Chapter 7
Social Economic Impacts for Covid-19 Pandemics Using Machine Learning Based Optimization Algorithm

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Abstract As the number of COVID-19 patients grows exponentially, not all cases are likely dealt with by doctors and medical professionals. Researchers will add to the fight against COVID-19 by developing smarter strategies to achieve accelerated control of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), virus that causes disease. Proposed method suggests best ways to optimize protection and avoid COVID-19 spread. Big benefit of the hybrid algorithm is that COVID-19 is diagnosed and treated more rapidly. Pandemic diseases possibilities are handling with help of Computational Intelligence, using cases and applications from current COVID-19 pandemic. This work discusses data that can be analyzed based on optimization algorithm which provides betterCOVID-19 detection and diagnosis. This algorithm uses a machine learning model to decide how the hazard function changes concerning characteristics of potential methods to find parameters in optimization of machine learning model, which has in many cases been shown to be accurate for actual clinical datasets.

Keywords Computational intelligence · Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) · COVID-19 · Optimization algorithm · Clinical datasets

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7.1 Social Impacts on COVID-19

Since December 2019, Wuhan has been expanding across the whole world with the new corona-virus (SARS-CoV-2). By 18 April worldwide more than 2 million confirmed cases and 150,000 deaths had been reported. (https://www.worldometers.info/coronavirus/). As cure or vaccination of a novel COVID-19 disease is not available, early detection must offer an incentive for suspected individuals to be isolated at once and to decrease risk that healthier population will get infected [1].

WHO has declared a coronavirus disease and it is currently expanding [2]. There are 3,581,884 confirmed cases, contributing to 248,558 deaths, were registered as of 4 May 2020 [3]. Biggest discrepancy between CoV-2 pandemic and associated viruses, such as SARS and MERS, is CoV-2's ability to expand easily through human interaction and leave about 20%, infected individuals, without symptoms [4].

Also, some studies have shown that CoV-2 disease is more severe for people with a poor immune system [5, 6]. This CoV-2 activity involves creation of a rigorous mathematical basis for controlling distribution and automation of complex decision-making tracking instruments.

It is necessary to develop, administer, evaluate and combine innovative strategies with cline trials and, in particular, the development of pharmaceutical evidence, genome and public health knowledge on an increasing network of people and the movements of the infected individuals.

By using these data, researchers determine how and where disease is likely to spread and alert certain areas of disease to fit arrangements needed by ML and AI. History of travel by infected individuals may be automatically monitored to examine epidemiological associations with disease transmission.

In other words, some influences on group transmission were studied. Effective and cost-effective technology to store and interpret such enormous data for further analysis needs to be built. Usage of cloud computing and AI solutions needs to be organized [7]. Alibaba has produced solutions for cloud and AI that support China, battle coronavirus, forecast outbreak peak, scale, and length and are reportedly carried out in real-world experiments in different regions of Chinese with 98% accuracy [8]. Currently, various institutes for public and personal care produce monumental amounts of data which are difficult to handle. For analysis and decoding the helpful information from these data, there is also a need for powerful machine-controlled data processing tools. This information is extremely helpful for health professionals who know why disease occurs and who can treat patients more efficiently and at higher cost. Data processing provides a new info on care that is successively beneficial as a medical call, such as medical appointments, insurance policy calls, treatment option, prognosis of health, etc., for creation of bodies.

Several primary-known research focus on various issues and data processing concerns in care. For each analysis and prediction of different diseases, data processing is also used. Some analytical study was designed to improve accessible data processing methods in the nursing sector in order to increase results and several studies have been developed into new treatment methods and frameworks.

