Mitigating COVID-19 Spread in Closed Populations Using Networked Robots and Internet of Things

Kennedy Chinedu Okafor, Kelvin Anoh, Titus I. Chinebu, Bamidele Adebisi and Gloria Azogini Chukwudebe

***Abstract*—Infectious diseases like COVID-19 have remained a primary public and global health concern. Internet of Things (IoT) of networked robots and physiological intervention can be combined to identify and control the spread of the different variants of COVID-19 disease. With this approach, governments and healthcare institutions can plan for such diseases in the future. This paper presents a compact computational model (CCM) to identify and control different COVID-19 variants using IoT-networked robots. The CCM comprises seven physiological variables (PV) and robotic identification (RI) of infected individuals as alternative intervention strategies. The study uses Market Place Service Robots that correctly identify PV and RI for positively infected individuals. The conditions of the existence and the solution of the deterministic model are derived from a compact flow architecture that we develop. We show that the model has COVID-19-free equilibrium and endemic equilibrium. While PV with appropriate isolation and hospital treatment reduces the COVID-19 disease impact by 19% more than RI alone, the study also shows that combining two PV with RI minimises the impact better than PV or RI alone, by 36% and 43%, respectively. When the PV control parameters are increased, up to five, in the presence of IoT and RI, up to 99.99% improvement is seen. With all seven PV control parameters in the presence of IoT and RI, the proposed CCM guarantees an infection-free population.**

***Index Terms*—Computational Intelligence, Computational Complexity, COVID-19 infection, Global Vaccination, Internet of Things, Market Place Service Robot, Smart Health Infrastructure.**

I. Introduction

On 31 December 2019, the World Health Organisation (WHO) "picked up a media statement" about the outbreak of a novel coronavirus [1], [2]. The virus was later identified as severe acute respiratory (SAR) syndrome coronavirus 2 (SARS-CoV-2) [1]–[3]. Reports showed that this infectious disease started in Wuhan City, China, in November 2019 [3], [4] and the disease caused by the SARS-CoV-2 is referred to as Coronavirus disease 2019 (COVID-19) [5]. On 11^{th} March 2020, WHO declared the disease a global pandemic due to its high spreading rate and fatalities, surpassing 118,000 people in over 114 countries with 4,291 deaths [6]. The early stages of COVID-19 are characterised by fever, cough, tiredness, and myalgia [7]. More extreme circumstances can result in pneumonia, an SAR respiratory illness, cardiac issues, and even death. As a temporary measure, national governments such as the United Kingdom enacted several lockdown rules and this crippled lots of economies. Market Place Service Robots (MPSRs) terminated at the edges of Internet of Things (IoT) networks can be combined with physiological strategies to mitigate the spread of COVID-19 disease in closed populations. We refer to a closed population as a deterministic sample cluster of a definite size (large or small) with predictors for COVID-19 spread. These time-varying predictors are widely used epidemic variables, namely susceptible $S(t)$, asymptomatically infected $A(t)$, vaccinated $V(t)$, exposed $E(t)$, hospitalised $H(t)$, symptomatically infected $I(t)$ and treated $T(t)$. These seven physiological variables will be hereinafter referred to as SAVEHIT.

Although the impacts of COVID-19 disease have been contained globally, its effects have not been eradicated. For example, the effects of the COVID-19 pandemic will incur about €18T global economic loss between 2020 and 2025 [8]. With smart infrastructure, such as MPSR, artificial intelligence (AI), data analytics, IoT and computational modelling, the endemic and economic effects of COVID-19 and its new variants can be mitigated. Smart healthcare infrastructure (SHI), such as stream robots, wearables, AI, and other IoT-driven systems, is now an active part of healthcare cyber-physical systems positioned to enhance the detection, reporting and control of infectious diseases, such as COVID-19, etc. For example, BlueDot – a Canadian startup tech company, warned early that the world might be experiencing a new virus outbreak using AI within the first 38 days of COVID-19 before the Chinese officials identified the virus [3].

IoT-based technologies are used to collect data for machine learning in managing COVID-19-infected patients [9]. Although there are different variants of COVID-19 [10], IoT devices are suitably used to identify and classify them correctly [11]. In the new system, variations are currently emerging. Some indicators include growth rate, changes in transmissibility, severity, or immune evasion, among others. With current dominant variants, variant classifications have been reported without compactness property [12]. Previous classifications of COVID-19 no longer meet requirements within the re-classified modifications, which became operative on April 1, 2022 [10]. New classifications include variants of concern (VoC), Variants of Interest (VoI), Variants under Monitoring (VuM), and De-escalated variants [10]. Several domestic and foreign health organisations, including the US Center for Disease Control and Prevention, England Public Health, and various COVID-19 Consortia in the UK, Canada, etc., use the following benchmarks to evaluate COVID-19 [10]: increased risk of "long COVID, increased risk of transmission, increased morbidity and increased death, capacity to evade

This research is partly sponsored by IEEE HAC/SIGHT - Focus on COVID-19 Response & Pressing Community Need (Project ID: 21-Cov2-185] and in part by Tetfund Nigeria under Postdoc Program on Resilient AI and Smart systems (TETF/ES/UNIV/IMO STATE/TSAS/2021). The authors thank A1Tronix and its partners for developing and testing the MPSR/CMPR.

K. C. Okafor and B. Adebisi are with the Manchester Metropolitan University, United Kingdom. Okafor is also with the Electrical and Electronic Engineering Science Department of the University of Johannesburg, South Africa, and the Department of Mechatronics Engineering, Federal University of Technology, Owerri, Nigeria (emails: k.okafor@mmu.ac.uk; b.adebisi@mmu.ac.uk).

K. Anoh is with the Electrical and Electronic Engineering Department, University of Chichester, United Kingdom (email: k.anoh@chi.ac.uk).

T. I. Chinebu is with the Department of Applied Science, Federal University of Allied Health Sciences, Enugu, Nigeria (chinebuifeanyi@fedcodtte.edu.ng).

G. A. Chukwudebe is with the Electrical and Electronic Engineering Department, FUTO, Nigeria (email:gloria.chukwudebe@futo.edu.ng).

detection by diagnostic procedures, immunity evasion, and ability to cause reinfections among others.

Computational modelling of infectious diseases, such as COVID-19, is another aspect of interventions. For instance, non-integer order differential equations in dynamical systems, classical mathematical models of the integer-order derivatives, and integer-order models using optimal control, among others, examined the impact of various non-pharmaceutical interventions on the control of the disease [13]–[15]. Fractional derivatives have been employed as a useful computational model, especially in epidemiological modelling of infectious diseases [16]. Examples of such models include Atangana-Baleanu and Caputo-Fabrizio [17], Caputo, Riemann-Liouville [18], Grunwald-Letnikov [19], Riemann-Liouville derivative [20] and Mittag-Leffler function [21]. The benefit of these compact models is to capture real-world problems in mathematical models, which is simpler to employ in theoretical analysis, numerical calculations and in planning interventions for future pandemics.

This article models COVID-19 spread in a closed population as a statistical process using a compact computational model (CCM). The model envisages an SHI of an IoT network where MPSRs operate at the edges. These specialist robots, MPSRs, are able to obtain COVID-19 health status of an individual at a distance of 100 m thereby minimising health risks to healthcare professionals. The proposed CCM uses seven physiological variables (i.e., SAVEHIT) as a deterministic variable (DV) and robotic identification and reporting (RI) parameters. We benchmark our model on the most widely used fractional derivative for modelling biological processes such as the generic Atangana-Baleanu derivative [17]. In terms of computational complexity, this will be used to validate the model because it captures memory impacts as it is a non-local and non-singular kernel [14]. We will show that the proposed model (i.e., CCM with DV+RI) outperforms existing computational models within SHI robotic execution time. Our idea is to demonstrate that deploying the CCM with DV+RI in a closed population can protect vulnerable persons from COVID-19 and future pandemics, thus, controlling its spread.

When fewer control variables are applied (e.g., three control variables), our results show that a maximum of 56.98% improvement was realised. This result is better by 1.98% than the ones reported by [22] when the fractional order derivative model alone was used. However, when the number of physiological control variables is increased (e.g., up to five), 99.99% improvement was achieved. This result is better by 9% than using AI classification model proposed by [4] and 43.01% than using the fractional order model proposed by [22]. With all seven SAVEHIT variables combined with RI and IoT, infectious diseases such as COVID-19 can be totally mitigated.

CCM users must understand which control variable is required among the seven (SVEAIHT) variables when implemented. The users will involve multidisciplinary experts (i.e., technical and non-technical). Depending on the resources provided to support the intervention, healthcare experts will receive training on which control variable(s) to enable at each investigation period. Engineers and technicians will be prepared to understand the operations of the robots and IoT networks and how to maintain their continuous service. Social scientists will be trained to explore the ethical issues in deploying the model during any epidemic scenario. Data scientists will be equipped with the data realised from the processes to interpret the data and propose what they can be used for.

