

UNIVERSITY OF CAPE COAST

DEPARTMENT OF MATHEMATICS

Neural Network Parameter Estimation for Covid-19 with Vaccinated and
Timely-Delayed Diagnosis

BY

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MAT 499: PROJECT WORK

A PROJECT WORK SUBMITTED TO THE DEPARTMENT OF
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DECLARATION

CANDIDATE'S DECLARATION

I, **Samuel Kwame Dassi**, hereby, declare that in the exception of references made to research works, this project is the result of my own research and that no part of it has been presented for another degree in this university or elsewhere.

SAMUEL KWAME DASSI	DATE
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SUPERVISOR'S DECLARATION

I hereby declare that the preparation and presentation of the project work was supervised in accordance with guidelines on supervision of project work laid down by the University of Cape Coast, Ghana.

DR. STEPHEN E. MOORE	DATE
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ABSTRACT

In this project work, the researcher studied how deep neural networks, a subset of machine learning could be used to study estimate parameter sets for simulating COVID-19 in Ghana and by extension West Africa. From 1000 data points generated for 200-day periods, a trend was analysed, and all 21 parameters were estimated for all 9 compartments. One of the main focuses of this study was to minimise the loss of the model. From the loss curve, the Mean Squared Error (MSE) for the model decreased drastically as the number of iterations (epochs) increased. After 100000 epochs, the Sum of Squares Error dropped to 4.8806. For public health benefits, it was recommended that the adoption of Artificial Intelligence (AI) is possible for the study of infectious diseases such as Covid 19.

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DEDICATION

This project work is dedicated to my mentor, Dr. Stephen E. Moore, and also to
Precious Edinam Atsufui Vifa

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Chapter 1

INTRODUCTION

1.1 Background of the Study

The COVID-19 pandemic, caused by the novel coronavirus SARS-CoV-2, emerged in December 2019 and has since had a profound impact on global health and socioeconomic systems [40]. COVID-19, also known as "coronavirus disease 2019," "SARS-CoV-2 infection," or simply "coronavirus," has spread rapidly across the globe as reported by the Centre for Disease Control (CDC) [7]

On March 11, 2020, the World Health Organization declared COVID-19 a global pandemic, highlighting the urgent need for international cooperation and response to combat its widespread transmission and impact on public health and economies [40]. Since then, various countries, including Ghana, have implemented strategies to mitigate the spread of the virus.

According to the Ghana Health Service [14], Ghana reported its first

confirmed case of COVID-19 on March 12, 2020, and has since implemented a range of measures to control the pandemic. These include widespread testing, contact tracing, treatment protocols, and public health campaigns to promote preventive measures.

However, the effectiveness of these strategies can be influenced by factors such as the timeliness of diagnosis. Timely and accurate diagnosis is crucial for identifying and isolating infected individuals promptly, breaking the chain of transmission, and implementing appropriate interventions to control the spread of the virus.

Despite the efforts, the impact of delayed diagnosis on the dynamics and stability of COVID-19 transmission remains relatively unexplored in Ghana. This project aims to address this gap by investigating how Artificial Intelligence (AI) could be used to study COVID-19 transmission in Ghana, specifically focusing on the implications of timely and delayed diagnosis. Utilizing mathematical modelling techniques, we will analyze the interplay between diagnostic delays, infection rates, and the overall spread of the virus.

The findings of this project will provide insights into the potential consequences of delayed diagnosis on disease transmission and public health outcomes in Ghana. Public health authorities can leverage on the power of AI to effectively study the disease. This information will be essential for optimizing public health interventions, resource allocation, and decision-making processes to effectively control the spread of COVID-19.

As of the project's commencement in June 2023, Ghana has reported a

total of approximately 171,653 confirmed cases and 1,462 deaths due to COVID-19 [14]. These statistics underscore the urgent need to evaluate the impact of diagnostic delays and devise strategies to ensure timely and accurate diagnosis for effective disease management.

1.2 Purpose of the Study

The purpose of this study is to investigate the global stability dynamics and sensitivity assessment of COVID-19 transmission in Ghana, focusing on the implications of timely and delayed diagnosis. By employing mathematical modeling techniques and Deep Neural Network in Machine Learning, this research aims to analyze the interplay between diagnostic delays, infection rates, and the overall spread of the virus. The findings of this study will provide insights into the potential consequences of delayed diagnosis on disease transmission and public health outcomes in Ghana.

This study seeks to address the current research gap regarding the impact of diagnostic delays on the dynamics and stability of COVID-19 transmission specifically within the Ghanaian context. By examining the relationships between diagnostic delays, infection rates, and the spread of the virus, this study will contribute to the existing body of knowledge on COVID-19 dynamics and control measures.

The findings of this study will have practical implications for policymakers, healthcare professionals, and stakeholders involved in the management and prevention of COVID-19 in Ghana. By quantifying the impact of timely and de-

layed diagnosis, this study will contribute to enhancing the effectiveness of testing strategies, resource allocation, and public health interventions, ultimately aiding in the control of the pandemic.

1.3 Objectives of the Study

1. To analyze the dynamics of COVID-19 transmission in Ghana.
2. To develop a deep neural network parameter estimation to study Covid-19 in Ghana.
3. To provide evidence-based recommendations for optimizing COVID-19 interventions in Ghana and by extension sub-Saharan Africa.

1.4 Organization of the Study

This work consists of five chapters. Chapter One considers in detail the introduction of the whole research which includes the Background of the Study, the Purpose of the Study, the Objective of the Study, and the Organisation of the Study. Chapter two contains the Literature Review which examines relevant literature related to Mathematical epidemiology, Mathematical Modelling, Disease Free Equilibrium, and Endemic equilibrium. The Methodology of the work is considered in Chapter Three. The chapter considers the process involved in solving Vaccinated, Susceptible (S), Self-quarantine susceptible (Sq), Exposed (E), Infectious with timely diagnosis (I1), Infectious with delayed diagnosis (I2), Hospitalized (H), Recovered (R) and the Viral spread in the environment (Vs) using

neural network architecture. In Chapter Four, Numerical Results of solving a VSSqEI1I2HVsR model with vital dynamics by various methods can be found. Finally, Conclusions and Recommendations are presented in Chapter Five.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

In this chapter, relevant works done in the area of Global Stability Dynamics and Sensitivity Assessment of COVID-19 with timely-delayed Diagnosis with emphasis on Ghana are analyzed. The discussion is partitioned into various parts:

- epidemiology and its related concepts
- Timely and Delayed Diagnosis of Covid-19 in Ghana
- Mathematical Modelling of Covid 19
- Stability Analysis of Covid 19
- Equilibrium Condition of Covid 19

- Basic Reproductive Number (R_0) and its implication of Mathematical Models

2.2 The Concept of Epidemiology

2.2.1 Meaning of Epidemiology

The term epidemiology is the scientific discipline dedicated to studying the distribution, determinants, and effects of health-related events within populations. Epidemiology plays a pivotal role in public health by investigating disease patterns, identifying causes, and informing strategies for disease prevention and control.

Epidemiology is the field of study that examines patterns of health and illness in populations as well as the contributing causes. The Greek word *epi*, which means upon, is the source of the phrase epidemiology. The Greek words for study and people are respectively *demos* and *logos*. According to this derivation, human populations are the only ones to which epidemiology applies. Hippocrates, a Greek physician who lived from 460 to 377 B.C.E., is frequently recognized as the father of epidemiology for his descriptions of the relationship between illness and environment. The study of epidemics believed to have been first described as epidemiology in 1802 by the Spanish doctor de Villalba in the work *Epidemiologia* (*Espanola*). Epidemiological research were not widely used until the 20th century [28] .

Epidemiology can therefore be said to be the study of how illnesses spread through populations, mainly through the human populations. Building models,

estimating parameters, examining the sensitivity of models to changes in the parameters, and doing numerical simulations are frequently the tasks included in the job of a mathematical epidemiologist. Epidemiological research involves studying patterns of disease occurrence (such as the number of cases, their location, and timing) and identifying risk factors that contribute to the development and spread of diseases. These risk factors can be related to various aspects, such as genetic factors, environmental exposures, lifestyle choices, socioeconomic factors, and infectious agents. The study of epidemiology has lots of public health uses. [35] outlined a number of concepts in epidemiology which play an important role in the construction of mathematical models.

2.2.2 Epidemiology of Covid-19

COVID-19, an infectious respiratory illness caused by the severe acute respiratory syndrome–coronavirus 2 (SARS-CoV2), has now spread to multiple countries including India. The pace at which the disease spread in the last 4 months, since it was first recognized in China, is unprecedented. This review of the epidemiology of COVID-19 summarizes the burden of infection, transmission dynamics, and other related epidemiological features. While countries such as China, Italy, and the United States have particularly high rates of infection, the disease is gradually spreading in India as well, threatening the health and economy of the country. Transmission in asymptomatic cases, early symptomatic phase, as well as limited access to testing in different settings are factors that have led to the rapid spread of infection. A large case series from China revealed that 81 percent of cases had mild symptoms, 14 percent had severe disease, and 5 percent were afflicted with

critical illness. While the mortality in China was reported as 2.3 percent, Italy, with a high proportion of elderly, reported a case fatality report of 7.2 percent due to higher infection and mortality rates among the elderly. Being a highly infectious disease, with a basic reproduction number between 2 to 3, COVID-19 is affecting a large number of healthcare workers, as evidenced by the fact that a sizeable portion of reported infections in the US included healthcare workers. Delivering health care for both COVID-19-affected individuals, as well those with other acute and chronic conditions, with limited access to healthcare facilities and services, are challenges for the health systems in low- and middle-income countries, which require immediate measures for health system strengthening across sectors [36].

2.2.3 Susceptible Individuals

Susceptible individuals are those individuals who are not infected, however, could become infected. A susceptible individual may become infected or remain susceptible. As the virus spreads from its source or new sources occur, more individuals will become infected, thus the susceptible population will increase for a period of time (surge period) [19].

In the context of COVID-19, susceptible individuals refer to those who have not yet been infected with the SARS-CoV-2 virus or who do not have sufficient immunity against the virus. Susceptibility to COVID-19 can vary among individuals based on factors such as age, underlying health conditions, and immune status. The individuals in the general population are considered susceptible. This includes people of all ages and health statuses who have not yet been infected or vaccinated

against COVID-19. Individuals who have not yet received the vaccine also remain susceptible to the virus. People with weakened immune systems, such as those undergoing chemotherapy, organ transplant recipients, or individuals with certain autoimmune disorders, may have a higher susceptibility to COVID-19 due to their reduced ability to fight off infections. Although children can contract and transmit COVID-19, they generally have a lower risk of severe illness. However, their susceptibility to infection can still contribute to the overall transmission dynamics. It's important to note that susceptibility to COVID-19 can change over time due to vaccination efforts, natural infection, and the emergence of new variants of the virus. Public health measures such as vaccination campaigns, mask-wearing, and physical distancing aim to reduce the susceptibility of individuals and slow the spread of the virus within the population [41]. According to the Ghana Health Service [15], Ghana's cases have recorded 171657 cases with the Ashanti Region having the highest number of cases. This is shown in the map below:

This implies that more Ghanaians became susceptible to the virus

2.2.4 Infectious Diseases

Infectious diseases are disorders that are caused by organisms, usually microscopic in size, such as bacteria, viruses, fungi, or parasites that are passed, directly or indirectly, from one person to another. Humans can also become infected following exposure to an infected animal that harbors a pathogenic organism that is capable of infecting humans. Infectious diseases are a leading cause of death worldwide, particularly in low-income countries, especially in young children [6]. In 2019, two infectious diseases - lower respiratory infections and diarrheal diseases - were

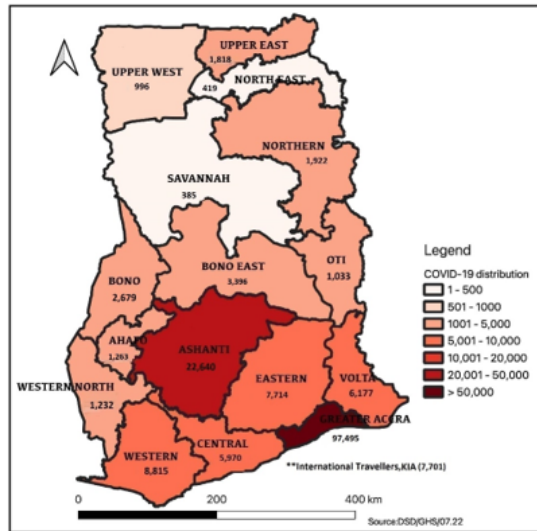


Figure 7: Cumulative cases of COVID-19 in Ghana by region, 24 Apr 2023

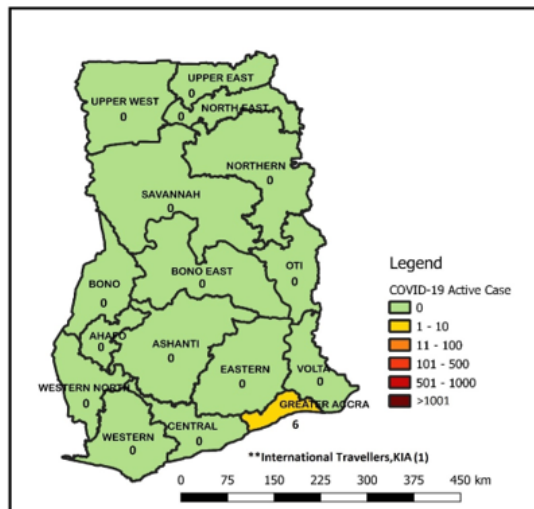


Figure 6: Active COVID-19 cases in Ghana by region, 24 Apr 2023

Figure 2.2.1: Active Covid-19 cases in Ghana by region

ranked in the top ten causes of death worldwide by the World Health Organization (WHO). Both of these diseases can be caused by a variety of infectious agents [40]. A newly emerged infectious disease, COVID-19, caused by the virus SARS-CoV-2, became a top cause of death in 2020. According to data analyzed by the Centers for

Disease Control and Prevention (CDC), COVID-19 was listed as the third leading cause of death in 2020 in the United States, behind heart disease and cancer[7].