Furthermore, it has been observed that a variety of data processing techniques, such as classification area units used by health services, increase their capacity to generate patient health calls. ML-based CT-Image Analytics Solution can be used to overcome various forms of pneumonia that can be useful in tracking COVID-19 patients [9]. In [10] Details are shown. Vaccine production is improved by use of multiple ML and AI methods, by studying gene sequences and molecular docking [11]. ML [12] is used to process vast quantities of data and smartly forecast disease transmission. It has proven potential to learn local dependencies between pixels implicitly. However, the pixel-specific loss function of these methods still limits the learning of multi-scale spatial limitations in an end-to-end training process, which lacks the capability to enhance. Compared to patching, labeling or class imbalance is a problem for CNNs trained on whole pictures. While patching methods can test a balanced amount of patches per class, pixels from various classes are frequently uneven in whole-image training methods. The spread of COVID-19 continues to seriously and significantly influence the global economy in the context of public health. Labor dislocation, collapse of companies and stock crashes are just some of the consequences of this global pandemic lockdown. The influence of COVID-19 will result in a global economic downturn in the year 2020, as well as a decrease in economic growth to 3% according to the International Monetary Fund (IMF). Rest of the chapter discussed in Sect. 7.2 is related works, system models in Sect. 7.3, results and discussion in Sect. 7.4 and conclusion in Sect. 7.5.

7.2 State of Art Methods

Tuli et al. (2020) enhanced statistical model applies to analyze and forecast epidemic's expansion [13]. Probable hazard of COVID-19 in countries around world has been forecast by using an improved ML model. This research has revealed that iterative weighting can be enhanced for creation of a predictive method for Generalized Inverse Weibull distribution. Framework was used on a cloud computing network to forecast growth behavior of disease more reliably and in real time. A more reliably data-driven methodology would be incredibly useful for government and people to proactively respond.

Dandekar et al. [14] global COVID-20 diagnostic model has been developed by introducing a neural network module to classical SIR epidemiological model. Trend breaks down the contribution to infection time series to examine as well as compare role of quarantine management policies in control of dissemination of the virus in heavily affected regions in Europe, North America, South America and Asia. Our findings for all continents are usually closely correlated between strengthening of quarantine controls learned from model and steps taken by respective governments of regions.

Abbasimehr and Paki [15] Three hybrid approaches are proposed to predict COVID-19 time series methods on integration of 3 deep learning models with Bayesian optimization algorithm, such as multi-head focus, LSTM and CNN. Both models are designed based on technique of multiple performance forecasting, which enables multiple time points to be expected. For each model, Bayesian optimization approach automatically chooses best hyper parameters and increases efficiency of forecasting. We also performed studies and tested suggested models against baseline model with publicly accessible disease data obtained from Johns Hopkins University's Coronavirus Resource Center.

Findings reveal that deep learning models are superior to benchmark models for short and long term predictions. In fact, for short-term predictions mean SMAPE of best deep learning model is 0.25 (10 days ahead). Best deep learning model even gets an average SMAPE of 2.59 for long-term forecasts?

Lu et al. [16] with data analysis, simulation, and optimization a hybrid prediction framework is proposed. To ensure precision and stability, multi-target optimizer is used as a prediction model, SVM. Data show, for example, that hybrid models proposed are superior to bottom-line models in both forecast accuracy and reliability, taking daily energy demand of US. Also, selection of input specifications is addressed, and findings indicate that method taking into account regular infections is most predictable and stable, and that it has a high potential in real-world applications.

Waheed et al. [17] A framework for producing synthetic CXR images is proposed by introducing a model called CovidGAN based on ACGAN (Auxiliary Classifier Generative Adversarial Network). Furthermore, we show that for COVID-19 detection, CNN efficiency can be improved with synthetic images produced by CovidGAN. Classification alone with CNN gave a precision of 85%. Accuracy increased to 95% by inserting synthetic images produced by CovidGAN. We hope that this approach will accelerate identification of COVID-19 and lead to stronger radiological systems.

