A Comparative Study of Administrative and Managerial Response Models for Effectively Controlling the Spread and the Aftermaths of COVID-19 Pandemic

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Table of Contents

List of Figures

List of Tables

Abstract

COVID-19 is a global pandemic that has emerged in Wuhan, Hubei Province, China in early December 2019 as "pneumonia of unknown etiology". The spread of the virus has shown very rapid growth within a couple of months and soon became a public health emergency of international concern that threaten the health and safety of global population. World Health Organization (WHO) officially declared COVID-19 as global pandemic on March 11, 2020 soon after there were over 118,000 coronavirus infections in over 110 countries and territories around the world. COVID-19's rate of fatalities is almost 20% and the rate of transmission is exponential in the number of infected subjects. All countries in the world have been affected by the COVID-19 outbreak. They all have responded with limited information and facing a lot of uncertainties. They have to respond at all levels of the institutions and society. There were various calls of response from different directions, domains and experts. The approach for the response to the pandemic also greatly varies from country to country. Countries have been challenged with a lot of issues such as underestimation, lack of establishment of central task force, conflicting orders from different authorities, late response or void, self-medication problem, information sharing and social media, shortage of protection gear, shortage of ventilators, identification of isolation centers, social challenges, migration and workers problem and supply chain disruption challenges response with different magnitude. The aim of the research was to analyze the COVID-19 spread in Ethiopia by developing machine learning models to predict COVID-19 cases, recoveries and deaths due to aforesaid pandemic for the short term and long-term period. The output is believed to be useful for timely administrative and managerial response for COVID-19 and resembling epidemics in the future. In order to conduct the experiments, a pre-contextual analysis have been carried out by gathering the relevant data through various platforms. The process of forecast modeling is done using time series analysis techniques and forecasting models for the short- and long-term predictions respectively between three days to ten days are developed using the world data as well as Ethiopia data. Long-short-term memory has superior performance than exponential smoothening, with a root mean squared error of 13.19 and a mean absolute percentage error of 13.12 for the daily cases forecast. Reports in the form of statistics of number of cases, recoveries and deaths along with progression were continuously published on the online dashboard of tableau.

Keywords;Coronavirus,COVID-19, Exponential smoothing, Forecasting

1. Introduction

1.1. Background

COVID-19 viral disease started in the December 2019 in China, has shown very rapid growth just within couple of months in different parts of the world infecting millions of people throughout the globe and has been the cause of death to millions [15]. COVID-19's rate of fatalities is almost 20% and the rate of transmission is exponential in the number of infected subjects. The virus has capability to quickly replicate inside the host, it can be transmitted from one person to another by means of saliva, touch or through sneezing, or any other means identified later. The virus carrier has a dangerous probability of transmission within one meter radius of the subject. The virus creates a number of diseases like pneumonia, heart failure, kidney failures and many other life-threatening respiratory conditions. As it has been shown in Figure 1.1 and 1.2, many countries and territories have been affected with this pandemic [14].

COVID-19 had enormous overall impact on the population including loss of economies, unemployment, mass migration, complete lockdown of cities and countries, halt of all kind of transportation, social stress, hunger and shortage of food, disruption of supply chain, disruption of all kind of services except few, shortage of essential medicines and many other problems in the society. Governments of different nations take various measures to combat the COVID-19 pandemic. In this research various decisions made by the governments has been discussed. There are three classes of nations: those, which have seen rapid spread of the COVID-19 in the population with the highest, medium and minimal rate of growth. The response models were tried to be analyzed to identify effective, structured response model which addresses the issue of prevention of the spread as well as integrate the response of various governmental organizations. The objective of this research is to discuss secondary problems in detail, which are born with this pandemic. Better management of these secondary problems can control the spread of the disease and hence can play a role in controlling the fatality rate. In absence of a vaccine, the only method to control the fatalities was to control the spread of the disease; therefore, most of the governments

were working on the methods of prevention, social distancing, controlled movements of goods and daily need items, and partial and full lockdown of the cities for different periods.

Here, the sequence of decisions taken by various countries have been identified, including UAE [1], China [4], USA, India etc. Their shortcomings have also been analyzed in responding above situation and the model corresponding outcomes in the form of a cause effect networks. The social stigma and the environment of fear and confusion among the populations have made it complex to implement the strict social distancing protocol for the prevention of the spread as reported by the various observers. Other factors, which make this problem interesting from the administrative and managerial point of view, are the observed difference in the rate of new cases and the number of fatalities among the populations of the nations, due to their different approaches of managing and administering the situations that arisen with this pandemic. This has been the main motivation to immediately list out the best practices for handling this pandemic in a better way.

WHO has published a number of guidelines [5], as well as other countries have also published guidelines for their populations [1] [2][4]. However, in the initial days of the spread, the disease had received very less or negligible focus from many countries like Italy, US, Germany, Spain and Iran where later the number of cases of COVID-19 were exponentially surged up to the last week of March 2020 as compared to the Indian, South Korean and late Chinese response models [6-9]. This difference in the number of new cases, rate of fatalities and spread of the pandemic is found to be statistically significant in our pre-contextual study and motivated us to design an integrated response model for the problem of managing the situations that are directly linked to COVID-19.

The properties of the COVID-19 virus, associated disease symptoms taken from various sources, preventive measures were key to stop community spread and the new social norms which are proven to be successful in controlling the spread. We emphasized the statistical significance of these measures for the purpose of administrative and managerial decision making for the better handling of this pandemic and its aftermaths.

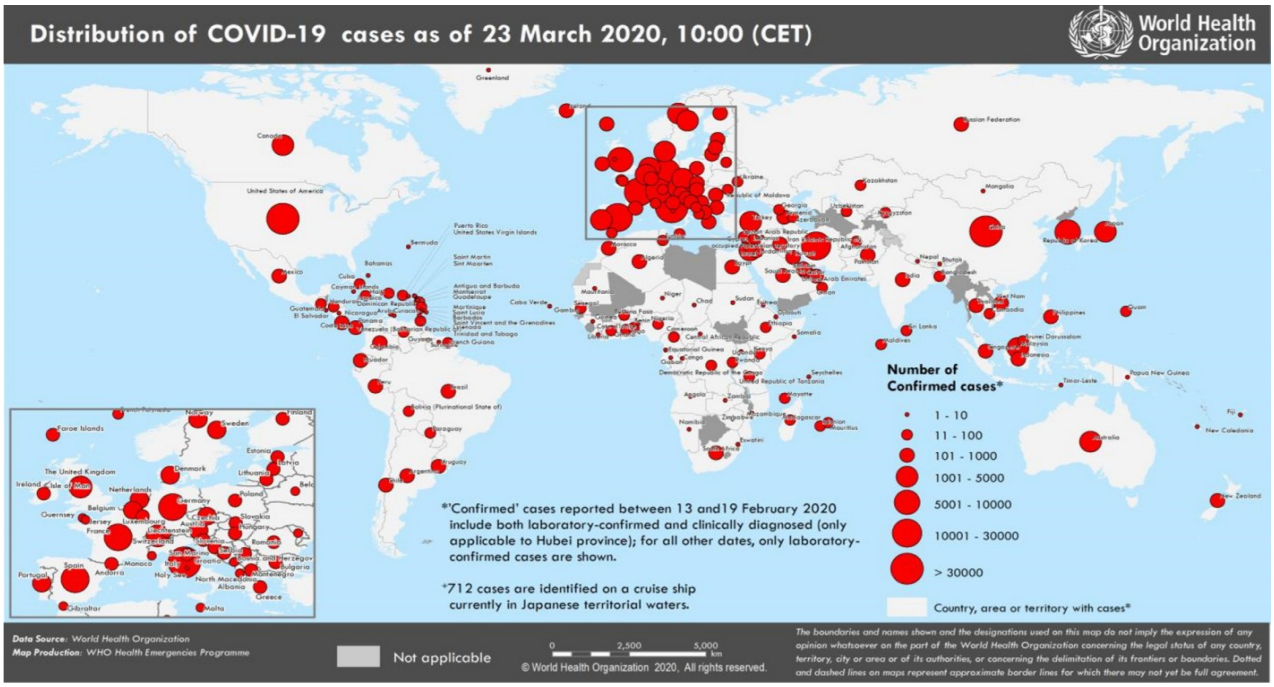


Figure 1 Countries, territories or areas with reported confirmed cases of COVID-19, 24 March 2020 [14]

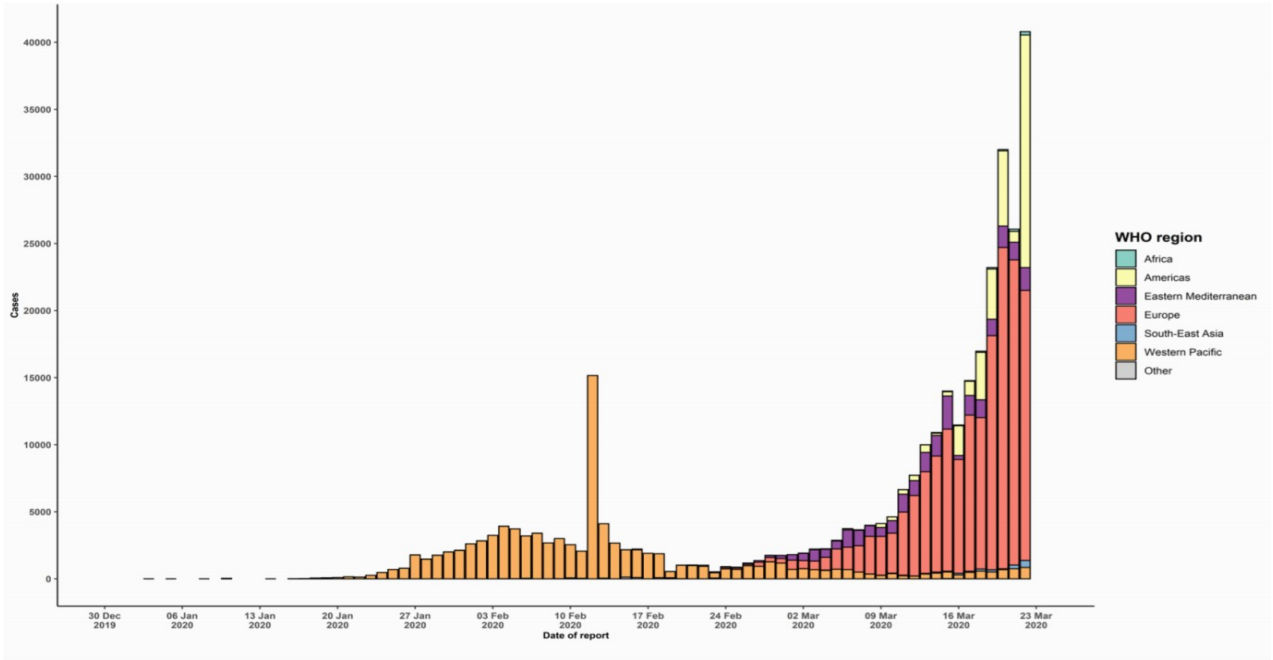


Figure 2 Epidemic curve of confirmed COVID-19, by date of report and WHO region through 23 March 2020[14]

1.2. COVID-19 Challenges

The main challenges experienced by many nations in managing this pandemic has been discussed as follows:

1.2.1. Underestimation

The governments of various countries including China, US, Italy, Spain, UK etc. have undergone through the problem of underestimation of the time to spread across geographical boundaries, cities, districts, across the streets of a city, in between neighbors and person to person, before the phase of community spread. This is mainly due to the limited understanding about the severity of the problem, lack of adequate knowledge of multiplication factor for COVID-19 and the exact mathematical model of the rate of growth. Which has led to underestimation or miscalculation of;

- Number of patients in each area in 24 hours, 3 days, and 7 days periods.
- Number of testing professionals needed to be deployed in each area.
- Number of testing kits required in an area
- Number of beds and hospital services required in the various time points in the future.
- Number of ventilators required in each city.
- Protective gears required for doctors, technicians, volunteers and many other people who are involved in managing the pandemic and its aftermath

Most of the countries have seen the corona virus as a mere source of a disease whose response model encompasses the limited number of people, respective ministries of health and ministry of home affairs only. unfortunately, this pandemic is associated with, or given birth to a number of other socio-economic problems which need immediate, structured response models from the governments and institutions across various specializations and disciplines.

In this model, we tried to discuss the secondary problems created by the COVID-19 pandemic across various countries and a parallel. We tried to identify a model for only those problems which

need immediate response and less emphasized on long-term problems created by this pandemic such as loss in economies, management of psychology and emotions of populations etc.

The following are the points, which show a series of unstructured responses taken across the globe which have created further panic and increased the complexity of management of the COVID-19 problem:

1.2.2. Lack of Establishment of Central Task Force

Most of the countries failed to realize the importance of immediate establishment of task force to centrally handle the situation during this pandemic. Some countries, which have established the task force have underestimated the required level of professional expertise in the task force, level of authority to be granted, allocation of funds for each task, and even in some cases the objectives of the central response team were not clear.

1.2.3. Conflicting Orders from Different Authorities

The problem of COVID-19 encompasses the problems related to mass migration, transportation, food, security, social welfare and many other problems which need immediate decision making. The following case is taken from the day lockdown was announced in India and the subsequent three days, which clearly depict the gap of appropriate response model:

In some Asian countries including India, it has been observed that at many occasions conflicting orders have been given by higher authorities to the lower level officials in various departments, without the knowledge of other departments, without marking the level of importance of the order and these mistakes have caused a huge cost in terms of human life.

For example, in one case in India 24th March 2020, the complete lockdown of all the cities was ordered by the ministry of home affairs and implemented with the help of strict measures from Police. But on the other hand, at the same time, some state governments have ordered the evacuation of stranded laborers from their working places to their hometowns. This has created a mess of hundreds of thousands of people waiting for transportation at their respective bus terminals. While, on the other hand, the ministry of transport already issued orders related to complete halt of movements of all the essential and non-essential goods as well as passenger vehicles, including edibles through any means of transportation. Even corrections of orders were

not well interpreted by the concerned officials, causing disruption in supply of vegetables, food, sugar and drugs to different regions.

This kind of situation can arise only when there is no central 24X7 task force, with appropriate influence and authority to issue non-conflicting directives on a continuous basis to effectively handle the pandemic and related situations. This mistake has caused the life of many people and left millions of people going to their home by mere foots.

1.2.4. Late Response or Void response

There were certain situations observed in in some countries like India where after 24th march 2020 complete lockdown, which are left unanswered because no one was allocated to manage those problems. For example, the problem of distribution of food and necessary medical support to the unorganized, unregistered middle class families, laborer and small-scale businessperson. The problem of maintaining a distribution channel of essential commodities like wheat flour, sugar, vegetables, rice and other essential items was not centrally modeled. The distribution of essential items have faced various problems due to restrictions on the transportation, wholesale, and retail sale of these items in the context of prolonged social distancing norms under complete or partial lock down.

In case of USA, the initial spread of the virus was slow and therefore, administration was sure to control the number of cases by social distancing guidelines. But, as seen in the last week of March and first week of April 2020, the number of cases was increased exponentially. Therefore, US Administration was overwhelmed with the spread of viruses. Ignoring the option of forced lockdown has complicated the problem of COVID-19 in USA resulting in an extent of 15000-19000 new cases per day in worst spread days of April, 2020 (first week).

In case of Iran, Italy, UK and Spain and Germany, there is similar pattern of COVID spread and almost 3000-5000 New cases have been recorded in every day starting from the last week of March. These countries had to take stricter measures after realizing the threat produced by the virus.

The countries like Saudi Arabia, India, South Korea belongs to a list of nations where spread of the disease has been blocked by strict protocols and lockdown measures. However, the cost of this

prolonged lockdown have been predicted in terms of loss of economy, loss of opportunities and jobs, complete shutdown of business and manufacturing activity and loss of social norms of life.

The countries like Ethiopia, Eretria, Zambia have reported fewer than 50 cases till first week of April and most of the African countries have not reached the mark of 300 cases in total. In this case, the immediate actions taken by the governments are appreciated across the African. The focus of these countries recommended to be to stop the COVID-19 disease into entering third stage. In this stage, also called community spread, it is not possible to find the source of spread and disease grows undocumented and untraceable form.

1.2.5. Self-Medication Problem

There has been some cases in IRAN and some parts of Africa in which people have tried to use methanol, raw Alcohol, sanitizers, Dettol and other local medicines in order to prevent the disease entering into their body but as a consequence many people have lost their lives including IRAN (300), African countries (2-10). This kind of practice could be stopped by providing a well-documented advisory to the general public.

1.2.6. Information Sharing and Social Media challenges

It has been observed that a number of social media platforms like TikTok, Facebook, and twitter have been heavily used by people to create awareness regarding lockdown period, spread of the disease, preventive measures and reporting food and shelter related problems in the remote areas where mainstream media and various officials cannot reach. At the same time, some people have used social media platforms to insert rumors, hate messages and wrong information regarding the coronavirus as seen in Pakistan, India and other Asian countries. Monitoring these groups on social media which indulge public fear in populations is a challenging task.

1.2.7. Shortage of Protection Gear

The teams of volunteers working along with health professionals and supply chain related activities need a complete protection which include N95 Face mask, Gloves, and protection jacket, but due to acute shortage of above protection gears almost all the countries have stopped the export of above material. Therefore, the shortage of protection gear for working professionals was the biggest challenge at this time.

