Global Review of Business and Technology (GRBT)

Vol. 2, No. 2, July, 2022 **ISSN: 2767-1941**

AN OVERVIEW OF ARTIFICIAL INTELLIGENCE AND NATURE INSPIRED OPTIMIZATION IN COMBATING COVID-19 EPIDEMIC

Nidhi Sharma, Indian Institute of Technology Roorkee, India (n_sharma@ma.iitr.ac.in)
Madhu Jain, Indian Institute of Technology Roorkee, India (madhu.jain@ma.iitr.ac.in)
Dinesh Sharma, University of Maryland Eastern Shore, USA (dksharma@umes.edu)

ABSTRACT

COVID-19 can be mitigated using artificial intelligence (AI) and nature-inspired optimization (NIO) strategies. In this study, we identify several COVID-19 targets that, if inhibited, could improve patient survival. A machine learning model to discuss a clinical data set of 65,000 patient records and 26 characteristics has been presented. The set of governing equations is used to analyze the transmission dynamics of various control methods as time-dependent interventions to identify contributions to the dynamic transmission of COVID-19. The focus of this review article is to present a state-of-art on prediction and control of COVID-19 using AI and NIO techniques. Also, the study presents an overview on resource management, vaccination prioritization, prevention, and control strategies as well as screening testing procedure optimization.

Keywords: COVID-19; Transmission dynamics: Artificial Intelligence; Nature Inspired Optimization.

1. INTRODUCTION

Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) causes Corona Virus Disease and for the last two years COVID-19 (C-19) has become a significant issue for every country. The rapid spread of C-19 has wreaked havoc and necessitated quick responses to mitigate its effects. Several studies in various scientific fields have begun investigating the issues to address them. Artificial intelligence (AI) is a field of study with numerous applications in addressing problems in many fields. AI is being used to combat the global viral epidemic that has been wreaking havoc since year 2020. AI applications in this field span a wide range of disciplines, including disease diagnosis based on testing and symptoms, patient monitoring, recognizing patient severity, processing C-19 accompanying imaging tests, epidemiology, pharmaceutical research, and so on. In C-19, AI can be used to improve mobile health apps that enable diagnosis, contact tracing, treatment, vaccination schedule and monitoring via smart devices such as watches, phones, laptops, and cameras.

Santosh (2020) emphasized the vital role of artificial intelligence in detecting and analyzing the C-19 outbreaks. AI can help ICU clinicians to allocate resources and make decisions by providing detailed information about the patient's need for ventilators and respiratory support. Rahmatizadeh et al. (2020) elaborated nicely on this aspect via AI approach. According to Gozes et al. (2020), C-19 occurrences were discovered and quantified using AI from chest X-ray and CT scan images. In another investigation, Soares (2020) used AI-based classifiers for the assessment of the outcome of C-19 RT-CR findings using 16 fundamental descriptors based on the whole blood sample. Miner et al. (2020) studied AI based technique for reducing frequent and unnecessary hospital visits in asymptomatic or mildly symptomatic patients. Battineni et al. (2020) investigated whether AI-based chatbots could be used in medical consultations, reducing the likelihood of infection transmission and hospital congestion, and thus preventing the smooth operation of essential care services. Randhawa et al. (2020) used machine learning on identified genomic markers to develop a strategy for quickly and reliably categorizing available SARS-CoV-2 genomes.

There are many C-19 challenges, such as determining the location of healthcare facilities based on resource demand and shelter-in-place orders in a way that does not overload hospitals and cause unnecessary disruptions. To deal with resource allocation, optimization techniques have been at the forefront of debate, development, and deployment. Martínez-Álvarez et al. (2020) presented a unique NIO for mimicking the transmission and infection of the coronavirus in healthy humans. Al-qaness et al. (2020) described a novel forecasting methodology that uses previously verified C-19 cases in China to predict and anticipate confirmed cases in the next ten days. Within the Susceptible-Exposed-

Infected-Recovered (SEIR) model developed by Kissler et al. (2020), Navascués et al. (2021) demonstrated their strategy by reducing the overall time necessary to eliminate C-19.

Several scientists and researchers have paid close attention to the current coronavirus pandemic and severe acute respiratory illness due to C-19. Each country and the world community have a huge issue because of the massive rise of infected persons in the waves of C-19. Despite different government efforts to stem the spread, more and more individuals are becoming afflicted. The newly emerging virus is also causing a new strain of illness in some countries. A World Health Organization (WHO) study shows that over a hundred million individuals have been affected, with over 2.5 million fatalities documented (WHO Dashboard). It is suggested that a social distance of 1.6 to 3 meters be employed to prevent the rapid growth of C-19 (Sun and Zhai 2020). In these conditions, discovering a suitable tool for the early identification of this disease has become a significant problem. Using speech for C-19 detection is a safer and simpler method for this analysis, as explained by Han et al. (2020).

By using computed tomography (CT) scans, C-19 can be identified. Houssein et al. (2021) presented specific segmentation approaches to extract areas of interest from C-19 CT scans to study the improved categorization. This study proposed the Manta Ray Foraging Optimization (MRFO) with Opposition-Based Learning (OBL) approach by adding an opponent-based learning approach to the existing manta ray foraging optimization (MRFO) technique. With the initial MRFO approach, there is a chance of being stuck in local optima, necessitating more research and exploitation. Therefore, it is advised that OBL in the initialization step of the MRFO, can be used to study the spread the population variation in the search space. As part of C-19, irradiation robots and spray disinfection were used to disinfect hospitals and public areas. The uses of robots for disinfection have not received enough attention in terms of adaptive and safe navigation. Because C-19 disinfection robots have adaptive programming, they slow down when objects or barriers are present to spray and light them in a way that ensures thorough C-19 disinfection. The butterfly optimization algorithm's (BOA) low accuracy and slow convergence are addressed in the study by EL-Hasnony et al. (2021) using a hybrid feature selection technique (BOA). The suggested technique is based on employing a wrapper framework to combine the BOA algorithm with Particle Swarm Optimization (PSO) as a search methodology. El-dosky et al. (2021) described the technique for identifying C-19 and distinguishing it from influenza types A, B, and C using cockroach-optimized deep neural networks. A cockroach optimization technique is used to improve the deep neural network hyper-parameters. In this method, viral gene sequences were used as input samples.