Han et al. [18] document our initiative to make COVID-19 screening with low labels highly reliable and interpretable. We suggest AD3D-MIL, in which a 3D chest CT is classified as a bag of instances. After potential contamination areas, AD3D-MIL wills semanticipate generation of deep 3D instances. To gain insight into contribution of individual instances to a bag mark, AD 3D-MIL further extends a centered pooling approach to 3D instances. Finally, AD3D-MIL discovers Bernoulli's bag-level label distributions for easier learning. 460 examples of CT have been collected, 230 examples of CT from 79 COVID-19 patients, 100 examples of CT in 100 typical pneumonia patients and 130 examples of CT in 130 pneumonia-free patients. A variety of observational tests indicate that precision of our algorithm amounts to 97.9%, 99.0%, and 95.7%, respectively. These benefits make our algorithm an important support method for COVID-19 screening.

Ouyang et al. [19] offers a new 3D CNN to focus areas of lung infection while taking diagnostic decisions. We then establish a double-sample approach to minimize imbalance. Largest multi centre CT data forCOVID-19 from 8 hospitals was analyzed in our system (to our greatest knowledge). We receives 2186 CTs for five-fold cross-validation in training-validation stage from 1588 patients. We use a further separate large-scale research range of 2796 CT scans in 2057 patients during testing stage. This method classify COVID-19 image with an area of 0.944 AUC, 87.5% precision, 86.9% sensitivity and 90.1% specificity and 82.0% F1-score. This output enables a radiologist withCOVID-19 diagnosis from CAP to likely benefit from this algorithm, especially at early stage of COVID-19.

Roy et al. [20] new completely annotated LUS dataset photos collected from numerous Italian hospitals are given, with labels indicating degree of severity of disease in graphic, video and pixel phases (segmentation masks). In specific, we are introducing a novel deep network from Spatial transformer networks concurrently anticipating magnitude of disease associated with an input structure and supplying pathological objects for weakly supervised localization. Also, we implement a new approach based on unanimous for efficient video-level frame score aggregation. Tests carried through on proposed dataset show successful findings on all tasks under review, opening way for potential DL studies on LUS data for COVID-19 aided diagnosis.

Yousri et al. [21] alternative method which extracted information from X-ray images leverages a new method of selection of features to create corresponding features. An improved cuckoo search optimization (CS) algorithm (free order) and four heavy doll distributions are thus proposed in place of Lévy flight, which will improve efficiency of algorithm throughout phase of COVID-19 classification optimization. Three grades, called daily patients, COVID-19, and pneumonia, are included in a classification process. Suggested FO-CS variants were validated in first sequence of experiments with eighteen UCI data sets. Two data-sets for COVID-19 X-ray images were considered for second series of experiments. Compared to good optimization algorithms, proposed solution results were compared. Results test supremacy of proposed method to provide precise results for UCI and COVID-19 data sets.

Khan et al. [22] benefits of hyperparameter optimization for a Gaussian process regression contains number of reported cases and deaths for 21, March 2020 to 10, 2020, were studied. Polynomial Regression is often contrasted. Gaussian Loop Regression model demonstrates better efficiency.

Kavadi et al. [23] propose a framework for the global COVID-19 pandemic prediction of PDR-NML. For statistical analysis of best parameters in data collection, we have employed progressive partial derivatives linear regression method. Next paradigm for standardized forecasts was nonlinear. Results indicate that in Indian community, suggested ML approach has outperformed state-of-the-art approaches and can also be a handy instrument for other nations to make predictions.

Jayakumar et al. [24] The COVID-19-pandemic unearthed seven lessons, the courses include corporate elements, education, on-line presence, network communication, cyber security, healthcare and the significance of life. The reaction to the unknown outbreak is more closely examined by this investigation. If a possible pandemic occurs in the future, it aims to offer the right approach.

Khalil et al. [25] the good education system has been stated to develop good people. In the course of growth, the nations that compromised their education live far behind. The combination of traditional education and e-learning is quite successful and many industrialized civilizations benefit. In recent years, COVID-19's rapid growth has put a stop to the traditional system of education.

Brohi et al. [26] Five advanced technologies have been shown, with extraordinary applications, capable of mitigating and eliminating COVID-19 difficulties. The technologies included Artificial Intelligence, 3d Printing, Big Data Analytics, HPC, TT. This research studies the application of COVID 19 technologies to promote future research and to build COVID 19 solutions with AI, 3DT, BDA, HPC, and TT. This research is based on research projects throughout the world.