1.2.8. Shortage of Ventilators

The number of ventilators available on 24th march in India were estimated to be 30000-40000, similarly in the USA almost 100,000 and similar or less in other countries. The expected number of medical resources required at the peak of the growth curve of the pandemic was much more the availability. Therefore, slowing down the disease with preventive measures like lockdown had been a challenging task for many countries. In the time span of 24th march to 2nd April, the preventive measures of India, China and South Korea seems to be successful in keeping the peak of the growth curve below the available resources like ventilators, but the countries like Italy, IRAN and SPAIN have failed to keep the curve in control and expected to run out of the resources in few days. On the other hand US, China and India have utilized this time window of lockdown to slow down the spread to manufacture the testing kits, ventilators and other resources.

1.2.9. Identification of Isolation Centers

Countries with larger populations like India have one doctor for every 8000 people, therefore the problem of identifying the number of doctors and the hospitals in each city is very important for controlling the pandemic. While China has built special hospitals for corona patients, India has acquired hotels, private hospitals, train bogies, schools and many other public infrastructure to create temporary isolation points across the nation.

1.2.10. Social Challenges

In India, while there has been 24X7 effort from Police and many other departments to contain the spread of virus by forcing people to stay inside homes, the population being habitual of staying out of workplaces find it very difficult to be inside homes during lockdowns. Also, foreign returnees have also ignored the ministry advice as well as 14 days home quarantine stamp which were put on the hand of returning international carriers were ignored by many people. Some religious places contained 200-2000 people in gathering even after declaration of section 144 of law, which causes no more than 2-5 people at one place. This kind of ignorance of the social distancing norms, society of India has quickly moved towards community spread of the virus. Similar situation observed in many other countries including US, IRAN, Saudi Arabia, Pakistan, Italy and Spain. The most important challenge identified at the time for containing the spread of this disease was to maintain social distancing norms in the society.

1.2.11. Supply Chain disruption

Due to prologue lockdown, supply of various basic needs have been disrupted in almost all the countries affected by Coronavirus. Some countries have effectively managed to install a parallel supply chain network with the help of university volunteers and local shopkeepers and ensured that basic items are provided to each family during the period of lockdown. Some state governments in India have provided 3 months advance ration to the people who are living below poverty line or those who need it. But for a number of successive lockdowns, it is a challenging task to maintain supply of each commodity while goods transportation is also down.

1.2.12. Migration and Workers Problem

The cities like London, New York, New Delhi and Vuhan host a large number of migrant workers, students and other out of the home people. Due to immediate need of lockdown, they all wanted to go back to their homes. But, it was a big challenge how to test and insure these migrants for infection and whether to allow them to move back without a mandatory 14 days quarantine period. In some parts of India and some cases of Vuhan the migrants were allowed to move, but it turned out that later these migrants have become positive in tests and caused more spread in the community. While in some cases migrants have been told to stay in the homes in their current cities which have faced a shortage of food and shelter. In order to support their stay, governments have provided exemption from rent, full salaries from their employers, exemption from various taxes and free food and medical services. In context of Ethiopia, following problems have been identified:

- Problem of value manipulation by some merchants and hiding some commodities even while the supply chain has been intact-lack of coordinated effort in response to the pandemic
- Problem of stigma and discrimination resulting from misunderstanding the social distancing recommendation and confusion regarding the virus.

1.3. Statements of Problem

One of the most critical challenges during the COVID-19 pandemic was the widespread underestimation of the virus's rapid transmission and its cascading impact on healthcare systems

and societies. Governments across the globe, including those of the US, Italy, Spain, and India, initially failed to grasp the severity of the virus's exponential spread, leading to significant miscalculations in preparedness and resource allocation. This underestimation resulted in dire shortages of essential medical supplies, including testing kits, hospital beds, ventilators, and personal protective equipment (PPE) for frontline healthcare workers. Compounding the issue was the absence of a centralized, authoritative task force in many countries, which led to fragmented and often conflicting responses. For example, in India, the sudden announcement of a nationwide lockdown without a clear, unified strategy caused chaos, as conflicting orders from different government bodies disrupted supply chains, triggered mass migrations, and left millions of daily wage workers stranded without access to food or shelter. Similarly, in the US, the delayed implementation of strict measures allowed the virus to spread unchecked, overwhelming healthcare systems during peak infection periods. The challenges faced during the COVID-19 pandemic were not unique to larger or more developed nations; Ethiopia encountered similar, if not more complex, issues in managing the crisis. Despite reporting fewer cases initially, Ethiopia grappled with systemic problems that hindered an effective response These systemic failures underscore the urgent need for a coordinated, data-driven, and proactive approach to pandemic management, emphasizing the importance of clear communication, centralized decision-making, and equitable resource distribution to mitigate the human and economic toll of future crises.

1.4. Research Questions

The followings are the major questions that help to address the challenge posed by COVID-19 pandemic to impact the positive aspects of decision makers.

1. What are the major challenges in combating the spreed of COVID-19 pandemic in Ethiopia and the world at large?
2. What are the major response model applied in different countries to deal with the spreed of the pandemic? And their pros and cons?
3. How to model this time series data to design a managerial response model ? And how to select advanced time series model?
4. How to evaluate the model and its result for future cases?

1.5. Objectives

The objective of this study has been to design and develop machine learning based response models for the purpose of estimation and prediction of different variables which govern the spread and losses due to COVID-19 and to construct appropriate response models for the organizations of different capacities.

The specific objectives can be understood as follows:

- To design and develop Machine learning models for comparative study of spread of the disease in different areas of Ethiopia.
- To predict number of infected people, number of deaths, and number of recovered people in each area under study.
- To compare the response models of various countries and design comprehensive response model for the study area of Ethiopia.
- To identify and publish shortcomings in handling this pandemic in different countries and to provide a suitable set of “best practices” for such kind of outbreak in future.

1.6. Significance and Justification

The research focused on the most important problem of the prediction of confirmed cases, number of resources required in each study area and in parallel addressing the secondary social problems during this outbreak. This research is highly significant as there is no means of stopping this disease from spread except if the society have up to date information and proper estimate of the required resources. This research can also help us in understanding the impact of the spread of the disease on economy and the state of other services in long term. This research is not only intended to collect the mistakes committed by various countries in early stages of occurrence of pandemic, but also focused on how we can learn from these mistakes for the future epidemics and pandemics in African peninsula and particularly in Ethiopia. Various kinds of community service projects can use outcomes of this research as guidelines and starting points in managing the epidemic situations in Ethiopia. The disease is not yet well understood globally as well as locally and there are emerging issues every time incorporating these emerging issues in the response model is very

important. We believed that this can help to control through well informed decision and consequently saves the lives of the people. Another justification for this research is to be cost-effective for controlling the disease by availing information for right decision making. Different countries may have different response model based on the contexts and therefore, this research is new in the sense that model is developed by learning from experience but taking into account the Ethiopian unique scenarios and contexts.

1.7. Beneficiaries

Various health planners, to allocate the volunteers, resources and medical equipment in those areas where the number of affected people is expected to be large, can use the outcomes of this research.

The primary beneficiary of this research can be hospitals and medical colleges, epidemic management institutes etc. The response models developed in this study can be used by any organization, which wants to address the problems created by this pandemic in the form of structured response. Planners and government institutions in designing strategies in current and future epidemics and pandemics as well recurrence of any such disease in society can use the comparative study performed in this research.

The secondary beneficiaries form this study are the organizations involved in managing post pandemic situations of social stigma and stress in the study area, the outcome of these topics can be used by media, entertainment industry and social welfare organizations in order to bring the social sentiments to normality after the disease is successfully handled.

2. Literature Review

COVID-19 has been emerged in Wuhan, Hubei Province, China in early December 2019 as "pneumonia of unknown etiology". It soon became a public health emergency of international concern that threaten the health and safety of global population [39, 40]. COVID-19 is caused by a new betacoronavirus related to the Middle East Respiratory Syndrome virus (MERS-CoV) and the Severe Acute Respiratory Syndrome virus (SARS-CoV). World Health Organization (WHO) officially declared COVID-19 as global pandemic on March 11, 2020. By the time of declaration of COVID-19 as global pandemic, there were over 118,000 coronavirus infections in over 110 countries and territories around the world.

We have observed that well-structured and resourceful health systems of developed nations have been overwhelmed by the corona virus pandemic [41]. US, Italy, Spain and France are among the first highly hit countries with the wave of corona virus infections. They have experienced a shortage of testing kits, personal protective equipment's, doctors and ventilators. The impact of corona virus is expected to be worsen in many of African countries where overall resources are limited and medical resources are scarce. Ventilators are among the highly demanded resources to treat severely sick COVID-19 patients. Ten African countries don't have ventilators at all. The intensive care facilities are also very few. For instance, Uganda has only 55 intensive care beds. WHO has identified top 13 African countries (Algeria, Angola, Cote d'Ivoire, Democratic Republic of the Congo, Ethiopia, Ghana, Kenya, Mauritius, Nigeria, South Africa, Tanzania, Uganda, Zambia) that can be severely affected by corona virus pandemic [42].

However, everything is not dark in the continent. Many of the African countries have been affected by the pandemic later where it gave them enough time to learn from the experiences of other severely affected countries. Countries like Senegal have also tremendous achievements. The country's famous $1 COVID-19 test kit and the race for a vaccine have been a great inspiration to the resource limited continent [43-45].

One of the main challenge is the uncertainty of the future. There is no known effective therapeutic mechanism or vaccine of corona virus so far despite tremendous global efforts by pharmaceutical companies. We can't be sure that when will be an effective medication or vaccine will be available. The only viable solution is well informed preventive measures. As a result, governments respond

through drastic measures including complete or partial lockdown, limiting travel and gatherings, closing of schools, enterprises, shopping malls, and so on. Resource limited nations may not be able to cope up with such measures. Having reliable information about when to act and to what extent is extremely important. According to *Jessica Fanzo's* article in Bloomberg, the not knowing or uncertainty about COVID-19 is especially worrisome in sub-Saharan Africa due to the continent's fragile food supply system [46]. The continent's health system is also incapable of handling new and re-emerging disease outbreaks. Enhancing our understanding about the spread of the outbreak will increase the effectiveness and efficiency of responses.

2.1. COVID-19 Responses of Selected Countries

All of the nations of the world have been affected by COVID-19 outbreak and have to respond with limited information and facing a lot of uncertainties. They have to respond at all levels of the institutions and society. There were various calls of response from different directions, domains and experts. The approach for the issue also greatly varies from country to country. The leadership role was taken by the government where frequent briefing has been made to inform the public. A lot of pressure was there for all involved and the pandemic demanded sense of urgency to adapt.

There can be a lot of health, social, and economic challenges and consequences that can happen due to any outbreak. Various measures can be taken to reduce some of the consequences in countries and address political, economic, administrative, regulatory, logistical, ethical, and social challenge by strengthening global preparedness to emerging epidemics [47]. Hence, governments tried to be adaptive.

It was a global crisis to almost every country in a unique way and can be very difficult to have a comprehensive comparison [48]. Governments have been widely observed that they have put adaptive governance into action within an extremely short time span. Among the popular responses, lock down was one of them which seems to have worked as social distancing and staying at home which has reduced transmission of the pandemic significantly and saving lives in the process [49].

The pandemic has shown that different countries have responded differently and there were also various alternatives of response strategies. The availability of various strategies creates an

opportunity of selecting an appropriate and best fit to the specific context. One of the issues is that various stakeholders and institutions have been involved in the response that have created confusion and ineffectiveness in some areas. It is not feasible to discuss the responses of all of the countries to the COVID-19 pandemic. Hence, we have purposively selected few countries and discuss their comprehensive response to COVID-19.

The country which has registered the 1st SARS-CoV-2 was China where all has begun with an ordinary moment when a group of people has admitted to the hospital that has sign of pneumonia turned out to have a new strain of coronavirus [50]. Hence, one of the countries that we have purposely selected to see its comprehensive response was China. It does make sense in all aspect of reason since it is believed the origin of the pandemic and had different way of responding to the pandemic. The SARS-CoV-2 high rate of transmission rate in China makes it a global pandemic in a short span of time. The early responses and strategies of response started in China with various measures including early reporting and situation monitoring, large-scale surveillance, and preparation of medical facilities and supplies. Those measures were stated successful in reducing the epidemic in China in general and in the epicenter Wuhan specifically. One of the priorities was developing resilience systems against infectious disease and that has to be a priority to any country. China has developed resilient system in its battle against the COVID-19 pandemic. One of the follow-up warnings by the experts was possible epidemic recurrence and stressed the need for caution.

The China's government experience with SARS has been helpful for their response to COVID-19. They have been strengthening their capacity for future outbreak responses by learning from SARS. This can be seen visibly with their response to COCID-19 as compared to SARS [51]. There was significant delay in notifying WHO of SARS outbreak that has been made after 300 cases and 5 deaths as compared to 27 cases and zero deaths in COVID-19. The WHO office of China office has been notified about after 27 pneumonia cases of unknown etiology detected in Wuhan, Hubei province, China [52]. The first response by the government of China was closing the market on January 1, 2020, as a method to terminate all meat trades, and then started environmental assessment to confirm the association and to prevent further transmission [53]. This response has happened just a few days after the 1st notification of the first COVID-19 pandemic. The country has pulled all of its efforts to capacitate its laboratories. The country was successful in compiling

massive dataset that have given a chance to enhance our understanding of the pandemic at the time of too much uncertainty and in demand of acting quickly around the globe [54]. The bioinformatics ability to analyze the data and the speed by which genome sequencing and data were obtained were very helpful [55].

In China, case identification and large-scale surveillance has been responded with large scale community level temperature screening that has been implemented through “installing infrared thermometers in airports, railway stations, long-distance bus stations, and ferry terminals”. They also have set up thousands of quarantine stations at multiple sites installed at in entrances and exits for passengers at stations. At later stages when the capacity has been built the search has been expanded to screen people at work, in shops and on streets. The government has also implemented technological based tracking systems that are mainly smartphone-based applications. They have used street cameras to identify people who travels without facemasks and those who have shown symptoms. The Chinese authorities have responded with lock down by closing the airports and suspension of all public transportations to prevent anyone from entering and leaving as preventive measure which has been started on January 24,2020 in Wuhan and Hubei province cities. The announcement of the lock down has been intentionally made a day before Spring Festival in China in order to reduce the very high population movement. Which has reduced the spread of the disease. Activities such as gatherings, festivities and similar events have been cancelled. The large-scale quarantine and lock down of millions of people has significantly affected the countries economy and slowed down its growth.

With respect to healthcare facilities and medical team preparations, the government of China has responded well. From the quick surge of the cases, it was clear for the government that the country’s health facilities would have been overwhelmed as has been seen in many nations. The country pulled out its experience and started building hospitals massively and fast. The Huoshenshan Hospital in Wuhan city was the 1st built with a brand-new facility that is fully equipped and has the capacity to treat 1,000 COVID-19 patients at once [56]. The new brand hospital with 269,000-square-foot was built just only within 10 days. Many more similar responses can be mentioned like the Leishenshan Hospital project with a 1,500-bed capacity built in almost in similar period.

The second country we have purposively selected to see its comprehensive response is USA because it was a significant nation in COVID-19 pandemic. The country has been leading in cases and deaths for long period of time and its response has been discussed in literatures comprehensively. The country has led the world in COVID-19 cases on March 26, 2020 which is exactly 3 months after the government of China has declared the novel coronavirus outbreak and 10 weeks after USA has registered the 1st infection of the pandemic with an estimated cases of 81,321 [57]. The number has surged to 690,714 cases, with 35,443 COVID-19 attributed deaths. The response of the country to the pandemic has been stated as below expected and uncoordinated that has been hindered with deficient political commitment and unclear goals and dysfunctional institutional dynamic [58]. The incoherent response undermined the legitimacy and created negative feedback from all stake holders. The nature of the COVID-19 pandemic of uncertainty and complexity contributed to delays and conflicting response that led to finger pointing. The pandemics nature is global boundary spanning crises that requires urgent response with too much uncertainty and scarce resources. The specific failures of COVID-19 responses were stated to be attributed to lack of agreed upon goals, lack of use of institutional structures that channel attention and resources in support of those goals, and ineffective mobilization of interests to support those actions.

When USA announced its 1st novel corona virus case on January 21, 2020, there was a clear call of rapid action and deployment by public health experts to address the pandemic and containment [59]. This clarity has not been shared with the political leaders who were unable or unwilling to acknowledge the threat and set up a clear vision for addressing it. They were slow to react which has far more consequence due to the nature of the outbreak. Instead of using and implementing experts' recommendation of the containment goals and measures, the administration has declared as foreign problem. Their response was also a reflective of this thought with travel restriction barring entry to foreign nationals who had visited China that has been in effect starting from January 31, 2020.

The response to the COVID-19 pandemic in the United States evolved over time and involved a mix of federal, state, and local measures. Here are some key aspects of the U.S. response: in the early stages (January to March 2020), the responses include **travel restrictions, state of emergency and social distancing and quarantine measures.** Early in the pandemic, the U.S.

imposed travel bans from China (January 2020) and later expanded restrictions to other countries, including Europe. The U.S. declared a public health emergency on January 31, 2020, followed by a national emergency on March 13, 2020, to unlock federal funds and resources. In March 2020, many states began implementing stay-at-home orders and closing non-essential businesses. The federal government, through the Centers for Disease Control and Prevention (CDC), issued guidelines for social distancing and the use of masks.

The federal government of US incorporates economic stimulus packages, operation warp speed and mask mandates. The federal government passed several major relief packages including CARES Act (March 2020): Provided direct payments to individuals, expanded unemployment benefits, small business loans, and funding for hospitals and healthcare systems, Subsequent Stimulus Packages: Further economic relief measures were passed, including the December 2020 stimulus package, which provided more direct payments and extended unemployment benefits. In May 2020, the U.S. government launched this initiative to expedite the development, manufacturing, and distribution of COVID-19 vaccines. There was significant debate over mask mandates. While many states and local governments implemented mask requirements, the federal government did not institute a nationwide mask mandate.