The C-19 epidemic has caused substantial hurdles for global supply networks. Multiple countrywide lockdowns continue to impede or even briefly halt the movement of raw materials and completed goods, affecting production. Countries have restricted travel and in-person commercial engagement to prevent coronavirus infection. In recent years, global events have compelled major organizations to reconsider their supply chains, stability and dependability in the face of an uncertain future. This is not only about C-19 but also about other externalities and government activities worldwide that have begun to disrupt supply chains, such as the increasing likelihood of trade wars, nationalism and protectionist tendencies, sustainability concerns, and human rights considerations. Since every nation needs many vaccines to reduce infection rates and avoid lockdowns, the C-19 vaccine supply chain is particularly challenging. Because each country needs to produce a certain number of COVID-19 vaccines to reduce infection rates and prevent lockdowns, the supply chain management for these vaccines is complicated. There are about 2–2.5 times the current population's vaccination doses necessary to vaccinate 100 percent of the world's population at least twice (16–20 billion doses). According to Rele (2021), even if 75 percent inoculation is achieved, 12-15 billion vaccinations will be required globally to contain the current outbreak. According to the WHO, 151 potential COVID-19 vaccines are being tested in preclinical research. Jarrett et al. (2020) studied how pharma industry may help to prevent vaccine counterfeiting by introducing better vaccine supply chain. Rele (2021) looked at the process of creating vaccines during pandemics and found holes and possibilities for future pandemics.

The researchers looked at AstraZeneca/Oxford, Pfizer/BioNTech, Johnson & Johnson Moderna, Novavax, CureVac's C-19 and other manufacturing units to enhance the vaccines under development, noting pre-pandemic production capacity and charting manufacturing partners across key supply chain branches. The vaccines are currently being sent by plane to worldwide locations since speed to market is viewed as vital for halting the pandemic's spread. Delivering them by sea is viewed as a longer-term option, and the current sense of urgency would have to subside significantly before enough trust could be created to enable delivery durations measured in weeks rather than hours. Craighead et al. (2020) explained that pandemics are unique types of supply chain disruptions, characterized by long-term disruption, a ripple effect of disruption spread, and severe unpredictability.
This section presents a state-of-art of AI and NIO used to detect C-19 infections, and according to the research cited, the most efficient use of emerging AI and NIO approaches can be done to manage the prevention and vaccination

measures of C-19. Figure 1 shows a chart that presents the number of articles published in "Science Direct." We are using some abbreviations in this article which are represented in Table 1. In section 2 we discuss several approaches including the basic concepts and applications of AI. Section 3 focuses on the NIO algorithm and its application in C-19. In Section 4, we focus on some models to emphasize the applications of AI and NIO for the mathematical modeling related to C-19. In section 5, we conclude the present study by highlighting the noble features and future challenges related to use of AI and NIO for combating COVID-19. The acronyms used in AI to combat the C-19 epidemic and their methodology are summarized in Table 2. An overview of the NIO's ideas to counter the C-19 epidemic is presented in Table 3. We look at how commuting AI can help tackle C-19. In addition, other AI technologies, such as deep learning, are being described.

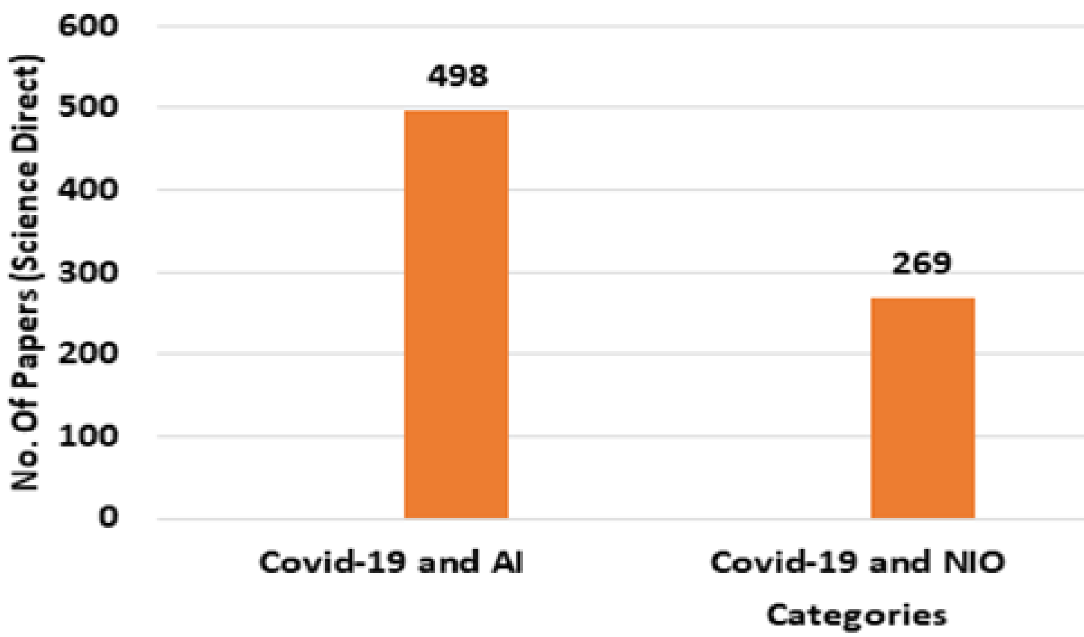

Figure 1: Papers published in Science Direct during March 2020- June 2022

Table 1: List of Abbreviations used			
ABCO	Artificial Bee Colony Optimization	**GA**	Genetic Algorithm
AI	Artificial Intelligence	**GRM**	Generalized Richards Model
ANFIS	Adaptive neuro-fuzzy inference system	**GWO**	Grey–Wolf optimizer
ANN	Artificial neural networks	**ML**	Machine learning
DL	Deep learning	**MSO**	Monkey Search Optimization
DNN	Deep neural networks	**NN**	Neural Networks
EA	Evolutionary algorithms	**GA**	Genetic Algorithm