The main contributions of this article are as follows:

- We develop an IoT-based model to manage infectious diseases, such as COVID-19, spread in a closed population. We install specialist robots, MPSR, at the network edges that automates the process and minimises health risks.
- Using the setup, we derive CCM that minimises contracting post-COVID-19 VoC when combined with DV and RI;
- We characterise the model to show COVID-19 infection-free equilibrium (CIFE), global stability of CIFE for post-covid-19, including existence and stability of infection endemic equilibrium (CIEE);
- For practical setup, we describe a proof of concept strategy for the IoT-networked robots for mitigating infectious diseases spread (e.g., COVID-19), potential issues, complexities that surround adaptation to existing health infrastructure and sustainability concerns.

SAVEHIT are well-known epidemic parameters that can be applied to any infectious disease, including waterborne disease, COVID-19, HIV, Tuberculosis, etc. Our study takes these seven physiological parameters (i.e., SAVEHIT) to propose a CCM in the presence of IoT and robots terminated at the edges of the IoT network. We adopted COVID-19 as an infectious disease example. If the detection properties of the robot can be modified, then our model can be extended to the new infectious disease study of interest. With the robots at the edges of the IoT network, the community, local or national governments can plan a well-coordinated health intervention for any selected closed population. For example, the robots can be used for immunisation at selected health centres (i.e., edges of the network) while the SAVEHIT data is collected through edge, fog and cloud networks for further analysis, planning and improvements. All of these can be operated in real-time. It allows multidisciplinary collaboration in planning and mitigating any future pandemics.

The remaining parts of the paper are organised as follows. Section II presents the system model, Section III presents the results and discussions and conclusion in Section IV.

II. System Model and Design

Consider a closed population of $N(t)$ persons. In this study, a closed population is a deterministic sample cluster of a definite size (large or small) with predictors for COVID-19 spread. These predictors are the seven well-known SAVEHIT epidemic parameters. These seven SAVEHIT parameters are time-varying; that is, each of them changes with time, t. These parameters can be investigated for any population size, $N(t)$, at any given time, t. Thus, if the population size changes from, say, N_1 to N_2, the CCM model continues to operate with the new population, and as such, we emphasise that the model adapts to the prevailing population size $N(t)$, thereby solving the scalability problem. In terms of the infrastructure, IoT technologies such as LoRa, amongst other LPWANs [23], is well-known for scalability, coverage and low-power consumption [24]. Robots terminated at the edges of the IoT network can always continue to assess any number of persons, provided it is electrically powered.

Figure 1 depicts an IoT network of MPSR for detecting and controlling COVID-19 disease spread in a closed population. The

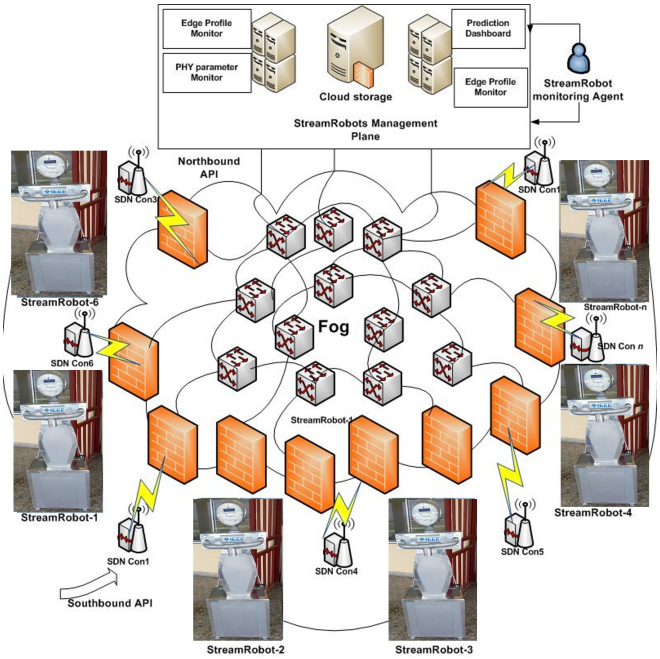

Figure 1: IoT-networked robots for identifying and controlling infectious disease spread (e.g., COVID-19) in a closed population. This proof of concept benefits from task-offloading in MPSR [25].

model shows proof of concept of DV + RI testbed used for the real-world demonstration of the study. Based on this, we present a COVID-19-based robotic CCM which uses a flow diagram shown in Figure 2 with the state variables. Attributes such as boundedness and positivity of solutions are discussed. The IoT network is terminated with robots (i.e., MPSR) that collect the COVID-19 status of an individual and report it for actions by healthcare professionals. These records are securely transmitted via SHI to the servers in an edge, fog or cloud computing fashion. Note that this study requires a robust technological infrastructure to deploy the CCM for disease control, such as COVID-19, in closed populations. This includes IoT infrastructure such as LoRA, MPSRs for autonomous tasks, MK 1000 IoT sensors for real-time data collecting, and a data analytics platform for pattern identification. On-the-fly processing from the edge locations in Figure 1 is facilitated by stream processing with kinesis, while identity access management (IAM) and cybersecurity controls guarantee data integrity.

To ensure patient privacy, the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) through the use of certificate authority and asymmetric cryptography in the architecture. Together, these elements create a functional CCM that improves resource allocation, response coordination, and disease monitoring in the fight against infectious diseases. We envisaged and accounted for scalability problems using the robotic and IoT infrastructure for a time-varying population, $N(t)$. For example, the more IoT-sensed traffic comes to the infrastructure load balancers, the more the system triggers robin-heuristics for autoscaling the predictor variables. This resilient, dynamic behaviour carries out fleet management, thereby addressing scalability concerns for closed population workloads. The infrastructure offers active-active fault tolerance and high availability as the IoT Arm® Cortex®-M0 32-bit SAMD21 CPU, the MKR 1000 WiFi can be employed with ECC508 crypto-chip security.

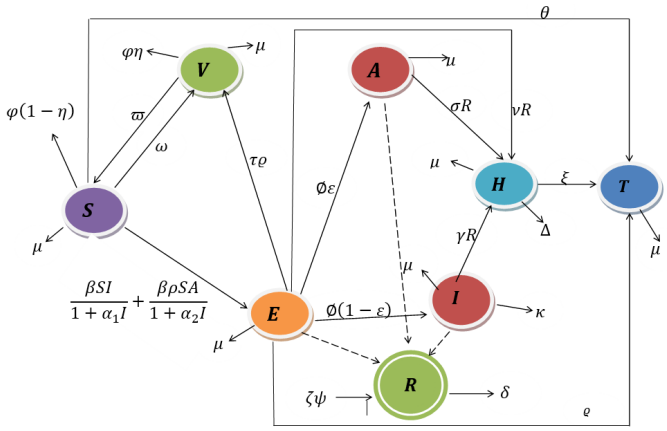

Figure 2: Compact flow diagram of the COVID-19 infection spread in a closed population.

In general, deploying robots across every foreseeable human traffic concourse in any community or population is practically impossible. On the other hand, it is possible to deploy SAVEHIT-aware robots at the strategic perimeters of any community to detect infectious diseases, such as COVID-19. Implementing networked robots and the IoT in managing pandemics requires a substantial upfront investment and continuous operating costs, but a worthy investment. In terms of hardware, robots, sensors, LPWANs, edge-Fog-Cloud networks and data centers, and technician and healthcare staff training are among the initial costs. Energy requirements, data administration, and maintenance are long-term costs. Through NPV, ROI calculations and cost-benefit evaluations, economic viability is evaluated with an eye on prospective improvements in disease surveillance, response times, and transmission risk reduction.

Long-term sustainability requires flexible and scalable solutions. For deploying networked robots and IoT in managing pandemics, the prerequisites for resources include highly skilled experts, adequate funding, cutting-edge technology such as API microservices and infrastructure security. However, the advantages of better disease control and public health outcomes can outweigh the initial capital invested at the beginning of the disease control or planning phase. To effectively deploy these technologies in pandemic management, it is imperative to ensure economic feasibility through careful analysis, scaling planning, and efficient resource management for closed populations.

Although there were, and still are, concerns about privacy and ethical issues in deploying IoT and robotic technologies in monitoring and controlling diseases, efforts are being made to enhance these in the scientific community. In the UK, Secure by Design is an essential strategy that enforces security features into IoT products from the design stage. Data collected from individuals will be transmitted over secure networks to ensure high data fidelity and privacy for everyone. During pandemics, public education on deploying IoT and robotic technologies will be promoted to enhance public awareness of the infrastructure used in mitigating the pandemic with a given population. Getting informed permission, guaranteeing data ownership rights and anonymity, and safeguarding sensitive health data with encryption and access controls are critical ethical issues. It is imperative to mitigate algorithmic bias, minimise monitoring

and stigmatisation, and guarantee equal access. Robotics and IoT technologies are used to monitor health and control disease while considering ethical issues. These comply with the HIPAA and GDPR.