Ozturk et al. [27], For the automatic detection of COVID-19 in X-ray pictures, DNN has been developed. In order to implement the classification model, the developed approach was called Dark CovidNet. A real-time object detection system was included in the created categorization model. The designed model featured a 17-compact layer number and had a 98.08% accuracy and an 87.02% multi-class value.

Beers et al. [28] A PGGAN was trained to synthesize medical images of fundus images that suggest premature vascular ROP and multimodal MRI images of the glioma. Progressive development of GANs involves the training of the image generator to initially generate synthetic images in low resolution (8 × 8 pixels), which are then fed into a discriminator which differentiates these synthetic images from the real down-sampled images. Additional convolutionary layers are then used to produce images that double the resolution before the goal resolution is reached. We show in this work that the medical images can be realistic in two independent fields; fundus photographs that indicate vascular pathology linked to premature retinopathy and gliome magnet resonance imaging in multimodal form. We also show that finely known pathological elements, such as retinal arteries and tumour heterogeneity, can be retained or strengthened using segmentation maps.

Xue et al. [29] Suggest two GAN networks, a Segmentor and a Critical network, which explored the link between a binary brain tumour map and MRI brain images. The critic has a multi-scale loss role to maximise whilst the segmentor is trained by the critic using just gradients, in order to minimize multi-scale loss function. We have demonstrated that a SegAN framework for the segmentation problem is more effective and stable and results in superior performance than the most advanced U-net segmentation process.

Schlegl et al. [30] The GAN study used patches in the retinal region for data distribution for healthy tissue. In the retinal pictures, GAN was then evaluated for anomaly on both unseen and healthy imaging patches.

Gozes et al. [31] Construction of a comprehensive COVID-19 illness diagnosis system involving pulmonary segregation, COVID-19 detection in CT images and the predefined COVID-19 threshold In the training phases as well as the test phases several data sets were involved, with the pre-trained ResNet50 network detection involving COVID-19. Ninety Eight percent, 94%, and 0, 9940 were the corresponding specifications, sensitivities, and the AUC values.

Lin et al. [32] Combined CRF and CNNs for the better exploitation of spatial links among pixels Conditional Random Fields Combined Deep CNNs were also employed with promising results in the field of segmentation of medical pictures. Ronneberger et al. [33] included an FCN, U-net in electron microscopic stacks for segmentation of neural structures. In certain ways geographical context information

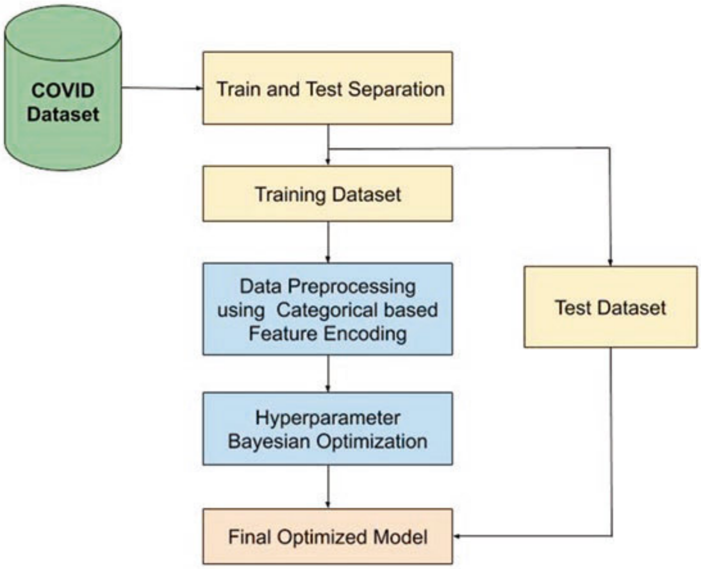

Fig. 7.1 Proposed Architecture

may be captured by using patches and multistage inputs. However, the computer costs for patch training are very costly and the location accuracy is in agreement.