2. REVIEW ON AI FOR COMBATING THE C-19 EPIDEMIC

The dynamics and early identification of C-19 using mathematical modeling and artificial intelligence (AI) have been the subject of various articles published in the last two years. This effort aims to offer the research community an in-depth summary of the techniques employed in these investigations and a discuss AI technique related to C-19. Fig. 2 displays the applications of AI techniques such as ML and DL in C-19. In table 2, we mention some important works that can help in understanding AI applications in the covid era.

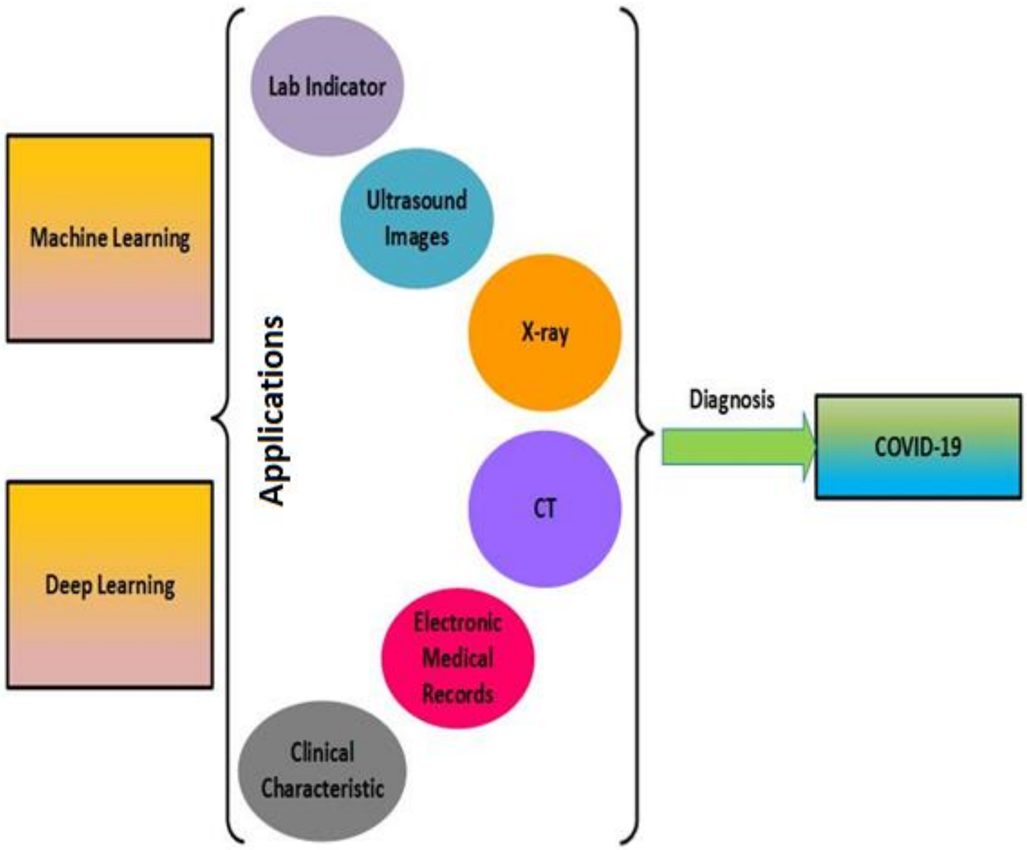

Figure 2: AI for C-19 diagnosis

Table 2: Literature review of AI and C-19 dependency

S. No	Authors (Year)	Topics	Methodology used	Remarks
1.	Chen and See (2020)	AI C-19: Rapid Review	PubMed and EMBASE databases for C-19	A thematic analysis and narrative review
2	Tayarani N. (2021)	AI in battling against C-19: A literature review	ANN, EA, DL, DNN,	Vaccine development
3.	Vaishya et al. (2020)	AI applications for C-19 pandemic	Database of Pubmed	Rapid review of the literature
4.	Khemasuwan and Colt (2021)	AI-based algorithms in the C-19 pandemic	ML and DL Algorithm	Detecting C-19 disease on medical imaging

5.	Islam et al. (2021)	C-19 Pandemic: Bibliometric Analysis	AI, ML, Bibliometric Analysis	A comprehensive picture of the global efforts to address C-19
6.	Mahdavi et al. (2021)	Exploration of C-19 mortality risk	Transparent Reporting of a multivariable prediction model	High predictive information contents in several non-invasive features
7.	Shamout et al. (2021)	Prediction of C-19 patients in the emergency department	DNN	Deterioration risk that learns from chest X-ray images
8.	Shi et al. (2021)	AI Techniques in Imaging Data Acquisition,	AI with X-ray, Segmentation	Use of radiology
9.	Nawaz et al. (2021)	Using AI in C-19 genome analysis	Learning using SPM and SP Techniques	Corpus development,
10.	Salman et al. (2020)	C-19 detection using AI	DL, ML	CNN model

3. REVIEW ON NIO IDEAS FOR COMBATING THE C-19 EPIDEMIC

Various Optimization techniques have been developed and deployed by industry experts and academics for the solutions to C-19 challenges. The nature-inspired optimization (NIO) is a significant area of research in computational intelligence, soft computing, and optimization. These methods have been used in resolving many issues related to C-19 such as determining the location of healthcare facilities according to resource demand and calculating logistic support, overload hospitals etc. In table 3, we mention some notable works that can help to understand the applications of NIO in the covid era.