A. Model Formulation

From Figure 2, let $N_1(t)$ be the human population at time t. We break this into seven mutually exclusive groups: 1) Susceptible individuals, $S(t)$ - who have not come in contact with COVID-19-infected individuals but are at risk of being infected with COVID-19 infection; 2) individuals who have received vaccination, $V(t)$, against COVID-19 infection; 3) non-vaccinated individuals exposed to COVID-19 infection, $E(t)$; 4) asymptomatic individuals – individuals infected without symptoms, $A(t)$; 5) symptomatic individuals –individuals infected with symptoms, $I(t)$. 6) individuals detected with COVID-19 infection and isolated for treatment in the hospital, $H(t)$; 7) individuals who recovered after treatment, $T(t)$. In this context, the Robots detect the exposed, infected without symptoms, and infected with symptoms to reduce the transmission rate, $R(t)$, due to contact.

B. Proposed Compact Computational Model

Figure 2 depicts the flow structure of individuals in a sample space with the possibility of acquiring COVID-19 at time t. We assume that mixing between people happens uniformly (i.e., compact homogeneity attribute). Only the exposed compartment after infection produces the population of people with either symptomatic or asymptomatic COVID-19 infection. We further assume that exposed individuals who may not be infectious may acquire some immunity through vaccination, reducing the risk of subsequent infection. On top of that, exposed persons develop some immunity from the infection, which lowers the chance of re-infection but does not completely shield them against contracting COVID-19 infection. The acquired vaccine-induced immunity of the vaccinated people may deteriorate with time. Susceptible individuals who have never been successfully vaccinated acquire infection with COVID-19, while those whose protective effect of vaccination has worn off move back to the susceptible compartment.

Consider a hybrid population sample of humans (Figure 2) and robots, which can be expressed as:

$$N(t) = N_1(t) + N_2(t) = \sum_{i=1}^{k} p_i(t) + \sum_{n=k+1}^{\infty} p_n(t) \tag{1}$$

where $N_1(t) = \sum_i p_i(t) = S(t)+V(t)+E(t)+A(t)+I(t)+H(t)+T(t)$ and $N_2(t) = \sum_n p_n(t) = R(t)$ denote the total population of robots. Following effective contact with symptomatic and asymptomatic COVID-19, the rate of infection is modelled as:

$$\lambda = \beta\left(\frac{I}{1+\alpha_1 I} + \frac{\rho A}{1+\alpha_2 I}\right) \tag{2}$$

where β is the effective contact rate (contact sufficient to result in COVID-19 infection) and the modification parameter $\rho \geq 1$ accounts for the relative infectiousness of individuals with asymptomatic COVID-19, where $\frac{1}{1+\alpha_1}$ and $\frac{1}{1+\alpha_2}$ measures the inhibitory effect from the behavioural change of susceptible individuals when their number increases or from the crowding effect of the infectious individuals [26].

Let ω be the susceptible population with successful vaccination, which wanes at a rate ϖ. The susceptible and vaccinated compartments are generated by the recruitment of individuals into the population from birth and immigration and successful vaccination against COVID-19 infection at the rates $\varphi(1-\eta)$ and $\varphi\eta$ respectively. Within the human population, natural death occurs at the rate μ. A fraction $\emptyset\varepsilon$ of newly infected susceptible individuals (exposed individuals) is assumed to undergo a fast progression directly to the asymptomatic infectious compartment $A(t)$, while the remainder $\emptyset(1-\varepsilon)$ progresses to a symptomatic infectious compartment.

At the edges of the IoT network, MPSRs detect all stages of COVID-19 infection; exposed, asymptomatic or symptomatic. These individuals are immediately taken to the isolation/hospitalised compartment at the rate υR, σR and γR, respectively, where υ, σ and γ are isolation/hospitalisation rate of exposed, infection without symptoms and infected with symptoms after being detected by MPSRs. ξ models a variable (i.e., increasing the recovered compartment) due to of the effective treatment of the isolated/hospitalised individuals. COVID-19 symptomatic infectious individuals and those hospitalised for treatment die due to the infection at the rate κ and Δ respectively.

Furthermore, ϱ is the reducing rate of the risk of COVID-19 infection due to the acquisition of immunity by the exposed individuals. These are moved to the treated and recovered, while some proportion denoted by $\tau\varrho$ is moved to the vaccinated compartment due to vaccination.

Assuming ζ is the effective performance rate of the robot (possible generation of data by the robot per individual) and δ is the rate at which the Robot breaks down. Based on these, the CCM is described as a system of nonlinear differential equations of the form:

$$\frac{dS(t)}{dt} = \varphi(1-\eta) + \varpi V t) + \theta T(t) - \left(\mu + \omega + \beta\left[\frac{I(t)}{1+\alpha_1 I} + \frac{\rho A(t)}{1+\alpha_2 I}\right]\right) S(t) \tag{3a}$$

$$\frac{dV(t)}{dt} = \eta\varphi + \tau\varrho E(t) + \omega S(t) - (\mu + \varpi) V(t) \tag{3b}$$

$$\frac{dE(t)}{dt} = \beta\left(\frac{I(t)}{1+\alpha_1 I} + \frac{\rho A(t)}{1+\alpha_2 I}\right) S(t) - (\mu + \tau\varrho + \upsilon R(t) + \varrho + \emptyset) E(t) \tag{3c}$$

$$\frac{dA(t)}{dt} = \emptyset\varepsilon E(t) - (\mu + \sigma R(t)) A(t) \tag{3d}$$

$$\frac{dI(t)}{dt} = \emptyset(1-\varepsilon) E(t) - (\mu + \kappa + \gamma R(t)) I(t) \tag{3e}$$

$$\frac{dH(t)}{dt} = (\upsilon E(t) + \sigma A(t) + \gamma I(t)) R(t) - (\mu + \Delta + \xi) H(t) \tag{3f}$$

$$\frac{dT(t)}{dt} = \xi H(t) + \varrho E(t) - (\mu + \theta) T(t) \tag{3g}$$

$$\frac{dR(t)}{dt} = \psi\zeta - \delta R(t). \tag{3h}$$

where $\zeta = \Lambda e^{-t(\pi-\widehat{\pi})}$, ψ = recruitment rate of robots, ζ = effective performance rate of the robot, δ = robot performance breakdown rate, Λ = possible generation of data by the robot

per individual ID t= time, π represents the distance at which the data is generated by the Robot and the battery life and $\widehat{\pi}$ = represents half of the distance and battery life understudy.

C. Positivity of Solution and Well-Posedness of the Model

The deterministic system model in (3) carries out two important tasks, namely: 1) monitors the dynamics of the interaction (transfer) effect of COVID-19 infection between the compartments; 2) track the impact of Stream Robot (i.e. MPSR) in detecting individuals infected with the COVID-19 virus.

The population under study relates to physical quantities and therefore cannot be negative. Given this scenario, there is a need to prove that all state variables are non-negative for all time (t). Also, the proof must establish (3) to be epidemiologically and mathematically meaningful in SHI. Thus, the solution of (3) with positive initial data will remain positive for all $t \geq 0$. This then means that it is feasible to have:

Lemma 1: The biologically feasible region

$$\mathcal{D} = (S(t) + V(t) + E(t) + A(t) + I(t) + H(t) + T(t) + R(t)) \in \mathbb{R}^8_+ : N_1 \leq \frac{\varphi}{\mu};\ N_2 \leq \frac{\psi\zeta}{\delta} \tag{4}$$

Proof: Notice from (1) that $\mathcal{D}$ is a positively invariant set since adding the first seven sub-equations, that is,

$$N_1(t) = S(t) + V(t) + E(t) + A(t) + I(t) + H(t) + T(t) \tag{5}$$

$$\frac{dN_1(t)}{dt} = \varphi - \mu(S(t) + V(t) + E(t) + A(t) + I(t) + H(t)) + T(t) - \Delta H(t) - \kappa I(t). \tag{6}$$

But at COVID-19 infection-free equilibrium, $\Delta H(t) = \kappa I(t) = 0$

$$\frac{dN_1(t)}{dt} = \varphi - \mu N_1(t). \tag{7}$$

Observe that $\frac{dN_1(t)}{dt}$ is bounded by $\varphi - \mu N_1(t)$, therefore

$$\frac{dN_1(t)}{dt} \leq \varphi - \mu N_1(t). \tag{8}$$

And so $\frac{dN_1(t)}{dt} < 0$ if $N_1(t) > \frac{\varphi}{\mu}$. Thus, from (2) and Gronwell's inequality, it follows that

$$N_1(t) \leq N_1(0)\, e^{-\mu t} + \frac{\varphi}{\mu}\left(1 - e^{-\mu t}\right). \tag{9}$$

By Birkhff and Rota's theorem on differential inequality [27]:

$$0 \leq N_1 \leq \frac{\varphi}{\mu}, \qquad t \longrightarrow \infty. \tag{10}$$

Therefore, $N_1(t) \leq \frac{\varphi}{\mu}$ provided $N_1(0) \leq \frac{\varphi}{\mu}$.