Infectious diseases can be caused by several different classes of pathogenic organisms (commonly called germs). These are viruses, bacteria, protozoa, and fungi. Almost all of these organisms are microscopic in size and are often referred to as microbes or microorganisms. Although microbes can be agents of infection, most microbes do not cause disease in humans. In fact, humans are inhabited by a collection of microbes, known as the microbiome, which plays important and beneficial roles in our bodies. The majority of agents that cause disease in humans are viruses or bacteria, although the parasite that causes malaria is a notable example of a protozoan. Examples of diseases caused by viruses are COVID-19, influenza, HIV/AIDS, Ebola, diarrheal diseases, hepatitis, and West Nile. Diseases caused by bacteria include anthrax, tuberculosis, salmonella, and respiratory and diarrheal diseases [6].

In epidemiology, infected individuals refer to people who have contracted a specific infectious disease. An infected individual is someone who has been exposed to a pathogen, such as a virus, bacteria, or parasite, and as a result, has developed the infection caused by that pathogen. In this project, Infectious individuals are represented by (I). It is partitioned into two, namely, infectious with timely diagnosis (I1), and infectious with delayed diagnosis (I2). Infected individuals can transmit the pathogen to susceptible individuals through various routes, such as direct contact, respiratory droplets, contaminated surfaces, or vectors like mosquitoes or ticks. COVID-19 is transmitted by means of contact (direct or indirect), droplet spray in short-range transmission, and aerosol in long-range

transmission (airborne transmission) [27]. Infected individuals are those individuals who have already been infected by the virus and can transmit it to those individuals who are susceptible. An infected individual may remain infected, and can be removed from the infected population to recover or die [19]. Following an infection, some individuals may develop immunity to the pathogen, either through natural infection or vaccination. Understanding the proportion of immune individuals within a population is crucial for assessing the overall risk and potential for future outbreaks.

2.2.5 Exposed Individuals

In epidemiology, the term “exposure” can be broadly applied to any factor that may be associated with an outcome of interest. When using observational data sources, researchers often rely on readily available (existing) data elements to identify whether individuals have been exposed to a factor of interest [38].

An exposed individual thus refers to a person who has come into contact with a specific factor or condition that is being investigated as a potential risk for a particular disease or health outcome. This factor could be an infectious agent, a chemical substance, a physical hazard, or any other variable that is believed to have a causal relationship with the disease under investigation. The concept of exposure is fundamental in epidemiological studies, as it helps researchers understand the relationship between a potential risk factor and the occurrence of a disease or health outcome. By comparing exposed individuals to unexposed individuals, researchers can assess the association between the exposure and the outcome and determine the strength of the relationship. For example, in the context of an infec-

tious disease outbreak, an exposed individual could be someone who has had close contact with an infected person or who has visited a location where the infection is known to be spreading. By studying exposed individuals and monitoring their health outcomes, epidemiologists can gain insights into the transmission dynamics, risk factors, and preventive measures related to the disease.

In the context of COVID-19, an exposed individual refers to someone who has had close contact with a confirmed or suspected case of COVID-19. Close contact generally means being within approximately 6 feet (2 meters) of an infected person for a prolonged period of time (usually 15 minutes or more) or having direct physical contact with respiratory secretions (such as being coughed or sneezed on) from an infected person. When a person is identified as an exposed individual, it means they are at a higher risk of developing COVID-19 themselves due to their close contact with an infected individual. Public health authorities often recommend that exposed individuals monitor themselves for symptoms, undergo testing, and take appropriate precautions such as self-isolation or quarantine to prevent further transmission if they become infected. A healthy person who is susceptible to developing a disease contacts another person who may have the sickness causing them to become exposed. Individuals exposed to the sickness may or may not contract it. Most of the time, these people are not contagious. We frequently use the assumption in mathematical models that everyone exposed will eventually contract the illness [28].

2.2.6 Hospitalized Individuals

Hospitalized individuals are patients who have been admitted to a hospital for medical treatment and care. In the case of COVID-19, hospitalized individuals are those who have been diagnosed with the disease and require hospitalization due to the severity of their symptoms or complications.

Numerous studies have examined the clinical presentation and course of COVID-19 in hospitalized individuals. For example, a study published in JAMA Network Open in 2021 analyzed data from over 3,000 hospitalized COVID-19 patients in the United States and found that older age, male sex, and the presence of comorbidities such as obesity, diabetes, and hypertension were associated with a higher risk of severe outcomes such as ICU admission, mechanical ventilation, and death [29].

Another study published in The Lancet Respiratory Medicine in 2020 examined the clinical characteristics and outcomes of 191 hospitalized COVID-19 patients in Wuhan, China, and found that respiratory failure was the most common complication, with 42 percent of patients requiring mechanical ventilation. The study also found that older age, lymphopenia, and elevated levels of some inflammatory markers were associated with a higher risk of death [10].

These studies and others highlight the importance of early detection and timely management of COVID-19 in hospitalized individuals, particularly for those with underlying health conditions or other risk factors for severe disease. They also emphasize the need for ongoing research to better understand the clinical course and outcomes of COVID-19 in different populations and settings.

A situational update on COVID-19 in Ghana, the seventh African country reporting the most cases shows some modifications occurring within the health system to curtail the outbreak, and its potential impact on the delivery of antenatal care services is also highlighted. With the discovery of the Delta variant in Ghana, the current attention is to prevent a third wave of infection, and also control and manage existing cases. Efforts to procure vaccines, vaccinate special populations, and sensitize the public on the implications of vaccine hesitancy are ongoing. Amidst these activities, we suggest some innovations and countermeasures to safeguard primary healthcare services and potentially reinvest efforts towards achieving sustainable development goal three within the context of maternal healthcare, citing examples specific to developing countries. [2]

Studies show that certain common medical conditions put people at higher risk for severe illness from COVID-19. These include metabolic disorders like type 2 diabetes and obesity, as well as heart conditions like high blood pressure (hypertension) and heart failure. People with these four conditions are more likely to be hospitalized with COVID-19 [30].

2.2.7 Recovered or Removed Individuals

The epidemiology of Covid-19 has been studied extensively, including the clinical presentation, transmission dynamics, and risk factors for severe disease and death. One important aspect of Covid-19 epidemiology is the number of individuals who have recovered from the disease or have been removed from the population due to death. Understanding the characteristics and outcomes of recovered or removed individuals is crucial for public health planning and response.

Studies have shown that the characteristics of recovered or removed individuals vary depending on several factors, including age, comorbidities, and severity of illness. A study conducted in China found that the median age of recovered individuals was 47 years, and the most common comorbidities were hypertension and diabetes [42]. Another study from Italy reported that the median age of deceased individuals was 80 years, and the most common comorbidities were hypertension, diabetes, and ischemic heart disease [31]. These findings suggest that older individuals and those with underlying health conditions are at a higher risk of severe disease and death from Covid-19.

Richardson et al (2020) indicated that the outcomes of recovered or removed individuals also vary depending on several factors, including age, comorbidities, and severity of illness. A study conducted in the United States found that the mortality rate among hospitalized Covid-19 patients was highest among those aged 65 years or older [33]. Another study from China reported that the mortality rate among critically ill Covid-19 patients was higher among those with comorbidities such as hypertension and diabetes [43]. These findings suggest that older individuals and those with underlying health conditions are at a higher risk of mortality from Covid-19.

Understanding the characteristics and outcomes of recovered or removed individuals has important public health implications. For example, public health officials can use this information to develop targeted interventions to prevent severe disease and death among high-risk groups. In addition, understanding the long-term health effects of Covid-19 among recovered individuals is important for developing post-acute care and rehabilitation services.

2.3 Timely and Delayed Diagnosis of Covid-19 in Ghana

Several studies have reported on timely diagnosis of Covid-19 in Ghana. A study conducted by Amo-Addae et al. (2020) reported that the median time from symptom onset to diagnosis was 4 days. The study also found that the median time from diagnosis to isolation was 1 day [4]. Another study by Agyeman et al. (2020) reported that the median time from symptom onset to diagnosis was 5 days [3]. The study also found that the median time from diagnosis to isolation was 1 day. These findings suggest that timely diagnosis of Covid-19 is possible in Ghana.

Several factors contribute to delayed diagnosis of Covid-19 in Ghana. These include limited testing capacity, delays in receiving test results, and stigma associated with the disease. A study conducted by Owusu et al. (2021) reported that the median time from symptom onset to testing was 5 days. The study also found that the median time from testing to receiving test results was 2 days [32]. Another study by Yawson et al. (2021) reported that fear of stigma was a major barrier to seeking timely diagnosis and treatment for Covid-19 in Ghana [44]. These findings suggest that delayed diagnosis of Covid-19 is a significant challenge in Ghana.

Timely diagnosis of Covid-19 is crucial for effective case management and control of the disease. Delayed diagnosis, on the other hand, can lead to increased transmission and mortality. Public health officials can use this information to develop targeted interventions to address the factors contributing to delayed diagnosis of Covid-19 in Ghana. These interventions may include increasing testing

capacity, improving the timeliness of test results, and addressing the stigma associated with the disease.

2.4 Mathematical Modelling of Covid 19

Mathematical modeling has been extensively used to understand the dynamics and spread of Covid-19. Several studies have used mathematical models to predict the future trajectory of the pandemic, estimate the impact of control measures, and evaluate the effectiveness of different interventions.

2.4.1 Types of Mathematical Modelling

1. SEIR model: The SEIR (Susceptible-Exposed-Infectious-Recovered) model is one of the most commonly used mathematical models for studying infectious diseases like COVID-19. This model divides the population into four compartments: susceptible, exposed (infected but not yet infectious), infectious, and recovered. The model tracks the flow of individuals between these compartments over time to simulate the spread of the disease. The flow diagram of an SEIR model is illustrated in Figure 2.4.1
2. SIR model: The SIR (Susceptible-Infectious-Recovered) model is a simpler version of the SEIR model that does not include an exposed compartment. This model assumes that individuals become infectious immediately after being infected and does not account for the asymptomatic period before symptoms appear. The flow diagram of a simple SIRS model is illustrated