Table 3: A literature review of NIO and C-19 dependency

S. No.	Authors (Year)	Topics	Methodology Used	Remark
1.	Qureshi et al. (2021)	Coronavirus disease detection	GA, Swarm Intelligence	NIA for brain MRI
2.	Salehan and Deldari (2021)	Corona virus optimization: a novel optimization algorithm	SIR model, Optimization algorithms, Meta-heuristic algorithms	Variables are taken as a set of disease symptoms
3.	Singh et al. (2020)	C-19: risk prediction through NIA	Hybrid Particle Swarm Optimization (PSO) and SCA (HPSOSCA)	Investigate the effect of age, systolic blood pressure, HDL-cholesterol
4.	Zreiq et al. (2020)	GRM for predicting C-19	GRM, Particle Swarm Optimization	Four phenomenological epidemic models
5.	Zivkovic et al. (2021)	Hybrid Genetic Algorithm for C-19	GA, ANFIS	Machine learning, Optimization
6.	Khalilpourazari and Hashemi Doulabi (2021)	Designing a hybrid reinforcement to predict C-19	GFO, SCA	Hybrid Q-learning based algorithm (HQLA)

7.	Issa and Elaziz (2020)	Analyzing C-19 virus based on improved Ions Motion Optimization algorithm	Smith–Waterman alignment algorithm, PSO, Pair wise local alignment	Fragmented Local Aligner Technique (FLAT)
8.	Agbehadji et al., (2020)	Review of Big Data Analytics	NI computing, AI, Big data	Contact tracing big data predictive analytics model
9.	Abualigah et al., (2021)	EA Optimization Algorithm for Multilevel Thresholding Segmentation of C-19 CT Images	Arithmetic Optimization Algorithm (AOA); meta-heuristics; Differential Evolution	Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Test (SSIM)

4. MATHEMATICAL MODELS: APPLICATIONS OF AI AND NIO IN C-19

For a very long time, mathematical models have produced quantitative data in epidemiology and offered helpful recommendations for handling outbreaks and formulating policies. For C-19 in particular, several modelling studies have been carried out. We are presenting two models here to describe the applications of AI and NIO in C-19.

4.1 Model 1: Classification and Severity Prediction Using a NIO Model

Suma et al. (2021) collected some data, which includes 26 distinct characteristics, medical symptoms, and other relevant personal data (C-19 dataset 2020). Six key variables in the dataset are thought to influence whether someone is infected. These variables are (i) Country (ii) Age (iii) Symptoms (iv) Severity (v) Contact (vi) Experience any additional symptoms

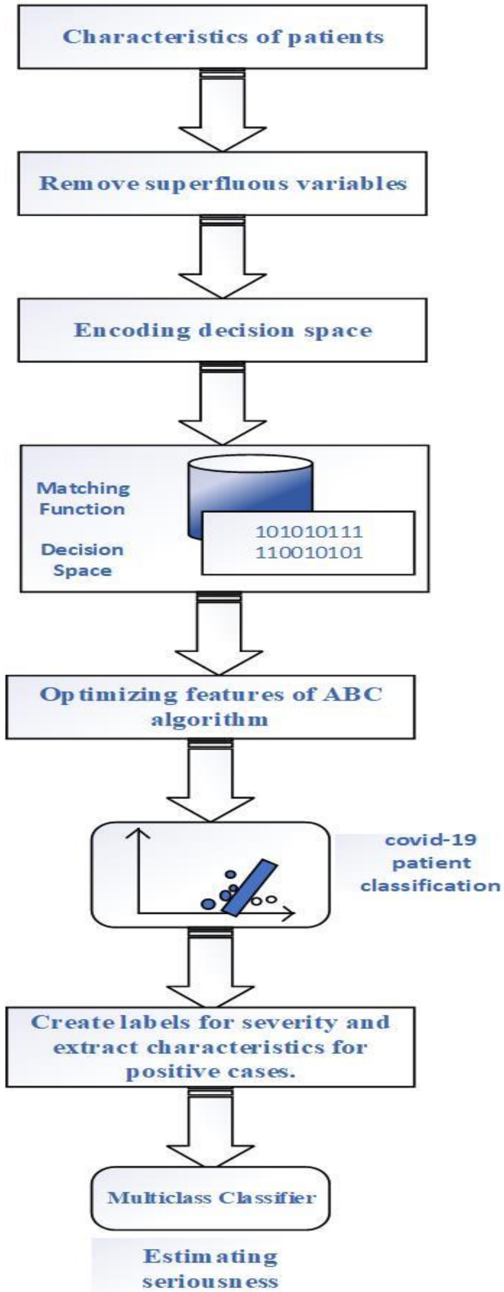

Figure 3: Predicting C-19 using clinical data

This study aims to identify C-19 instances and forecast their severity by analyzing the symptom data. We are presenting the procedure for predicting C-19 using clinical data. The ABC algorithm is used to choose the best characteristics, binary classifier SVM to forecast, and multiclass LR model is shown in fig. 3. Out of minimal clinical data, an effective early illness detection system has been established by Suma et al. (2021), which aided doctors in making the right choices. We are summarizing that model as follows.

