan, D., Bhatia, H., Sai, V.V.R. and Satija, J. (2020) *P-FAB: A Fiber-Optic Biosensor Device for Rapid Detection of COVID*-19, Transactions of the Indian National Academy of Engineering, Springer, June.

27 Kohli, K.K. (2020) *New Smartphone-Based Portable Test May Detect Covid 19 in 30 Minutes*, April, http://dx.doi.org/10.1039/D0LC00304B

28 Luminostics, https://luminostics.com/technology#phosphors

29 Wang, J. (2020) *AZO Sensors, New Optical Biosensor for Detecting Coronavirus*, Medical Sensor, Biosensor, April.

30 GOQii, https://indianexpress.com/article/technology/tech-news-technology/meet-the-worlds-first-smart-wrist-band-that-can-detect-body-temperature (18 July, 2020).

31 Waltz, E., https://spectrum.ieee.org/the-human-os/sensors/chemical-sensors/device – monitor-coronavirus-in-the-air

32 Crotti, N. (2020) *Ohio State Researchers Developing a Breathalyzer for COVID-19*, Medical Design and Outsourcing, July.

33 Brussels (2020) *Saliva Test Instantly Detects Coronavirus with Lasers*, https://www.photonics.com/Articles/Saliva_Test_Instantly_Detects_Coronavirus_with/a65721, April.

34 Shabbir, A., Shabbir, M., Javed, A.R., Rizwan, M., Iwendi, C. and Chakraborty, C. (2022) 'Exploratory data analysis, classification, comparative analysis, case severity detection, and internet of things in COVID-19 telemonitoring for smart hospitals', *J. Exp. Theor. Artif. Intell.*, pp.1–28.

35 Haleem, A. and Vaishya, J.M. (2020) 'Effects of COVID 19 pandemic in daily life', *Curr. Med. Res Pract.*, https://doi.org/10.1016/j.cmrp.2020.03.011

36 Bai, H.X., Hsieh, B., Xiong, Z., Halsey, K., Choi, J.W., Tran, T.M.L., Pan, I., Shi, L.B., Wang, D.C., Mei, J., Jiang, X.L., Zeng, Q.H., Egglin, T.K., Hu, P.F., Agarwal, S., Xie, F.F., Li, S., Healey, T., Atalay, M.K. and Liao, W.H. (2020) 'Performance of radiologists in differentiating COVID-19 from non-COVID-19 viral pneumonia at chest CT', *Radiology*, Vol. 296, No. 2, August, pp.E46–E54.

37 Hu, Z., Ge, Q., Jin, L. and Xiong, M. (2020) *Artificial Intelligence Forecasting of COVID-19 in China*, 17 February, arXiv preprint, arXiv: 2002.07112.

38 Viashya, R., Javid, M., Khan, I.H. and Haleem, A. (2020) 'Artificial intelligence (AI) applications for COVID-10 pandemic', *Diabetes Metab. Syndr.: Clin. Res. Rev.*, Elsevier, Vol. 14, pp.337–339.

39 Chadaga, K., Chakraborty, C., Prabhu, S., Umakanth, S., Bhat, V. and Sampathila, N. (2022) 'Clinical and laboratory approach to diagnose COVID-19 using machine learning', *Interdiscip Sci.*, February, doi: 10.1007/s12539-021-00499-4.PMID: 35133633; PMCID: PMC8846962.

40 Bhuyan, H.K., Chakraborty, C., Shelke, Y. and Pani, S.K. (2021) 'COVID-19 diagnosis system by deep learning approaches', *Expert Syst.*, e12776, Advance Online Publication, https://doi.org/10.1111/exsy.12776

41 Shi, F., Wang, J., Shi, J., Wu, Z., Wang, Q., Tang, Z., He, K., Shi, Y. and Shen, D. (2021) 'Review of artificial intelligence techniques in imaging data acquisition, segmentation, and diagnosis for COVID-19', *IEEE Rev Biomed Eng.*, Vol. 14, pp.4–15, doi: 10.1109/ RBME.2020.2987975. Epub 2021 Jan 22. PMID: 32305937.

42 Amin, J., Sharif, M., Gul, N., Kadry, S. and Chakraborty, C. (2022) 'Quantum machine learning architecture for COVID-19 classification based on synthetic data generation using conditional adversarial neural network', *Cognit Comput.*, Vol. 14, No. 5, pp.1677–1688, doi: 10.1007/s12559-021-09926-6. Epub 2021 Aug 10. PMID: 34394762; PMCID: PMC8353617.

43 Biswas, K. and Sen, P. (2020) *Space-Time Dependence of Coronavirus (COVID-19) Outbreak*, arXiv preprint arXiv: 2003.03149, 6 March.

44 Stebbing, J., Phelan, A., Griffin, I., Tucker, C., Oechsle, O., Smith, D. and Richardson, P. (2020) 'Covid-19: combining antiviral and anti-inflammatory treatments', *Lancet Infect. Dis.*, 7 February.

45 Sethy, P.K., Behera, S.K., Ratha, P.K. and Biswas, P. (2020) 'Detection of coronavirus disease (COVID-19) based on deep features and support vector machine', *Int. J. Math. Eng. Manag. Sci.*, Vol. 5, No. 4, pp.643–651.

46 Ravi, V., Narasimhan, H., Chakraborty, C. and Pham, T.D. (2021) 'Deep learning-based meta-classifier approach for COVID-19 classification using CT scan and chest X-ray images', *Multimed. Syst.*, 6 July, pp.1–15, doi: 10.1007/s00530-021-00826-1.Epub ahead of print, PMID: 34248292; PMCID: PMC8258271.

47 Almeida, J.S. (2002) 'Predictive nonlinear modeling of complex data by artificial neural networks', *Curr. Opin. Biotechnol.*, Vol. 13, No. 1, pp.72–76.

48 Car, Z., Segota, S.B., Andelic, N., Lorencin, I., Mrzljak, V., Modeling the Spread of COVID-19 infection using a multilayer perceptron', *Comput Math Methods Med.*, Vol. 2020, Article ID: 5714714, p.10.

49 Nandagopal, V., Geeitha, S., Kumar, K.V. and Anbarasi, J. (2019) 'Feasible analysis of gene expression–a computational based classification for breast cancer', *Measurement*, Vol. 140, pp.120–125.