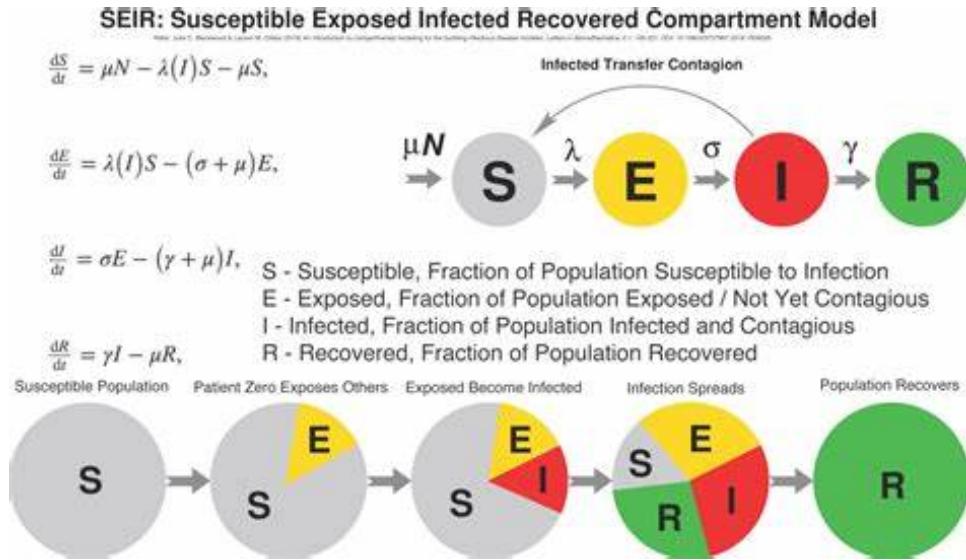


Figure 2.4.1: Flow diagram of the SEIR epidemic Model

in figure 2.4.2

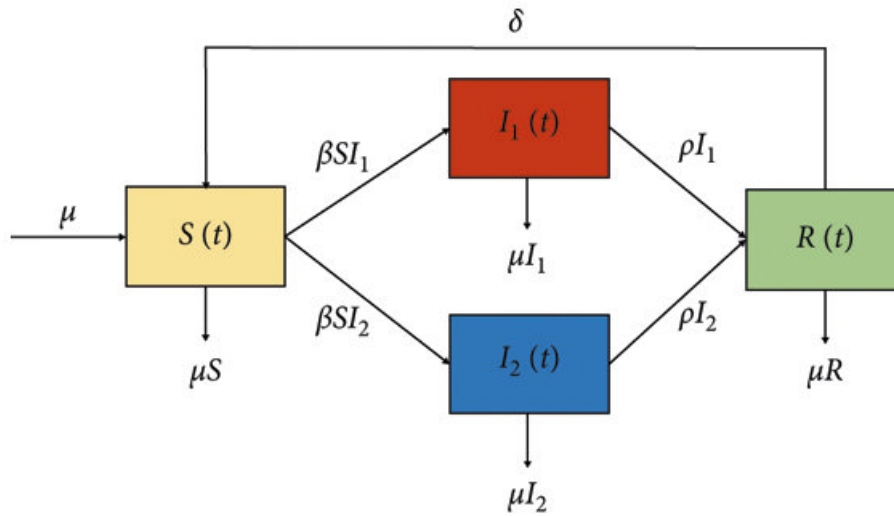


Figure 2.4.2: Flow diagram of SIRS epidemic model

3. Agent-based models: Agent-based models simulate the behaviour of individual agents (e.g. people) and their interactions within a population. These

models can be used to study the impact of social distancing measures, contact tracing, and other interventions on the spread of COVID-19.

4. Network models: Network models represent the connections between individuals in a population as a network and simulate the spread of the disease through this network. These models can be used to study the impact of super-spreader events and the effectiveness of targeted interventions.
5. Bayesian models: Bayesian models use statistical methods to estimate the parameters of a disease model based on observed data. These models can be used to make predictions about the spread of COVID-19 and the impact of interventions.

Overall, mathematical modeling has played a critical role in understanding the spread and impact of Covid-19 and has provided insights into the effectiveness of different interventions. However, it is important to note that these models are based on simplifying assumptions and may not fully capture the complexity of the pandemic. It needs to be understood that different models have different strengths and weaknesses, and the choice of model depends on the specific research question being addressed.

2.4.2 Advantages of Mathematical Modelling

1. Transmission dynamics: Mathematical models have been used to estimate the basic reproduction number (R_0) of the virus, which represents the average number of secondary infections caused by an infected individual. Estimates of R_0 vary depending on the population, location, and time period, but

generally range from 2 to 3. Modeling studies have also investigated the role of asymptomatic and pre-symptomatic transmission, the effect of age and comorbidities on transmission, and the impact of non-pharmaceutical interventions (NPIs) such as mask-wearing and social distancing [21].

2. Impact of interventions: Mathematical models have been used to evaluate the effectiveness of various NPIs, such as school closures, workplace distancing, and travel restrictions. Modeling studies have also investigated the impact of vaccination on reducing transmission and mortality. These studies have highlighted the importance of early implementation of interventions and the need for a combination of strategies to control the pandemic [12] [23].
3. Forecasting: Mathematical models have been used to forecast the trajectory of the pandemic, including the number of cases, hospitalizations, and deaths. These models have been updated over time to incorporate new data and improve the accuracy of predictions. Modeling studies have also investigated the potential impact of new virus variants on transmission and the effectiveness of vaccines [13].
4. Optimizing vaccination strategies: Mathematical models have been used to optimize vaccination strategies for COVID-19, such as prioritizing vaccination for certain age groups or occupations. These models consider factors such as the risk of severe disease and the likelihood of transmission to others to determine the most effective vaccination strategy.
5. Understanding the impact of population heterogeneity: Mathematical models have been used to understand the impact of population heterogeneity on the transmission of COVID-19. These models consider factors such as

age, occupation, and underlying health conditions to determine how different subpopulations contribute to the spread of the disease.

6. Modeling the impact of new variants: Mathematical models have been used to model the impact of new variants of COVID-19 and predict how they may affect the trajectory of the pandemic. These models consider factors such as the transmissibility and severity of the new variant to estimate its impact on the spread of the disease.

2.4.3 Limitations to Using Mathematical Modelling

1. Assumptions: Mathematical models rely on a set of assumptions about the disease, the population being studied, and the interventions being implemented. These assumptions may not always accurately reflect reality, and the model results may be sensitive to the assumptions made.
2. Data availability: Mathematical models rely on data to estimate parameters such as the infection rate and the effectiveness of interventions. However, data on COVID-19 is often incomplete or uncertain, which can limit the accuracy of model predictions.
3. Complexity: COVID-19 is a complex disease with many factors that can influence its transmission and impact. Mathematical models are simplifications of this complexity and may not capture all of the relevant factors.
4. Generalizability: Mathematical models are often developed for specific populations and settings and may not be generalizable to other populations or settings.

5. Interpretation: The interpretation of mathematical model results can be complex and may require expertise in mathematics, epidemiology, and public health. Misinterpretation of model results can lead to incorrect conclusions and inappropriate policy decisions.

Despite these limitations, mathematical models have been useful tools for understanding the transmission dynamics of COVID-19 and predicting the impact of interventions. Careful consideration of the assumptions made in models and the data used to parameterize them is important for ensuring that model results are accurate and informative

2.5 Stability Analysis of Covid-19

The COVID-19 pandemic has had a significant impact on global health and has resulted in widespread morbidity and mortality. Mathematical modeling has been widely used to study the transmission dynamics of COVID-19 and to inform public health policy. Stability analysis is one approach used in mathematical modeling to study the long-term behavior of a system.

Several studies have used stability analysis to study the transmission dynamics of COVID-19. For example, Feng et al. (2021) used a stability analysis to investigate the impact of contact tracing on the spread of COVID-19. They found that contact tracing can be an effective intervention for controlling the spread of the disease if it is implemented quickly and efficiently [11]. Similarly, Liu et al. (2020) used a stability analysis to study the impact of quarantine and

isolation measures on the transmission dynamics of COVID-19. They found that early implementation of quarantine and isolation measures can significantly reduce the spread of the disease [26].

Harko et al. (2020) used stability analysis to investigate the impact of vaccination on the transmission dynamics of COVID-19. They found that vaccination can be an effective intervention for controlling the spread of the disease if a sufficiently high vaccination rate is achieved . Another study by Li et al. (2021) used a stability analysis to investigate the impact of super-spreader events on the transmission dynamics of COVID-19. They found that reducing the number of super-spreader events can significantly reduce the spread of the disease [17] [24].

Stability analysis has also been used to evaluate the impact of specific interventions on the spread of COVID-19. For example, Chen et al. (2021) used a stability analysis to investigate the effectiveness of social distancing measures in controlling the spread of COVID-19. They found that social distancing measures can be effective in reducing the transmission rate of the disease if they are implemented early and consistently.

Stability analysis has also been used to evaluate the impact of travel restrictions on the spread of COVID-19. For example, Zou et al. (2020) used a stability analysis to investigate the impact of travel restrictions on the transmission dynamics of COVID-19. They found that travel restrictions can be an effective intervention for limiting the spread of the disease if they are implemented early and are sufficiently strict.

Stability analysis is a valuable tool for understanding the transmission

dynamics of COVID-19 and for evaluating the impact of interventions aimed at controlling the spread of the disease. Several studies have used stability analysis to investigate the effectiveness of interventions such as contact tracing, quarantine and isolation measures, vaccination, social distancing, and travel restrictions. These studies have provided valuable insights into the long-term behavior of the system and have informed public health policy.

2.5.1 Advantages of Using Stability Analysis of Covid-19

1. **Predicting Long-Term Behavior:** Stability analysis allows researchers to study the long-term behavior of the system and to predict the trajectory of the pandemic over time. This can be critical for informing public health policy and resource allocation. For example, a study by Harko et al. (2020) used stability analysis to predict the long-term behavior of the COVID-19 pandemic and to evaluate the impact of different interventions on the trajectory of the disease.

[?] **valuating the Impact of Interventions:** Stability analysis allows researchers to evaluate the impact of interventions aimed at controlling the spread of COVID-19. For example, a study by Liu et al. (2020) used stability analysis to evaluate the effectiveness of quarantine and isolation measures in reducing the transmission rate of the disease.

2. **Informing Policy Decisions:** Stability analysis can provide valuable insights into the effectiveness of different policy interventions and can inform policy decisions aimed at controlling the spread of COVID-19. For example, a study by Feng et al. (2021) used stability analysis to evaluate the impact of

contact tracing on the spread of COVID-19 and to inform the development of contact tracing policies.

3. Identifying Critical Parameters: Stability analysis can identify critical parameters of the model that impact the long-term behavior of the system. This can help researchers to prioritize data collection and inform the development of more accurate models. For example, a study by Li et al. (2021) used stability analysis to identify the impact of super-spreader events on the transmission dynamics of COVID-19.
4. Comparing Different Models: Stability analysis can be used to compare the long-term behavior of different models of COVID-19 transmission dynamics. This can help researchers to identify the best model for predicting the trajectory of the pandemic and for informing public health policy. For example, a study by Chen et al. (2021) used stability analysis to compare the long-term behavior of different models of COVID-19 transmission dynamics with and without social distancing measures.

Stability analysis is a valuable tool for studying the transmission dynamics of COVID-19 and for informing public health policy. It allows researchers to predict the long-term behavior of the system, evaluate the impact of interventions, inform policy decisions, identify critical parameters, and compare different models. While there are limitations to using stability analysis in COVID-19 modeling, such as simplifying assumptions and uncertainties in model parameters, its advantages make it an important tool for understanding and controlling the spread of the disease. See [17], [11], [26], [8],[24]

2.5.2 Limitations to Using Stability Analysis of Covid-19

1. Simplifying assumptions: Stability analysis often relies on simplifying assumptions about the underlying system, which may not fully capture the complexity of COVID-19 transmission dynamics. For example, stability analysis may assume that the population is homogeneous, or that the disease spreads through a single mode of transmission. In reality, the population is heterogeneous and the disease can spread through multiple modes of transmission, which may impact the accuracy of stability analyses.
2. Uncertainty in model parameters: Stability analysis relies on accurate estimation of model parameters, such as the transmission rate and recovery rate. However, these parameters are often uncertain, particularly early in the pandemic when data is limited. This uncertainty can impact the accuracy of stability analyses and the validity of conclusions drawn from them.
3. Limited ability to capture short-term dynamics: Stability analysis is often used to study the long-term behavior of a system, but may not capture short-term dynamics such as the impact of policy interventions or changes in behavior. Short-term dynamics can be critical for understanding the effectiveness of interventions and forecasting the trajectory of the pandemic.
4. Limited ability to capture spatial dynamics: Stability analysis is often used to study the dynamics of the disease at a population level, but may not capture the spatial dynamics of the disease, such as the impact of regional differences in policy or behavior. This can limit the ability of stability analysis to inform local policy decisions.

Overall, while stability analysis is a valuable tool for understanding the transmission dynamics of COVID-19, it is important to recognize its limitations and to use it in conjunction with other modeling approaches and empirical data to inform public health policy.

2.6 Equilibrium Condition of Covid-19

Equilibrium condition is an important concept in the mathematical modeling of infectious diseases, including COVID-19. In an equilibrium state, the number of new infections is equal to the number of recoveries or deaths, and the disease prevalence remains constant over time. In this review, we examine the literature on the equilibrium condition of COVID-19 and its relevance for understanding the transmission dynamics and control of the disease. Several studies have used the equilibrium condition to study the transmission dynamics of COVID-19. For example, Harko et al. (2020) used the equilibrium condition to derive analytical solutions for the Susceptible-Infected-Recovered (SIR) model of COVID-19 transmission dynamics. They found that the equilibrium state is stable under certain conditions and that the disease prevalence can be controlled through interventions such as vaccination [18].

Similarly, Zhang et al. (2020) used the equilibrium condition to study the impact of interventions such as quarantine and social distancing on the transmission dynamics of COVID-19. They found that these interventions can be effective in reducing the disease prevalence and preventing the healthcare system from becoming overwhelmed [45].