Optimizing the Selection of Features

I. We employ the ABC algorithm given in table 4. to choose the best characteristics from the provided feature set is follows:

Table 4: Algorithmic procedure for ABC
Initialize: Set up a decision space with size (η,ρ) and random values. **Input:** Enter the number of iterations, the lower and upper bounds. **Repeat** -Find a fresh answer for each problem that the employee bee was given the original answer -Assess the quality of the options and select the best one -Create a probability vector that observer bees may utilize -Based on probability values, the answer is selected by onlooker bees -Update selected by spectator bees -Select the best option after evaluating its quality -If a solution has been left unfinished, introduce the scout bee. -Save the best answer, then raise the number of iterations. Until iteration count exceeds the ceiling value Bring back the best solution that was previously stored.

II. Choosing an appropriate objective function that can assess the value of the selected solution is the most crucial part of the optimization procedure. In terms of feature components, the objective function π is represented as

$$\pi = \frac{1}{\eta}\sum_{i=1}^{\eta} \frac{\left\{\sum_{i=1}^{\rho} score(match(s_i^j, v_i^j)\right\}}{\rho} \tag{1}$$

In this case, ρ indicates the count of features in each vector, and η indicates the total counts of vectors offered in the retrieved COVID data set. To compare the pertinent feature component in the dataset with the k^{th} vector and the j^{th} point in the i^{th} vector of the solution space, s_i^j performs this comparison.

III. The algorithm operates in accordance with how bees find food. Tasks are allocated to worker bees, observer bees, and scout bees according to their type.

IV. This work provides a multilayer quality assessment technique to locate the present solution's best neighbor. The definition of this quality grading function is the ranks given to the features, and it is written as $\beta = \frac{1}{a}\sum_{j=1}^{\rho} r_j\ m$, where a represents the total number of features that are active in the solution. Here m is the rank proportionality constant, chosen as 0.5, is used.

V. The winning solution is determined by its highest g value, and it is then designated as the neighbor solution and included in the update process. The updated equation changes as

$$y'_{ij} = y_{ij} + r[y_{wj} - y_{ij}] \tag{2}$$

VI. The best feature set is then passed on to the stage that predicts the COVID infection status of patients. SVM, a method for supervised machine learning, has been utilized for this.

Results and Discussions

This model uses the machine learning algorithms to classify patient circumstances into COVID positive and negative states and predict severity status. To do this, the authors have taken collection of 65,000 patients record. The test data included 19661 items out of which 17808 patients are C-19 positives. It can be shown that 17128 were accurately predicted and designated as True Positives (T_P), 680 patients were incorrectly forecasted as negative, suggesting False Negatives (F_N). Like this, 1200 true negative instances (T_N) were predicted out of the real negative cases, while the remaining 669 cases were falsely forecasted as positive (F_P).

$$Accuracy = \frac{T_P+T_N}{T_P+T_N+F_N+F_P} \tag{3}$$

Using equation (3), 94 percent of the model's performance was found to be accurate overall. Precision measures the percentage of accurate positive predictions compared to all positive forecasts. Thus, we obtain

$$Precision = \frac{T_P}{T_P+F_P} \tag{4}$$

$$Recall = \frac{T_P}{T_P+F_N} \tag{5}$$

Here, a machine learning model is created based on optimization for screening C-19 patients. Despite discovering new variations, the pandemic threat does not appear to have subsided. These mutations would be able to double the spreading rate, according to studies by Suma et al. (2021). The unique approach that has been developed correctly predicted the severity status of C-19 by using textual data.

4.2 Model 2: Optimum Control for C-19 Spread Prevention Strategy

The formulation of a deterministic model for C-19 is provided by Madubueze et al. (2020). In this work, they extended this model of Gumel et al. (2004) for managing the SARS epidemic to control C-19. The notations and parameters used in this model are given in table 5.

Table 5: Notations and Parameters used for of the Model Formulation	
Notations	
$S_c(t)$	Susceptible
$E_x(t)$	Exposed
$Q_r(t)$	Quarantined
$I_{\widetilde{H}}(t)$	Infectious not Hospitalized
$I_H(t)$	Hospitalized/Isolated Infectious
$R_v(t)$	Recovered
$T_P(t)$	Total Population
Parameters	
$\delta(t)$	Public health education rate over time
$\tau(t)$	Quarantine rate over time
$\eta(t)$	The isolation rate over time for infectious persons who were not hospitalized
β	Transmission rate
γ_1	The rate of recovery for infected people who are not hospitalized
γ_2	Recovery rate of hospitalized/isolated persons
w_s	After the incubation period, the rate of progression from quarantine to the susceptible compartment
ρ	Rate of progression from infected not hospitalized compartment for exposed patients who missed quarantine.
σ_1	Rate of those that were isolated after developing symptoms when in the quarantine period
p_1	The rate of C-19 patients that come from a high-risk neighborhood.
p_e	Fraction of exposed quarantined persons
d_1	The fatality rate caused by infected patients who were not hospitalized
d_2	The fatality rate caused by infected patients who were hospitalized/isolated
r	Immigration rate
z_1, z_2, z_3	Modification factors for those who have been exposed, quarantined or hospitalized/isolated.

Madubueze et al. (2020) enhanced their approach by including public health education and the option of returning to the $S_c(t)$ for those in $Q_r(t)$ who test negative for C-19. Persons from high-risk zones and contacts of individuals who tested positive for C-19 are housed in the quarantined compartment. These people are held for the duration of the virus's incubation phase. During this time test for infected persons was conducted. Those who tested negative were returned to the $S_c(t)$ compartment while those who tested positive were moved to the $I_H(t)$ compartment. Those who miss quarantine, but test positive is placed in the $I_{\widetilde{H}}(t)$ compartment, where they can either recover because to their high immunity or be transferred to the hospitalized/isolated infectious compartment.
The total population at time t is

$$T_P(t) = S_c(t) + E_x(t) + Q_r(t) + I_H(t) + I_{\widetilde{H}}(t) + R_v(t) \quad \textbf{(6)}$$