There were many challenges of COVID-19 response in US. One of thes challenges is **Political Polarization**: The pandemic response in the U.S. was highly politicized, with stark divisions over mask mandates, social distancing measures, and the role of government in managing the crisis. The other challenge is **Healthcare System Strain**: Hospitals and healthcare workers faced extreme strain, particularly during surges driven by new variants of the virus, as ICU capacities were overwhelmed. **Inequities** is also a challenge: Disparities in healthcare access, economic impacts, and vaccine distribution were evident, with underserved communities, particularly Black and Latino populations, disproportionately affected.

Another country with well reported response is Netherland. In short period of time the political leader of the Netherlands developed a shared vision that have been accepted by all involved even if there can be numerous alternatives as a path. This could have been a major challenge in other situations where there are decisions that needs to be made fast and scattered at the same time across various organizations. Government’s hand has been tied to adapt to the threat of COVId-19

pandemic within a short period of time. There was a genuine risk of transmission beyond control if not dealt with quick and adequate response. The entire system of public, private and semi-public actors had to respond instantly in a coordinated way with considerable uncertainty about the situation. It required adaptability specifically in domains such as hospital capacity, testing and contact tracing, food supply assurance, medical equipment supply, Prescription drug supply and funding to keep the economy running. Netherlands initially implemented the so called “smart lockdown” policy which is a policy where pandemic protection and controlling measures were encouraged rather than enforced. Individuals have much more responsibility that allowed them a significant level of flexibility to adapt to the local settings as they found fit. The success of this approach with comparison to other alternatives has not been exhaustively studied. However, this approach has been effective and allowed the country for rapidly scaling up the responses while keeping the economy running. The “smart lock” down policy has been appreciated by many citizens because it was not a complete lockdown and mandatory stay at home policy. Individuals were encouraged to stay at home but they can move when it is necessary. It has been state that the policy had minimized the potential negative impact on the Dutch economy, although the effects have still been very severe. There were critics of the policy as well with compelling arguments. WHO was one of the major organization that has criticized the Netherlands government for not being able to provide adequate testing kits to control transmission of the pandemic [60]. The Netherlands government response was criticized further due to delaying in production and ordering of personal protective equipment (PPE) for health care workers and face masks for the public. The government has orchestrated stakeholders to develop virus tracking app for use by the public and was successful in developing an app called “appathon”. The app has failed spectacularly due to the issue of privacy.

When we see a little bit in detail about the response of the Netherlands to the COVID-19 pandemic. It is important to set the context a little bit. The pandemic has caught many countries and the world by surprise. It didn’t allow them time to reflect before acting quickly since its consequence has spread throughout the world very quickly. The important issues is selecting the right order to respond to different changes, selecting the proper level of response and the stability to change.

3. Methodology

This research involves estimation and prediction of an exponentially growing pandemic in Ethiopia and compares the performance of developed models across various countries and explains why there is a difference in the number of affected people in each case. The nature of disease was to spread in space and time exponentially in absence of appropriate protective measures. Therefore, this research has been a kind of longitudinal study which models the situation in the form of a time series model and tries to estimate important predictors of the spread and effect of the disease in an area. The key performance indicators for comparison of effective controlling of disease by various countries can be seen in terms of: early lockdown, home screening, quarantine facilities, infrastructure for isolation, government commitment to take issue seriously, awareness creation levels, people adherence to the standard precautions set by concerned stakeholder, religious and cultural beliefs, weather condition etc. However, we won't model the question of interstate spread of the pandemic for keeping our focus on the study area.

The following tasks and procedures mainly be carried out;

- Data acquisition and preprocessing
- Modeling the spread of COVID-19 in Ethiopia
- Time series forecasting of COVID-19 cases, deaths and recoveries

It has also been described with the following steps which are exploratory data analysis, data collection, preprocessing, data encoding, model building and model evaluation.

3.1. Data Collection

The data related to pandemic for countries like USA, Italy, Spain IRAN (that are highly affected by COVID-19) used from online authentic data sources as well as countries like China, India and South Korea where the effect of the disease is slow, the data taken from online as well as offline

measures. Hence, for international rate of spread, we collect the data from authentic websites like https://www.worldometers.info/coronavirus. In the case of Ethiopia, the data related to various variables of interest collected by physical visits to related hospitals and health centers. These data collection from Ministry of Health, Addis Ababa and the designated isolation centers for COVID-19.

Therefore, various essential data for this study collected from the following sources:

- COVID-19 National Task Force
- National Public Health Emergency Operation Center (NPHEC)
- Federal Ministry of Health (FMoH)
- Ethiopian Public Health Institute (EPHI)
- Quarantine, Isolation, and Treatment Centers
    - Eka Kotebe Isolation | Treatment center
    - Millinium Hall
    - COVID-19 Center at Adama
- Testing laboratories and Research centers of COVID-19
    - The Armauer Hansen Research Institute (AHRI)
    - National Animal Health Diagnosis and Investigation Center (NAHDIC)
- DHIS-2 based comprehensive and fully digitized database

Following procedures were used to collect data from various sources in Ethiopia:

1. **Questionnaires:** We collected the qualitative data at different level of details of the number of cases, recoveries and mortalities form of questionnaires. The questionnaires were distributed and analyze.
2. **Interviews:** Telephonic and Skype Interviews were good sources of data especially in this kind of risky pandemic situation where it is difficult for researchers to physically go to remote areas. We tried semi-structured interviews to collect the data for our model building purpose. The

interviews were collected from various health experts, volunteers and health workers deployed by the government at various levels.

3. **Documented Data:** There are various online and offline portals, news papers, ministry of health offices and the hospitals which directly record the data related to growth of pandemic on daily basis.

3.2. Sampling Technique

A non-probability purposive sampling technique used, to deliberately select participants based on specific characteristics, knowledge, or experiences relevant to the research question. This method is particularly useful when studying complex issues like the challenges of COVID-19, as it allows us to focus on individuals or groups who can provide in-depth insights into the problem. Moreover, in this purposive sampling this study focus on some target key stakeholders from the selected government sectors to address COVID-19 challenges, particularly in the Ethiopian context. Those key stakeholders are healthcare professionals, government officials, and community leaders included in our studies to gather data using our questioners attached in Appendix I.

3.3. Data Preprocessing

Once data was collected from various sources, we perform preprocessing order to manage data quality problems. For detecting data quality issues, we use statistical summary measure and visualization techniques. After detection of data quality problems, various data quality problem mitigation strategies would be applied to make the data ready for model building like handling missing values, managing outliers, removing noisy data, normalization and dealing other consistency issues.

3.4. Data Encoding

This step is required in order to prepare the data in required format by different machine learning models. The encoding of data was done into excel sheets and can be converted into csv files as per the requirement of selected machine learning models.

3.5. Descriptive Analysis of Spread of COVID-19

All of the daily level visualization and the time series data on COVID-19 of Ethiopia were available in an interactive dashboard at tableau public https://public.tableau.com/profile/dr.tilahun.melak#!/vizhome/covid19Ethiopia/EthipiaCovid19. We hoped that it would provide compiled daily level COVID-19 information and trend on and progression of the virus in various countries of the continent. The dashboard would be updated frequently until the pandemic has not been significant health threat.

3.6. Modeling

Modeling was the first step in this research. Appropriate ML models selected for the task of learning from past data and predict the spread as an outcome in the future. For each model input and output features, their scale and the nature of mapping between input and output decided. The following machine learning models have been proposed:

Univariate Time Series Models: A univariate ML Model is based on the past data taken from one variable, it learns the parameters of the model from past few instances of the data called lag. The purpose of various univariate models like AR(q), MA(q) etc.is to learn the stationary, error, random and trend components in the past observations and predict future cases based on the past data. The main models in this class we propose to implement are: Autoregressive Models with a lag value of *q steps* based on the ACF(auto-correlation function) and PACF(partial autocorrelation function) profile of the observed data.

Multivariate Time Series Models: The limitation of univariate time series models is not being able to capture the effect of different variables on a single outcome variable. In multivariate time series model, we propose to model the growth of COVID-19 as a function of various parameters including the number of existing infectious cases, number of cures per week, availability of doctors and medical staff etc. The models like ARIMA(p,d,q) and ARMA models can be used along with recurrent neural network model and vector autorgeression models for implantation of multivariate time series of COVID-19 observations.

Advanced Time Series Models: Advanced models include Models based on the hybrid statistical models for time series, Ensemble models, deep learning models for the modeling of exponential

growth of the pandemic including the effect of quantitative and qualitative factors. In this class of models we intend to integrate the clinical reasons of spread of the disease constrained under the behavioral constraints designed from the populations and situational constraints taken from the capacity and availability of the resources. However, this kind of models can learn only in case of smoothly growing functions in their basic form, but the COVID-19 problem has some of the unique features like: asymptomatic spreader can cause sudden spikes in the number of cases in an area. A complete adherence to the lockdown by population can significantly decrease the rate of growth from exponential to linear in few successive weeks. Therefore, we plan to include such kind of novel aspects in the modelling of spread equation by substituting weighted effect of these features in the model equation.

Based on the outcome of selected ML and statistical models, an appropriate response model designed for the purpose of management of the spread of disease that can be used by the teams of volunteers, university and other responding organizations.

The response models developed based on the above study shall be focused on controlling various quantities like number of new cases, mortality rate and to increase the number of cured cases. The managerial models to control the spread shall predict the necessary course of preventive actions in each scenario. This kind of model, can be developed using decision tree mechanism at the different levels of disease. Also, in order to control the mortality rates, the model shall be designed for various hospitals and isolation centers, which recommend the managerial practices learned from cases becoming negative after the necessary isolation period. Therefore, primary parameters for the control of spread and mortality of the disease across Ethiopia selected by our research are the number of cases with recent travel history, number of cases reported with unconfirmed symptoms, number of confirmed symptoms and contact tracing networks and their transformation into number of confirmed cases, available number of hospitals, beds, protection gears, number of medical staffs exposed to the disease (rate of infection of medical professionals in every study area) etc. At the same time secondary variables which affect the spread and mortality rates are related to the behavior of population like: adherence of lockdown, extent of social distancing, willingness to report the individual cases in early stages, social stigma and stress during lockdown and isolation period, availability of basic information and household facilities to the general public.

Some of the primary data about the COVID-19 cases, recoveries and deaths of Ethiopia have been tried to be integrated from different sources. The data sources include: COVID-19 National Task Force, National Public Health Emergency Operation Center (NPHEC), Federal Ministry of Health (FMoH), Ethiopian Public Health Institute (EPHI), DHIS-2 based comprehensive and fully digitized database

The daily level COVID-19 global dataset has been retrieved from the day level information on covid-19 affected cases at Kaggle (https://www.kaggle.com/sudalairajkumar/novelcorona-virus-2019-dataset. Kaggle, a subsidiary of Google LLC, is an online community of data scientists and machine learning practitioners. Kaggle allows users to find and publish data sets, explore and build models in a web-based data-science environment, work with other data scientists and machine learning engineers, and enter competitions to solve data science challenges. The dataset contains three attributes; confirmed cases, recovered and deaths. The sub dataset of Ethiopia has been selected. It has been pre-processed to identify if there are missing values, outliers and noise. Tableau
(www.tableausoftware.com) public have been used for visualization and understanding of the data.

This research involves estimation and prediction of an exponentially growing pandemic in Ethiopia and compares the performance of developed models across various countries and explains why there is a difference in the number of affected people in each case. The nature of disease is to spread in space and time exponentially in absence of appropriate protective measures. Therefore, this research is a kind of longitudinal study which models the situation in the form of a time series model and tries to estimate important predictors of the spread and effect of the disease in an area. The key performance indicators for comparison of effective controlling of disease by various countries can be seen in terms of: early lockdown, home screening, quarantine facilities, infrastructure for isolation, government commitment to take issue seriously, awareness creation levels, people adherence to the standard precautions set by concerned stakeholder, religious and cultural beliefs, weather condition.
All of the daily level visualization and the time series data on COVID-19 of Ethiopia are available in an interactive dashboard at tableau public

https://public.tableau.com/profile/dr.tilahun.melak#!/vizhome/covid19Ethiopia/EthipiaCovid19. We hope that it provide compiled daily level COVID-19 information and trend on and progression of the virus in various countries of the continent. The dashboard will be updated every day until the pandemic will not be significant health threat.

Exponential smoothing have been used as major forecasting method in this study. They are relatively simple but popular due to their nature of robustness and flexibility. These methods comprise of a number of family of forecasting [1-6]. Exponential smoothing methods are based on averaging values over multiple periods in order to reduce noise and they are data driven where time series components are estimated directly from the data without a predetermined structure. The time series comprises of systematic components; level, trend and seasonality, and a non-systematic component noise. The assumption is that the systematic component can only be observable with an added noise. These components are commonly be either additive or multiplicative and with the combination a lot of different models (up to 30) can be generated [7, 8]. These are large number of models. The visualizations of the pattern of the progression of the pandemic shows no seasonal pattern. Hence, the focus of modeling has been limited to non-seasonal smoothing models.

The quality of the model has been described with forecasting accuracy metrics. The following common performance accuracy metrics have been used;

Root Mean Squared Error (RMSE): provides the mean average absolute error which is the same units as the data series.

$$\text{RMSE} = \sqrt{\frac{1}{v}\sum_{i=1}^{v} {e_t}^2} \qquad (1)$$

Where e_t is the forecast error (residual) for time period *t* and *v* is validation period

Mean Absolute Error (MAE): provides the absolute error.

$$\text{MAE} = \frac{1}{v}\sum_{i=1}^{v}|e_t| \tag{2}$$

Mean Absolute Scaled Error (MASE): measures the magnitude of the error compared to the magnitude of the error of a naive one-step ahead forecast as a ratio. A naive forecast assumes that the value today will be the same tomorrow. MASE is a normalized metrics that is defined for all values and weighs errors evenly. Hence, it can effectively be used for comparing the quality of different forecast methods. It can also be used for time series that contain zero unlike MAPE.

$$\text{MASE} = \frac{\frac{1}{v}\sum|e_t|}{\frac{1}{v-1}\sum_{i=2}^{v}|y_t - y_{t-1}|} \tag{3}$$

$y_t y_t$
Where is the actual value

Mean Absolute Percentage Error (MAPE): measures percentage of the error compared to the magnitude of the data. It is a normalised metrics which can be used to compare the quality of different models. However, MAPE has limitations such as it weights some errors more heavily than others and it is undefined for data with values of zero.

$$\text{MAPE} = \frac{1}{v}\sum_{i=1}^{v}\left|\frac{e_t}{y_t}\right| \times 100 \tag{4}$$

$$\text{MAPE} = \frac{1}{v}\sum_{i=1}^{v}\left|\frac{e_t}{y_t}\right| \times 100 \tag{4}$$

Akaike Information Criterion (AIC): penalizes complex models to prevent over fitting. Let *k* be the number of estimated parameters including initial states, and SSE, the Sum of the Squared Errors. Then

$$\text{AIC} = \text{v} * \log\left(\frac{SSE}{v}\right) + 2 * (k+1) \tag{5}$$

For all of the above equations *t* is the index of a period in a time series, *v* is time series length and e_t is the difference between the actual value y_t and the forecast value at time *t*:

With the proposed method, COVID-19 pandemic trend of Ethiopia has been forecasted. The result will be updated every ten days until such time where the pandemic is no longer a significant health threat.

3.3.1 *Long Short-Term Memory (LSTM)*

LSTM is a variation of recurrent neural networks. LSTM was created to address the vanishing gradient problem and identify long-term dependencies in a sequence without overlooking short-term trends. LSTMs may model temporal dependencies over a wider range of time periods. A hidden layer in LSTM networks is referred to as an LSTM memory cell. To avoid irrelevant perturbations from changing the memory units, LSTM cells use a multiplicative input gate to regulate the memory units. Similar to how a multiplicative output shields adjacent cells from present memory disturbances later, the LSTM memory cell receives a forget gate. With the use of this gate, LSTM may learn to erase outdated data from memory [26]. As more parameters may be learned due to the LSTM cell, long-term memory is added in a way that is even more efficient. This makes it the most effective recurrent neural network for predicting, particularly when your data show a longer-term trend.

LSTM does processing, classification, and time series-based forecasting efficiently. To resolve the long-term reliance issue, long-short-term memory is developed as an upgraded version of the recurrent neural network (RNN). The LSTM structure is arranged in a chain, just like the RNN. However, LSTM uses four interacting layers as the repeating module as opposed to a single tanh layer [27]. The structure of the LSTM's hidden layers is more intricate. Each hidden layer of the LSTM contains a gate and a memory cell. Input gate I, forget gate f, output gate o, and self-connected memory cells c make up the majority of a memory block. The activations' entry into the memory cell is managed by the input gate. The output gate gets information about what cell activations to output to the succeeding network. The forget gate assists in clearing the network's memory cells and erasing previous input data. To further enable long-term access and storage of the information by the memory cells, multiplicative gates are applied with caution. The vanishing

gradient issue can be successfully mitigated by such a structure [28]. Because of this, LSTM is an architecture that works well for issues involving long-term dependencies, as shown in Figure 3.