The equilibrium condition is relevant for understanding the control of COVID-19. If the disease prevalence is above the equilibrium level, the number of new infections will increase over time, while if the disease prevalence is below the equilibrium level, the number of new infections will decrease. Therefore, interventions aimed at reducing the disease prevalence, such as vaccination, social distancing, and quarantine, can bring the disease below the equilibrium level and reduce the number of new infections over time.

The equilibrium condition can also be used to evaluate the impact of different interventions on the transmission dynamics of COVID-19. For example, a study by Tang et al. (2020) used the equilibrium condition to evaluate the effectiveness of travel restrictions in controlling the spread of COVID-19. They found that travel restrictions can be effective in reducing the disease prevalence and preventing the spread of the disease across borders [37].

One limitation of using the equilibrium condition in COVID-19 modeling is that it assumes a homogeneous population, which may not accurately capture the complexity of the disease transmission dynamics. Furthermore, the equilibrium condition may not be applicable in situations where the disease prevalence is changing rapidly, such as during a surge in cases.

The equilibrium condition is a useful concept in understanding the transmission dynamics and control of COVID-19. It allows researchers to study the stability of the disease prevalence over time and to evaluate the effectiveness of interventions aimed at reducing the disease prevalence. While there are limitations to using the equilibrium condition in COVID-19 modeling, its relevance in understanding the control of the disease makes it an important tool for informing

public health policy.

2.7 Basic Reproductive Number (R_0) and it's Implication of Mathematical Models

The basic reproductive number (R_0) is a fundamental concept in epidemiology that represents the average number of secondary infections generated by a single infected individual in a susceptible population. In the context of COVID-19, R_0 is an important parameter in mathematical models that are used to study the transmission dynamics of the disease and to evaluate the impact of interventions aimed at controlling its spread. In this review, we examine the literature on R_0 and its implications for mathematical models of COVID-19.

Several studies have used R_0 to model the transmission dynamics of COVID-19. For example, a study by Liu et al. (2020) used an SEIR (Susceptible-Exposed-Infectious-Removed) model to estimate the R_0 of COVID-19 in Wuhan, China and found it to be 3.77. Similarly, a study by Sanchez et al. (2020) estimated the R_0 of COVID-19 to be 2.2 based on data from China, and found that the disease was highly transmissible. See [25] and [34]

R_0 has important implications for the control of COVID-19. If R_0 is greater than 1, the disease will continue to spread and the epidemic will continue to grow. If R_0 is less than 1, the disease will eventually die out. Therefore, interventions aimed at reducing R_0 , such as vaccination, social distancing, and quarantine, can be effective in controlling the spread of the disease.

Mathematical models that incorporate R_0 can be used to evaluate the impact of different interventions on the transmission dynamics of COVID-19. For example, a study by Kucharski et al. (2020) used a mathematical model to evaluate the effectiveness of different interventions, including social distancing and school closures, in reducing R_0 and controlling the spread of the disease. They found that a combination of interventions was necessary to reduce R_0 below 1 and control the epidemic [20].

A study by Adom et al. (2021) used an SEIR (Susceptible-Exposed-Infectious-Removed) model to estimate the R_0 of COVID-19 in Ghana and found it to be 1.66, indicating that the disease was moderately transmissible. Similarly, a study by Asamoah et al. (2020) estimated the R_0 of COVID-19 in Ghana to be 2.00 based on data from the early stages of the pandemic [1] and [5].

R_0 has important implications for the control of COVID-19 in Ghana. If R_0 is greater than 1, the disease will continue to spread and the epidemic will continue to grow. If R_0 is less than 1, the disease will eventually die out. Therefore, interventions aimed at reducing R_0 , such as vaccination, social distancing, and quarantine, can be effective in controlling the spread of the disease in Ghana.

Mathematical models that incorporate R_0 can be used to evaluate the impact of different interventions on the transmission dynamics of COVID-19 in Ghana. For example, a study by Adom et al. (2021) used a mathematical model to evaluate the effectiveness of different interventions, including social distancing and mask-wearing, in reducing R_0 and controlling the spread of the disease in Ghana. They found that a combination of interventions was necessary to reduce R_0 below 1 and control the epidemic [1]. In the earlier periods of the virus in

Ghana, Moore et al (2022) observed a basic reproductive number of 1.04 and thus recommended that all persons should keep to the regular washing of hands with soap and alcohol-based sanitizer whenever they use public facilities since this will help reduce the spread of the virus by exposed individuals. They also noticed that timely diagnosis can reduce the number of exposed individuals in Ghana, hence, they suggest that the government should increase its efforts in diagnoses so as to reduce the number of infected individuals in each community [35].

One limitation of using R_0 in COVID-19 modeling is that it assumes a homogeneous population, which may not accurately capture the complexity of the disease transmission dynamics. Furthermore, R_0 may not be applicable in situations where the disease transmission dynamics are changing rapidly, such as during a surge in cases.

In conclusion, R_0 is a fundamental concept in epidemiology that has important implications for mathematical models of COVID-19. It allows researchers to model the transmission dynamics of the disease and to evaluate the impact of interventions aimed at controlling its spread. While there are limitations to using R_0 in COVID-19 modeling, its relevance for understanding the transmission dynamics and control of the disease makes it an important tool for informing public health policy.

Chapter 3

METHODOLOGY

3.1 Introduction

This chapter focuses on the analysis and prediction of COVID-19 trends in Ghana using Python and neural network techniques. In this chapter, we will explore the use of machine learning algorithms to predict the spread of COVID-19 and assess the sensitivity of the predictions to various factors such as diagnosis time delays and travel restrictions.

The COVID-19 pandemic has had a significant impact on countries around the world, including Ghana. As the number of cases continues to rise, it is essential to understand the dynamics of the disease's spread and to develop effective strategies for controlling its transmission. This chapter addresses these issues by analyzing the global stability dynamics of COVID-19 and assessing the sensitivity of the predictions to timely-delayed diagnoses in Ghana.

To achieve this objective, we will use Python programming language to analyze the data and build a neural network model for predicting the spread of COVID-19. We will use various techniques such as data preprocessing, feature engineering, and model selection to develop an accurate and reliable model. Once the model is developed, we will assess its sensitivity to various factors and evaluate its performance using appropriate metrics.

3.2 Data

As our study involved the application of Neural Networks on the study spread of COVID-19 data was a key aspect of the research. The data used in the various model consists of the COVID-19 data generated over a period of 200 periods (days). From day 0 to day 200, 1000 data points were generated. The total population size (N) was 30417856. Everyone starts out as susceptible except for those initially exposed, infected, and hospitalized. The first two cases of COVID-19 in Ghana were reported on March 12, 2020. The cases were both imported from Norway and Turkey by two Ghanaian citizens who had returned to Ghana as reported by the Ghana Health Service.

3.3 Model Formulation

The total human population size of Ghana as denoted by (N) is divided into Vaccinated (V), Susceptible (S), Self-quarantine Susceptible (S_q), Exposed (E), Infectious with timely diagnosis (I_1), Infectious with delayed diagnosis (I_2), hos-

pitalized (H) and recovered (R). The viral spread in the environment is denoted as (V). The recovered population at some time become susceptible to the virus. This was due mainly to the persistent mutation and behavior of the SARS-COV2 virus. COVID-19 has been changing and evolving since it was first identified in December 2019. The virus that causes COVID-19, known as SARS-CoV-2, is an RNA virus, which means that it has a high mutation rate and can undergo genetic changes over time. One of the earliest known changes to SARS-CoV-2 occurred in January 2020, when a variant of the virus emerged in Wuhan, China. This variant, known as the D614G mutation, is thought to have increased the virus's ability to infect human cells and may have contributed to its increased transmissibility [7].

Since then, numerous variants of SARS-CoV-2 have emerged, some of which have been associated with increased transmissibility, severity of disease, and resistance to vaccines. These include the Alpha, Beta, Gamma, and Delta variants, among others. The emergence of new variants of SARS-CoV-2 highlights the need for ongoing surveillance and monitoring of the virus to understand its evolution and to develop effective strategies for controlling its spread. Hence for the total human population at time t we have

$$N(t) = V(t) + S(t) + Sq(t) + E(t) + I1(t) + I2(t) + H(t) + R(t)$$

It is also considered that all parameters are positive and it is only the $I1$, $I2$, and H compartments that experience disease-induced death at a rate, d .

The compartmental flow diagram is illustrated in the figure below

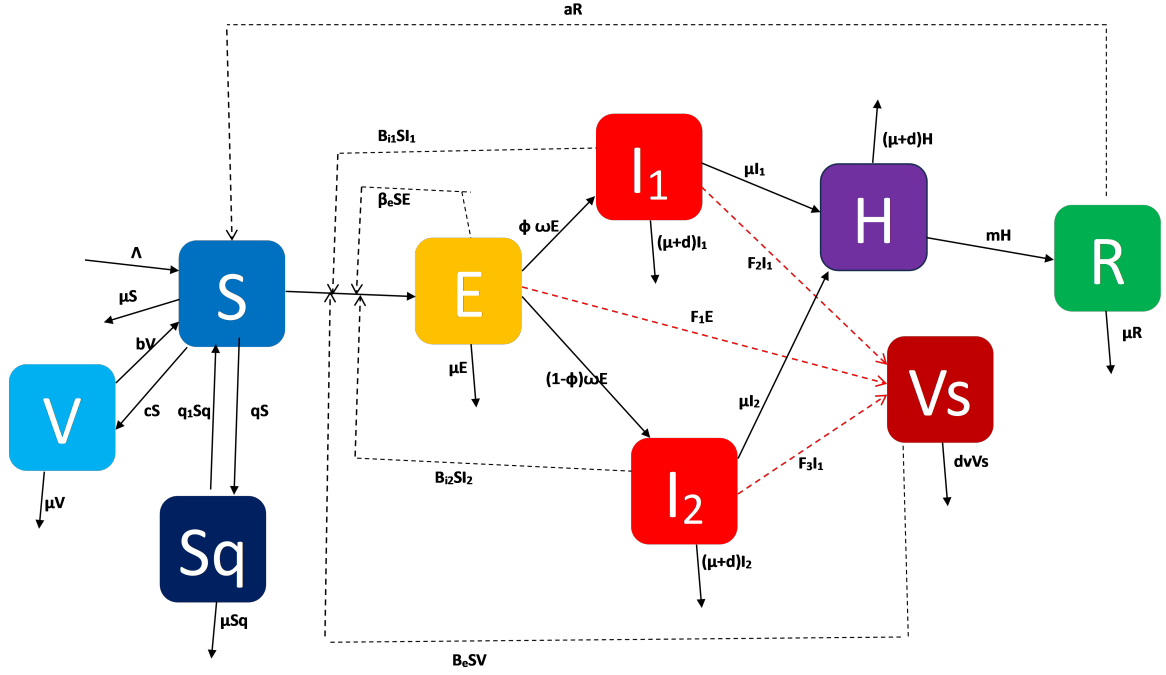


Figure 3.3.1: Flow diagram of VSSqEI1I2HVsRS Covid 19 model

Consider the system of Ordinary Differential Equations (ODEs):

$$\begin{aligned}
 \frac{dV}{dt} &= aS - \mu V - bV \\
 \frac{dS}{dt} &= \Lambda + bV - \lambda S + q1Sq - (\mu + q)S + cR \\
 \frac{dSq}{dt} &= qS - q1Sq - \mu Sq \\
 \frac{dE}{dt} &= \lambda S - \omega E - \mu E \\
 \frac{dI1}{dt} &= \phi\omega E - \gamma1I1 - \mu I1 - dI1 \\
 \frac{dI2}{dt} &= (1 - \phi)\omega E - \gamma2I2 - \mu I2 - dI2 \\
 \frac{dH}{dt} &= \gamma1I1 + \gamma2I2 - mH - \mu H - dH \\
 \frac{dR}{dt} &= mH - \mu R - cR \\
 \frac{dVs}{dt} &= f1E + f2I1 + f3I2 - dvVs
 \end{aligned} \tag{3.3.1}$$

The various compartments are explained in the table.