By immigration/birth of the no-risk population, a fraction $(1 - p_1)$ of total people are added to the population in the $S_c(t)$ compartment at a constant rate, r. The remaining proportion p_2 of people in quarantine return to the susceptible compartment after 14 days without symptoms at a constant rate, w_s. People leave the vulnerable compartment either through infection caused by the illness or through the rate of infection. Direct contact with infectious human pollutants or droplets causes infection. We are representing a systematic diagram of the C-19 model with respect to this problem. The public health education/awareness campaign, $\delta(t) \in [0,1]$ decreases the rate of infection, F_I, and its effectiveness is time dependent. The infection's rate is given by

$$F_I = \frac{\beta(I_{\widetilde{H}}(t) + z_1 E_x + z_2 Q_r + z_3 I_H)}{T_P} \quad (7)$$

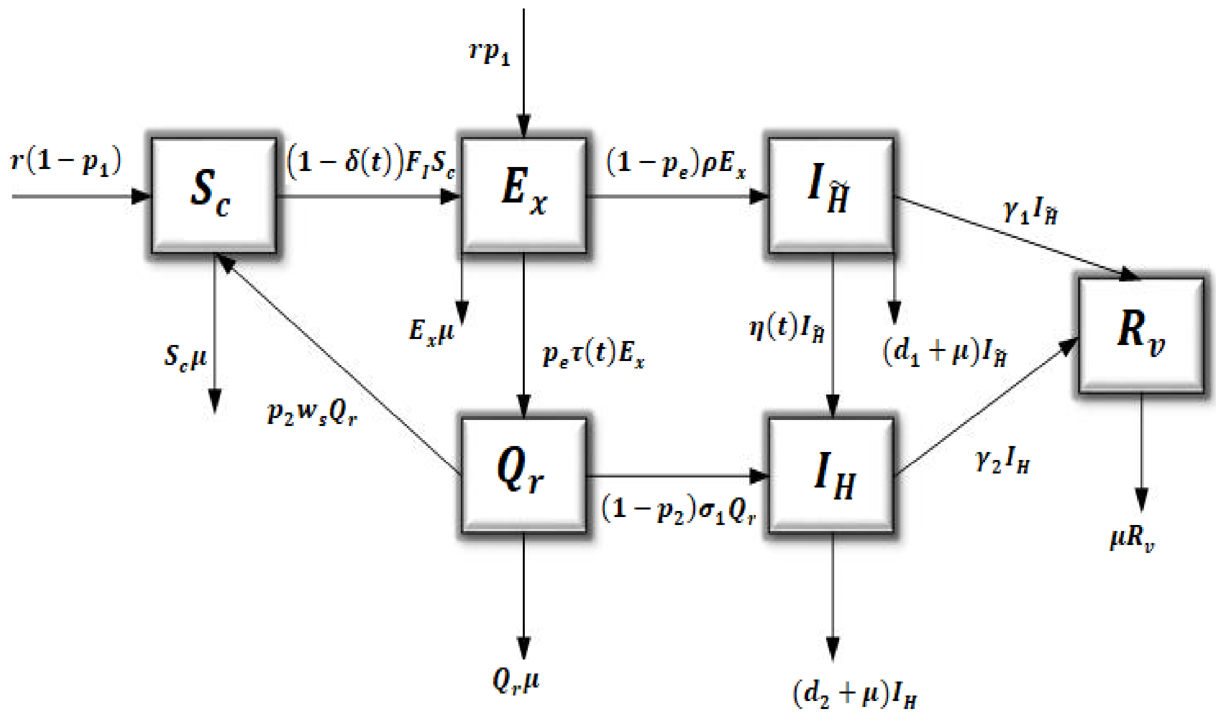

Figure 4: Transmission dynamic of model.

From the transmission rate which is represented by fig. 4, the model equations are derived as follows:

$$\left.\begin{aligned}
\frac{dS_c}{dt} &= r(1-p_1) + p_2 w_s Q_r - \big(1-\delta(t)\big)F_I S_c - S_c\mu \\
\frac{dE_x}{dt} &= rp_1 + \big(1-\delta(t)\big)F_I S_c - p_e\tau(t)E_x - (1-p_e)\rho E_x - E_x\mu \\
\frac{dQ_r}{dt} &= p_e\tau(t)E_x - p_2 w_s Q_r - (1-p_2)\sigma_1 Q_r - Q_r\mu \\
\frac{dI_{\tilde{H}}}{dt} &= (1-p_e)\rho E_x - \gamma_1 I_{\tilde{H}} - \eta(t)I_{\tilde{H}} - d_1 I_{\tilde{H}} - \mu I_{\tilde{H}} \\
\frac{dI_H}{dt} &= (1-p_2)\sigma_1 Q_r + \eta(t)I_{\tilde{H}} - \gamma_2 I_H - \eta(t)I_{\tilde{H}} - d_2 I_H - \mu I_H \\
\frac{dR_v}{dt} &= \gamma_2 I_H + \gamma_1 I_{\tilde{H}} - \mu R_v
\end{aligned}\right\} \qquad (8)$$

Our objective is to minimize the cost function which is framed as follows:

$$G\big(\delta(t),\tau(t),\eta(t)\big) = \int_0^{t_f} \left(I_{\tilde{H}}(t) + \frac{1}{2}x_1\delta^2(t) + \frac{1}{2}x_2\tau^2(t) + \frac{1}{2}x_3\,\eta^2(t)\right) dt \qquad (9)$$

The parameters x_1, x_2, and x_3 are the balancing cost factors. The terms $\frac{1}{2}x_1\delta^2(t)$, $\frac{1}{2}x_2\tau^2(t)$, and $\frac{1}{2}x_3\,\eta^2(t)$ represent the expenditure done on the public health education, quarantine, and isolation, respectively. A six-compartmental model for C-19 transmission dynamics was analyzed by Gumel et al. (2004). Imported cases and community growth are considered in the human-to-human transmission model. In the model, a region of invariance has been identified. In addition, by using AI to predict future infection rates, NIO techniques have been used to optimize the decision variables so as predict the public health education rates over time, quarantine rates over time, and isolation rates over time for infectious individuals who were not hospitalized.