7.3 System Model

Framework Model optimizes model for a precise forecast of COVID-19 cases, of increasing and decreasing numbers of cases in near future, and of date on which pandemic can be expected to end in different countries. Figure 7.1 represents proposed architecture.

7.3.1 Preprocessing Dataset

In terms of 80% and 20%, dataset is separated into train and test datasets. For model testing and optimization, we use train dataset. In categorical feature encoding stage, categorical dependent feature encoding technique can handle missing values, as seen in Fig. 7.1. Then dataset number variable can be translated into diagnostic target variable that has two categories: involvement and lack of cardiac disease.

7.3.2 Hyper-Parameter Bayesian Optimization (HBO)

After preprocessing of test and train dataset, binary classification using Bayesian optimization target variable is utilized. Bayesian Optimization is utilized to tune hyper parameters. Hyper-parameter optimization is to determine right hyper-parameters for a given method that provides best results when evaluated on a validation range. In form of equation, hyper-parameter optimization is given as:

$$x^* = \arg\min_{x \in X} f(x) \tag{7.1}$$

In this f(x), target score that is evaluated in validation score is to be minimized; x* is a set of hyper parameters that generate lowest score and any value in X field can be taken by x. Problem with optimizing hyper parameters is that testing objective role to find answer is incredibly expensive. We must train a model on training data, forecast validation data and, while trying various parameters, calculate the validation metrics. This process cannot be done manually, with a large number of hyper-parameters and models like assemblies or DNN which take days to practice.

For a great number of hyper-parameters, manual search is intractable. Even these strategies are inefficient because, when choosing next hyper-parameters to evaluate, they do not take previous assessments into account. They waste a large amount of time testing wrong set of hyper-parameters many times. On other hand, Bayesian optimization considers prior tests before determining next test hyper parameter set. It encourages itself to focus on those areas of search space that it believes would offer most promising validity scores by choosing its hyper-parameter combinations in an educated way. Usually, to get to optimal range of hyper-parameter values, this approach requires less iteration. And we can confidently assume that, after diligent reading, Bayesian optimization is extended to widely utilized machine learning methods [34].

As collection of hyper-parameters greatly influences efficiency of model, hyper-parameters can be very complex. Careful tuning of these hyper-parameters is, therefore, necessary. Grid quest (GS) is used in previous studies for hyper-parameter tuning of models [35] that have fewer hyper-parameters in their methods, but it will be difficult for our proposed model because our model requires a large number of hyper-parameters. Bayesian optimization is an efficient method of globally maximizing objective functions that are expensive to assess [36].

Bayesian hyper-parameter optimization strategy that was used to optimize proposed model is presented in this subsection. Majority of problems with machine optimization are black box problems where f(x) is a black box function. It is field that is most useful for Bayesian optimization techniques. Model used for this method is considered a surrogate model to simulate objective function. A popular model of surrogacy for Bayesian optimization is Gaussian Procedures (GPs) [37, 38]. A Gaussian process is used to model unknown goal feature space (GP). GPs offer an ability to set previous distributions over smooth, covariant and mean space.

A typical choice of covariance function is Matern kernel 2.5, which is utilized in proposed method. Task of procurement function is to help us to achieve best objective function. Acquisition functions are determined to conform to an intrinsic, strong acquisition feature meaning. It optimizes acquisition feature to get next measurement stage. Ensuring typical acquisition functions are expected, MPI and UCB. EI, most used acquisition feature, will be used in proposed model. Suppose that f is objective function and that xt is its sampling point:

$$x_t = \arg\max_x u\left(x \mid \mathcal{D}_{1:t-1}\right) \tag{7.2}$$

Where u is the feature of acquisition that in our case is Expected Improvement (EI) and $\mathcal{D}_{1:t-1} = \left\{\left(x_1, y_1\right), \ldots, \left(x_{1-1}, y_{1-1}\right)\right\}$, contain t-1 samples that were drawn from f so far.