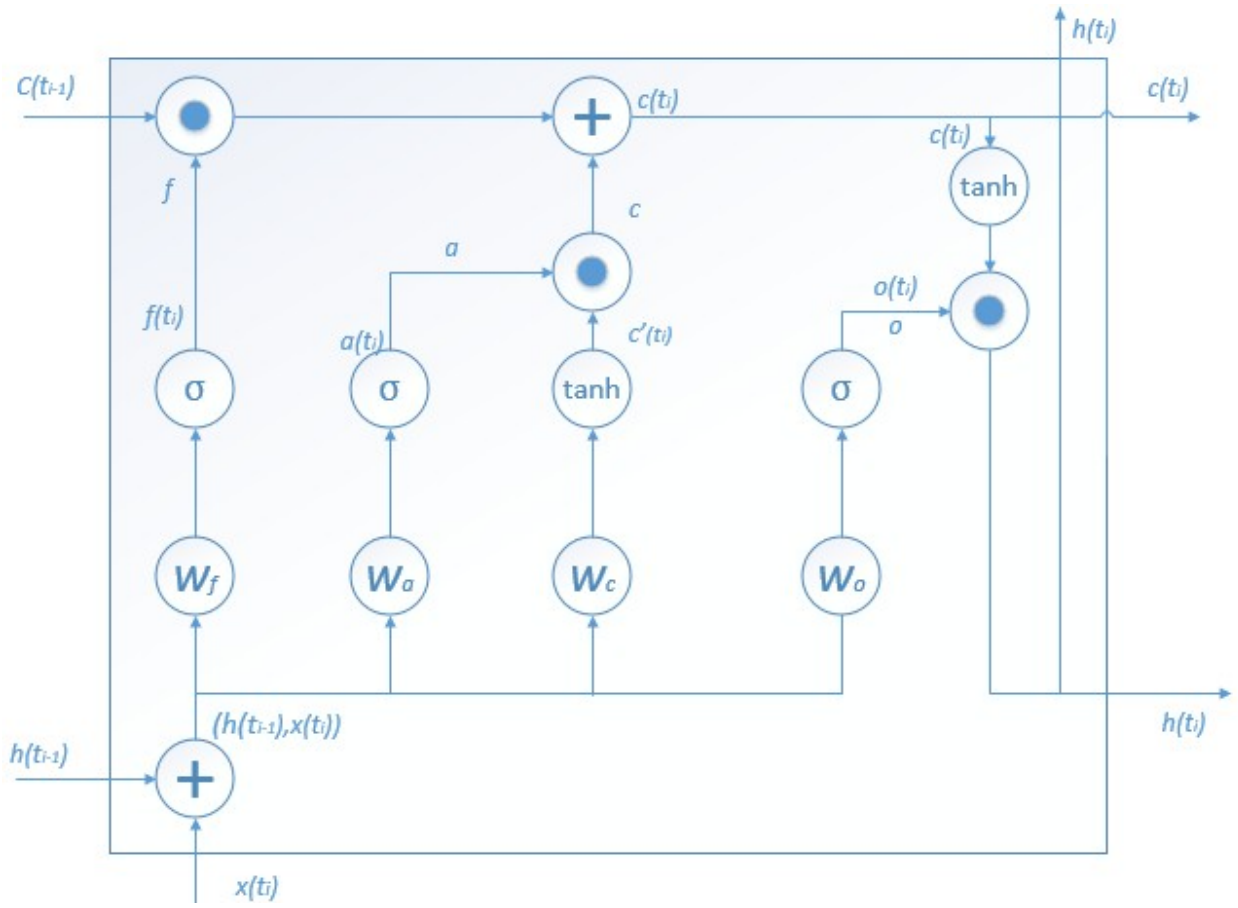


Figure 3 LSTM architecture [21]

The operation of LSTM is as follows:

The forget gate $f(t_i)f(t_i)$ uses $x(t_i)x(t_i)$ and $h(t_{i-1})h(t_{i-1})$ as input to compute the information to be preserved in $c(t_{i-1})c(t_{i-1})$ using a sigmoid activation.

The input gate $a(t_i)a(t_i)$ takes $x(t_i)x(t_i)$ and $h(t_{i-1})h(t_{i-1})$ to compute the value of $c(t_i)c(t_i)$.

The output gate $o(t_i)o(t_i)$ performs regulation on the output of LSTM cell by considering $c(t_i)$ $c(t_i)$ and applying both sigmoid and tanh layers. Mathematically, the forward learning of the LSTM is as follows:

$$a(t_i) = \sigma(w_a x(t_i) + w_{ha} h(t_{i-1}) + b_a) a(t_i) = \sigma(w_a x(t_i) + w_{ha} h(t_{i-1}) + b_a)$$

(4)

$$f(t_i) = \sigma(w_f x(t_i) + w_{hf} h(t_{i-1}) + b_f) f(t_i) = \sigma(w_f x(t_i) + w_{hf} h(t_{i-1}) + b_f)$$

(5)

$$c(t_i) = f_t X c(t_{i-1}) + a_t X tanh(w_c x(t_i) + w_{hc}(h(t_{i-1}) + b_c))$$
$$c(t_i) = f_t X c(t_{i-1}) + a_t X tanh(w_c x(t_i) + w_{hc}(h(t_{i-1}) + b_c)) \quad \textbf{(6)}$$

$$o(t_i) = \sigma(w_o x(t_i) + w_{ho} h(t_{i-1}) + b_o) o(t_i) = \sigma(w_o x(t_i) + w_{ho} h(t_{i-1}) + b_o)$$

(7)

$$h(t_i) = o(t_i) X tanh(c(t_i)) h(t_i) = o(t_i) X tanh(c(t_i)) \quad \textbf{(8)}$$

Where $x(t_i)x(t_i)$ is the input value, $h(t_i)h(t_i)$ and $h(t_{i-1})h(t_{i-1})$: the output value at time points $t_i t_i$ and $t_{i-1}t_{i-1}$, $c(t_i)c(t_i)$ and $c(t_{i-1})c(t_{i-1})$: cell state at time points $t_i t_i$ and $t_{i-1}t_{i-1}$, $\overrightarrow{W} = \{w_a, w_f, w_c, w_o\} \overrightarrow{W} = \{w_a, w_f, w_c, w_o\}$: weight matrices of input gate, forget gate, internal state and output gate and $\vec{a} = \{a(t_i), f(t_i), c(t_i), o(t_i)\} \vec{a} = \{a(t_i), f(t_i), c(t_i), o(t_i)\}$: Output results for input gate, forgate gate, internal state and output gate,

$\sigma\sigma$ and tanh are activation functions, and X indicates point-wise multiplication. Overall, the LSTM learns using the following steps: Compute the LSTM output using equations 4 to 8 (forward learning). Then, compute the error between the resulting data and the input data of each layer. The error is reversely propagated to the input gate, cell, and forget gate. Based on the error term, the weight of each gate is updated using an optimization algorithm. The above four-step processes are repeated for a given number of iterations, and the optimal values of weights and biases are obtained.

LSTM forward learning is the process of computing the LSTM output, as shown in the equations. Then the error is calculated between each layer's output data and input data. The input gate, cell, and forget gate all experience reverse propagation of the error. An optimization technique is used to

change each gate's weight based on the error term. The aforementioned procedures are repeated for a certain number of iterations in order to acquire the ideal weights and biases [29].

A lot of variants of LSTM have been used for forecasting. There are also hybrid approaches like CNN with LSTM that have been widely implemented in forecasting [30, 31, 32–34]. The combination is usually justified by aiming to utilize the feature extraction capabilities of models like CNN and LSTM's long-term dependency identification capabilities. However, the detailed study by Greff et al. indicated that variants of LSTM don't significantly improve upon the standard LSTM architecture [35]. They have carried out large-scale analysis of eight LSTM variants on three representative tasks: speech recognition, handwriting recognition, and polyphonic music modeling. Their result is an important work that shows the effectiveness of LSTM. Hence, we have used LSTM to forecast Covid 19 cases, deaths and recoveries in Ethiopia.

Hyperparameter Setting

When the model's high-level parameters are selected and set up optimally, the majority of deep learning models can perform well. Depending on the type of model being used, different configuration parameters must be set. Some deep learning configuration parameters include the number of hidden layers, the number of units in each hidden layer, the number of epochs, the loss function, the learning rate, the batch size, dropout, the type of activation functions, and Lag**.** Even though deep learning techniques show great potential for forecasting problems, their performance is highly dependent on the values of an initial set of parameters called hyperparameters [32]. This makes hyperparameter tuning a very important task and has received significant attention in deep learning-based power load forecasting. However, there are several hyperparameters that require adequate tuning to attain desirable performance. The problem can easily become an NP-hard problem. One of the approaches to tuning hyperparameters is using metaheuristic-based approaches [32, 36, 37]. In this research, we have used random search to optimize hyperparameters for LSTM because it is simple to implement and has been used effectively in previous studies [35].

Number of Hidden Layers

Neural networks are built from at least three layers: the input layer, the hidden layer, and the output layer. The number of hidden layers can be one or more. Deciding how many hidden layers to use and how many units each layer should contain is an important factor when it comes to the accuracy

of a given model. If we increase the number of hidden layers, then the neural network complexity increases. For this study, the LSTM model was set to have two hidden layers.

Number of Units

Selecting the optimal number of neurons for each layer in the LSTM network is not a straightforward task. If the number of neurons is very small, the LSTM will not be able to memorize all the necessary information to perform prediction optimally. Also, if the number of neurons is very high, the LSTM will overfit on the training instances and will not demonstrate suitable generalization to accurately forecast the test set. In the LSTM model, setting the number of units in both layers to 32 worked the best.

Number of Epochs

A single iteration over all training instances is referred to as one training epoch. Using too few numbers of epochs can cause a model to not capture enough information from the training dataset, hence leading to underfitting, and using too many numbers of epochs can cause the model to overlearn from the training dataset, hence it can't generalize to a new dataset. Therefore, finding a suitable epoch number is vital to achieving a model with high performance. The proposed model has the best performance after running 20 rounds. Hence, the selected epoch is 20.

Loss Function

Selecting the right loss function for a deep learning problem is crucial. A loss function is an object that measures how often a model makes an incorrect prediction. Loss is the prediction error of the neural net. And the method to calculate the loss is called the loss function. The loss is used to calculate the gradients. And gradients are used to update the weights of the neural net. In this study, MSE (mean squared error) is used to measure loss during model training. MSE is used for regression tasks. It is calculated by taking the mean of squared differences between actual and predicted values.

$$MSE = \frac{\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}{n} MSE = \frac{\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}{n} \quad (9)$$

Learning Rate

Learning rate is an important hyperparameter that adjusts the extent of change to the model weights. Choosing the best learning rate is essential to obtaining a model with high performance. After experimenting with various learning rates, 0.1 was found to fit the dataset well.

Batch Size

Batch size is the number of trainable instances used to train a model before updating its trainable model variables, weights and biases. In every single training step, a batch of samples is propagated through the model and then backward propagated to calculate gradients for every sample. Batch size has a critical impact on the convergence of the training process as well as on the resulting accuracy of the trained model. Typically, there is an optimal value or range of values for batch size for every neural network and dataset. Different neural networks and different datasets may have different optimal batch sizes. Two of the main potential consequences of using small or large batch sizes are generalization and convergence speed. We have to choose a batch size that will be neither too small nor too large. We needed to find one that would be optimal for the specific neural network and dataset we are using. The LSTM model worked best with a batch size of 20.

Lag

Lag is how far back a model has to look in the past to predict the present or future values. Exploring the nature of the dataset to identify areas where a strong dependency exists between the past and future data points is important for the accuracy of the model to be trained. In Figure 4, it can be seen that adjacent values in our dataset have a strong correlation.

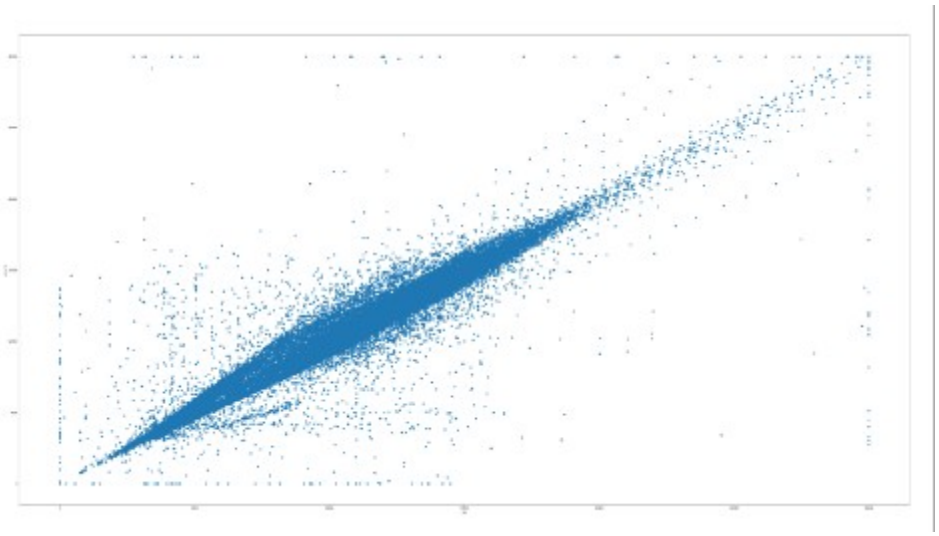


Figure 4 Lag plot, lag=1

Optimizer

Optimizers are algorithms or methods used to minimize an error function (loss function) or to maximize the efficiency of production. Optimizers are mathematical functions that are dependent on the model's learnable parameters, i.e., weights and biases. It helps to know how to change the weights and learning rates of neural networks to reduce losses. Optimizers are very crucial to increasing the accuracy of a model.

Adam: It is an optimizer that calculates the learning rate for each parameter that is shown by its developers to work well in practice and to compute favorably against other adaptive learning algorithms [38]. Adam optimization is an extension of stochastic gradient descent to update network weights during training. Adam Optimizer updates the learning rate for each network weight individually. The Adam optimizers inherit the features of both the Adagrad and RMS prop algorithms. In Adam, instead of adapting learning rates based upon the first moment (mean), as in RMS Prop, it also uses the second moment of the gradients. It means the uncentered variance by the second moment of the gradients (we don’t subtract the mean). The Adam optimizer has several benefits, due to which it was widely used and has been used in this study.

4. Results and Discussion

4.1. Descriptive Analysis of COVID-19 in Ethiopia

All of the daily visualisation and the time series data on COVID-19 of Ethiopia is available in an interactive dashboard at tableau public https://public.tableau.com/profile/dr.tilahun.melak#!/vizhome/COVID-19DashboardEthiopia/COVID-19Ethiopia?publish=yes as it has been shown on Figure 5 (accessed on February 27, 2020). The visualisation consists of two dashboards. The first dashboard shows daily level cumulative cases, total recoveries, total deaths and mortality rates. Mortality Rate% is calculated with the formula of Sum([Deaths])/sum([Confirmed]) and it has the value 1.55%. Confirmed Cases in Ethiopia has been shown in a bar chart of the dashboard. The plot of sum of Confirmed for Observation Date Day. Color shows sum of Confirmed. Size shows sum of Confirmed. The marks are labeled by sum of Confirmed. The data is filtered on Observation Date, which includes dates on or after 5/9/2020. Observation Date Day ranges from May 9, 2020 to February 27, 2021. Sum of Confirmed ranges from 210 on May 9, 2020 to 158,053 on February 27, 2021. Recoveries in Ethiopia has also been shown in a bar chart in the dashboard entitled with Recoveries. The plot of sum of Recovered for Observation Date Day. Color shows sum of Recovered. Size shows sum of Recovered. The marks are labeled by sum of Recovered. The data is filtered on Observation Date, which includes dates on or after 5/1/2020. Observation Date Day ranges from May 1, 2020 to February 27, 2021. Sum of Recovered ranges from 66 on May 9, 2020 to 134,736 on February 27, 2021. Deaths in Ethiopia has also been shown in a bar chart in the dashboard entitled with Deaths. The plot of sum of Deaths for Observation Date Day. Color shows sum of Deaths. Size shows sum of Deaths. The marks are labeled by sum of Deaths. The data is filtered on Observation Date, which includes dates on or after 5/14/2020. Observation Date Day ranges from May 14, 2020 to February 27, 2021. Sum of Deaths ranges from 5 on May 14, 2020 to 2,354 on February 27, 2021. The other dashboard shows a week ahead forecasts of COVID-19 cases, recoveries and deaths. It indicates the trend of sum of actual & forecast for Observation Date Day. Color shows details about Forecast indicator. The marks are labeled by sum of actual & forecast.

Publication of the interactive COVID-19 dashboard of Ethiopia has been started on June 07, 2020. We believe that it will provide compiled daily level COVID-19 information and

progression of the virus. The dashboard will be updated regularly until the pandemic will not be a significant public health threat to Ethiopia.