Hence, $\mathcal{D}$ is a positively invariant set; so, the model is well-posed analytically and epidemiologically. Thus, the dynamical flow of the model can sufficiently be considered in $\mathcal{D}$.

D. Equilibrium and Stability Analysis

The analysis of epidemiological models for SHI requires the determination of the asymptotic behaviour of their solution. This is usually based on the associated equilibria [28]. It is clear to note that the model has two equilibria, namely: CIFE, (i.e., Γ_0 and the CIEE (Γ_1). These equilibria are obtained by setting the right-hand sides of (3) to zero.

E. Local Stability of CIFE

The CIFE, Γ_0, of (3), obtained by setting the RHS (3) to zero is given by:

$$\begin{aligned}\Gamma_0 &= (S_0,\ V_0,\ E_0,\ A_0,\ I_0,\ H_0,\ T_0,\ R_0)\\ &= (S_0,\ V_0,\ 0,\ 0,\ 0,\ 0,\ 0,\ R_0).\end{aligned} \tag{11}$$

At COVID-19 infection-free equilibrium, COVID-19 infection is absent in the population and thus, all the compartments related to infection transmission will be equal to zero, that is, $E_0 = A_0 = I_0 = H_0 = T_0 = 0$. Therefore,

$$\varphi(1-\eta) + \varpi V_0 - (\mu + \omega) S_0 = 0 \tag{12a}$$

$$\varphi\eta + \omega S_0 - (\mu + \varpi) V_0 = 0 \tag{12b}$$

$$\psi\zeta - \delta R_0 = 0. \tag{12c}$$

From (3), we then obtain (13a)

$$R_0 = \frac{\psi\zeta}{\delta} \tag{13a}$$

$$V_0 = \frac{\varphi\eta + \omega S_0}{\mu + \varpi} \tag{13b}$$

$$S_0 = \frac{\varphi(1-\eta) + \varpi\left(\frac{\varphi\eta + \omega S_0}{\mu+\varpi}\right)}{\mu + \omega}. \tag{13c}$$

By rearranging and substituting (13b) into (13c), then

$$\varphi(1-\eta)(\mu+\varpi) + \varpi\ \varphi\eta + \varpi\omega S_0 = (\mu+\varpi)(\mu+\omega) S_0 \tag{14a}$$

$$\varphi\mu + \varphi\varpi - \varphi\mu\eta - \varphi\varpi\ \eta + \varpi\ \varphi\eta = \left(\mu^2 + \mu\omega + \mu\varpi\right) S_0 + \varpi\omega S_0 - \varpi\omega S_0 \tag{14b}$$

$$\frac{\varphi\mu + \varphi\varpi - \varphi\mu\eta}{\mu^2 + \mu\omega + \mu\varpi} = S_0 \tag{14c}$$

$$\frac{\varphi(\varpi + \mu(1-\eta))}{\mu(\mu + \omega + \varpi)} = S_0. \tag{14d}$$

By substituting (14d) with (13b), then

$$V_0 = \frac{\varphi\eta + \omega\left(\frac{\varphi(\varpi+\mu(1-\eta))}{\mu(\mu+\omega+\varpi)}\right)}{\mu + \varpi} \tag{15a}$$

$$V_0 = \frac{\varphi\eta\mu(\mu + \omega + \varpi) + \omega\varphi(\varpi + \mu(1-\eta))}{\mu(\mu+\varpi)(\mu+\omega+\varpi)} \tag{15b}$$

$$V_0 = \frac{\varphi\eta}{\mu+\varpi} + \frac{\omega\varphi(\varpi + \mu(1-\eta))}{\mu(\mu+\varpi)(\mu+\omega+\varpi)}. \tag{15c}$$

CIFE, Γ_0 of the model is determined based on the threshold parameter known as the basic reproduction number (BRN) [66]. The BRN is designated as R_{CR} describes the average number of newly infected individuals generated from a single (one) infectious individual at the beginning of the infectious process. To compute R_{CR}, we then find the non-negative matrix F of new COVID-19 Infection (Transmission) terms and the M-matrix V of transfer (Transition) terms.

By properties of determinants a matrix, we note that: 1) If every element in a row (or column) of an $n \times n$ (i.e., a square) matrix is zero, then the value of the determinant will be zero; 2) If the corresponding elements are equal in two rows (or columns) of an $n \times n$ matrix is zero, then the value

$$V := \begin{bmatrix} 0 & \beta p S_0 & \beta S_0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, F := \begin{bmatrix} \mu + \tau\varrho + \nu R_0 + \varrho + \phi & 0 & 0 \\ -\phi\varepsilon & \mu + \sigma R_0 & 0 \\ -\phi(1-\varepsilon) & 0 & \mu + \kappa + \gamma R_0 \end{bmatrix}, \; FV^{-1} = \begin{bmatrix} \frac{\beta\rho\emptyset\varepsilon S_0}{\alpha_1} + \frac{\beta\emptyset(1-\varepsilon)S_0}{\alpha_2} & \frac{\beta\rho S_0}{\mu+\sigma R_0} & \frac{\beta S_0}{\mu+\kappa+\gamma R_0} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

where $\alpha_1 = (\mu + \tau\varrho + \nu R_0 + \varrho + \emptyset)(\mu + \sigma R_0)$ and $\alpha_2 = (\mu + \tau\varrho + \nu R_0 + \varrho + \emptyset)(\mu + \kappa + \gamma R_0)$. (16)

of the determinant will be zero. Since (16) satisfies these two properties, then $\left|FV^{-1}\right| = 0$. Let $\Phi = FV^{-1}$, then

$$\begin{aligned} R_{CR} &= \frac{1}{2}\left(trace\ (\Phi) + \sqrt{(trace\ (\Phi))^2 - 4det(\Phi)}\right) \\ &= \frac{1}{2}(trace\ (\Phi) + trace\ (\Phi)) = \frac{1}{2}(2(trace\ (\Phi))) \\ &= trace\ (\Phi) = \frac{\beta\rho\emptyset\varepsilon S_0}{\alpha_1} + \frac{\beta\emptyset(1-\varepsilon)S_0}{\alpha_2}. \end{aligned} \tag{17}$$

This implies that the basic reproduction number of COVID-19 infection $R_{CR} = trace\ (\Phi)$ is now given by

$$R_{CR} = \max\{R_{0A},\ R_{0I}\} \tag{18}$$

where R_{0A}, represents the basic reproduction number of the infectious without symptoms and R_{0I}, is the basic reproduction number of the infectious with symptoms. Therefore, we obtain

$$R_{0A} = \frac{\beta\rho\emptyset\varepsilon\varphi(\varpi + \mu(1-\eta))}{\mu(\mu + \omega + \varpi)\alpha_1} \tag{19a}$$

$$R_{0I} = \frac{\beta\emptyset\varphi(1-\varepsilon)(\varpi + \mu(1-\eta))}{\mu(\mu + \omega + \varpi)\alpha_2} \tag{19b}$$

$$R_{CR} = \frac{\beta\emptyset\varphi(\varpi + \mu(1-\eta))\left[\rho\varepsilon\frac{\left(\mu+\kappa+\gamma\frac{\psi\zeta}{\delta}\right)}{\left(\mu+\sigma\frac{\psi\zeta}{\delta}\right)} + (1-\varepsilon)\right]}{\mu(\mu+\omega+\varpi)\alpha_2}. \tag{19c}$$

Lemma 2: The CIFE of (3) given by (11) is locally asymptotically stable if $R_{0A} \leq 1$ and $R_{0I} \leq 1$ (or $R_{CR} \leq 1$) and unstable if $R_{0A} > 1$ and $R_{0I} > 1$ (or $R_{CR} > 1$).

The epidemiological suggestion is that COVID-19 infection can be eradicated from the population only when the basic reproduction number is less than the unity (*i.e.*, $R_{CR} < 1$). This means that R_{0A} must be less than unity($R_{0A} < 1$) and R_{0I} less than unity ($R_{0I} < 1$), if the initial concentration of the models compartments is in the basin of attraction of Γ_0. The local stability of the COVID-19 infection-free equilibrium point is computed with the Jacobian matrix of (3) at CIFE and thus:

$$J(\Gamma_0) = \begin{bmatrix} J_{1,1} & \varpi & 0 & J_{1,4} & J_{1,5} & 0\theta & 0 & \\ \omega & J_{2,2} & J_{2,3} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & J_{3,3} & J_{3,4} & J_{3,5} & 0 & 0 & 0 \\ 0 & 0 & J_{4,3} & J_{4,4} & 0 & 0 & 0 & 0 \\ 0 & 0 & J_{5,3} & 0 & J_{5,5} & 0 & 0 & 0 \\ 0 & 0 & J_{6,3} & J_{6,4} & J_{6,5} & J_{6,6} & 0 & 0 \\ 0 & 0 & \varrho & 0 & 0 & \xi & J_{7,7} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\delta \end{bmatrix} \tag{20}$$

where $J_{1,1} = -(\mu + \omega)$,$J_{1,4} = -\beta\rho S_0$, $J_{1,5} = -\beta S_0$, $J_{2,2} = -(\mu + \varpi)$, $J_{2,3} = \tau\varrho$, $J_{3,3} = -(\mu + \tau\varrho + \nu R_0 + \varrho + \emptyset)$, $J_{3,4} = \beta\rho S_0$, $J_{3,5} = \beta S_0$, $J_{4,3} = \emptyset\varepsilon$, $J_{4,4} = -(\mu + \sigma R_0)$, $J_{5,3} = \emptyset(1-\varepsilon)$, $J_{5,5} = -(\mu + \kappa + \gamma R_0)$, $J_{6,3} = \nu R_0$, $J_{6,4} = \sigma R_0$, $J_{6,5} = \gamma R_0$, $J_{6,6} = -(\mu + \Delta + \xi)$, $J_{7,7} = -(\mu + \theta)$.