Table 3.1: Compartmental Explanations

Compartments	Explanations
V	Vaccinated class
S	Susceptible
Sq	Self-quarantine susceptible
E	Exposed
I1	Infectious with timely diagnosis
I2	Infectious with delayed diagnosis
H	Hospitalized
Vs	The viral spread in the environment
R	Recovered
N	Total human population

The parameters values used in the model are indicated in the Tables 3.2 and 3.4

Table 3.2: Parameters used in the DINN model and their descriptions

Parameter	Description
Λ	Recruitment rate
a	Vaccination rate. Percentage of the susceptible class that got vaccinated
b	Percentage of the vaccinated class that lost their vaccination
c	Percentage of recovered class who become susceptible to the virus after time t
q	Self-quarantined rate of the susceptible
$q1$	Transition rate of self-quarantined individuals to the susceptible
βe	Transmission rate from the exposed to the susceptible
$\beta i1$	Transmission rate from the infectious with timely diagnosis to the susceptible
$\beta i2$	Transmission rate from the infectious with delayed diagnosis to the susceptible
βv	Transmission rate from the susceptible to the exposed (infected by virus)
$\frac{1}{\omega}$	Incubation period
Φ	Proportion of the infectious with timely diagnosis
$\frac{1}{\gamma 1}$	Waiting time of the infectious for timely diagnosis
$\frac{1}{\gamma 2}$	Waiting time of the infectious for delayed diagnosis
μ	Natural human death rate
d	Disease-induced death rate
m	Recovery rate of the hospitalized
$f1$	Virus released rate of the exposed
$f2$	Virus released rate of the infectious with timely diagnosis
$f3$	Virus released rate of the infectious with delayed diagnosis
dv	Decay rate of virus in the environment

Table 3.3: Parameters and Values

Parameters	Values	Parameters	Values
a	0.73589	βe	6.0380e-8
b	0.32	$\beta i1$	3.8196e-8
c	0.936	$\beta i2$	1.4286e-5
Λ	1319.294	Φ	0.9000
q	0.0333	$\gamma 1$	0.5000
$q1$	1.6945e-5	$\gamma 2$	0.0714
d	0.006139	m	4.2578e-5
$f1$	0.0178	βv	4.00199e-8
$f2$	0.3115	ω	1/5.2
$f3$	4.6131e-5	μ	4.2578e-5
dv	0.3117		

3.4 Using Neural Network to Predict the Spread of Covid-19 in Ghana

3.4.1 Introduction

A neural network is a type of machine learning algorithm that is modeled after the structure and function of the human brain. It consists of layers of interconnected nodes, or artificial neurons, that process and transmit information. Neural networks have become increasingly popular in recent years due to their ability to learn complex patterns and make accurate predictions on a wide range of tasks such as image classification, language translation, and speech recognition.

In a neural network, each node receives input data and performs a simple mathematical operation on it. The output of each node is then passed on to other nodes in the network, which allows the network to learn increasingly complex patterns and relationships within the data. The weights and biases of the connections between the nodes are adjusted during training to minimize the difference between the predicted output and the actual output.

Neural networks have found applications in a wide range of fields, including computer vision, natural language processing, and finance. They have been used to develop self-driving cars, improve medical diagnoses, and even create artwork. While neural networks have shown great success in many areas, they can be difficult to train and require large amounts of data and computational resources. However, with advancements in technology and research, neural networks are likely to continue to be an important tool for machine learning and artificial intelligence

in the future. See [16] [22]

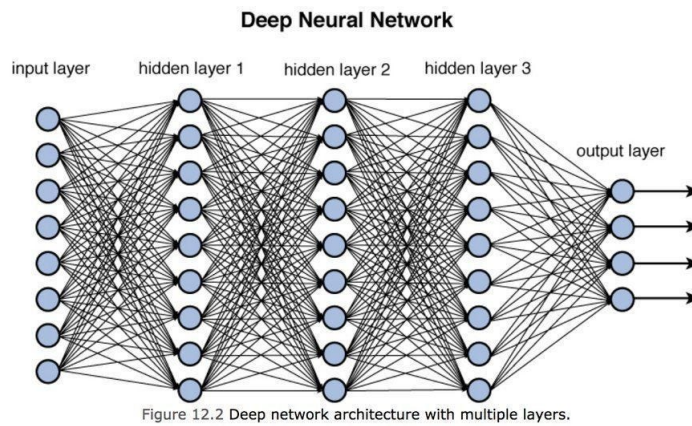


Figure 3.4.1: The structure of a deep neural network



Figure 3.4.2: The Neural network works as the brain functions

Using a neural network to predict the spread of Covid 19 in Ghana is an attempt to dig into the new space of Artificial Intelligence and Machine Learning to the benefit of the Ghanaian health sector. In the study of Covid 19, Neural Network

was employed to study and predict the spread of COVID-19 by analyzing data generated. The neural network was trained to learn the patterns and relationships within the data and make predictions about the future spread of the disease.

Once trained, the neural network can be used to make predictions about the spread of the disease in Ghana and by extension the Sub Saharan Africa to help public health officials to make informed decisions about how to allocate resources and implement interventions to slow the spread of the disease.

3.4.2 How the Neural network works

A neural network works by processing and transmitting information through interconnected nodes, or artificial neurons, that are organized into layers. The input layer receives input data, which is then passed through one or more hidden layers before reaching the output layer, which produces the final output of the network.

Each node in the network performs a simple mathematical operation on its inputs, such as a weighted sum or a non-linear activation function. The output of each node is then passed on to other nodes in the network, which allows the network to learn increasingly complex patterns and relationships within the data.

During training, the weights and biases of the connections between the neurons in the network are adjusted to minimize the difference between the predicted output and the actual output. This is typically done using a process called backpropagation, which calculates the gradient of the loss function with respect to each weight and bias in the network and updates them accordingly. The various processes that the Neural Network passes are explained in the next subsection.

3.4.3 Components of Neural Network

A neural network is made up of various components that work in tandem to process and transmit information through the network. These components include an input layer, hidden layers, and an output layer. All these layers work together to effectively predict the spread of the Covid 19 and the other compartments. The input layer is responsible for receiving input data, while the hidden layers are responsible for carrying out the bulk of the computation in the network. The output layer produces the final output of the network.

The neurons in a neural network are the basic processing units and are responsible for receiving inputs from other neurons and producing an output. The connections between neurons are determined by weights and biases, which are adjusted during training to minimize the difference between the predicted output and the actual output. An activation function is used to introduce non-linearity into the network by transforming the output of a neuron into a non-linear function of its input.

Finally, the loss function measures the difference between the predicted output and the actual output. This function is used during training to adjust the weights and biases of the network to minimize the loss. Overall, these components work together to allow the network to learn complex patterns and make accurate predictions on

3.4.4 Deep Implicit Neural Network (DINN)

A deep Implicit Neural Network (DINN) is a type of neural network that is designed to learn implicit functions. Similar to other neural networks, it consists of input and output layers, as well as multiple hidden layers that perform computations on the input data in this case eight(8) hidden layers.

The key difference between DINN and other neural network architectures like Convolutional Neural Networks (CNN) for image recognition and Recurrent Neural Networks (RNN) for sequential data is that it learns an implicit function instead of an explicit function. In an explicit function, the output is a direct function of the input. In contrast, an implicit function describes a relationship between the input and output without explicitly defining the function. DINN can learn these implicit functions by using a loss function that measures the difference between the predicted output and the actual output.

Deep Implicit Neural Network (DINN) was used because it is a powerful and innovative type of neural network that has shown great potential in learning implicit functions and solving complex problems in various fields. The simple and deep neural networks are illustrated in figure 3.4.3

3.5 The Activation Functions Used in the Model

The activation function in a neural network is a crucial component of each artificial neuron (also known as a node or unit). It introduces non-linearity to the network, allowing it to learn and approximate complex relationships in the data.

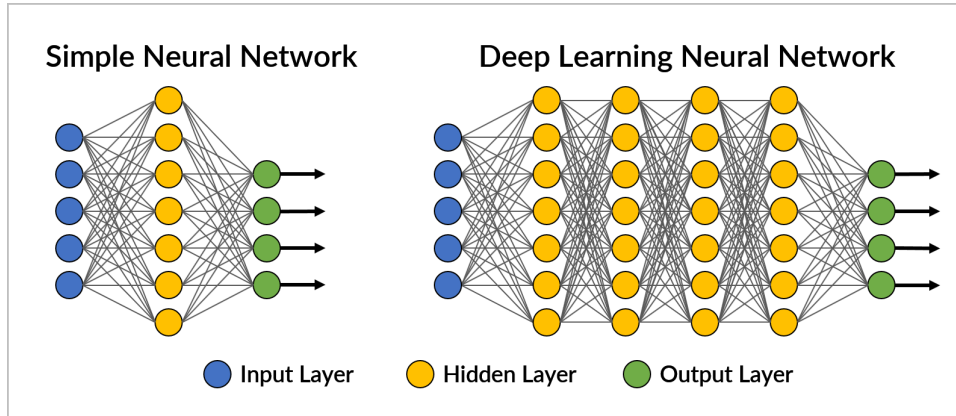


Figure 3.4.3: A simple and Deep Neural network

When information is passed through an artificial neuron, the activation function determines whether the neuron should be "activated" (i.e., produce an output) based on the weighted sum of its inputs. The activation function adds flexibility to the model, enabling it to model non-linear mappings between inputs and outputs.

Mathematically, the activation function takes the weighted sum of inputs (including a bias term) and applies a transformation to produce the output of the neuron. The output is then passed to the next layer of neurons or used as the final output of the neural network.

There are several popular activation functions used in neural networks:

1. Sigmoid Function (Logistic Function):

$$f(x) = \frac{1}{1 + e^{-x}}$$

The sigmoid function squashes the output between 0 and 1, making it useful for binary classification problems. However, it suffers from the vanishing gradient

problem, which can slow down the learning process in deep networks.

2. Rectified Linear Unit (ReLU):

$$f(x) = \max(0, x)$$

ReLU sets negative values to zero and keeps positive values unchanged. It is widely used due to its simplicity and ability to address the vanishing gradient problem.

3. Leaky ReLU:

$$f(x) = \begin{cases} x, & \text{if } x > 0 \\ \alpha x, & \text{otherwise} \end{cases}$$

Leaky ReLU is a variant of ReLU that introduces a small slope for negative inputs (typically α is a small positive value), preventing neurons from completely dying.

4. Hyperbolic Tangent (tanh):

$$f(x) = \frac{2}{1 + e^{-2x}} - 1$$

Tanh squashes the output between -1 and 1, making it useful for classification problems that need outputs ranging from negative to positive.

In this model, the Rectified Linear Unit and the Hyperbolic Tangent functions were implemented. This was because of the following benefits

For Rectified Linear Unit (ReLU):

1. ReLU is a simple activation function, computationally efficient, and easy to implement. It only involves a thresholding operation that sets negative values to zero.
2. ReLU helps alleviate the vanishing gradient problem, which can occur with activation functions like sigmoid or tanh. By eliminating negative values, ReLU ensures that gradients do not become too small during backpropagation, leading to faster convergence during training.
3. ReLU neurons can be sparsely activated, meaning that they are either fully active (output is positive) or inactive (output is zero). This sparsity property can make the network more efficient in terms of computation and memory usage.

For the Hyperbolic Tangent (tanh):

1. The tanh activation function outputs values between -1 and 1, which can be useful for tasks where the output needs to be centered around zero. All the twenty-one (21) parameters were forced to be within the (-1,1) range
2. The tanh function is an improvement over the sigmoid function. It is a scaled and shifted version of the sigmoid, and it suffers less from the vanishing gradient problem.
3. Like ReLU, tanh also introduces non-linearity to the network, allowing it to model more complex relationships in the data.

3.6 The Processes of the Neural Network

3.6.1 Forward Propagation

Forward propagation is the process by which input data is processed through a neural network to produce an output. It involves passing the input data through the layers of the network, with each layer carrying out a specific computation on the data.

The process of forward propagation begins with the input layer, which receives input data in the form of a vector or matrix. The input data is then passed forward through the hidden layers of the network, with each layer performing a linear transformation on the input data followed by a non-linear activation function. The linear transformation involves multiplying the input data by a weight matrix

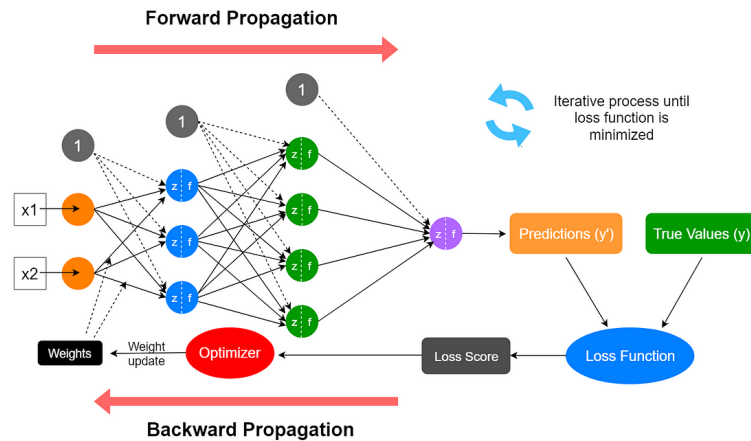


Figure 3.6.1: The Forward Propagation Process of Neural Network

and adding a bias vector. The weight matrix and bias vector are parameters of the neural network that are learned during training to minimize the difference between

the predicted output and the actual output. This can be expressed mathematically as:

$$z = Wx + b$$

where:

z is the output of the linear transformation

W is the weight matrix, with dimensions $(m \times n)$, where m is the number of neurons in the current layer and n is the number of neurons in the previous layer

x is the input data, with dimensions $(n \times 1)$, where n is the number of neurons in the previous layer. The nine compartments for Vaccinated (V), Susceptible (S), Self-quarantine Susceptible (Sq), Exposed (E), Infectious with timely diagnosis (I1), Infectious with delayed diagnosis (I2), hospitalized (H), viral spread in the environment (V) and recovered (R).

b is the bias vector, with dimensions $(m \times 1)$

The non-linear activation function introduces non-linearity into the network by transforming the output of the linear transformation into a non-linear function of its input using the two functions: ReLU and tanh.