For t = 1,2,3 … repeat:

- Find next sampling point by maximizing role of acquisition over GP. $x_t = \arg\max_x u\left(x \mid \mathcal{D}_{1:t-1}\right)$
- Obtain a potentially noisy sample by testing objective function f. $y_t = f(x_t) + \epsilon_t$
- Add new sample (x_t, y_t) to previous samples $\mathcal{D}_{1:t} = \mathcal{D}_{1:t-1}, \left(x_t, y_t\right)$ and update the GP.

7.4 Results and Discussion

For the COVID-19 forecast, the outcomes and discussion of the suggested approach using Bayesian optimization are used and we assess success with various performance metrics. Finally, there is an experiment to equate efficiency of proposed model with other applications of machine learning. Using measurement metrics such as sensitivity, precision, specificity, AUC of ROC maps and F1-score to assess effectiveness of proposed system. Precision is proportion of overall subjects accurately identified.

$$Accuracy = \frac{\sum TP + \sum TN}{\sum TP + \sum TN + \sum FP + \sum FN} \tag{7.3}$$

Number of patients with a positive condition is sensitivity.

$$Sensitivity = Recall = \frac{\sum TP}{\sum TP + \sum FN} \tag{7.4}$$

Specificity is percentage of individuals who have no negative illness. Recall is same as sensitivity.

$$Specificity = \frac{\sum TN}{\sum TN + \sum FP} \tag{7.5}$$

Precision is defined as subjects correctly classified subjects as positive from total subjects.

$$Precision = \frac{\sum TP}{\sum TP + \sum FP} \tag{7.6}$$

A harmonic means of accuracy and recall is F1-Score. These are

$$F1 - Score = \frac{2 \times Recall \times Precision}{Recall \times Precision} \tag{7.7}$$

where TP and FP represent correct and incorrect classification of COVID-19 subjects. Similarly, TN and FN denote percentage of subjects not possessing heart disease who are correctly and incorrectly listed, respectively. Plots of TPR and FPR plots at various gradient thresholds ROC (Receiver Operating Characteristic Curve).

$$TPR = \frac{\sum TP}{\sum TP + \sum FN} \tag{7.8}$$

$$FPR = \frac{\sum TN}{\sum TN + \sum FP} \tag{7.9}$$

7.4.1 Dataset

Various databases have been made freely accessible in this respect. More data must be recorded, produced and analyzed as COVID-19 spreads globally [39, 40]. Covid-19 is a set of data held by Our world in Data from COVID-19. Data regarding confirmed cases, deaths and tests are updated regularly. Dataset is available on https://ourworldindata.org/coronavirus-source-data

To define prediction effects, confusion matrix shown in Fig. 7.2 is used. Description of estimation outcomes of all dataset instances used for research is included.

Table 7.1 shows the proposed model performance with different performance metrics and its data on training and testing. The metrics used for evaluation are accuracy, Specificity, Sensitivity and F1-Score.

Figure 7.3 shows the proposed testing model results. X axis represents performance metrics and Y axis represents values obtained. Maroon color indicates the testing data. The proposed model achieves accuracy is 0.93, Specificity is 0.97, Sensitivity is 0.87 and F1-Score is 0.91 respectively.

Figure 7.4 shows the proposed training model results. X axis represents performance metrics and Y axis represents values obtained. Maroon color indicates the training data. The proposed model achieves accuracy is 0.87, Specificity is 0.91, Sensitivity is 0.83 and F1-Score is 0.85 respectively.