In this subsection, the performance analysis of the threshold quantities R_{0A}, R_{0I} and R_{CR} to ascertain the effectiveness of vaccine strategy and the robotic detection impacts within a COVID-19-infected population.

Theorem 1: The CIFE with vaccination effect on COVID-19 infected individuals and effective Robotic detection of individuals infected with COVID-19 exists and is locally asymptotically stable if $R_{0A(\omega)} \leq 1$ and $R_{0I(\omega)} \leq 1$ or $R_{CR(\omega)} \leq 1$ and $R_{0A(R_0)} \leq 1$, $R_{0I(R_0)} \leq 1$ or $R_{CR(R_0)} \leq 1$.

Proof: The partial derivative of $R_{0A(\omega)}$ *and* $R_{0I(\omega)}$ (*or* $R_{CR(\omega)}$) with respect to ω are shown in (21) in the next page: where $B = \left(\mu + \tau\varrho + \nu\frac{\psi\zeta}{\delta} + \varrho + \emptyset\right)$, $C = \left(\mu + \kappa + \gamma\frac{\psi\zeta}{\delta}\right)$, and $G = \left(\mu + \sigma\frac{\psi\zeta}{\delta}\right)$.

This implies that the value of R_{0A} and R_{0I}(or R_{CR}) decreases as ω increases when the partial derivative $\frac{\partial R_{0A}}{\partial\omega}$ and $\frac{\partial R_{0I}}{\partial\omega}$ $\left(\text{or } \frac{\partial R_{CR}}{\partial\omega}\right)$ are less than zero. Vaccination is effective as ω approaches infinity. Since $R_{0A} + R_{0I} = R_{CR}$, therefore,

$$\frac{\partial R_{0A}}{\partial R_0} + \frac{\partial R_{0I}}{\partial R_0} = \frac{\partial R_{CR}}{\partial R_0}, \tag{23}$$

it follows that $\frac{\partial R_{CR}}{\partial R_0}$ results as shown in (24).

Also, the robotic detection of COVID-19-infected individuals reduces the contact rate of the infectious individuals with the susceptible individuals, thereby reducing the effective transmission rate. Therefore, a highly effective vaccine administration to the susceptible population with elevated successful detection of the infected (infectious) individuals can lead to effective COVID-19 infection control.

III. Simulation Results and Discussion

We use numerical simulation to demonstrate the effect of various control strategies on the transmission dynamics of COVID-19 infection. The simulation implements the proposed CCM model in (3) on MATLAB (version R2023b) using DV and RI control variables over a [0, 100] time interval. We also adopt the initial conditions $S(0) = 5000$, $V(0) = 1500, E(0) = 2003$, $A(0) = 416$, $I(0) = 208$, $H(0) = 404$, $T(0) = 115$ and $R(0) = 500$ described in [29], [30]. The step size used for the simulation is $h = 0.02$ and $N_h = 100$.

A. Evaluation of CCM Under Different Control Strategies

Figure 3 shows the varying effect of υ, σ and γ, that is, effective detection of COVID-19 infective by stream robots on the exposed, asymptotically infected and symptomatically infected population. From these results, we observe that as the value of υ, σ and γ increases from 0.005 to 1.0, the population of the infected persons gradually decreases; this will help in reducing the number of effective contacts between the infected and the susceptible individuals in the population consequently resulting in few infections. By implication, the results indicate that MPSRs effectively detect infected individuals and can significantly reduce COVID-19 infection in a population.

A high value of υ, σ and γ indicates that the robotic control is highly effective while a low value indicates the reverse. This demonstrates that the fight against COVID-19 infection can be successfully addressed if measures that can reduce the spread

$$\frac{\partial R_{0A}}{\partial \omega} = -\frac{\beta\rho\emptyset\varepsilon\varphi\mu\left(\varpi+\mu\left(1-\eta\right)\right)\left(\mu+\tau\varrho+\nu\frac{\psi\zeta}{\delta}+\varrho+\emptyset\right)\left(\mu+\sigma\frac{\psi\zeta}{\delta}\right)}{\left[\mu\left(\mu+\omega+\varpi\right)\left(\mu+\tau\varrho+\nu\frac{\psi\zeta}{\delta}+\varrho+\emptyset\right)\left(\mu+\sigma\frac{\psi\zeta}{\delta}\right)\right]^2} < 0 \tag{21a}$$

$$\frac{\partial R_{0I}}{\partial \omega} = -\frac{\beta\emptyset\varphi\mu(1-\varepsilon)\left(\varpi+\mu\left(1-\eta\right)\right)\left(\mu+\tau\varrho+\nu\frac{\psi\zeta}{\delta}+\varrho+\emptyset\right)\left(\mu+\kappa+\gamma\frac{\psi\zeta}{\delta}\right)}{\left[\mu\left(\mu+\omega+\varpi\right)\left(\mu+\tau\varrho+\nu\frac{\psi\zeta}{\delta}+\varrho+\emptyset\right)\left(\mu+\sigma\frac{\psi\zeta}{\delta}\right)\right]^2} < 0 \tag{21b}$$

$$\frac{\partial R_{CR}}{\partial \omega} = -\frac{\beta\emptyset\varphi\mu\left(\varpi+\mu\left(1-\eta\right)\right)\left[\rho\varepsilon\left(\mu+\kappa+\gamma\frac{\psi\zeta}{\delta}\right)+\left(1-\varepsilon\right)\left(\mu+\sigma\frac{\psi\zeta}{\delta}\right)\right]BCG}{\left[\mu\left(\mu+\omega+\varpi\right)BCG\right]^2} < 0. \tag{21c}$$

$$\frac{\partial R_{0A}}{\partial R_0} = -\frac{\beta\rho\emptyset\varepsilon\varphi\mu\left(\varpi+\mu\left(1-\eta\right)\right)\left(\mu+\omega+\varpi\right)\left[\sigma\left(\mu+\tau\varrho+\nu R_0+\varrho+\emptyset\right)+\nu\left(\mu+\sigma R_0\right)\right]}{\left[\mu\left(\mu+\omega+\varpi\right)\left(\mu+\tau\varrho+\nu R_0+\varrho+\emptyset\right)\left(\mu+\sigma R_0\right)\right]^2} < 0 \tag{22a}$$

$$\frac{\partial R_{0I}}{\partial R_0} = -\frac{\beta\emptyset\varphi\mu\left(1-\varepsilon\right)\left(\varpi+\mu\left(1-\eta\right)\right)\left(\mu+\omega+\varpi\right)\left[\gamma\left(\mu+\tau\varrho+\nu R_0+\varrho+\emptyset\right)+\nu\left(\mu+\kappa+\gamma R_0\right)\right]}{\left[\mu\left(\mu+\omega+\varpi\right)\left(\mu+\tau\varrho+\nu R_0+\varrho+\emptyset\right)\left(\mu+\kappa+\gamma R_0\right)\right]^2} < 0. \tag{22b}$$

$$\frac{\partial R_{CR}}{\partial R_0} = -\Bigg[\frac{\beta\rho\emptyset\varepsilon\varphi\mu\left(\varpi+\mu\left(1-\eta\right)\right)\left(\mu+\omega+\varpi\right)\left[\sigma\left(\mu+\tau\varrho+\nu R_0+\varrho+\emptyset\right)+\nu\left(\mu+\sigma R_0\right)\right]}{\left[\mu\left(\mu+\omega+\varpi\right)\left(\mu+\tau\varrho+\nu R_0+\varrho+\emptyset\right)\left(\mu+\sigma R_0\right)\right]^2} \tag{24a}$$

$$+\frac{\beta\emptyset\varphi\mu\left(1-\varepsilon\right)\left(\varpi+\mu\left(1-\eta\right)\right)\left(\mu+\omega+\varpi\right)\left[\gamma\left(\mu+\tau\varrho+\nu R_0+\varrho+\emptyset\right)+\nu\left(\mu+\kappa+\gamma R_0\right)\right]}{\left[\mu\left(\mu+\omega+\varpi\right)\left(\mu+\tau\varrho+\nu R_0+\varrho+\emptyset\right)\left(\mu+\kappa+\gamma R_0\right)\right]^2}\Bigg]. \tag{24b}$$

of the infection such as vaccination and robotic control, are put in place. Also, measures like minimising contact between the infected and susceptible and using stream robots to detect and report infected individuals through IoT networks are impactful.