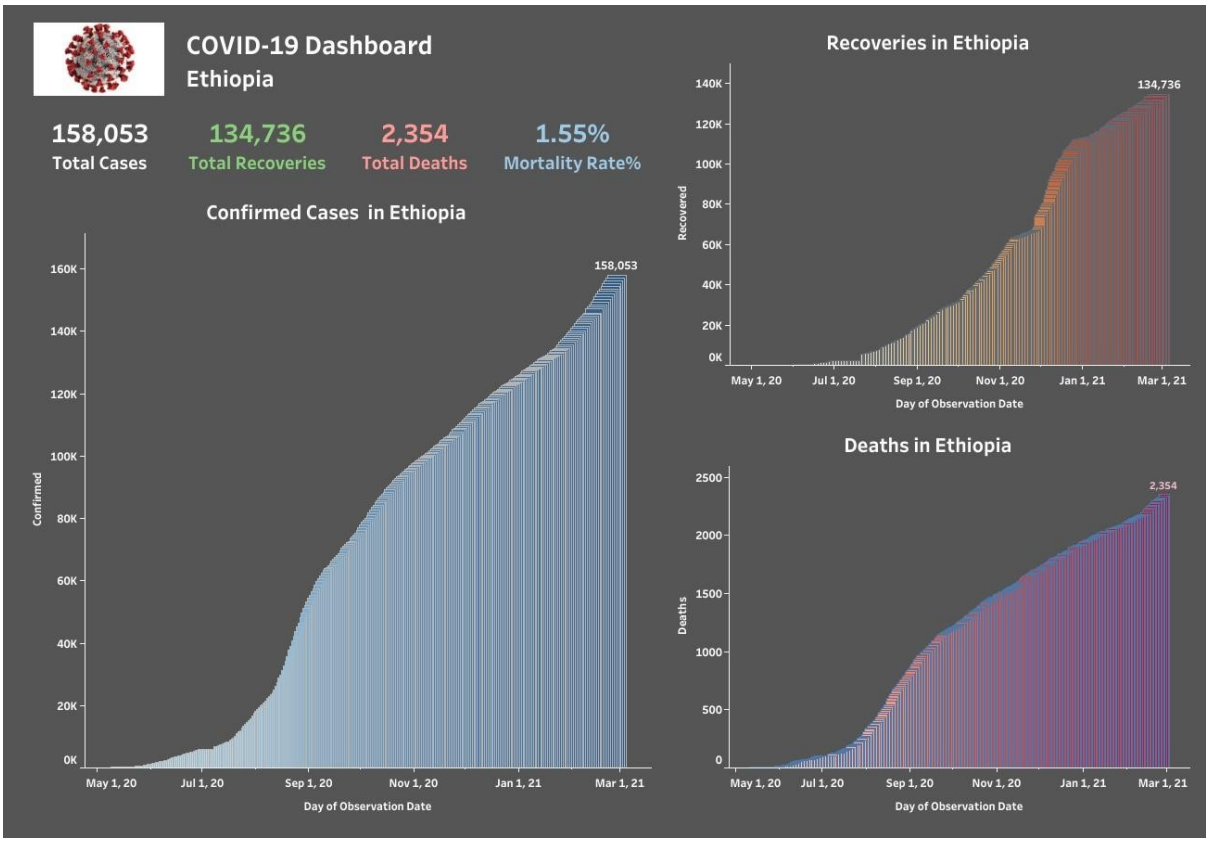


Figure 5 Ethiopia COVID-19 Dashboard (accessed on February 27, 2021)

4.2. Time Series

The time series of Ethiopia has been shown in Figure 6 (accessed on February 27, 2021). The figure shows the trend of sum of Confirmed, Recoveries and Deaths for Observation Date Day broken down by Observation Date Year. Color shows sum of Confirmed, Recoveries and Deaths.

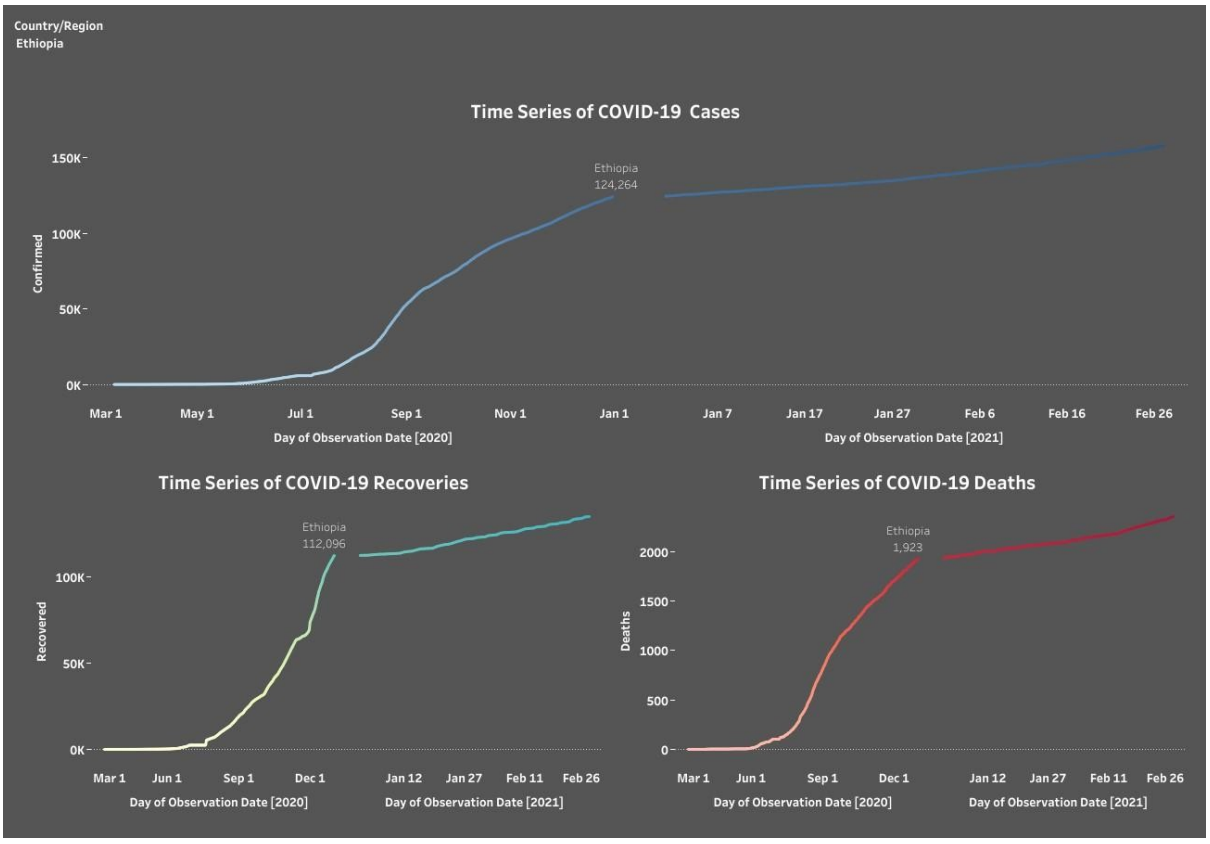


Figure 6 Ethiopia COVID-19 Time Series of Confirmed Cases, Recoveries and Deaths

4.3. Forecast

4.3.1. Exponential Smoothening

The forecasts of confirmed cases in Ethiopia with 95% prediction intervals produced on February 27, 2021 has been shown in Figure 7. All forecasts were computed using exponential smoothing. The forecast shows multiplicative level, multiplicative trend and no seasonality. The vertical axis is confirmed cases and the horizontal axis is time in exact dates. A week ahead mean estimate (point forecast) for confirmed cases was 164,228. The model, quality metrics and smoothing coefficient of the forecast has been shown in Table

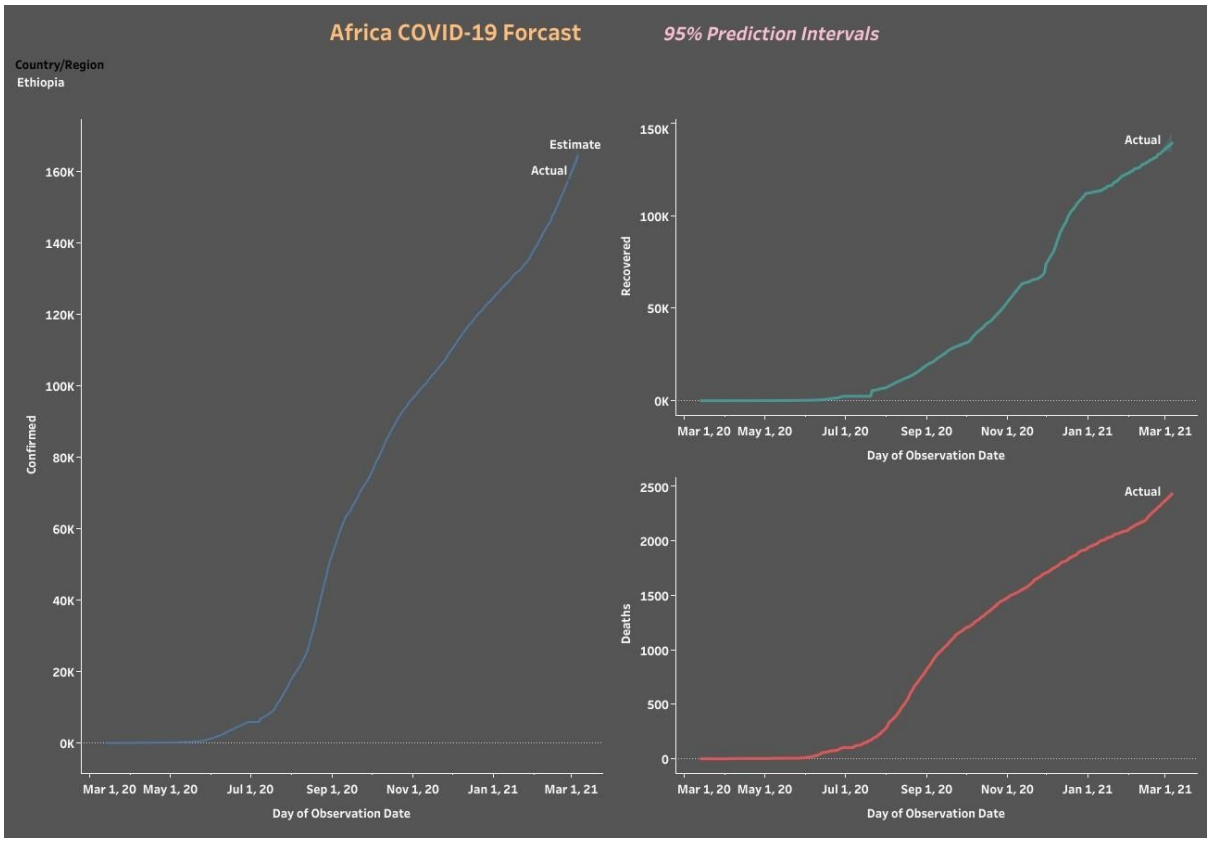


Figure 7 Ethiopia COVID-19 Time Series of Confirmed Cases, Recoveries and Deaths

Table 1 Ethiopia COVID-19 Forecast Performance of Confirmed Cases

Model			Quality Metrics					Smoothing Coefficients		
Level	Trend	Season	RMSE	MAE	MASE	MAPE	AIC	Alpha	Beta	Gamma
Multiplicative	Multiplicative	None	186	128	0.25	0.1%	1,265	0.500	0.340	0.000

Then, the forecast of the recovered cases of the Ethiopia has been computed. The forecasts of recovered cases with 95 % prediction intervals produced on February 27, 2021 has been shown in Figure 7. The forecast shows Additive level, Additive trend and no seasonality. The mean estimate (point forecast) for the recoveries was 139,363 with the 95% prediction intervals. Additionally, the model, quality metrics and smoothing coefficient of the forecast has been shown in Table 2.

Table 2 Ethiopia COVID-19 Forecast Performance of Recovered Cases

Model			Quality Metrics					Smoothing Coefficients		
Level	**Trend**	**Season**	**RMSE**	**MAE**	**MASE**	**MAPE**	**AIC**	**Alpha**	**Beta**	**Gamma**
Additive	Additive	None	641	424	0.61	0.5%	1,561	0.500	0.500	0.000

A week ahead forecast of COVID-19 related deaths of the has been computed. The forecast of deaths with 95% prediction intervals produced on February 27, 2021 has been shown in Figure 7. The forecast shows Additive level, Additive trend and no seasonality. The mean estimate (point forecast) for deaths was 2,428 with the 95% prediction. Additionally, the model, quality metrics and smoothing coefficient of the forecast has been shown in Table 3.

Table 3 Ethiopia COVID-19 Forecast Performance of Deaths

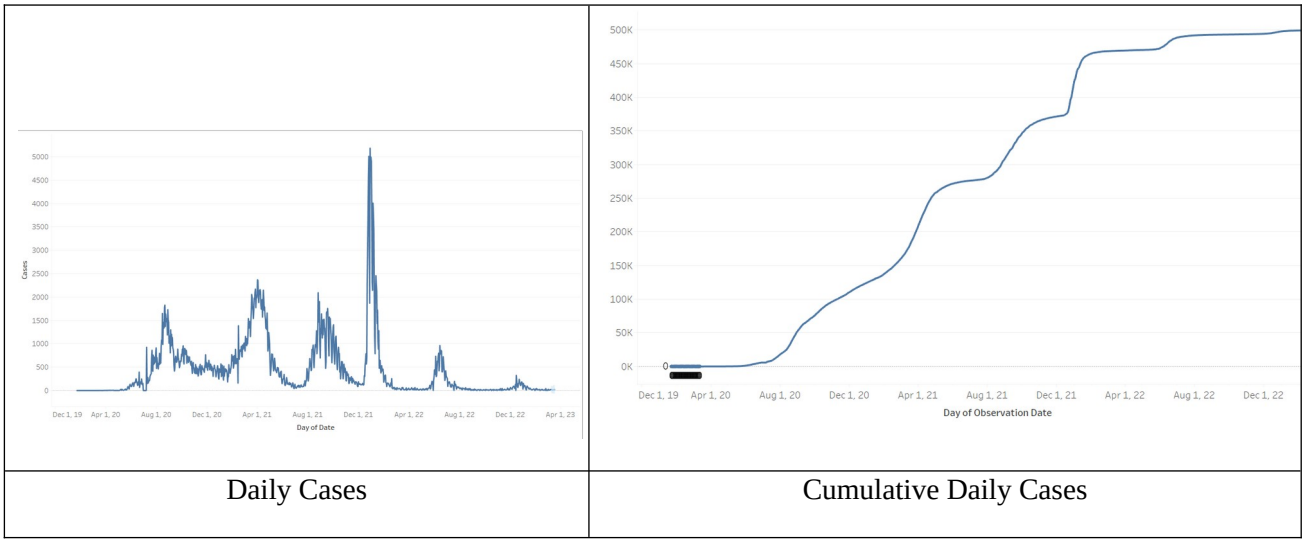
Model			Quality Metrics					Smoothing Coefficients		
Level	**Trend**	**Season**	**RMSE**	**MAE**	**MASE**	**MAPE**	**AIC**	**Alpha**	**Beta**	**Gamma**
Additive	Additive	None	5	4	0.55	0.2%	400	0.500	0.207	0.000

The last forecast was carried out for Covid-19 cases, deaths and recoveries using the dataset from January 22, 2020 – March 8, 2023. Figure shows daily cases and cumulative daily cases progression in the specified time frame. The forecasts with 95% prediction intervals produced on March 8, 2023. All forecasts were computed using exponential smoothing. The forecast shows Additive level, no trend and Additive seasonality. A week ahead mean estimate (point forecast) for confirmed cases which are not cumulative cases was 13. The model, quality metrics and smoothing coefficient of the forecast has been shown in Table 4.

Table 4 Evaluation result of Exponential Smoothening for Confirmed Cases

Model			Quality Metrics					Smoothing Coefficients		
Level	**Trend**	**Season**	**RMSE**	**MAE**	**MASE**	**MAPE**	**AIC**	**Alpha**	**Beta**	**Gamma**

Additive	None	Additive	36	22	0.25	52.3%	883	0.239	0.000	0.300



Daily Cases | Cumulative Daily Cases

Figure 8 Progression of Daily Cases and Cumulative Daily Cases

4.3.2. Deep Learning Based Covid-19 Forecasting

The predicted trends for the total number of confirmed, recovered, and deaths of COVID-19 cases in Ethiopia are discussed in this section. The selected deep learning models for forecasting is LSTM because of its ability to identify long-term dependencies in a sequence without overlooking short-term trends. The detail workflow has been shown in Figure 8. The dataset consists of three time-series data sets: cumulative confirmed cases, cumulative recovered cases, and cumulative deaths. Each of the three time-series data was forecasted by separately feeding the data into LSTM. The Covid-19 dataset has been used to experiment the stated deep learning model after preprocessing including checking the missing data points and normalization with the MinMaxScaler. Evaluation metrics MAE, RMSE, and MAPE were used to evaluate the performance of each model. The comparison results between exponential smoothening and LSTM has been performed.