The output of the last layer of the network is the final output of the network. This output can be used to make a prediction or to compute the loss function, which measures the difference between the predicted output and the actual output.

3.6.2 Backward Propagation

Backward propagation, also known as backpropagation, is the process by which the error between the predicted output and the actual output of a neural network is used to update the weights and biases of the network. It involves calculating the gradient of the loss function with respect to the weights and biases of the network, and then using this gradient to update the weights and biases through an optimization algorithm such as gradient descent.

The backward propagation process can be broken down into several mathematical operations:

1. Loss function calculation:

The first step of the backward propagation process is to compute the loss function, which measures the difference between the predicted output and the actual output. There are several types of loss functions, including mean squared error, cross-entropy, and hinge loss.

$$L = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

where:

L is the mean squared error loss function

N is the number of training examples

y_i is the actual output for the i -th training example

\hat{y}_i is the predicted output for the i -th training example

2. Calculate the gradient of the loss function:

The next step is to compute the gradient of the loss function with respect to the weights and biases of the network. This is done using the chain rule of calculus to propagate the error backward through the layers of the network. The gradient is typically computed using a technique called automatic differentiation.

$$\frac{\partial L}{\partial W} = \frac{1}{N} X^T (\hat{y} - y) + \lambda W$$

where:

$\frac{\partial L}{\partial W}$ is the gradient of the loss function with respect to the weight matrix W

X is the input data matrix

y is the actual output vector

\hat{y} is the predicted output vector

N is the number of training examples

λ is the regularization parameter.

3. Weight and bias updates:

Once the gradient of the loss function has been computed, it is used to update the weights and biases of the network through an optimization algorithm (gradient descent). The weight and bias updates are typically proportional to the negative gradient of the loss function, and the learning rate determines the step size of the updates.

$$W = W - \alpha \frac{\partial L}{\partial W}$$

$$b = b - \alpha \frac{\partial L}{\partial b}$$

where:

W is the weight matrix

b is the bias vector

α is the learning rate

$\frac{\partial L}{\partial W}$ is the gradient of the loss function with respect to the weight matrix

$\frac{\partial L}{\partial b}$ is the gradient of the loss function with respect to the bias vector.

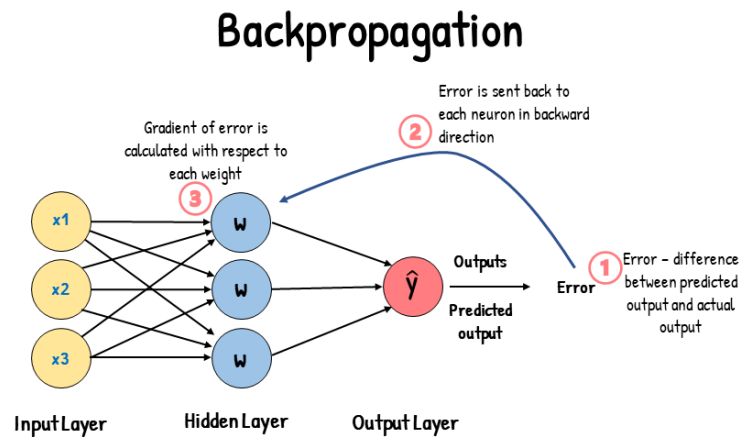


Figure 3.6.2: The Backward Propagation Process of Neural Network

3.7 Learning Rate used in Training the Neural Network Model

The learning rate is a hyperparameter used in training machine learning models, particularly in gradient-based optimization algorithms, to control the step size at each iteration during the optimization process. The learning rate decides how quickly or slowly a model learns from the data during training. Common learning rate values are between 0.1 and 0.00001

The learning rate can be represented by η and is typically a small positive number between 0 and 1. The learning rate is used to update the model's parameters, such as the weights and biases, based on the gradient of the loss function with respect to the parameters. The update rule for a parameter w using SGD with a learning rate η and a gradient ∇L is given by:

$$w = w - \eta \nabla L \quad (3.7.1)$$

This equation means that the current value of the parameter w is updated by subtracting the product of the learning rate η and the gradient of the loss function ∇L with respect to the parameter w . The learning rate determines the step size of the update and can have a significant impact on the convergence of the optimization process.

A learning rate of 0.001 was defined for training the model. The CyclicLR scheduler was used to implement a cyclical learning rate policy that gradually varies the learning rate between the base learning rate of 0.000001 and the max

learning rate of 0.1 over a cycle. The cycle is determined by the step size of 4000, which indicates the number of steps to increase the learning rate from the base learning rate to the max learning rate.

3.7.1 Scheduling the Learning Rate

The Cyclic Learning Rate (CLR) scheduler, also known as the CyclicLR scheduler, is a learning rate scheduling technique used during the training of neural networks. It introduces cyclical variations in the learning rate over the course of training instead of using a fixed learning rate. The main benefit of using the CyclicLR scheduler includes:

1. **Faster convergence:** By varying the learning rate in a cyclic manner, the CyclicLR scheduler enables the model to explore different learning rates during training. This exploration can lead to faster convergence, especially in cases where a single fixed learning rate might not be optimal for the entire training process. The cyclic behavior can help the model to escape sharp local minima and find better solutions.
2. **Improved generalization:** The cyclical learning rate policy helps the model generalize better to unseen data. It allows the model to avoid getting stuck in narrow areas of the loss landscape and encourages exploration of diverse regions, which can lead to better generalization to the test data.
3. **Avoidance of early stopping:** In traditional training with a fixed learning rate, the learning rate may decay over time to help the model fine-tune its parameters near the end of training. However, this gradual decay can result

in early stopping, where the model converges prematurely before reaching an optimal solution. With a cyclic learning rate, the learning rate periodically increases, which can prevent early stopping and continue exploration of the parameter space.

4. Robustness to hyperparameter choices: The CyclicLR scheduler is generally less sensitive to the initial choice of learning rate hyperparameters. Since it allows the learning rate to vary over cycles, it can adapt to different learning rates during the training process, making it more robust to hyperparameter choices.
5. Easy implementation: The CyclicLR scheduler is relatively simple to implement. It doesn't require complex modifications to the model architecture, and most deep learning frameworks, like PyTorch and TensorFlow, provide built-in support for this scheduler.

3.7.2 Optimization to determine the Learning Rate

In machine learning and neural networks, an optimizer is an algorithm used to optimize or update the parameters of the model during the training process. The goal of optimization is to find the set of model parameters that minimize the loss function or error. The optimization process involves iteratively adjusting the model's parameters based on the gradients of the loss function with respect to those parameters. The gradients indicate the direction and magnitude of the steepest ascent or descent for the loss function, guiding the optimizer in updating the parameters to reduce the loss.

There are different optimization algorithms that can be used.

Stochastic Gradient Descent (SGD): This is a basic and widely used optimization algorithm that updates the model's parameters by taking a step in the direction of the negative gradient of the loss function. It can suffer from slow convergence and oscillations, but it serves as the basis for many other advanced optimizers.

Adam (Adaptive Moment Estimation): Adam is an adaptive learning rate optimization algorithm that combines the benefits of AdaGrad and RMSprop. It adapts the learning rates for each parameter based on historical gradient information.

RMSprop (Root Mean Square Propagation): RMSprop is an adaptive learning rate optimization algorithm that maintains a moving average of the squared gradients for each parameter. It scales the learning rates based on the magnitude of recent gradients.

Adagrad (Adaptive Gradient Algorithm): Adagrad is an adaptive learning rate optimization algorithm that adapts the learning rates for each parameter based on the historical sum of squared gradients.

Adadelata: Adadelata is an extension of Adagrad that addresses some of its drawbacks by using a decaying average of squared gradients.

AdamW: An improved version of Adam that adds weight decay regularization to the optimization process.

Nesterov Accelerated Gradient (NAG): An extension of SGD that uses

momentum to accelerate the optimization process and reduce oscillations.

AdaBound and other variants: Optimizers that combine the benefits of adaptive learning rates and the stability of fixed learning rates.

In this project, the Adam (Adaptive Moment Estimation) optimization algorithm was implemented due to the following benefits:

1. It combines the benefits of other optimization algorithms, making it a powerful choice for many deep-learning tasks. Here are three advantages of Adam over other optimization algorithms:
2. One of the key advantages of Adam is its ability to adapt the learning rate for each parameter individually. Unlike traditional optimization methods with fixed learning rates, Adam calculates individual learning rates based on the historical first-order moments (the mean) and second-order moments (the uncentered variance) of the gradients for each parameter. This adaptivity allows Adam to handle sparse and noisy gradients more effectively, leading to faster convergence and better performance on complex models.
3. Adam incorporates a momentum term, similar to momentum-based optimization algorithms like Nesterov Accelerated Gradient (NAG). The momentum helps the optimization process to continue moving in the same direction even if the gradients change direction. This can lead to faster convergence, especially in regions with small gradients or plateaus.
4. Adam is relatively simple to implement and has shown excellent performance across a wide range of deep learning tasks and architectures. It doesn't require manual tuning of learning rate schedules, like in some other optimiza-

tion algorithms. Additionally, Adam’s adaptive learning rate updates allow it to handle large-scale neural networks efficiently. The algorithm’s efficiency is attributed to its adaptive learning rate, which reduces the need for extensive hyperparameter tuning, making it easier to use for various applications.

3.7.3 Loss Function

In machine learning, the loss function, also known as the cost function or objective function, is a mathematical function that measures the difference between the predicted output of a machine learning model and the actual output from the training data. The goal of training a machine learning model is to minimize the value of the loss function, which indicates how well the model is able to make predictions on the training data.

The choice of loss function depends on the problem being solved and the type of output the model is producing. For example, mean squared error (MSE) loss is commonly used in regression problems, while cross-entropy loss is commonly used in classification problems. In general, the loss function takes as input the predicted output of the model and the actual output from the training data, and outputs a numerical value that represents the difference between the two. In this project, the mean squared error MSE loss function for the model was calculated as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

where:

MSE is the mean squared error loss function

n is the number of training data points

y_i is the actual output for the i -th training data point

\hat{y}_i is the predicted output for the i -th training data point

The goal of training a machine learning model is to minimize the value of the loss function, typically by adjusting the weights and biases of the model through the optimization algorithm (Adam optimizer). The process of adjusting the weights and biases to minimize the loss function is known as training the model.

In conclusion, the process of training the Neural Network can be summarized in Table 3.3:

Table 3.4: Hyperparameters used in the DINN model

Hyperparameter	Value
Activation Function	ReLU and Hyperbolic Tangent (tanh)
Optimizer	Adam
Learning Rate	0.001
Loss Function	Mean Squared Error (MSE)
Epochs	100000
Learning Rate Scheduler	CyclicLR
Step Size	4000
Number of hidden layers	8
Number of nodes	20 height

Chapter 4

NUMERICAL RESULTS

4.1 Introduction

In this chapter, the numerical results from the neural network are presented. Graphs, parameter estimated from the neural network, and evaluation metrics are elaborated. The parameters were used to simulate the disease induced compartments.

4.2 Results

The results from the analysis show that most of the disease-induced compartments peaked as early as within the first ten days. The number of the exposed population even was falling but still displayed a high level. While the vaccination class drastically fell to almost 0 after a few days, the infectious and hospitalized population

still need to be handled well in order to avoid another surge.