We also investigate the performance of the proposed CCM in the absence of vaccination and robotic control as shown in Figure 4. In this case, only the immune system combats the infection. It can be observed that the infection continues to exist in the population, indicating that the immune system alone is not an effective control strategy.

In Figure 5, we compare the results of robotic detection with and without vaccination based on the proposed CMM. Note that the role of robots is to detect and report COVID-19-infected persons at the edges of the IoT network. The results show that in the absence of control, the exposed, asymptomatically infected, and symptomatically infected population continuously increases, indicating that COVID-19 may not be eradicated from such a population.

On the other hand, with vaccination and robots to detect infected individuals, the results show that there will be a rise in the number of vaccinated, isolated/hospitalised due to effective identification by robots and treatment/recovery. This is because of successful and effective vaccination with effective robotic detection leading to correctly identified persons being isolated/hospitalised and thus will be treated and subsequently recover from the infection.

From Figure 5, Table I presents the percentage decrease of exposed, asymptomatically infected, and symptomatically infected using either vaccination or robotic control strategies and a combination of both strategies. This shows only a vaccine control strategy is applied for COVID-19 infections. Obviously, applying only vaccination as a control strategy for COVID-19 infection shows a little above-average effect on the infection, thus insufficient to eradicate the exposed, asymptotically infected, and symptomatically infected population.

Table I: Percentage decrease in the number of Exposed, Asymptomatically Infected, and Symptomatically Infected when only vaccination control (η and ω) is applied.

Vaccination Control	**No Control**	**With Control**	**% Decrease**
Exposed	3111.2592	1385.8839	55.46
Asymptomatic	1602.4767	532.573	66.77
Symptomatic	716.2707	242.0808	66.20

Table II shows the result of the robotic control strategy for COVID-19 infection. The percentage decrease of the exposed is below average, while the percentage decrease of the asymptomatically and symptomatically infected is slightly above the average. This implies that robotic control only as a strategy is not enough to eradicate COVID-19 infection in the population.

Table II: Percentage decreases in the number of Exposed, Asymptomatically Infected, and symptomatically Infected when Robotic control measure (υ, σ and γ) is applied.

Robotic Control	No control	With control	% Decrease
Exposed	3111.2592	1970.8572	36.65
Asymptomatic	1602.4767	689.4637	56.98
Symptomatic	716.2707	328.1867	54.18

Although the two control strategies (i.e., robotic and vaccination) demonstrated in Tables I and II significantly minimise the infection when applied separately, however, neither of them is robust enough to eradicate the infection from the population.

Finally, Table III shows the percentage decrease in the number of COVID-19 infections when the two control strategies are combined. Combining the two control strategies greatly affects the infection in the population. From this result, it

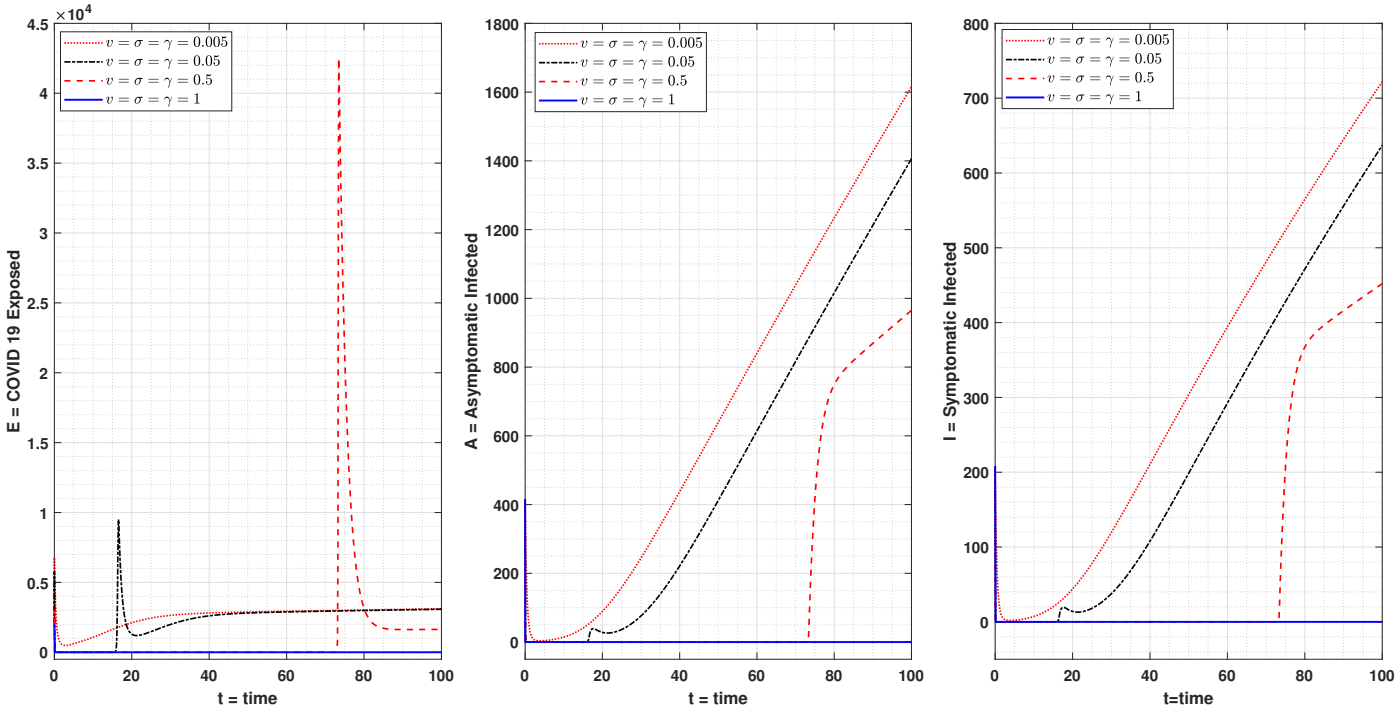

Figure 3: Impact of Robotic Control Parameters on exposed, asymptomatically infected and symptomatically infected population.

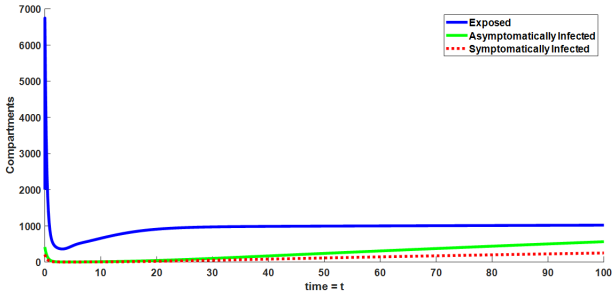

Figure 4: Effect of immunity as a control strategy on the exposed, asymptomatically, and symptomatically infected ($\tau = 0.25$ and $\varrho = 0.25001$ and vaccine rate of $\eta = 0.95$ and 0.75).

Table III: Percentage decrease in the number of Exposed, Asymptomatically and Symptomatically Infected when Vaccination and Robotic controls (η, ω, υ, σ and γ) are applied.

Vaccination and Robotic Controls	No Control	With control	% Decrease
Exposed	3111.2592	0.3775	99.99
Asymptomatic	1602.4767	0.3775	99.98
Symptomatic	716.2707	0.3775	99.95

was observed that combined intervention of vaccination and robotic control ($\eta, \omega, \upsilon, \sigma$and$\gamma$) is a better control strategy for COVID-19 infection and needs to be effectively deployed to reduce COVID-19 infection to the barest minimum within the population even in future pandemics.

B. Complexity Analysis of the Proposed Model

Consider $n \rightarrow f(n)$ in our computational engine where n denotes the size of inputs and $f(n)$ is observed for worst-case complexity. The number of computational elementary operations $O(n)$ performed on n is typically used to define time complexity, where computational operations are considered to take a constant amount of time on a machine and change only by a constant factor when performed on another machine.

Considering Figure 6, the proposed CCM with DV+RI uses more resources than the EBMOChOA-FW [31] but less than three other models [32]. The implications for (3) is that this has established strong existence and uniqueness results, unlike the Atangana-Baleanu fractional derivative scheme that uses Banach fixed point theorem and whose numerical method is based on the collocation approach. Finally, the EBMOCChOA-FW scheme is badly amortised regarding space complexity but offers optimal CPU latency.