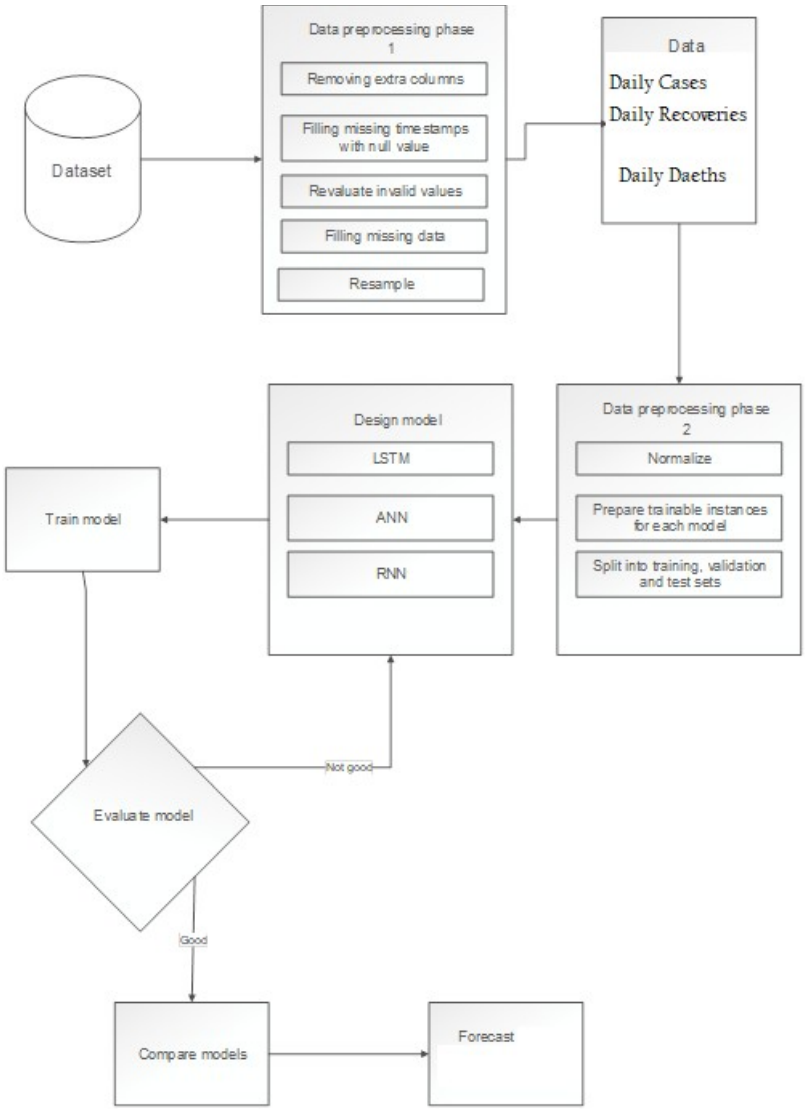


Figure 9 Deep Learning Based Forecasting

The plot of the dataset with daily cases, recoveries and deaths have been shown in Figure 9, Figure 10, and Figure 11 respectively.

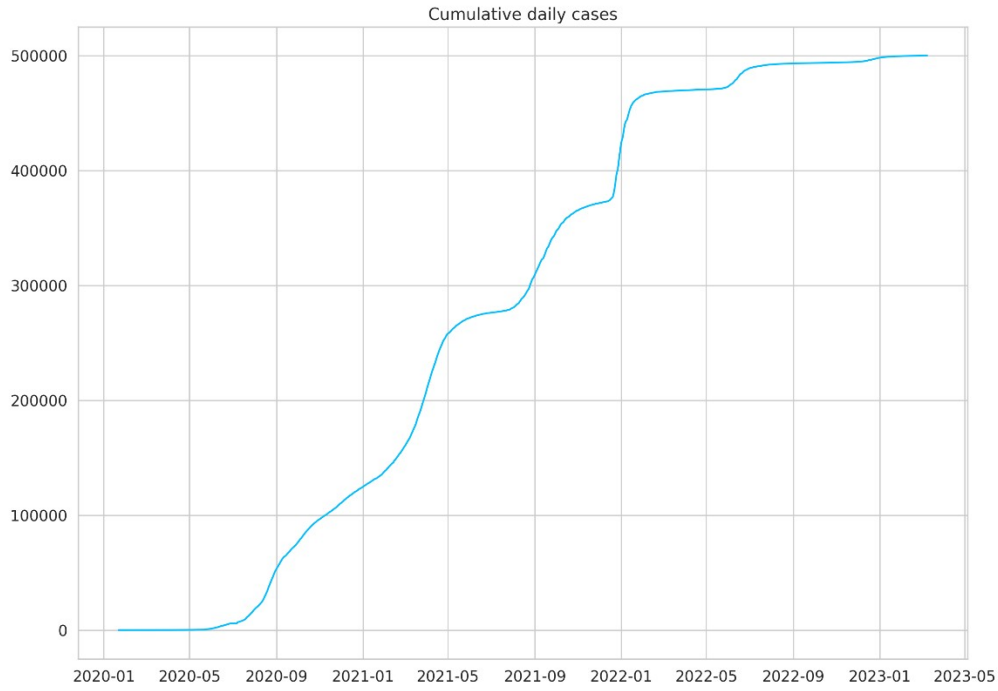


Figure 10 Cumulative Daily Cases

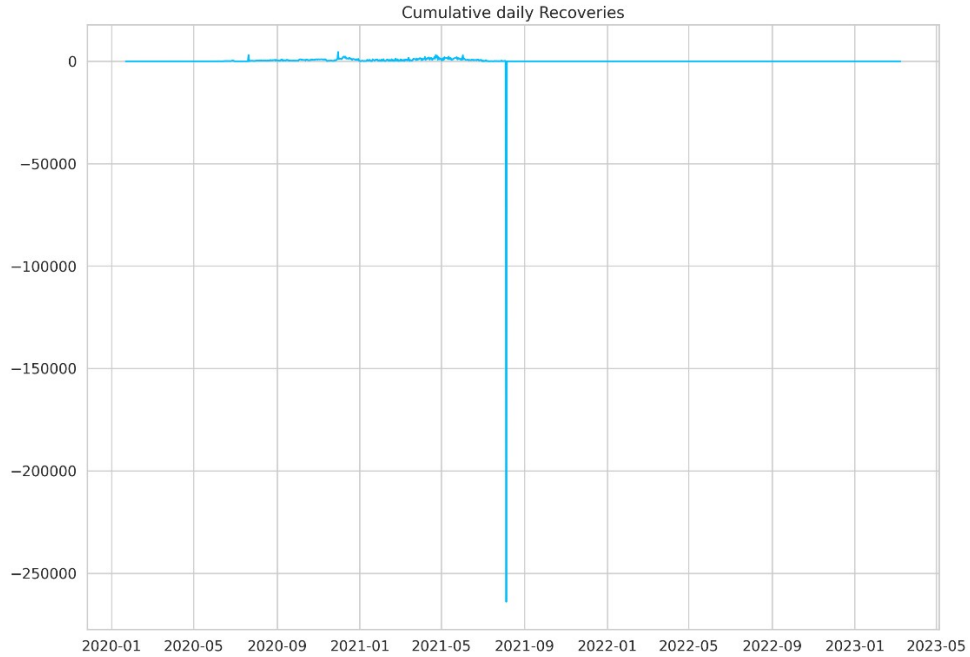


Figure 11 Cumulative Daily Recovered

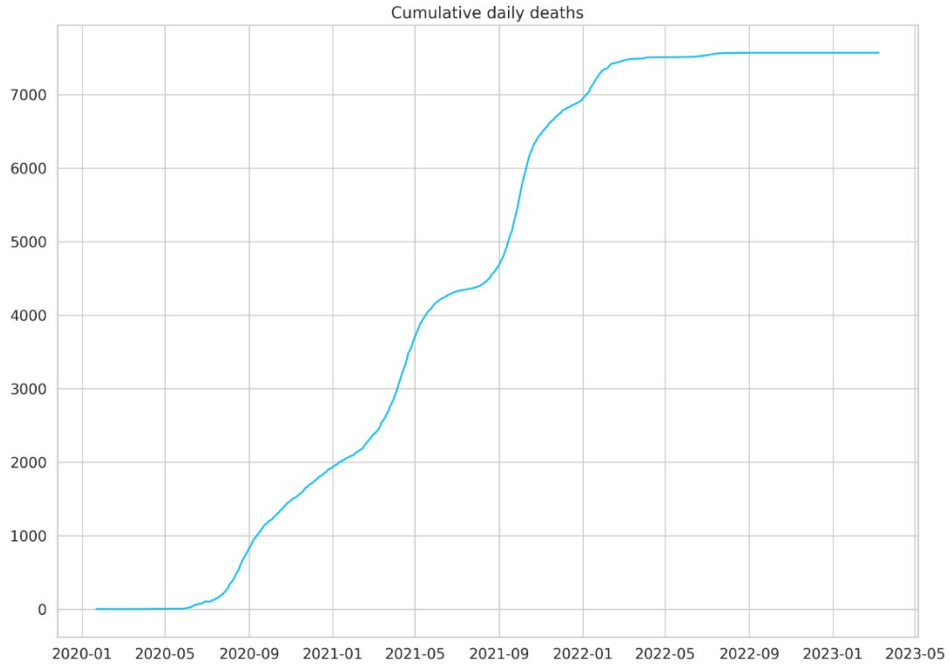


Figure 12 Cumulative Daily Deaths

The plot of the dataset with daily cases, recoveries and deaths have been shown in Figure 12, Figure 13, and Figure 14 respectively. This is not a cumulative case. When we observe the figures individually, there is spike in the middle around January, 2022 that could be due to different reason.

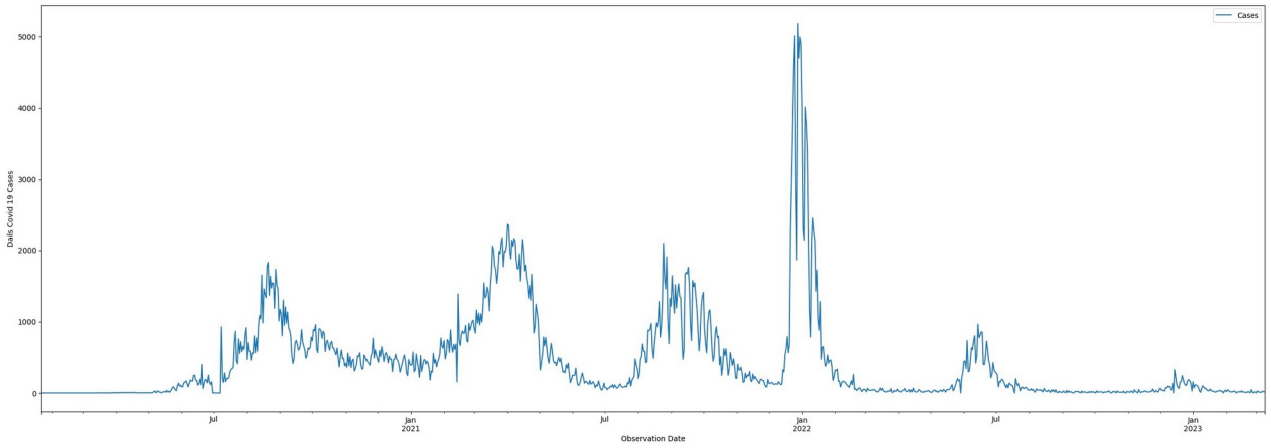


Figure 13 Daily Cases

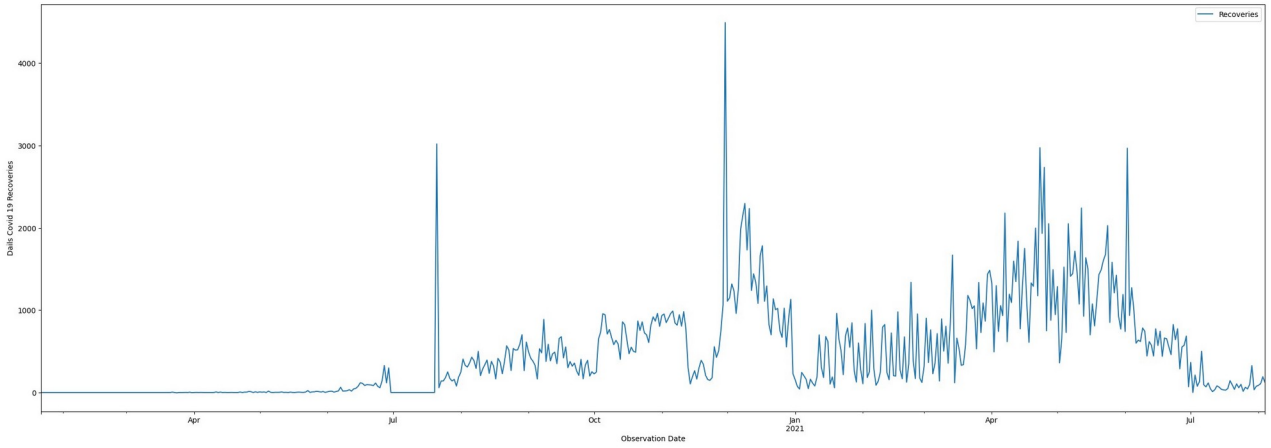


Figure 14 Daily Recoveries

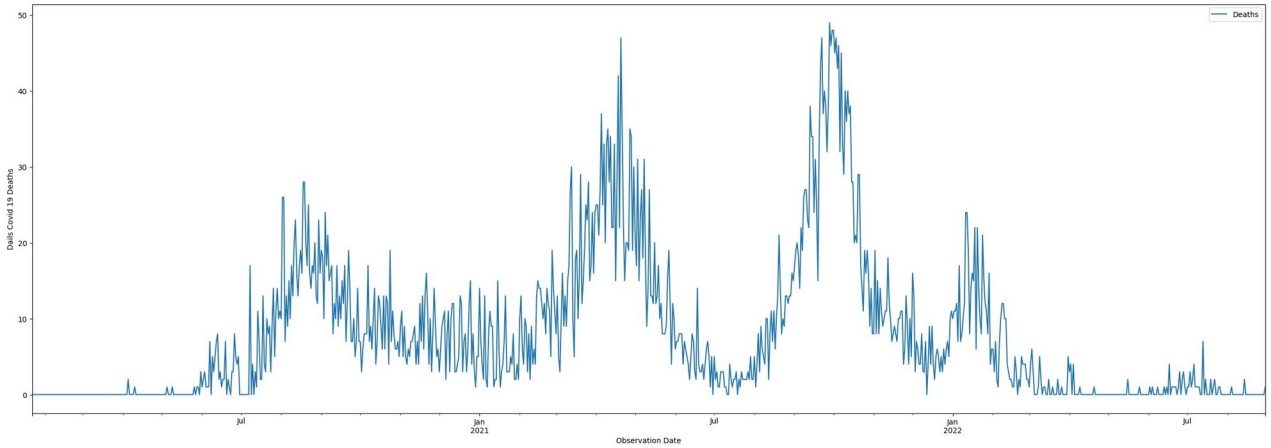


Figure 15 Daily Deaths

The dataset has been divided into three sets: training, validation and test sets. The training set is inputted to the deep learning model. The validation set has been fed into the model to optimize the parameters of the model, as it gives insight on how the model is performing on data it has not been exposed to. The test set is used for evaluating the predictive power of the built model. For training 80% of the data has been used, for validation 10% of the dataset has been used and the remaining 10% have been used for testing.

The proposed LSTM Covid-19 predictor contains three methods which are a constructor that initialize all helper data and create the layers, a reset_hidden_state that are being used to reset_hidden_state since stateless LSTM has been used and forward that get the sequences, pass all of them through the LSTM layer, at once. To obtain the forecast, we run our linear layer over the

output of the previous time step. The plot of the train and test loss have been shown in Figure 15, Figure 16, and Figure 17 respectively.

Table 5 LSTM Network Parameters and Shape

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, None, 32)	4,352
lstm_1 (LSTM)	(None, 32)	8,320
dropout (Dropout)	(None, 32)	0
dense (Dense)	(None, 1)	33