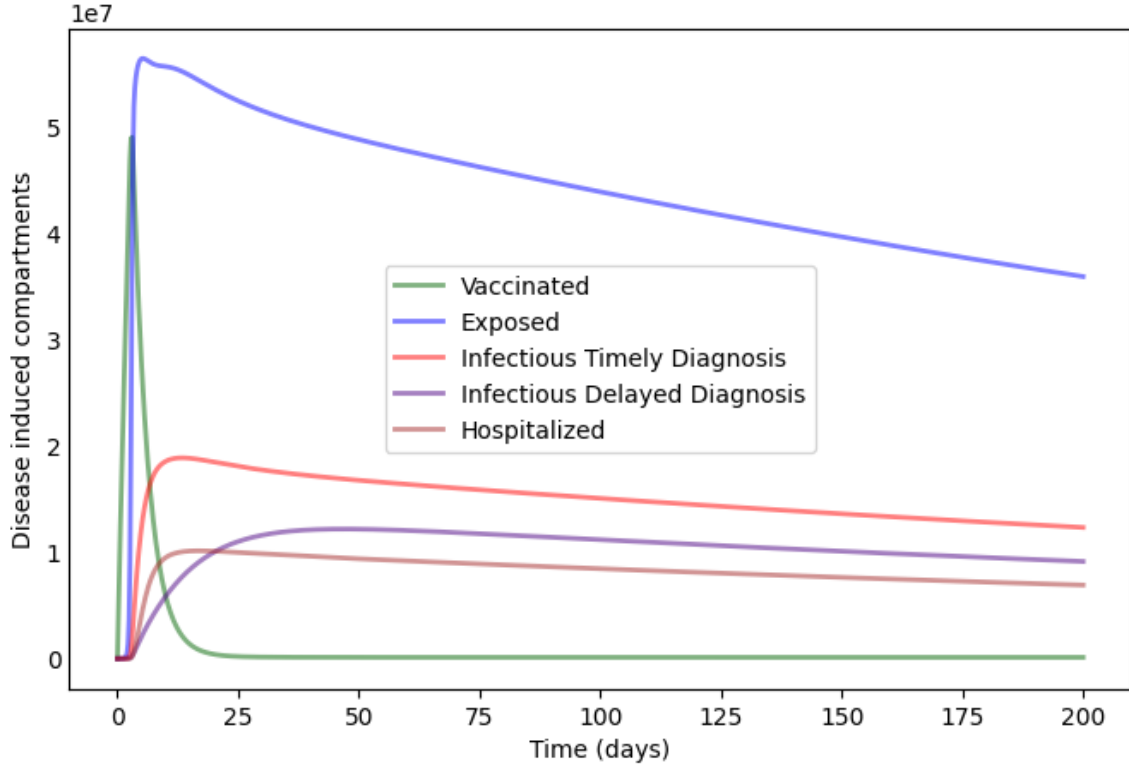


Figure 4.2.1: disease induced compartments

4.3 Model Architecture

PyTorch, one of Python's popular libraries was used to train the neural network model. There were eight (8) hidden layers in addition to the input and output layers. With this, the output of one hidden layer was used as an input for the next hidden layer. This process of forward propagation made the network learn all the patterns of the data. The network architecture is defined using several fully connected linear (dense) layers. The input layer takes a single-time step value.

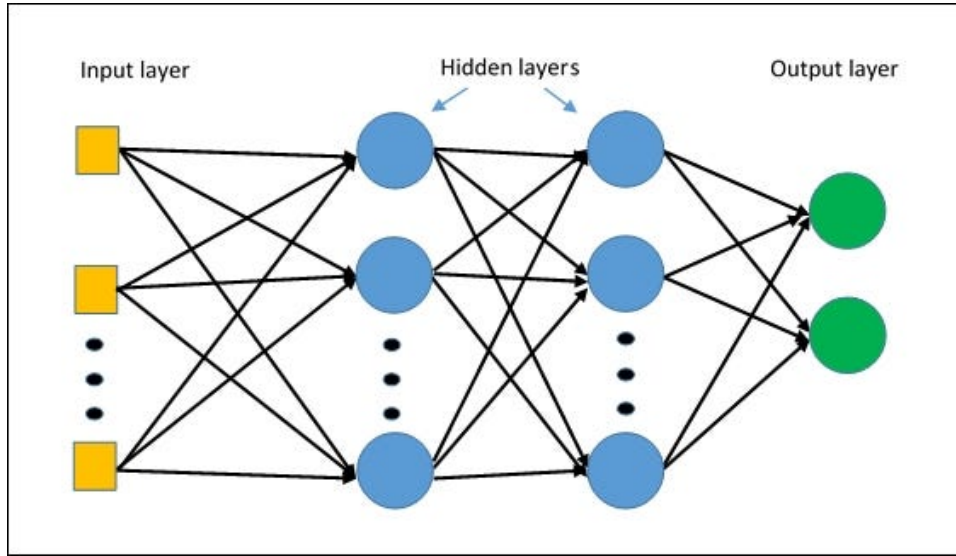


Figure 4.3.1: The layers of a model Architecture ()

It has 1 input unit and 20 output units. The subsequent layers each have 20 input units and 20 output units. Each layer applies the ReLU activation function to the output of the previous layer. The output layer has 20 input units and 9 output units, corresponding to the 9 compartments being predicted. The forward propagation was applied to take the batch of time steps as input and produced predictions for the nine compartments as output. Each fully connected layer was applied sequentially, followed by a ReLU activation function until the final output for the compartments. This architecture captured the mapping between time steps and compartment predictions, allowing the neural network to learn the dynamics of the disease spread over time.

4.4 Sensitivity Analysis

In this section, few of the parameters were considered and studied to observe their effect on the disease induced compartments. Such parameters include rate of self-quarantine (q), vaccination rate (a) and recruitment rate (Λ).

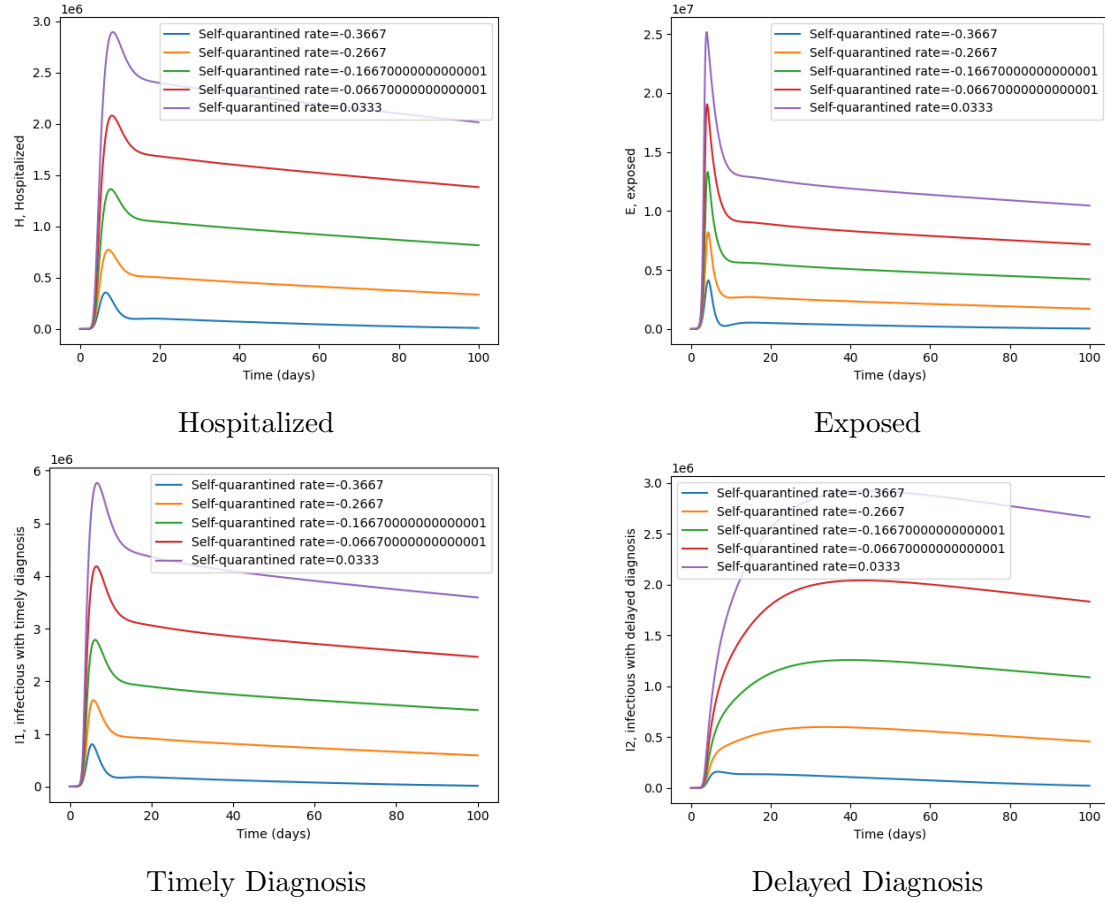


Figure 4.4.1: Effect of changes in the self-quarantined rate on Hospitalized, Exposed, Timely and Delayed Diagnosis class

As indicated in Fig 4.4.1 a change in the rate at which people quarantine themselves drastically changes the number of people in the hospitalized and exposed class. It also reduced the number of patients diagnosed of the virus. Re-

garding the rate at which the virus spread in the community, enforcing rules on self quarantine will affect how the virus spread in the environment and on surfaces. Scientists found that severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) was detectable in aerosols for up to three hours, up to four hours on copper, up to 24 hours on cardboard and up to two to three days on plastic and stainless steel [39].

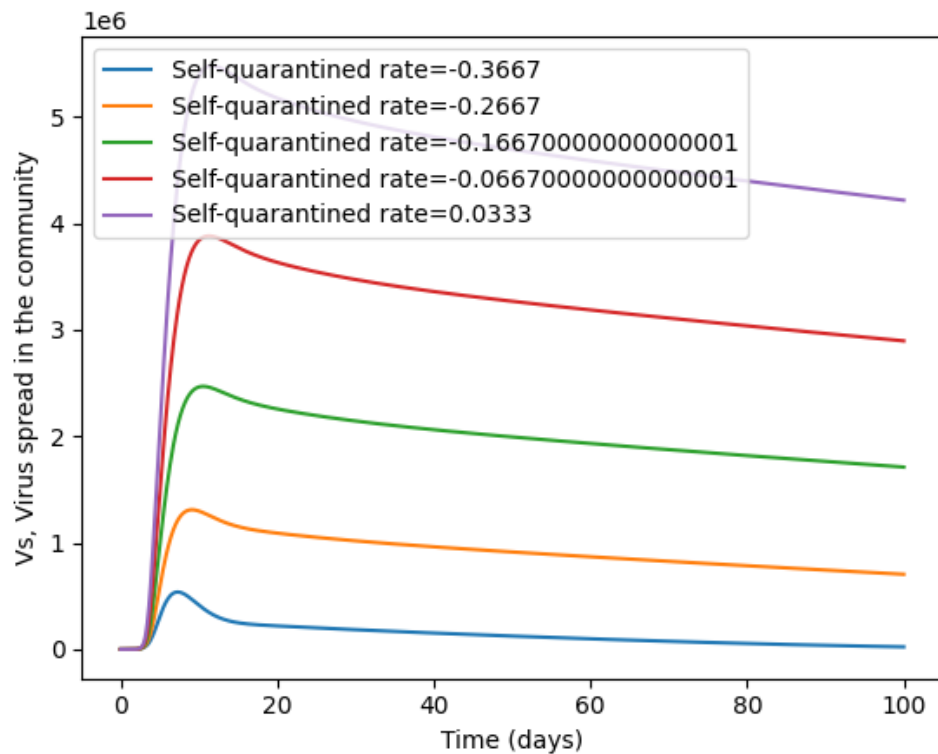


Figure 4.4.2: Effect of change in the self-quarantined rate on the viral spread in the community

Considering how changes in the vaccination rate impacts the disease induced compartments, Figure 4.4.3 confirms that intensifying the vaccination drive will yield positive results. A surge in vaccination rate pushes the recovered class to increase. The more people get vaccinated, the more people recover from the

infection. And at the same time more people get diagnosed early. This timely diagnosis makes decision making and intervention measures effective.