C. Comparison with Other Models

Our results show that when smaller number of control variables are applied (e.g., three control variables, as in Table II), a maximum of 56.98% improvement was realised. This result is better by 1.98% than the ones reported by [22] when the fractional order derivative model alone was used. However, when the number of physiological control variables is increased (e.g., up to five, as in Table III), 99.99% improvement was achieved. This result is better by 9% than using AI classification model proposed by [4] and 43.01% than using fractional order model proposed by [22].

D. Sustainability of the Proposed CCM

The SAVEHIT epidemic parameters are well-established in the literature. In most cases, not all seven parameters can be combined to manage an existing or outbreak infectious disease due to economic, technical, social, and ethical limitations. The efficacy of these styles of combinations is demonstrated in Table

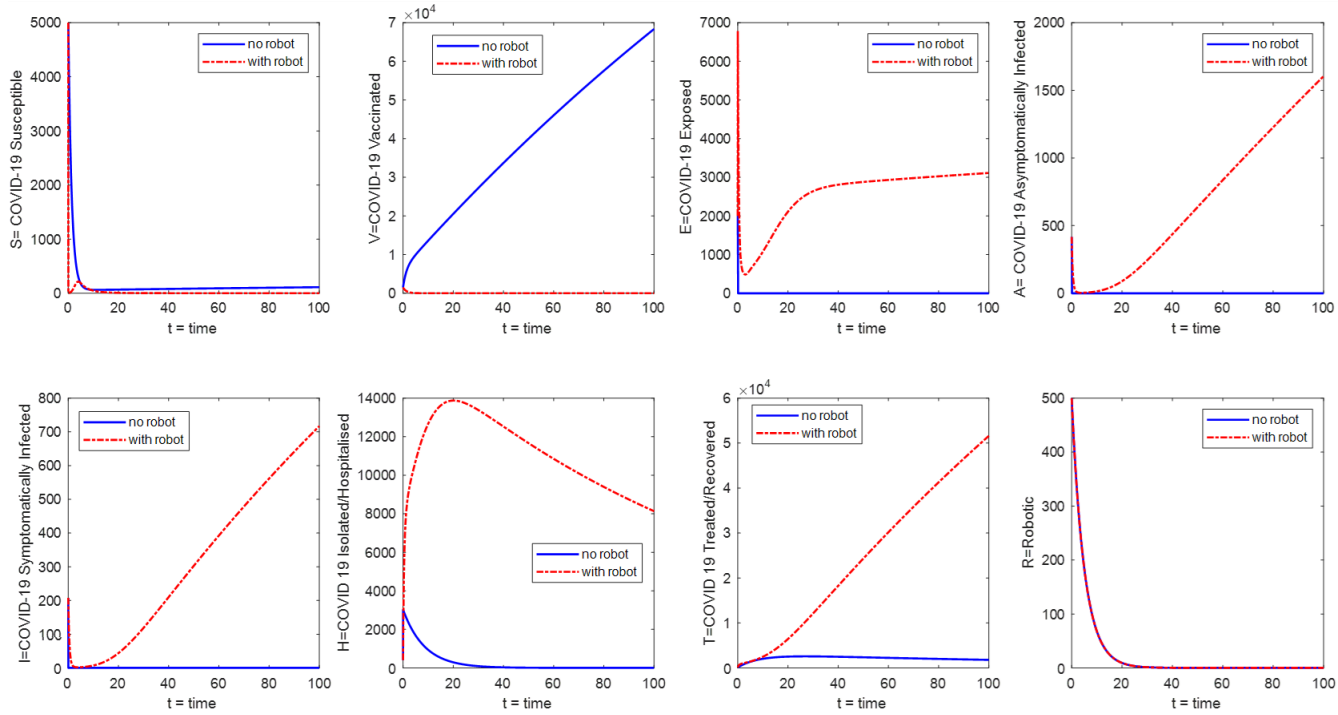

Figure 5: Simulation results of the CCM model showing with and without combined vaccination and Robotic controls.

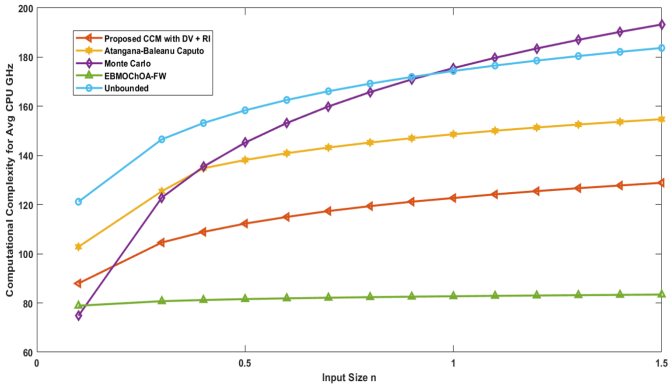

Figure 6: Comparative assessment of the computational complexity analysis of the proposed CCM with other models.

I (for two parameters), Table II (for three parameters) and Table III (for five parameters). Practically, the efficacy realised from applying two parameters (as in Table I) is smaller than the ones realised from applying increased control parameters (as in Table III). Consequently, the long-term effectiveness and sustainability of the proposed model hinge on economic, technical, social, and ethical limitations.

For long-term effectiveness and sustainability, one, longitudinal and real-world trials and indicators like transmission rates, morbidity, mortality, and healthcare resource use should be used to evaluate how well the model controls the disease. Two, CCMs have the ability to adjust to new threats so that they are capable of managing novel infections and evolving epidemiological conditions. Three, the maintenance, obsolescence, energy efficiency, and environmental impact of the necessary technological infrastructure, such as IoT sensors and networked robots, must be taken into account. Four, while comparing the CCM with alternative strategies, cost-effectiveness studies should take into account both the short- and long-term advantages. Five, it is important to evaluate the model's resistance to outside influences such natural disasters and socioeconomic upheavals. Six, communication and participatory decision-making are essential for community participation, trust, and acceptance over time. Seven, it is imperative to guarantee continuous adherence to ethical standards and regulatory compliance.

Ultimately, boosting innovation and constant improvement is critical to raising the effectiveness and sustainability of the CCM. By methodically addressing these variables, stakeholders may maximise the model's effectiveness in controlling infectious diseases and fostering public health resilience.

E. Integrating Proposed CCM with Existing Healthcare Systems and Emergency Response Protocols

For any disease control in any given community, the healthcare team usually documents the SAVEHIT statistics of the community. These parameters were the ones used in the proposed CCM model. For example, every healthcare system, including the NHS in the UK, has an Electronic Health Records system stored in a highly secure server and network. IoT and Robots proposed in this study can be used to complement the existing network infrastructure.

Based on these, the proposed CCM can be integrated with emergency response procedures and current healthcare systems to efficiently manage emergency and existing healthcare situations within the emergency and outpatient departments of hospitals. These will reduce care time in emergencies, conventional outpatient departments and during pandemics. For seamless integration into workflows and protocols, with clearly defined responsibilities and communication channels,

collaboration between emergency responders, public health agencies, healthcare providers, and technology vendors is necessary. Advanced analytics could be used to connect CCM data with current healthcare data to improve situational awareness and decision-making. Clinical decision-making and epidemic response can be aided by real-time data, predictive analytics, and evidence-based guidelines provided by decision support systems in the scaled CCM. With documented materials, procedures, and simulation exercises, it is essential to train emergency responders and healthcare professionals on how to use the CCM within a deployment context using system guidelines. Emergency Operation Centres (EOCs) and the CCM could be connected to improve resource allocation and communication in times of crisis.

Maintaining regulatory compliance with data privacy and security standards such as GDPR and HIPAA is imperative in context. Persistent assessment and enhancement of the integration procedure, grounded on feedback and optimal methodologies, often guarantee the CCM's efficacy and flexibility in response to changing healthcare exigencies and hazards.

F. Future Research Directions

To improve our study, the following research direction would involve physically installing robots at the edges of the IoT network in real-time for any selected population in monitoring any infectious disease, such as COVID-19. Data collected from this can be used by data scientists and AI professionals using any data analytics method (descriptive, predictive or prescriptive analytics) to inform healthcare professionals and governments on the mitigation route. Different LPWANs can be used to study various phenomena in IoT network. LoRaWAN is a well-perceived LPWAN for IoT networks due to its tripartite merits, such as scalability, data rate and low power consumption.

IV. Conclusion

This paper develops a computation model for mitigating infectious disease spread, such as COVID-19, in a closed population. The study uses specialist robots, MPSR, installed at the edges of the IoT network to identify and report the spread of the disease. Based on this setup, the study develops a compact computational model that demonstrates the role of combining seven physiological intervention variables (i.e., vaccination of susceptible population, recruitment rate, isolation/hospitalisation of exposed, isolation/hospitalisation of asymptomatically infected, isolation/hospitalisation of symptomatically infected, treatment and natural immunity) with robotic identification and reporting over an IoT network to control the spread of the disease. Although applying either of the control strategies (i.e., physiological interventions or robotic identification and reporting) reduces the endemic impacts of the disease, our results show that when both strategies are combined, better results are realised. With vaccination alone, 19% recovery is seen more than using robots alone. However, 36% recoveries are recorded when robotic identification and reporting are combined with vaccination. Applying vaccination and robotic control, 43% of the population recovered more than using robotic control alone. It follows that combining vaccination of the susceptible population with robotic identification and reporting of exposed, asymptomatically, and symptomatically infected persons over an IoT network is a better strategy to minimise the spread of infectious diseases such as the COVID-19 pandemic within a population. When further physiological control variables are added, such as treatment, recruitment rate, and immunity, more population recovered. As these control parameters are increased up to five in the presence of IoT and Robotic Identification, COVID-19 disease is better reduced up to 99.99%. When all seven parameters are applied in the presence of IoT and Robotic Identification, an infectious-free population is achieved.