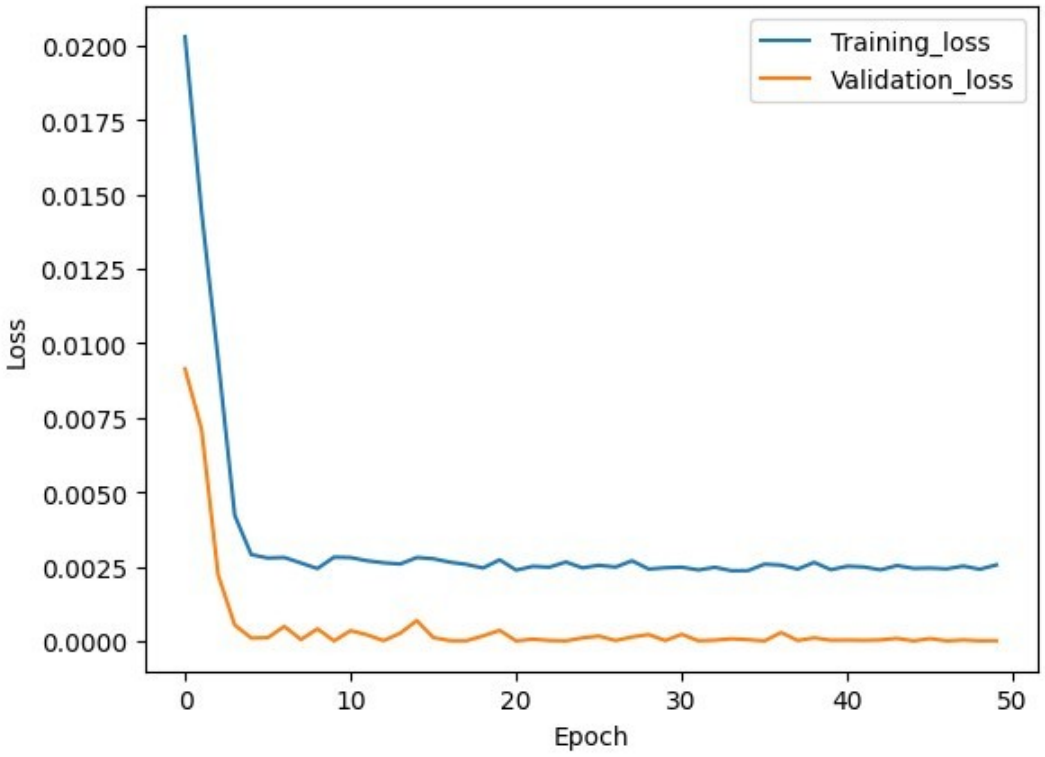


Figure 16 Loss vs. Epoch plot for Daily Cases

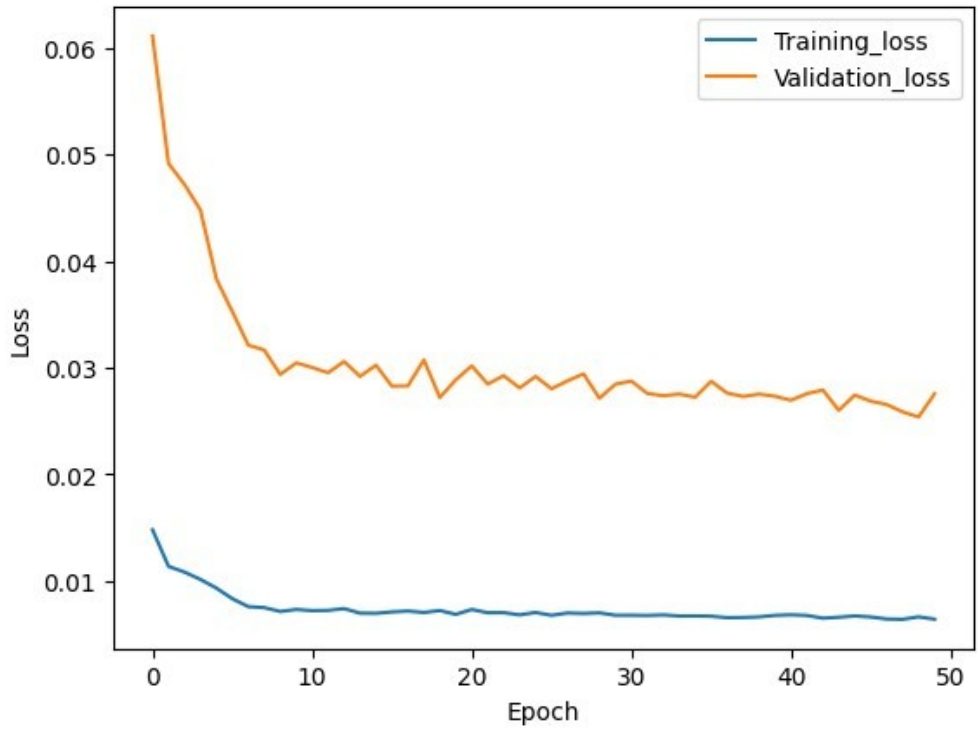


Figure 17 Loss vs. Epoch plot for Daily Recoveries

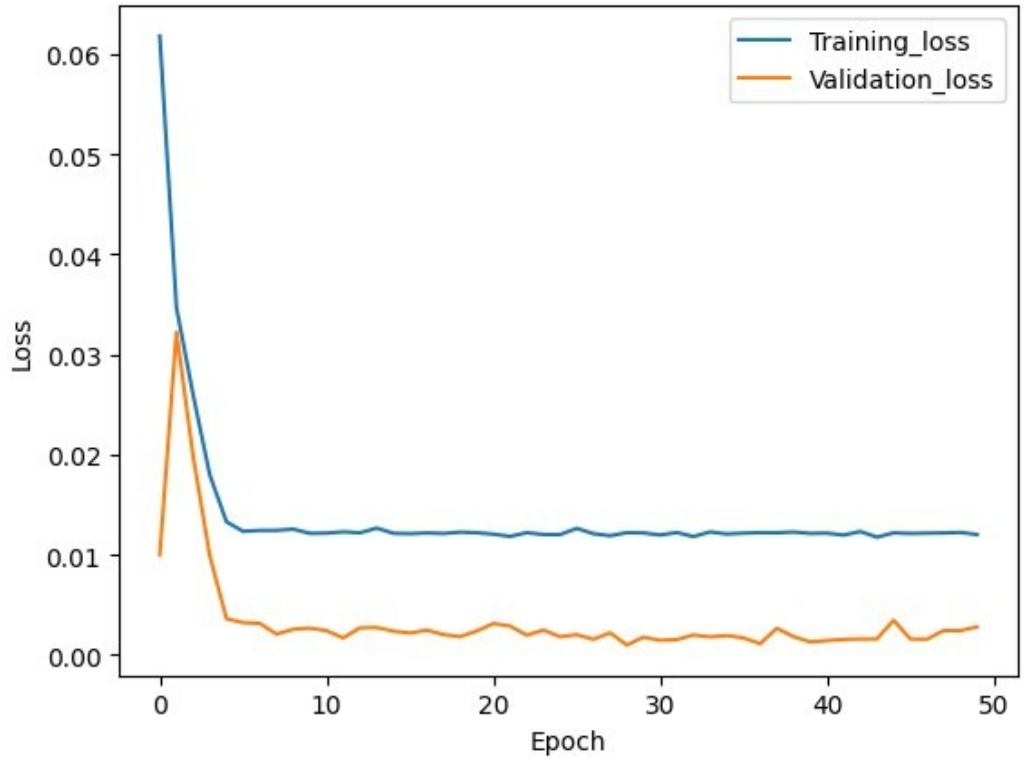


Figure 18 Loss vs. Epoch plot for Daily Deaths

From the above loss graphs, the model's performance doesn't show that of much improvement after few epochs.

Figure 19, Figure 20, Figure 21 exhibit the actual vs predicted Covid-19 for daily cases, daily recoveries and daily deaths.

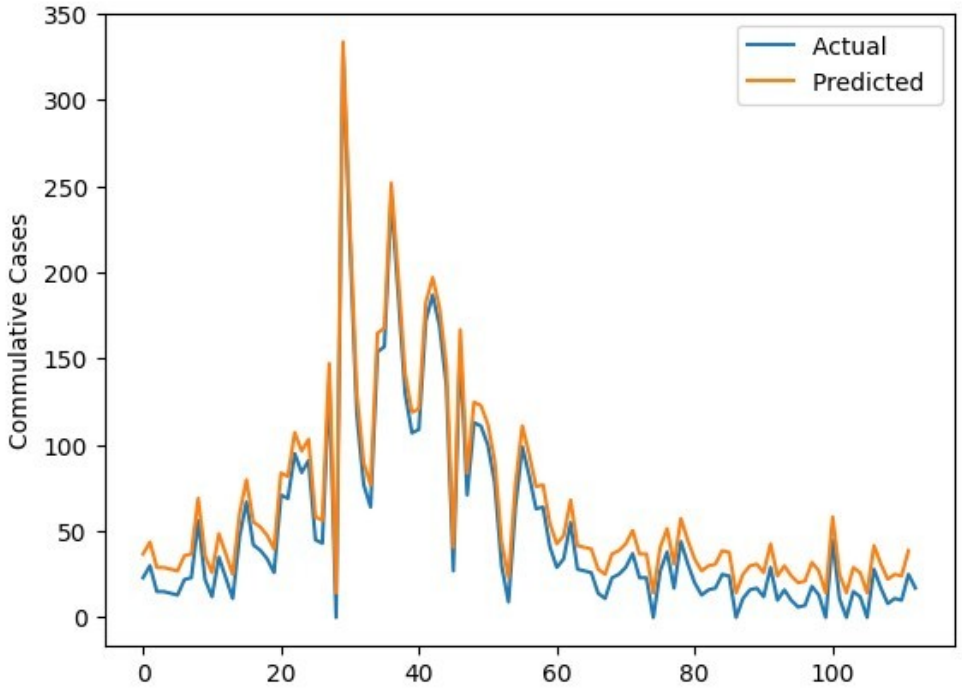


Figure 19 LSTM Model Daily Forecasted Cases vs Actual Cases

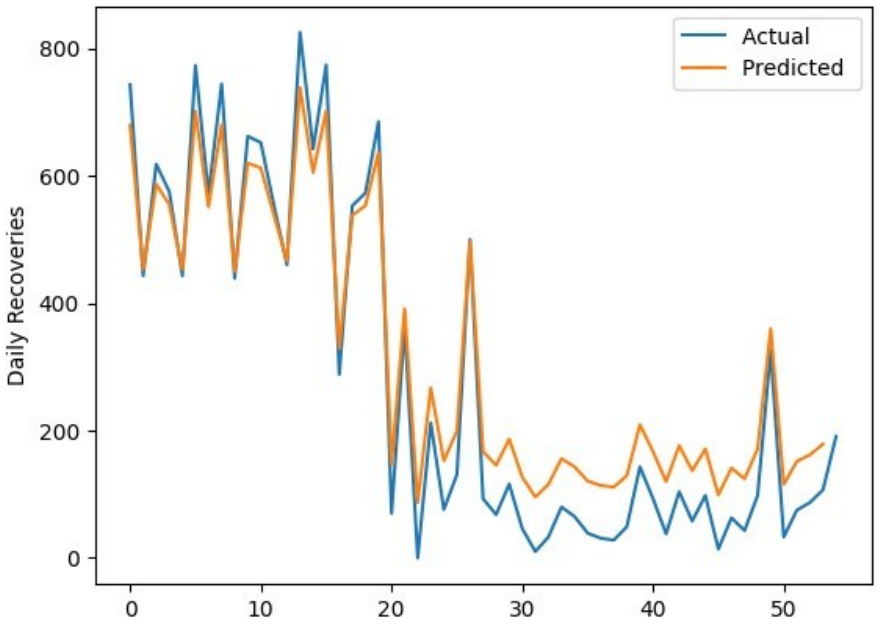


Figure 20 LSTM Model Daily Forecasted Recoveries vs Actual Recoveries

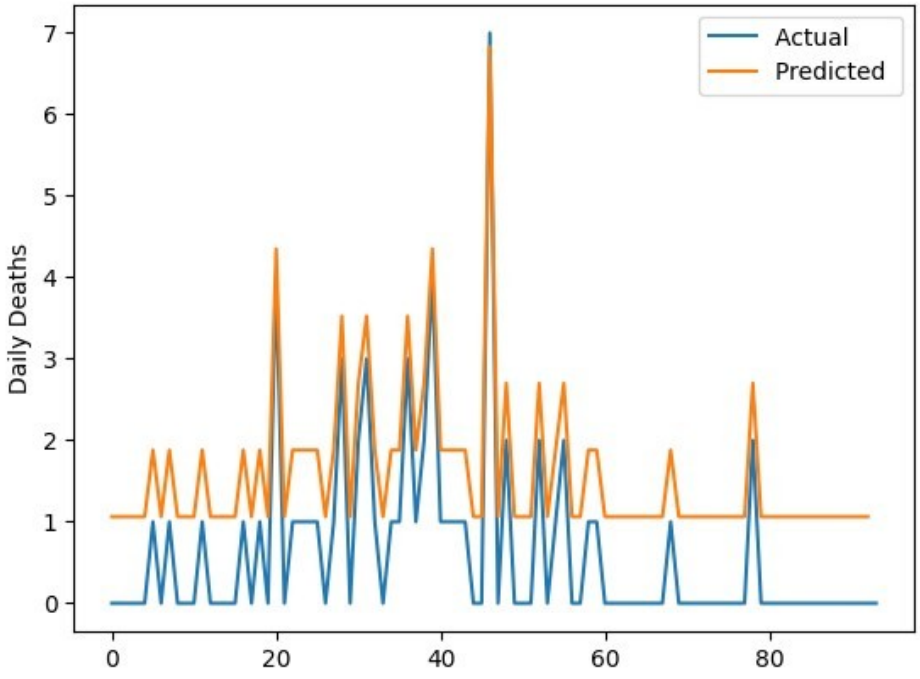


Figure 21 LSTM Model Daily Forecasted Deaths vs Actual Deaths

4.3.3. Evaluation

Visualization of important metrics, time series visualizations and forecasting of the Covid-19 in Ethiopia were being carried out continuously. The corresponding results and figures were published in real-time using tableau public. This was done with the intention of providing valuable information to timely Covid-19 response. The last forecasting has been done for Covid-19 cases, deaths and recoveries using the dataset from January 22, 2020 – March 8, 2023 with the aid of mainly two models. The first is exponential smoothing as it has been shown in the result. We found exponential smoothing models very convenient for this specific task due to their robustness and flexibility. The other model that has been used for the forecasting is LSTM which is a variation of recurrent neural networks and more appropriate because of its ability to identify long-term dependencies in a sequence without overlooking short-term trends. The performance evaluation of Covid-19 forecasting models has been done using RMSE, MSE, and MAPE. The result of performance for exponential smoothing and LSTM models in terms of RMSE and MAE for Covid-19 cases using the dataset from January 22, 2020 – March 8, 2023 is shown in the Table 4 and Table 6.

Table 6. RMSE and MAE Results of LSTM for Cases, Recoveries and Deaths

		Training	Validation	Test
Daily Cases	RMSE	55.15	13.81	13.19
	MAE	19.72	13.80	13.12
Daily Recoveries	RMSE	614.47	375.60	64.51
	MAE	94.16	289.18	58.78
Daily Deaths	RMSE	1.73	0.96	0.97
	MAE	1.22	0.92	0.95

From the performance results, it can be seen that there is LSTM is better than exponential smoothening in terms of the error values of RMSE and MAE.

5. Discussion

At the beginning of the pandemic, there were popular global alarm by a Harvard University professor who stated that 40-70% of the world population will be infected with corona virus in the coming year [61]. Chancellor Angela Merkel has also similarly warned Germany about the possible sever impact of the pandemic where 70% of the population can be infected [62]. The warnings were made at the time where we have learned little about the pandemic and it could have been unfold in various ways. We have enhanced our understanding and insight about the pandemic every single day and we have to integrate this knowledge into every single decisions that we make.

The projections about the pandemics impact on Africa are more or less related with the response and resources. A more specific insight about the impact of the pandemic can be obtained through thorough investigations on the potential association of resources with covid-19 related mortalities [63]. However, many are stating that COVID-19 will have a devastating effect on Africa unless significant interventions are being taken soon on infection prevention and control measures [64, 65]. The continent has responded by starting with the establishments of an African task force for coronavirus preparedness and response (AFTCOR) that focuses on six areas: laboratory diagnosis and subtyping; surveillance; infection prevention and control in healthcare facilities; clinical treatment of people with severe COVID-19; risk communication; and supply chain management and stockpiles [66]. Has the spread of the virus increased rapidly, many of the countries of the continent will not even afford large scale diagnosis let alone the treatment of large number of severely sick COVID-19 patients.

We believe that our limited understanding on the progression of the pandemic and not knowing about how it will unfold will worsen the situation. It is believed that the forecasting of the cumulative reported COVID-19 cases, recoveries, and deaths for African countries will significantly reduce uncertainties to all COVID-19 decision makers at all level and guide their actions. Long-short-term memory has superior performance than exponential smoothening, with a root mean squared error of 13.19 and a mean absolute percentage error of 13.12 for the daily cases forecast. The forecasting results might not be the best in terms of the major evaluation metrics but it is real time and reliable that can provide very important insights in continuous basis. Analyses in

this study provided real time forecasting that can guide Ethiopia to take the necessary measures to intervene early.

6. Conclusion

COVID-19 is caused by a new betacoronavirus related to the Middle East Respiratory Syndrome virus (MERS-CoV) and the Severe Acute Respiratory Syndrome virus (SARS-CoV). It was a global pandemic that has affected the global population by becoming a public health concern. The spread of the virus has shown very rapid growth within a couple of months and soon became a public health emergency of international concern that threaten the health and safety of global population. World Health Organization (WHO) officially declared COVID-19 as global pandemic on March 11, 2020. All countries of the world has All countries in the world have been affected by the COVID-19 outbreak. They all have responded with limited information and facing a lot of uncertainties. There were a lot of challenges including underestimation, lack of establishment of central task force, conflicting orders from different authorities, late response or void, self-medication problem, information sharing and social media, shortage of protection gear, shortage of ventilators, identification of isolation centers, social challenges, migration and workers problem and supply chain. In this research we have analyze the COVID-19 spread in Ethiopia and to be able to develop machine learning models to predict the number of cases and possible number of deaths due to aforesaid pandemic for the short term and long-term period. The objective of this research project was to investigate the spread of COVID-19 in Ethiopia and develop machine learning models that could be used to forecast, both in the short and long term, the number of cases and potential deaths associated with the pandemic. It is anticipated that the output would help managerial and administrative staff respond appropriately and on time to COVID-19 and other similar outbreaks in the future. The research team carried out a precontextual analysis and obtained the relevant data from multiple web sites in order to carry out the studies. Time series analysis approaches are used in the forecast modeling process, and world data is used to construct forecasting models for short- and long-term projections, respectively, ranging from three to ten days. The predicted trends for the total number of confirmed, recovered, and deaths of COVID-19 cases in Ethiopia have been carried out with deep learning model. LSTM have been used to conduct the forecasting. The dataset consists of three time-series data sets: cumulative confirmed cases, cumulative recovered cases, and cumulative deaths. Long-short-term memory has superior

performance than exponential smoothening, with a root mean squared error of 13.19 and a mean absolute percentage error of 13.12 for the daily cases forecast. Reports in the form of statistics of number of cases, recoveries and deaths along with progression were continuously published on the online dashboard of tableau.

For the future this study can be enhanced with more advanced deep learning algorithms to increase the model system wise performance. This study shows the need of local data management repositories and data collection strategies still needs more work. Finally, we recommend this study to provides valuable insights that can inform future preparedness and response strategies for similar global health crises.