5. CONCLUSIONS

The virus C-19 is dangerous and contagious. More than two hundred and eight nations and territories throughout the world have already been touched by this sickness, which is outbreaking across the entire planet. The current study is done to present an overview of AI and NIO technology utilized to combat the C-19 issue at multiple scales, including medical image processing, illness tracking, outcome prediction, and medications. We have reviewed important features of C-19 which have many applications of AI and NIO. These articles have many models which can be used to tackle critical C-19 scenario. The suggested methods may solve optimization problems and identify effective solutions faster and with fewer iterations than certain well-known optimization techniques. We have suggested that a machine learning method which is optimization-based, can be used to screen C-19 patients. We have discussed, in this study, a new mathematical model to highlight the scope of such model for C-19 by involving the interventions of isolation, quarantine, and public health education. The coronavirus pandemic has created a lot of clinical and cultural challenges, and modern technologies including AI and NIO may be used to address these challenges. This suggests that even if these interventions are implemented in a timely manner, C-19 may not be eliminated completely but the transmission of C-19 can be eliminated by further measures by using AI and NIO.

REFERENCES

Abualigah, L., Diabat, A., Sumari, P., & Gandomi, A. H. (2021). A novel evolutionary arithmetic optimization algorithm for multilevel thresholding segmentation of COVID-19 CT images. *Processes*, *9*(7), 1-37.

Agbehadji, I. E., Awuzie, B. O., Ngowi, A. B., & Millham, R. C. (2020). Review of big data analytics, artificial intelligence and nature-inspired computing models towards accurate detection of COVID-19 pandemic cases and contact tracing. *International Journal of Environmental Research and Public Health*, *17*(15), 1–16.

Al-qaness, M. A. A., Ewees, A. A., Fan, H., & Abd El Aziz, M. (2020). Optimization method for forecasting confirmed cases of COVID-19in China. *Journal of Clinical Medicine*, *9*(3), 1-15.

Battineni, G., Chintalapudi, N., & Amenta, F. (2020). AI chatbot design during an epidemic like the novel coronavirus. *Healthcare (Switzerland)*, *8*(2), 1–8.

Chen, J., & See, K. C. (2020). Artificial intelligence for COVID-19: Rapid review. *Journal of Medical Internet Research*, *22*(10), 1-12.

Craighead, C. W., Ketchen, D. J., & Darby, J. L. (2020). Pandemics and supply chain management research: Toward a theoretical toolbox . *Decision Sciences*, *51*(4), 838–866.

El-dosuky, M. A., Soliman, M., & Hassanien, A. E. (2021). COVID-19 vs influenza viruses: A cockroach optimized deep neural network classification approach. *International Journal of Imaging Systems and Technology*, *31*(2), 472–482.

EL-Hasnony, I. M., Elhoseny, M., & Tarek, Z. (2021). A hybrid feature selection model based on butterfly optimization algorithm: COVID-19 as a case study. *Expert Systems*, *39*(3), 1-28.

Gumel, A. B., Ruan, S., Day, T., Watmough, J., Brauer, F., Van Den Driessche, P., Gabrielson, D., Bowman, C., Alexander, M. E., Ardal, S., Wu, J., & Sahai, B. M. (2004). Modelling strategies for controlling SARS outbreaks. *Proceedings of the Royal Society B: Biological Sciences*, *271*(1554), 2223–2232.

Gozes, O., Frid-Adar, M., Sagie, N., Zhang, H., Ji, W., & Greenspan, H. (2020). Coronavirus detection and analysis on chest CT with deep learning, *ArXiv Preprint*, *4*, 1–8.

Han, J., Qian, K., Song, M., Yang, Z., Ren, Z., Liu, S., et al. (2020). An early study on intelligent analysis of speech under Covid-19: Severity, sleep quality, fatigue, and anxiety. *Proceedings of the Annual Conference of the International Speech Communication Association, INTERSPEECH*, *2020-Oct*, 4946–4950.

Houssein, E. H., Emam, M. M., & Ali, A. A. (2021). Improved manta ray foraging optimization for multi-level thresholding using COVID-19 CT images. *Neural Computing and Applications*, *33*(24), 16899–16919.

Islam, M. M., Poly, T. N., Alsinglawi, B., Lin, L. F., Chien, S. C., Liu, J. C., & Jian, W. S. (2021). Application of artificial intelligence in COVID-19 pandemic: Bibliometric analysis. *Healthcare (Switzerland)*, *9*(4), 1–10.

Issa, M., & Elaziz, M. A. (2020). Analyzing Covid-19 virus based on enhanced fragmented biological local aligner using improved ions motion optimization algorithm. *Applied Soft Computing Journal*, *96*(11), 1-13.

Jarrett, S., Wilmansyah, T., Bramanti, Y., Alitamsar, H., Alamsyah, D., Krishnamurthy, K. R., et al. (2020). The role of manufacturers in the implementation of global traceability standards in the supply chain to combat vaccine counterfeiting and enhance safety monitoring. *Vaccine*, *38*(52), 8318–8325.

Khalilpourazari, S., & Hashemi Doulabi, H. (2021). Designing a hybrid reinforcement learning based algorithm with application in prediction of the COVID-19 pandemic in Quebec. *Annals of Operations Research*, *312,* 1261–1305.

Khemasuwan, D., & Colt, H. G. (2021). Applications and challenges of AI-based algorithms in the COVID-19 pandemic. *BMJ Innovations*, *7*(2), 387–398.