References

[1] WHO, "Archived: WHO Timeline - COVID-19," 2020, (accessed: 26 Dec. 2023). [Online]. Available: https://shorturl.at/PQY45

[2] ——, "Listings of WHO's response to COVID-19," 2020, (accessed: 26 Dec. 2023). [Online]. Available: https://shorturl.at/rzEZ3

[3] Z. Allam, "The first 50 days of covid-19: a detailed chronological timeline and extensive review of literature documenting the pandemic," *Surveying the Covid-19 pandemic and its implications*, p. 1, 2020.

[4] C. Iwendi, A. K. Bashir, A. Peshkar, R. Sujatha, J. M. Chatterjee, S. Pasupuleti, R. Mishra, S. Pillai, and O. Jo, "Covid-19 patient health prediction using boosted random forest algorithm," *Frontiers in public health*, vol. 8, p. 357, 2020.

[5] UKHSA, "COVID-19: epidemiology, virology and clinical features," 2020, (accessed: 26 Dec. 2023). [Online]. Available: https://shorturl.at/lACVY

[6] T. A. Ghebreyesus, "WHO Director-General's opening remarks at the media briefing on COVID-19 - 11 March 2020," 2020, (accessed: 26 Dec. 2023). [Online]. Available: http://tinyurl.com/mrx3mrtx

[7] C. Biscayart, P. Angeleri, S. Lloveras, T. d. S. S. Chaves, P. Schlagenhauf, and A. J. Rodríguez-Morales, "The next big threat to global health? 2019 novel coronavirus (2019-ncov): What advice can we give to travellers?–interim recommendations january 2020, from the latin-american society for travel medicine (slamvi)," p. 101567, 2020.

[8] M. N. Gita Gopinath, Petya Koeva Brooks and R. Anspach, "Transcript of the World Economic Outlook Update Press Briefing," 2021, (accessed: 22 Jan. 2023). [Online]. Available: https://shorturl.at/fgBJO

[9] A. Castiglione, M. Umer, S. Sadiq, M. S. Obaidat, and P. Vijayakumar, "The role of internet of things to control the outbreak of covid-19 pandemic," *IEEE Internet of Things Journal*, vol. 8, no. 21, pp. 16 072–16 082, 2021.

[10] "SARS-CoV-2 variants of concern as of 12 January 2023," 2023, accessed: 19 Jan. 2023. [Online]. Available: https://shorturl.at/bijH0

[11] N. Anjum, M. Alibakhshikenari, J. Rashid, F. Jabeen, A. Asif, E. M. Mohamed, and F. Falcone, "Iot-based covid-19 diagnosing and monitoring systems: A survey," *IEEE ACCESS*, vol. 10, pp. 87 168–87 181, 2022.

[12] M. Miotto, L. Di Rienzo, G. Gosti, L. Boâ, G. Parisi, R. Piacentini, A. Boffi, G. Ruocco, and E. Milanetti, "Inferring the stabilization effects of sars-cov-2 variants on the binding with ace2 receptor," *Communications biology*, vol. 5, no. 1, p. 20221, 2022.

[13] M. A. Noor, A. Raza, M. S. Arif, M. Rafiq, K. S. Nisar, I. Khan, and S. F. Abdelwahab, "Non-standard computational analysis of the stochastic covid-19 pandemic model: An application of computational biology," *Alexandria Engineering Journal*, vol. 61, no. 1, pp. 619–630, 2022.

[14] A. Omame, N. Sene, I. Nometa, C. I. Nwakanma, E. U. Nwafor, N. O. Iheonu, and D. Okuonghae, "Analysis of covid-19 and comorbidity co-infection model with optimal control," *Optimal Control Applications and Methods*, vol. 42, no. 6, pp. 1568–1590, 2021.

[15] T. N. Sindhu, A. Shafiq, and Q. M. Al-Mdallal, "On the analysis of number of deaths due to covid- 19 outbreak data using a new class of distributions," *Results in Physics*, vol. 21, p. 103747, 2021.

[16] A. Omame, D. Okuonghae, U. K. Nwajeri, and C. P. Onyenegecha, "A fractional-order multi-vaccination model for covid-19 with non-singular kernel," *Alexandria Eng. J.*, vol. 61, no. 8, pp. 6089–6104, 2022.

[17] M. Arfan, H. Alrabaiah, M. U. Rahman, Y.-L. Sun, A. S. Hashim, B. A. Pansera, A. Ahmadian, and S. Salahshour, "Investigation of fractal-fractional order model of covid-19 in pakistan under atangana-baleanu caputo (abc) derivative," *Results in Physics*, vol. 24, p. 104046, 2021.

[18] A. M. Balint, S. Balint, and A. Neculae, "On the objectivity of mathematical description of ion transport processes using general temporal caputo and riemann-liouville fractional partial derivatives," *Chaos, Solitons & Fractals*, vol. 156, p. 111802, 2022.

[19] S. Chatterjee, S. Biswas, A. Majee, S. Sen, D. Oliva, and R. Sarkar, "Breast cancer detection from thermal images using a grunwald-letnikov-aided dragonfly algorithm-based deep feature selection method," *Computers in biology and medicine*, vol. 141, p. 105027, 2022.

[20] M.-G. Ri and C.-H. Yun, "Riemann-liouville fractional derivatives of hidden variable recurrent fractal interpolation functions with function scaling factors and box dimension," *Chaos, Solitons & Fractals*, vol. 156, p. 111793, 2022.

[21] P. O. Mohammed, C. Kürt, and T. Abdeljawad, "Bivariate discrete mittag-leffler functions with associated discrete fractional operators," *Chaos, Solitons & Fractals*, vol. 165, p. 112848, 2022.

[22] D. Okuonghae and A. Omame, "Analysis of a mathematical model for covid-19 population dynamics in lagos, nigeria," *Chaos, Solitons & Fractals*, vol. 139, p. 110032, 2020.

[23] A. Ikpehai, B. Adebisi, K. M. Rabie, K. Anoh, R. E. Ande, M. Hammoudeh, H. Gacanin, and U. M. Mbanaso, "Low-power wide area network technologies for internet-of-things: A comparative review," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 2225–2240, 2018.

[24] K. Anoh, D. Bajovic, A. Ikpehai, B. Adebisi, and D. Vukobratovic, "Enabling peer to peer energy trading in virtual microgrids with lp-wan," in *IEEE EUROCON 2019-18th International Conference on Smart Technologies*, 2019, pp. 1–5.

[25] K. C. Okafor and O. M. Longe, "Smart deployment of iot-telosb service care streamrobot using software-defined reliability optimisation design," *Heliyon*, vol. 8, no. 6, 2022.

[26] J. Zhang, J. Jia, X. Song *et al.*, "Analysis of an seir epidemic model with saturated incidence and saturated treatment function," *The Scientific World Journal*, vol. 2014, 2014.

[27] P. Driessche and J. Watmough, "Reproduction numbers and sub-threshold endemic equilibria for compartmental models of disease transmission," *Mathematical biosciences*, vol. 180, no. 1-2, pp. 29–48, 2002.

[28] J. P. La Salle, *The stability of dynamical systems*. SIAM, 1976.

[29] A. I. Abioye, O. J. Peter, H. A. Ogunseye, F. A. Oguntolu, K. Oshinubi, A. A. Ibrahim, and I. Khan, "Mathematical model of covid-19 in nigeria with optimal control," *Results in Physics*, vol. 28, p. 104598, 2021.

[30] I. A. Baba, B. A. Baba, P. Esmaili *et al.*, "A mathematical model to study the effectiveness of some of the strategies adopted in curtailing the spread of covid-19," *Computational and mathematical methods in medicine*, vol. 2020, 2020.

[31] J. Piri, P. Mohapatra, H. K. R. Singh, B. Acharya, and T. K. Patra, "An enhanced binary multiobjective hybrid filter-wrapper chimp optimization based feature selection method for covid-19 patient health prediction," *IEEE Access*, vol. 10, pp. 100 376–100 396, 2022.

[32] G. Fort, B. Pascal, P. Abry, and N. Pustelnik, "Covid19 reproduction number: Credibility intervals by blockwise proximal Monte Carlo samplers," *IEEE Transactions on Signal Processing*, vol. 71, pp. 888–900, 2023.