7. References

1 National Guidelines for Clinical Management and Treatment of COVID-19 March 19, 2020, Government of Dubai.

2 Tingbo LIANG - Handbook of COVID-19 Prevention and Treatment-Zhejiang University School of Medicine (2020)

3 Department of Health and Social Care (DHSC), Public Health Wales (PHW), Public Health Agency (PHA) Northern Ireland, Health Protection Scotland (HPS), Public Health England - COVID-19_ Guidance for in

4 Prevention from Novel Coronavirus COVID-19, Saudi Gazzatte,2020

5 World Health Organization - Clinical management of severe acute respiratory infection (SARI) when COVID-19 disease is suspected_ Interim guidance V1.2 (13 March 2020)-World Health Organization (2020)

6 Team NCPERE. Vital surveillances: the epidemiological characteristics of an outbreak of 2019 novel coronavirus diseases (COVID-19) – China. China CDC Weekly. 2020;2(8):113-22.

7 Yang X, Yu Y, Xu J, Shu H, Xia J, Liu H et al. Clinical course and outcomes of critically ill patients with SARS-CoV-2 pneumonia in Wuhan, China: a single-centered, retrospective, observational study. Lancet Respir Med. 2020. Epub 2020/02/28. doi: 10.1016/S2213-2600(20)30079-5. PubMed PMID: 32105632.

8 Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y et al. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. Lancet. 2020;395(10223):497-506. Epub 2020/01/28. doi: 10.1016/S0140-6736(20)30183-5. PubMed PMID: 31986264.

9 Zhou F, Yu T, Du R, Fan G, Liu Y, Liu Z et al. Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: a retrospective study. Lancet, 2020. doi: 1016/S0140-6736(20)30566-3

10 Cheung JC, Ho LT, Cheng JV, Cham EYK, Lam KN. Staff safety during emergency airway management for COVID-19 in Hong Kong. Lancet Respir Med. 2020. Epub 2020/02/28. doi: 10.1016/S2213-2600(20)30084-9. PubMed PMID:32105633.

11 Schiavo,R.(2007) Health Communication: From Theory to Practice. USA: Jossey Bass

12 www.wikipedia.org accessed on 12 April 2020

13 https://www.worldometers.info/coronavirus/ accessed on date 13 April 2020

14 WHO, Coronavirus disease 2019 (COVID-19), situation Report – 63

15 WHO, Coronavirus disease 2019 (COVID-19), situation Report – 128

16 Zhang Z et.al. Daily Tracking and Forecasting of the Global COVID-19 Pandemic Trend Using Holt–Winters Exponential Smoothing (3/27/2020

17 Hyndman RJ, Koehler AB, Snyder RD, Grose S. A state space framework for automatic forecasting using exponential smoothing methods. International Journal of Forecasting. 2002; 18(3):439–454.

18 Taylor JW. Exponential smoothing with a damped multiplicative trend. International Journal of Forecasting. 2003; 19(4):715–725.

19 Makridakis S, Andersen A, Carbone R, Fildes R, Hibon M, Lewandowski R, et al. The accuracy of extrapolation (time series) methods: Results of a forecasting competition. Journal of Forecasting. 1982 ; 1(2):111–153.

20 Makridakis S, Hibon M. The M3-Competition: results, conclusions and implications.

21 International Journal of Forecasting. 2000; 16(4):451–476.

22 https://doi.org/10.1016/S0169-2070(00)00057-1.

23 Makridakis S, Spiliotis E, Assimakopoulos V. The M4 competition: 100,000 time series and 61 forecasting methods. International Journal of Forecasting. 2020; 36(1):54–74.

24 Forecasting: Principles and Practice by Hyndman and Athanasopoulos at www. otexts.org/fpp/7/4

25 Shmueli G. Practical Time Series Forecasting: A Hands-On Guide. CreateSpace Independent Publishing Platform.2 edition.2011:12-43

26. Lara-Benitez, M. Carranza-Garcia, J.C. Riquelme, 2021.An experimental review on deep learning architectures for time series forecasting Int. J. Neural Syst., 31 (3) (2021), 10.1142/s0129065721300011

27. Hasan-Al-Shaikh, Rahman, Md. A., & Zubair, A. (2019). Electric Load Forecasting with Hourly Precision Using Long Short-Term Memory Networks. *2019 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, 1–6. https://doi.org/10.1109/ECACE.2019.8679244

28. Jian Zheng, Cencen Xu, Ziang Zhang, & Xiaohua Li. (2017). Electric load forecasting in smart grids using Long-Short-Term-Memory based Recurrent Neural Network. *2017 51st Annual Conference on Information Sciences and Systems (CISS)*, 1–6. https://doi.org/10.1109/CISS.2017.7926112

29. Greff, K., Srivastava, R. K., Koutnik, J., Steunebrink, B. R., & Schmidhuber, J. (2017). LSTM: A Search Space Odyssey. *IEEE Transactions on Neural Networks and Learning Systems*, *28*(10), 2222–2232. https://doi.org/10.1109/TNNLS.2016.2582924
30. W. Chandramitasari, B. Kurniawan, and S. Fujimura, "Building deep neural network model for short term electricity consumption forecasting," in *Proceedings of the 2018 International Symposium on Advanced Intelligent Informatics (SAIN)*, pp. 43–48, IEEE, Yogyakarta, Indonesia, August 2018.
31. Shao, X., Kim, C.-S., & Sontakke, P. (2020). Accurate Deep Model for Electricity Consumption Forecasting Using Multi-channel and Multi-Scale Feature Fusion CNN–LSTM. *Energies*, *13*(8), 1881. https://doi.org/10.3390/en13081881
32. Bacanin, N., Jovanovic, L., Zivkovic, M., Kandasamy, V., Antonijevic, M., Deveci, M. and Strumberger, I., 2023. Multivariate energy forecasting via metaheuristic tuned long-short term memory and gated recurrent unit neural networks. *Information Sciences*, *642*, p.119122.
33. Ullah, F.U.M., Ullah, A., Khan, N., Lee, M.Y., Rho, S. and Baik, S.W., 2022. Deep learning-assisted short-term power load forecasting using deep convolutional LSTM and stacked GRU. *Complexity*, *2022*.
34. Lim, S.C., Huh, J.H., Hong, S.H., Park, C.Y. and Kim, J.C., 2022. Solar Power Forecasting Using CNN-LSTM Hybrid Model. *Energies*, *15*(21), p.8233.
35. Greff, K., Srivastava, R.K., Koutník, J., Steunebrink, B.R. and Schmidhuber, J., 2016. LSTM: A search space odyssey. *IEEE transactions on neural networks and learning systems*, *28*(10), pp.2222-2232.
36. Stoean, C., Zivkovic, M., Bozovic, A., Bacanin, N., Strulak-Wójcikiewicz, R., Antonijevic, M. and Stoean, R., 2023. Metaheuristic-Based Hyperparameter Tuning for Recurrent Deep Learning: Application to the Prediction of Solar Energy Generation. *Axioms*, *12*(3), p.266.
37. Stoean, C., Zivkovic, M., Bozovic, A., Bacanin, N., Strulak-Wójcikiewicz, R., Antonijevic, M. and Stoean, R., 2023. Metaheuristic-Based Hyperparameter Tuning for Recurrent Deep Learning: Application to the Prediction of Solar Energy Generation. *Axioms*, *12*(3), p.266.
38. Bikal Basnet. (2016). *LSTM Optimizer Choice? – Data Science & Deep Learning*. https://deepdatascience.wordpress.com/2016/11/18/which-lstm-optimizer-to-use/
39. Li Q, Guan X, Wu P, et al. Early Transmission Dynamics in Wuhan, China, of Novel Corona virus Infected Pneumonia; 2020.

40. WHO. WHO Statement Regarding Cluster of Pneumonia Cases in Wuhan, China; 2020. https://www.who.int/china/news/detail/09-01-2020-who-statement-regarding-cluster-ofpneumonia-cases-in-wuhan-china
41. The Guardian. Coronavirus is the biggest disaster for developing nations in our lifetime. http://www.msn.com/en-xl/lifestyle/coronavirus/coronavirus-is-the-biggest-disaster-for-developing-nations-in-our-lifetime/ar-BB130rH7?li=BBQbcGp&ocid=spartanntp_edu
42. Velavan TP, Meyer CG. The COVID-19 epidemic. Trop Med Int Health. 2020. DOI: https://doi.org/10.1111/tmi.13383. [PMC free article] [PubMed] *
43. Aljazeera. Senegal's $1 COVID-19 test kit and the race for a vaccine. https://www.aljazeera.com/programmes/countingthecost/2020/04/senegal-1-covid-19-test-kit-race-vaccine-200425131112353.html
44. WHO Regional Office for Africa. **WHO ramps up preparedness for novel coronavirus in the African region.** https://www.afro.who.int/news/who-ramps-preparedness-novel-coronavirus-african-region.
45. J Nkengasong. China's response to a novel coronavirus stands in stark contrast to the 2002 SARS outbreak response Nat Med (2020). ttps://doi.org/10.1038/s41591-020-0771-1
46. Bloomberg. Covid-19 Threatens to Starve Africa. https://www.bloomberg.com/opinion/articles/2020-04-27/covid-19-threatens-to-starve-africa
47. Sigfrid L, Bannister PG, Maskell K, Regmi S, Collinson S, Blackmore C, et al. Addressing political, economic, administrative, regulatory, logistical, ethical, and social challenges to clinical research responses to emerging epidemics and pandemics: a systematic review. Lancet. 2019;394:S86.
48. Janssen, M., & Van der Voort, H. (2020). Agile and adaptive governance in crisis response: Lessons from the COVID-19 pandemic. *International journal of information management*, *55*, 102180.
49. Flaxman, S., Mishra, S., Gandy, A., Unwin, H. J. T., Mellan, T. A., Coupland, H., & Bhatt, S. (2020). Estimating the effects of non-pharmaceutical interventions on COVID-19 in Europe. Nature. https://doi.org/10.1038/s41586-020-2405-7.
50. xAlTakarli, N. S. (2020). China's Response to the COVID-19 Outbreak: A Model for Epidemic Preparedness and Management. Dubai Medical Journal, 3 (2), 44–49.

51. Wu Z, McGoogan JM. Characteristics of and important lessons from the coronavirus disease 2019 (COVID-19) outbreak in China: summary of a report of 72 314 cases from the Chinese Center for Disease Control and Prevention. JAMA. 2020 Feb;323(13):1239.
52. Wu Z, McGoogan JM. Characteristics of and important lessons from the coronavirus disease 2019 (COVID-19) outbreak in China: summary of a report of 72 314 cases from the Chinese Center for Disease Control and Prevention. JAMA. 2020 Feb;323(13):1239.
53. World Health Organization. Novel Coronavirus (2019-nCoV) Situation Report - 1. 2020. Available from: https://apps.who.int/iris/ handle/10665/330760.
54. Kupferschmidt K, Cohen J. China's aggressive measures have slowed the coronavirus. They may not work in other countries. 2020. Available from: https://www.sciencemag.org/ news/2020/03/china-s-aggressive-measureshave-slowed-coronavirus-they-may-notwork-other-countries.
55. Zhu N, Zhang D, Wang W, Li X, Yang B, Song J, et al. A novel coronavirus from patients with pneumonia in China, 2019. N Engl J Med. 2020 Feb 20;382(8):727–33.
56. Lihua Z, Kun L, Yining P, Yimeng Z. Workers race against time to build 'high-speed' hospitals. China Daily. 2020. Available from: https://www.chinadailyhk.com/article/119829.
57. McNeil, D. G. Jr. (2020, March 26). The U.S. now leads the world in confirmed coronavirus cases. The New York Times. https://www.nytimes.com/2020/03/26/health/usa-coronavirus-cases. html
58. Carter, D. P., & May, P. J. (2020). Making sense of the US COVID-19 pandemic response: A policy regime perspective. *Administrative Theory & Praxis*, *42*(2), 265-277.
59. Parodi, S. M., & Liu, V. X. (2020). From containment to mitigation of COVID-19 in the US. JAMA: The Journal of the American Medical Association, 323 (15), 1441–1442. doi:10.1001/ jama.2020.3882.
60. Klaassen, N., & Van Mersbergen, S. (2020). WHO kritisch: Nederland, vaar niet blind op groepsimmuniteit. AD. Retrieved from https://www.ad.nl/binnenland/who-kritischnederland-vaar-niet-blind-op-groepsimmuniteit~a99537fa/.
61. Nash C. Mediaite. Harvard Professor Sounds Alarm on 'Likely' Coronavirus Pandemic: 40% to 70% of World Could Be Infected This Year. [https://www.mediaite.com/news/harvard-professor-sounds-alarmon- likely-coronavirus-pandemic-40-to-70-of-world-could-be-infected-this-year/] Accessed: 2020-02-18.

62. BBC News. Coronavirus: Up to 70% of Germany could become infected—Merkel [https://www.bbc.co. uk/news/world-us-canada-51835856] Accessed: 2020-03-15.

63. Ji Y,Ma Z, Peppelenbosch MP, Pan Q. Potential association between COVID-19 mortality and health-care resource availability. *Lancet Glob Health*. Published online February 25, 2020. doi:10.1016/ S2214-109X(20)30068-1

64. Velavan TP, Meyer CG. The COVID-19 epidemic. Trop Med Int Health. 2020. DOI: https://doi.org/10.1111/tmi.13383. [PMC free article] [PubMed] *

65. Bloomberg. Covid-19 Threatens to Starve Africa. https://www.bloomberg.com/opinion/articles/2020-04-27/covid-19-threatens-to-starve-africa

66. Nkengasong JN, MankoulaW. Looming threat of COVID-19 infection in Africa: act collectively, and fast. Lancet. Published online February 27, 2020. doi:10.1016/S0140-6736(20)30464-5

Appendix I

Questionnaire

To:_____

Addis Ababa

Request: To Collaborate for A Comparative Study of Administrative and Managerial Response Models for Effectively Controlling the Spread and the Aftermaths of COVID-19 Pandemic

COVID-19 is a global pandemic. World Health Organization (WHO) officially declared it as global pandemic on March 11, 2020 soon after there were over 118,000 coronavirus infections in over 110 countries and territories around the world. The aim of this research project was to analyze the COVID-19 spread in Ethiopia and to be able to develop machine learning models to predict the number of cases and possible number of deaths due to aforesaid pandemic for the short term and long-term period. The output is expected to be useful for timely and suitable response of administrative and managerial personal for COVID-19 and resembling epidemics in the future. In order to conduct the experiments, the research team has performed a pre-contextual analysis and gathered necessary data. Thank you for agreeing to participate in this research. Your voluntary participation and accurate response to questions have added value to the successful completion of this research. The information you will give will enable us to critically analyze the subject matter. Therefore, please answer all questions. Your response will be kept confidential. Thank you in advance for your kind cooperation and for sparing your precious time to respond to the questions.

Thank you in advance for your collaboration.

Instruction: Please indicate the following by ticking ✔️

Section 1: General Information

1. Name of the Organization:…….
2. What is the involvement/role of your organization in COVID-19 Pandemic? Tick everything applicable

   COVID-19 National Task Force ☐

   National Public Health Emergency Operation Center (NPHEC) ☐

   Quarantine, Isolation, and Treatment Centers ☐

   Testing laboratories and Research centers of COVID-19 ☐
3. In which one of the following responses does your organization involved

   Administrative ☐

   Managerial ☐

   Both ☐

   Others (please specify)……
4. In which one of the following responses does the institution involved? Tick everything applicable

   Communicating COVID-19 related information to the public ☐

   Communicating reports on reports on the spread of the epidemic and the statistics on the number of COVID-19 cases and deaths ☐

   Providing free, reliable COVID-19 testing ☐

   Providing special protections to vulnerable groups at higher risk ☐

   Providing personal protective equipment to healthcare workers ☐

   Others (please specify)……

Section 2: COVID-19 Preparedness and Response

1. **Did your organization develop a formal COVID-19 preparedness and response plan?**

   Yes ☐

   No ☐

   In progress ☐

2. **When was the plan first implemented?**

   _____ (Date)

3. **Who was involved in the development of the response plan? (Select all that apply)**

Ministry of Health ☐

Local government officials ☐

Public health experts ☐

Community representatives ☐

Other (please specify): _____

4. **What were the key strategies outlined in the response plan?**

Social distancing measures ☐

Quarantine and isolation protocols ☐

Testing and contact tracing ☐

Public health communication ☐

Vaccination roll-out ☐

Other (please specify): _____

Section 3: Resource Management

1. **How were medical and personal protective equipment (PPE) distributed within your region?**

Centralized distribution (by government) ☐

Decentralized distribution (by local entities) ☐

Other (please specify): _____

2. **Did you face any shortages in PPE, medical supplies, or personnel?**

Yes, PPE shortages ☐

Yes, medical supply shortages ☐

Yes, personnel shortages ☐

No shortages experienced ☐

3. **Were additional healthcare facilities set up during the pandemic?**

Yes ☐

No ☐

In progress ☐

4. **Was adequate financial support provided for COVID-19-related expenses?**

Yes ☐

No ☐

Partially ☐

Section 4: Public Health Communication

1. **How did you communicate COVID-19 related information to the public?**

   National and local TV/radio ☐

   Social media platforms ☐

   Printed materials (e.g., posters, leaflets) ☐

   Public announcements (e.g., via local authorities) ☐

   Other (please specify): _____

2. **Did you experience challenges in reaching vulnerable populations (e.g., elderly, remote communities)?**

   Yes ☐

   No ☐

   Not applicable ☐

3. **Was there public education on hygiene, social distancing, and vaccination?**

   Yes ☐

   No ☐

   Partially ☐

Section 5: COVID-19 Testing

1. **Was widespread COVID-19 testing implemented in your region?**

   Yes, for the general population ☐

   Yes, for specific high-risk groups ☐

   No ☐

2. **What were the main challenges in testing and contact tracing efforts?**

   Limited testing supplies ☐

   Delays in test results ☐

   Inadequate contact tracing resources ☐

   Public resistance to testing ☐

   Other (please specify):_____