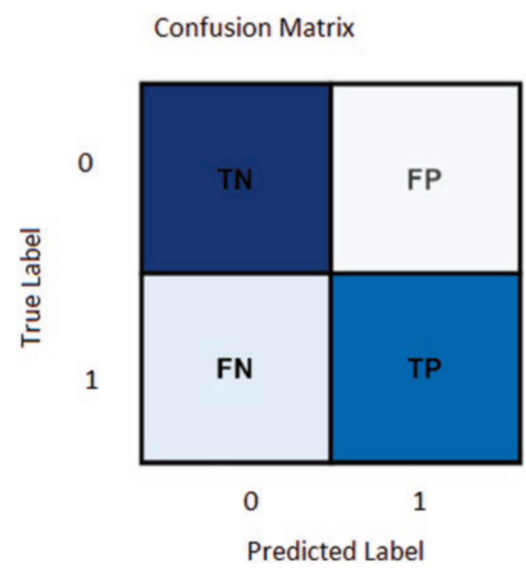

Fig. 7.2 Confusion matrix of proposed model

Table 7.1 Performance of Proposed model

Performance metrics	Data	
	Testing	Training
Accuracy	0.93	0.87
Specificity	0.97	0.91
Sensitivity	0.87	0.83
F1-Score	0.91	0.85

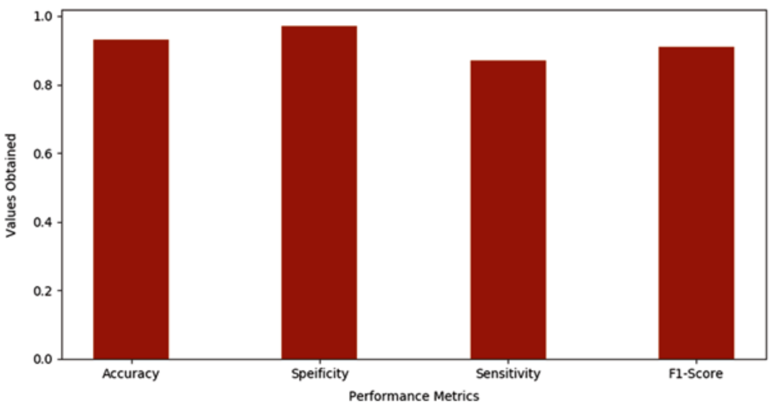

Fig. 7.3 Proposed testing model performance

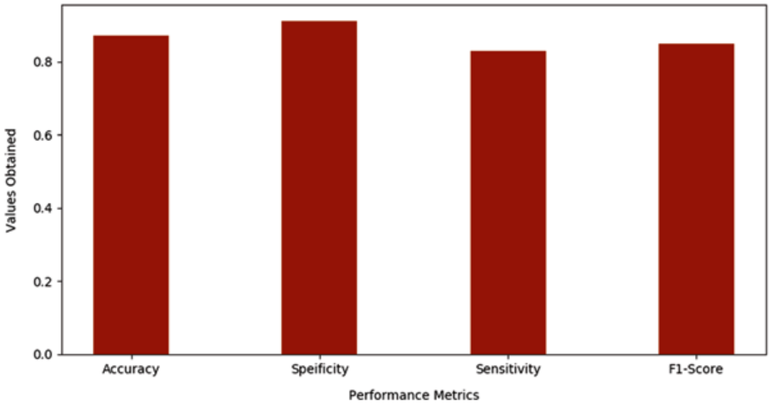

Fig. 7.4 Proposed training model performance

7.5 Conclusion

Proposed model is used to optimize model for reliable evaluation of COVID-19 cases, increase and decrease in cases in foreseeable future, and date when pandemic could be predicted to end in different countries. Based on optimization algorithm that offers improved COVID-19 identification and diagnosis, data can be analyzed. Bayesian optimization was used by proposed approach as a hyper-parameter optimization strategy that has proven to be a very successful method to get right hyper-parameters. Using four separate assessment parameters, namely precision, sensitivity, specificity, F1-score, proposed model was evaluated. Proposed diagnostic approach would improve consistency of decision-making during diagnosis of COVID 19 process on basis of experimental results. Future work concentrates on need for research in the areas of security and privacy issues related to technologies used for COVID-19 developments. Furthermore, technology should be utilized to assist and motivate frontline healthcare practitioners and officials in the fight against COVID-19.

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