Kissler, S., Tedijanto, C., Lipsitch, M., & Grad, Y. H. (2020). Social distancing strategies for curbing the COVID-19 Epidemic. *MedRxiv*, 2020(*1)*, 1-21.

Madubueze, C. E., Dachollom, S., & Onwubuya, I. O. (2020). Controlling the spread of COVID-19: Optimal control analysis. *Computational and Mathematical Methods in Medicine*, *2020*, 1-14.

Mahdavi, M., Choubdar, H., Zabeh, E., Rieder, M., Safavi-Naeini, S., Jobbagy, Z., et al. (2021). A machine learning based exploration of COVID-19 mortality risk. *PLOS ONE*, *16*(7), 1-20.

Martínez-Álvarez, F., Asencio-Cortés, G., Torres, J. F., Gutiérrez-Avilés, D., Melgar-García, L., Pérez-Chacón, Rubio, et al. (2020). Coronavirus optimization algorithm: A bioinspired metaheuristic based on the COVID-19 propagation model. *Big Data*, *8*(4), 308–322.

Miner, A. S., Laranjo, L., & Kocaballi, A. B. (2020). Chatbots in the fight against the COVID-19 pandemic. *NPJ Digital Medicine*, *3*(1), 1–4.

Navascués, M., Budroni, C., & Guryanova, Y. (2021). Disease control as an optimization problem. *PLOS ONE*, *16(9)*, 1-32.

Nawaz, M. S., Fournier-Viger, P., Shojaee, A., & Fujita, H. (2021). Using artificial intelligence techniques for COVID-19 genome analysis. *Applied Intelligence*, *51*(5), 3086–3103.

Qureshi, K. N., Alhudhaif, A., Qureshi, M. A., & Jeon, G. (2021). Nature-inspired solution for coronavirus disease detection and its impact on existing healthcare systems. *Computers & Electrical Engineering*, *95*(10), 1-10.

Rahmatizadeh, S., Valizadeh-Haghi, S., & Dabbagh, A. (2020). The role of artificial intelligence in management of critical COVID-19 patients. *Journal of Cellular and Molecular Anesthesia*, *5*(1), 16–22.

Randhawa, G. S., Soltysiak, M. P. M., El Roz, H., de Souza, C. P. E., Hill, K. A., & Kari, L. (2020). Machine learning using intrinsic genomic signatures for rapid classification of novel pathogens: COVID-19 case study. *PLOS ONE*, *15*(4), 1-24.

Rele, S. (2021). COVID-19 vaccine development during pandemic: gap analysis, opportunities, and impact on future emerging infectious disease development strategies. *Human Vaccines & Immunotherapeutics*, *17*(4), 1122–1127.

Salehan, A., & Deldari, A. (2021). Corona virus optimization (CVO): a novel optimization algorithm inspired from the Corona virus pandemic. *The Journal of Supercomputing, 78*, 5712–5743.

Salman, F. M., Abu-Naser, S. S., Alajrami, E., Abu-Nasser, B. S., & Ashqar, B. A. M. (2020). COVID-19 Detection using artificial intelligence. *International Journal of Academic Engineering Research*, *4*(3), 18–25.

Santosh, K. C. (2020). AI-driven tools for coronavirus outbreak: Need of active learning and cross-population train/test models on multitudinal/multimodal data. *Journal of Medical Systems*, *44*(5), 93-97.

Shamout, F. E., Shen, Y., Wu, N., Kaku, A., Park, J., Makino, T., et al. (2021). An artificial intelligence system for predicting the deterioration of COVID-19 patients in the emergency department. *NPJ Digital Medicine*, *4*(1), 1-11.

Shi, F., Wang, J., Shi, J., Wu, Z., Wang, Q., Tang, Z., et al. (2021). Review of artificial intelligence techniques in imaging data acquisition, segmentation, and diagnosis for COVID-19. *IEEE Reviews in Biomedical Engineering*, *14*, 4–15.

Singh, N., Singh, S. B., Houssein, E. H., & Ahmad, M. (2020). COVID-19: risk prediction through nature inspired algorithm. *World Journal of Engineering*, *19,* 3–12.

Soares, F. (2020). A novel specific artificial intelligence-based method to identify COVID-19 cases using simple blood exams, *MedRxiv*, *2020(1)*, 1-16.

Suma, L. S., Anand, H. S., & Vinod chandra, S. S. (2021). Nature inspired optimization model for classification and severity prediction in COVID-19 clinical dataset. *Journal of Ambient Intelligence and Humanized Computing*, *7*, 1-13.

Sun, C., & Zhai, Z. (2020). The efficacy of social distance and ventilation effectiveness in preventing COVID-19 transmission. *Sustainable Cities and Society*, *62*(11), 1-10.

Tayarani N., M.-H. (2021). Applications of artificial intelligence in battling against COVID-19: A literature review. *Chaos, Solitons & Fractals*, *142*(1), 1-31.

Vaishya, R., Javaid, M., Khan, I. H., & Haleem, A. (2020). Artificial Intelligence (AI) applications for COVID-19 pandemic. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*, *14*(4), 337–339.

Zivkovic, M., K, V., Bacanin, N., Djordjevic, A., Antonijevic, M., Strumberger, I., & Rashid, T. A. (2021). Hybrid genetic algorithm and machine learning method for COVID-19 cases prediction, *Proceedings of International Conference on Sustainable Expert Systems*. Springer, Singapore, *2021*, 169–184.

Zreiq, R., Kamel, S., Boubaker, S., A Al-Shammary, A., D Algahtani, F., & Alshammari, F. (2020). Generalized Richards model for predicting COVID-19 dynamics in Saudi Arabia based on particle swarm optimization Algorithm. *AIMS Public Health*, *7*(4), 828–843.