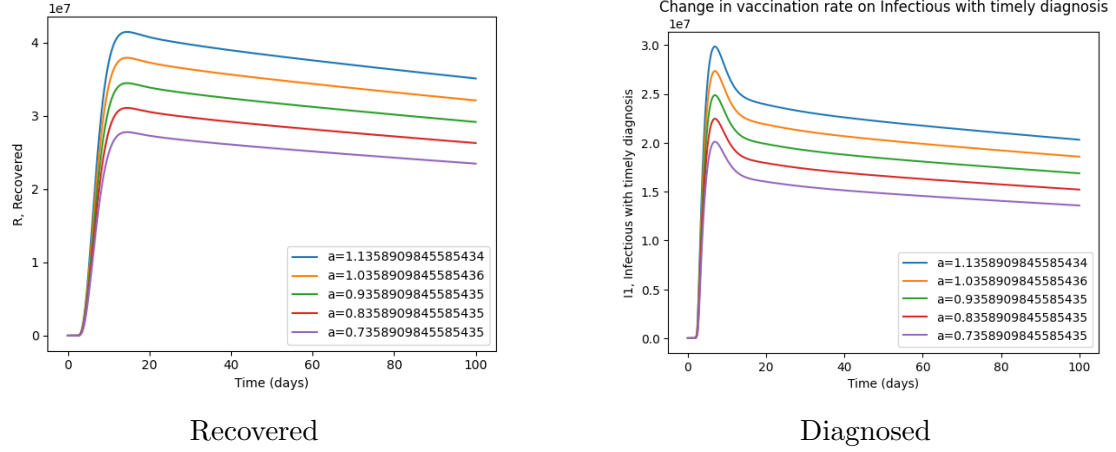


Figure 4.4.3: Effect of changes in the vaccination rate on Recovered and Diagnosed class

Due to the limited number of beds in the country's hospitals, it is suggested that measures be taken to speed up the recovery rate of those hospitalized. Generally, the outbreak had had a toll on the few facilities in the hospitals including beds, oxygen, OPD and even health officials. As indicated in Figure 4.4.4, increasing the recovery rate among the hospitalized patients can increase the number of people who recover from the infection. Measures such as the approval of drugs to treat the infection will assist with the fight. The FDA has approved an antiviral drug called remdesivir (Veklury) to treat COVID-19 in adults and children who are age 12 and older. Remdesivir may be prescribed for people who are hospitalized with COVID-19 and need supplemental oxygen or have a higher risk of serious illness [9]

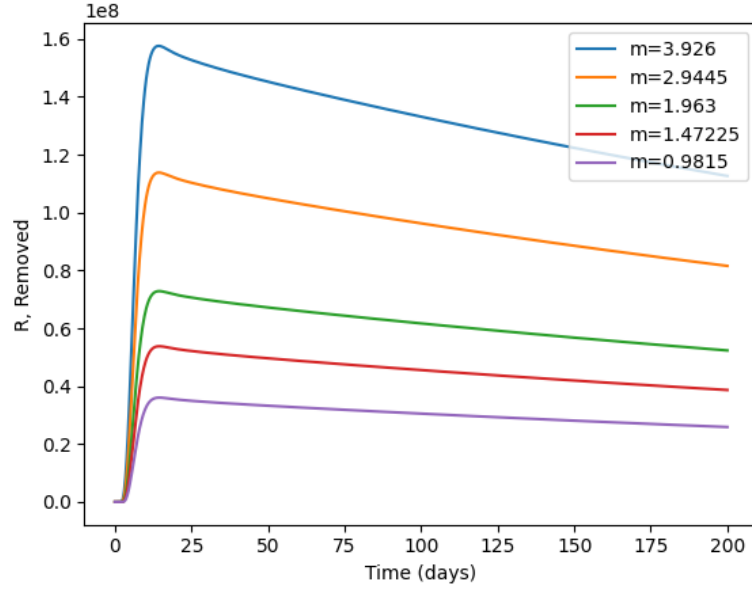


Figure 4.4.4: Recovery rate of the hospitalized patients

4.5 Parameter Estimation From Neural Network

To obtain the optimum parameter values for the network, learnable parameters were set up using Python's library called PyTorch. These parameters were optimized during training to find the best values that minimized the error and improved the model's performance. these parameters were initialized randomly and updated through back-propagation during training with the goal to find parameter values that result in a model that could fit the observed data well. At every iteration during training, the estimated parameter were compared to the initial parameter values from literature After the parameter estimation, an error of 4.8806 was recorded. This is a minimal error for the model. These parameters estimated from the neural network were scaled within $[0,1]$

The new parameters estimated from the neural network training is sum-

marized in Table 4.1 as compared with their corresponding literature parameters . These new parameter sets are within the error of 4.8806.

Table 4.1: Comparison of Literature parameters and Neural Network Parameters

Literature Parameters	Values	Neural Network Parameters	Values
a	0.73589	a	0.56949
b	0.32	b	0.3316
c	0.936	c	0.6511
Λ	1319.294	Λ	0.2726
q	0.0333	q	0.6133
q1	1.6945e-5	q1	0.7294
d	0.006139	d	0.1841
f1	0.0178	f1	0.2841
f2	0.3115	f2	0.5517
f3	4.6131e-5	f3	0.6142
dv	0.3117	dv	0.6086
βe	6.0380e-8	βe	0.1044
$\beta i1$	3.8196e-8	$\beta i1$	0.4950
$\beta i2$	1.4286e-5	$\beta i2$	0.11405
Φ	0.9000	Φ	0.1941
$\gamma1$	0.5000	$\gamma1$	0.2238
$\gamma2$	0.0714	$\gamma2$	0.6271
m	4.2578e-5	m	0.5479
βv	4.00199e-8	βv	0.1164
ω	1/5.2	ω	0.4710
μ	4.2578e-5	μ	0.0383

Using these new parameter sets yielded Figure 4.5.1 for the disease induced compartments for 300 days. While the Exposed classed plateaued early, those in the timely diagnosis class were not as much as those in the delayed class. The Hospitalized class was the last to plateau. This was due to the insufficient hospital facilities in the country. Also the drug for treatment of Covid-19 patients was unavailable in the initial periods of the pandemic.

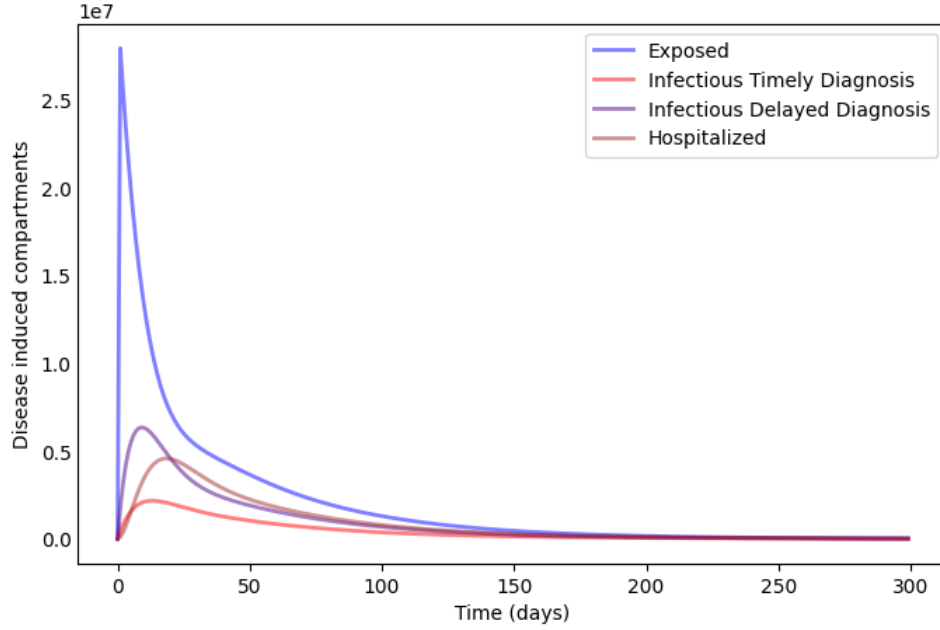


Figure 4.5.1: Disease induced compartments for the neural network parameter estimation

4.6 Model Evaluation

After training the model the loss of epoch generated the figure below: The figure shows the relationship between the number of training epochs and the value of the loss function. The neural network tries to optimize the objective function. This function is typically a measure of how well the network is performing on the training. Loss functions are used to determine how well the neural network is performing by measuring the difference between the predicted output and the actual output.

The objective of training a neural network is to minimize the loss function. The lower the loss, the better the performance of the network. A high loss indicates that the network is not performing well and needs to be adjusted. Typically, during

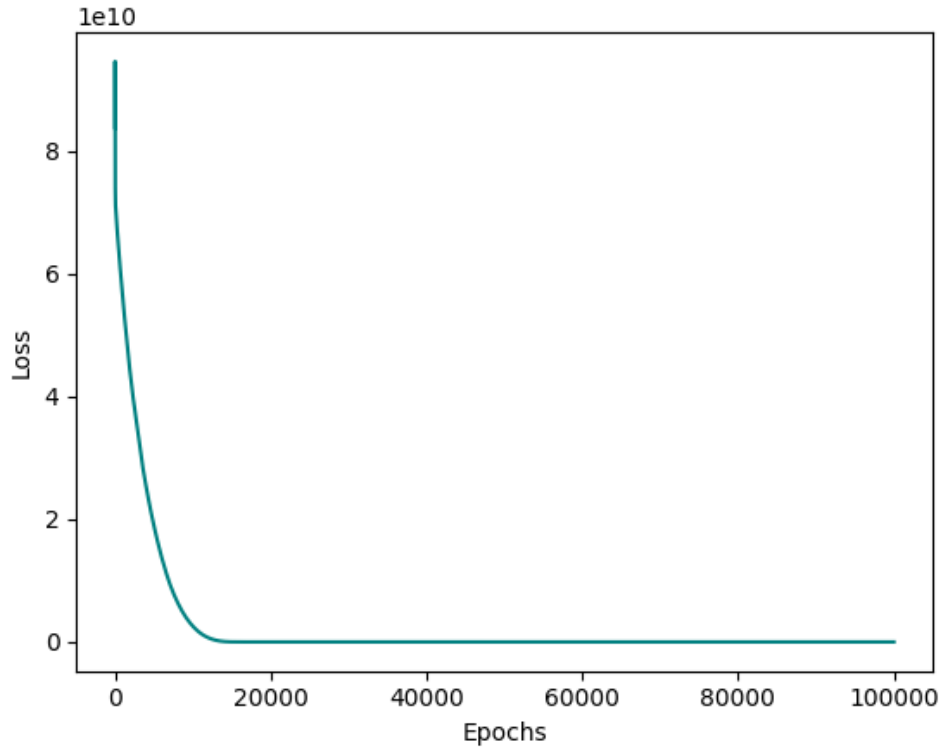


Figure 4.6.1: The loss after Training the Deep Neural Network Model

the training of a neural network, the loss value should decrease over time as the network learns to make better predictions on the training data. As illustrated in the loss curve in Figure 4.3.1, as the number of epochs increased from 0 to 100000, the model was able to learn better and make better predictions for all the compartments. Since the loss is reduced drastically to 4.8806 on the 100000th iteration, it indicates that the network is performing well and accurately predicting the output. This was possible after several parameter tuning was done on the training.

The loss is based on the Mean Squared Error (MSE) which measures the average squared differences between predicted and actual values. It is thus calculated as

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

where:

N is the number of training examples

y_i is the actual output for the i -th training example

\hat{y}_i is the predicted output for the i -th training example

The inverse relationship between the loss and accuracy indicates that the model has a higher accuracy due to the small loss value. The MSE loss serves as a measure of how well the model's predictions match the actual data and how well the dynamics of the model satisfy the defined equations.

Chapter 5

CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

In this project, a deep neural network was developed and implemented to study and predict the dynamics of Covid 19. Python Programming Language was used to develop the model

5.2 Conclusion

In this project, Deep Neural Network was used to model and predict the Covid-19 model. The rapid spread of COVID-19 across the world and the increasing number of deaths require urgent actions from all sectors. Future prediction of

potential infections will enable authorities to tackle the consequences effectively. Furthermore, it is necessary to keep up with the number of infected people by performing regular check-ups, and it is often vital to quarantine infected people and adopt medical measures. Additionally, attention should be given to several other factors to curb the spread of COVID-19, such as the environmental effects and the similarities among the most affected areas, and careful measures should be adopted. In this project, AI-based techniques were proposed for the prediction and diagnosis of COVID-19

5.3 Recommendation

For further research work on studying the spread and prediction of Covid 19 in Ghana and generally in West Africa, the following recommendations are worth considering:

1. The neural network model should be trained on a diverse dataset that represents various aspects of the COVID-19 pandemic, such as demographic information, clinical data, geographical distribution, and temporal trends. Incorporating data from different sources and regions can improve the generalizability of the model. Moreover, ongoing data updates and validation are crucial to maintain model accuracy as the pandemic evolves.

2. In neural network models, especially deep learning architectures, the black-box nature of the model can hinder interpretability. Researchers should focus on methods to understand which features or input variables contribute most to the model's predictions. Techniques like feature importance analysis, saliency maps,

and gradient-based attribution methods can provide insights into the decision-making process of the model.

3. Neural networks tend to memorize noise in data if not carefully regularized. To ensure the model's robustness and generalization, techniques like dropout, regularization, and data augmentation should be employed during training. Future research should conduct rigorous cross-validation experiments to assess the model's performance on unseen data from different sources or time periods. Moreover, ensembling multiple neural network architectures or combining them with other machine learning techniques can enhance predictive performance and make the model more adaptable to changes in the pandemic dynamics. Additionally, considering the ethical implications, privacy concerns, and potential biases in most health-related data and model predictions it is essential to consider responsible AI deployment in healthcare scenarios like COVID-19 prediction.

4. Evaluating the model's performance on a validation set or test set is recommended to ensure that the model generalizes well to new, unseen data and is not overfitting to the training data. Additional metrics such as accuracy, precision, recall, F1-score, can also be used to evaluate how best the model performs.

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